Max-min fairness for demand side management under high RES penetration: Dealing with undefined consumer valuation functions

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Max-min Fairness for Demand Side Management Under High RES Penetration: Dealing With Undefined Consumer Valuation Functions

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***Abstract*—In energy communities with high penetration of renewables, electricity supply can become scarce during certain periods. In such cases, the objective of a resource allocation algorithm can be to minimize the disutility of the worst-off user of the community. This paper presents the problem of finding an optimal max-min fair allocation of available energy. A mixed-integer linear formulation is used to tackle the problem, so that the worst-off user's disutility is minimized. The allocation results are compared to the standard approach that optimizes the system's Social Welfare. The users' disutility function models for electricity consuming devices, are based on their time-under-unsatisfied-demand, which is a measurable and comparable metric and does not rely on the user's self reported valuation for energy consumption.**

***Index Terms*—Fairness, High RES Penetration, Energy Communities**

I. Introduction

A. Motivation and Background

Future smart grids need to accommodate the proliferation of small-scale distributed assets. In residential neighborhoods, local generation typically comes from intermittent, renewable energy sources (RES). Thus, it is mainly the demand side that offers itself for control capabilities, however, with demand side management, the comfort of consumers comes in the loop. This means that traditional optimization approaches that were applied for generators should be re-examined and re-evaluated.

Traditional power system optimization considers the objective of cost minimization given inelastic demand. The cost of energy generation can be defined fairly well, based mainly on the operational cost of the generators. However, when demand is elastic and included in the optimization, two serious complications arise. First, users' utility functions are notorious for not being well-defined. In other words, with humans in the loop, maximizing social welfare is no longer well-defined. Second, the very objective of social welfare maximization itself becomes subject to reconsideration, since there might be use cases where a different objective is more relevant.

The contribution of this paper is twofold. First, we propose novel models for the two most energy-consuming classes of residential loads, namely Thermostatically Controlled Loads (TCLs), including Air-Conditioners, Water Heaters etc., and Storage-and-Charging Loads (SCLs), including en-route charging electric vehicles, washing machines, etc. We define the user's payoff (cost) based on the time that the task of the device remains unsatisfied. Thus, we side-step the problem of defining the consumer's valuation for energy, and consider the total time under non-accomplished task as a homogeneous, comparable and well-defined cost function.

The second contribution relates to formulating and solving an optimization problem that considers the minimization of the maximum agents' cost as the objective, instead of the average/aggregated agents' cost.

B. Relevant Literature

Demand Response mechanisms have been studied extensively in the literature. The typical approach is to conceptualize a valuation function that captures the end-user's monetary value for energy, so that standard optimization approaches can be applied. Characteristic examples of such schemes include dual decomposition [1] and other types of Lagrangian relaxations (e.g. [2], [3]), while game-theoretic techniques also have their fair share [4]. However, the research community has not yet reached consensus on reliable methods for defining user valuation functions. Indicative approaches include questionnaire surveys [5], data acquisition via serious games [6] and data-driven approaches [7], while there are also voices of critique to the up to date definitions of valuation functions [8].

From the viewpoint of an aggregator or operator, user valuation functions are sometimes considered as known [9] or discovered via iterative exchange of price signals [10], and sometimes truthfully reported due to an incentive compatible mechanism [11]. However, all the above methods implicitly assume that the end-user is capable of defining his/her own valuation function, and then the problem for the aggregator or operator is reduced to discovering these functions and optimizing the social welfare.

Opting for fairness instead of social welfare maximization is a different approach. Max-min fairness is a formulation that is vastly utilized in other fields (e.g. cloud applications [12]) and is associated with various concepts such as fairness of resource allocation (i.e. minimizing the cost of the most underprivileged

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entity), robustness (i.e., solving for the worst-case scenario) towards risk [13] or towards system security [14]. In particular, within Smart Grid related research, this alternative objective has been leveraged in order to minimize the risks of medium-term [15] or long-term [16] decisions of a microgrid operator. Also, a minimax formulation has been adopted in demand side management problems where the objective is to minimize the peak-to-average ratio of electricity consumption [17], [18].

In contrast to the studies mentioned previously, in this paper the maximization of the minimax problem is not across time, but across users. The objective is to achieve a fair allocation of available resources. Max-min fairness is a widely utilized concept in resource allocation, whereas in demand side management literature, there are surprisingly few studies that consider it as a requirement. In [19], fairness is defined using the Shapley value, whereas in [20] and [21] fairness is assessed on the basis of equally distributing electricity costs among users, based on their level of effect on the community's electricity cost. In [22], a maxmin fairness algorithm is provided for a system that accepts or rejects appliance tasks depending on their priority. However, the authors based their solutions on heuristics and not on optimization techniques.

C. Contributions and Organization

In this paper, we define a cost function of a device based on the time that its task is not satisfied, so as to have a metric that is measurable and comparable across different devices. We use this cost metric to solve for a min-max fair allocation of available resources. This formulation is relevant for a number of use cases, including but not limited to:

- A local energy community that opts for a fair allocation rather than a welfare-optimizing one.
- An aggregator that wants to minimize the possibility of a user experiencing discomfort in situations where the user's utility function cannot be defined mathematically (which is typically the case with real users).
- A retailer/aggregator that wants to upgrade the worst-case performance of the resource allocation algorithm, in order to reduce the possibility of losing a client (assuming that the most unsatisfied clients churn first).

II. System Model

Given a time horizon, continuous time is divided into timeslots of equal duration in set T. We consider a set N of $|N|$ electricity consuming devices, where each device's consumption is controlled by an agent. Each agent $i \in N$, controls the device's consumption in horizon T:

$$\boldsymbol{x_i} = \{x_i^1, x_i^2, ..., x_i^{|T|}\} \tag{1}$$

We consider a setting with limited resources. An aggregator/retailer is constrained on the amount of total energy consumption:

$$\sum_{i \in N} x_i^t \leq L^t, \forall t \in T \tag{2}$$

These constraints (one per timeslot), can model different use cases, however in this paper, we consider the case where parameters L^t represent the output of intermittent generation (RES) in a microgrid, and a consumption greater than L^t would be infeasible or very expensive to serve.

Each device $i \in N$ is modeled by a set of constraints and a cost function $\theta_i(\boldsymbol{x_i})$ that captures the device's waiting time for the completion of the device's task. Subset $N_{TCL} \subset N$ contains the TCL units and subset $N_{SCL} \subset N$ contains the SCL units, where $N_{TCL} \cup N_{SCL} = N$ and $N_{TCL} \cap N_{SCL} = \emptyset$. For each family of devices, we present the models below.

A. Storage-and-Charging Loads

An SCL $i \in N_{SCL}$ is constrained by an upper and lower power consumption level:

$$x_i^{min} \leq x_i^t \leq x_i^{max} \tag{3}$$

and it cannot be charged before arrival:

$$x_i^t = 0, t < arr_i \tag{4}$$

Also, an SCL i has a certain requirement E_i for charging energy that must be fulfilled, and the State-Of-Energy (SOE), of the SCL, follows a certain transition function

$$\eta_i \sum_{t \in T} x_i^t = E_i \tag{5}$$

$$SOE_i^t = SOE_i^{t-1} + \eta_i x_i^t \tag{6}$$

where parameter η_i relates to charging efficiency. When charging at full power capacity x_i^{max}, the SCL's energy demand will be fulfilled in a total of $\lceil E_i/\eta_i x_i^{max} \rceil$ timeslots, where $\lceil \cdot \rceil$ denotes rounding to the nearest integer above. When the controlled power is generally lower than $\eta_i x_i^{max}$, the SCL will suffer an extra waiting time (beyond $\lceil E_i/\eta_i x_i^{max} \rceil$). Let the binary variable u_i^t denote whether in timeslot t, agent i still has unsatisfied demand:

$$u_i^t = \begin{cases} 1, & SOE_i^t - E_i < 0 \\ 0, & SOE_i^t - E_i \geq 0 \end{cases} \tag{7}$$

Then, the extra waiting time is defined as a function of $\boldsymbol{x_i}$, as follows:

$$\theta_{SCL}(\boldsymbol{x_i}) = \sum_{t \in T} u_i^t - \lceil E_i/\eta_i x_i^{max} \rceil - arr_i \tag{8}$$

where in order to define the net waiting time, from the total timeslots that the SCLs energy requirement was not satisfied, we subtract those that were before its arrival as well as those that the SCL would need to wait if it was charging at $\lceil E_i/\eta_i x_i^{max} \rceil$.

B. Thermostatically Controlled Loads

For TCL $j \in N_{TCL}$ let C_j^t denote the temperature measured by the TCL's sensor. The transition function of the temperature is defined as:

$$C_j^t = C_j^{t-1} + ins_j(C_{env}^t - C_j^{t-1}) + con_j x_j^{t-1} \tag{9}$$

where C^t_{env} is the environment's temperature, ins_j is a parameter related to temperature decay (e.g. insulation) and con_j is a conversion factor (from electrical power to thermal energy). Similarly to constraints (3) and (4), for TCLs we have:

$$x_j^{min} \leq x_j^t \leq x_j^{max} \tag{10}$$

$$x_j^t = 0, t < arr_j, t > dep_j \tag{11}$$

where arr_j and dep_j are the times where the TCL is turned on and off respectively.

The set points of the TCL controller are denoted as C_j^{min} for minimum comfortable temperature and C_j^{max} for maximum comfortable temperature. We assume that when the temperature C_j^t is within $[C_j^{min}, C_j^{max}]$, the demand is considered satisfied. Let u_j^t denote whether the temperature is beyond the comfort levels in a timeslot that the device is turned on:

$$u_j^t = \begin{cases} 1, & C_j^t \notin [C_j^{min}, C_j^{max}] \wedge t \in [arr_j, dep_j] \\ 0, & C_j^t \in [C_j^{min}, C_j^{max}] \vee t \notin [arr_j, dep_j] \end{cases} \tag{12}$$

The number of timeslots that the temperature preference is not satisfied is:

$$\theta_{TCL}(\boldsymbol{x_j}) = \sum_{t \in T} u_j^t \tag{13}$$

Note that the timeslots in which the TCL is turned off do not count in the devices θ.

III. Problem Formulation

We consider the problem of an Aggregator that needs to minimize the maximum waiting time across the devices in its portfolio:

$$\begin{aligned} \min_{\boldsymbol{x_n}, \forall n \in N} \max_{n \in N} & \{\theta_{f(n)}(\boldsymbol{x_n})\} \\ & s.t. (2) - (13) \end{aligned} \tag{14}$$

where

$$f(n) = \begin{cases} SCL, & n \in N_{SCL} \\ TCL, & n \in N_{TCL} \end{cases} \tag{15}$$

A. Reformulations

Problem (14) cannot be tackled directly because of constraints (7) and (12). We reformulate constraint (7) as:

$$SOE_i^t - E_i - (1 - u_i^t)M < 0 \tag{16}$$

$$SOE_i^t - E_i + u_i^t M \geq 0 \tag{17}$$

For constraint (12), we introduce auxiliary binary variables uA_j^t and uB_j^t, to denote whether the temperature of TCL j is above or below comfort limits respectively:

$$uA_j^t = \begin{cases} 1, & C_j^t > C_j^{max} \wedge t \in [arr_j, dep_j] \\ 0, & C_j^t \leq C_j^{max} \vee t \notin [arr_j, dep_j] \end{cases} \tag{18}$$

$$uB_j^t = \begin{cases} 1, & C_j^t < C_j^{min} \wedge t \in [arr_j, dep_j] \\ 0, & C_j^t \geq C_j^{min} \vee t \notin [arr_j, dep_j] \end{cases} \tag{19}$$

TABLE I: Illustrative example general parameters

t	1	2	3	4	5	6	7	8	9
L^t	4	4	2	2	2	2	2	2	2
C^t_{env}	78	78	85	85	90	100	100	90	90

Indicator constraints (18) & (19), are relaxed as in (20) - (25):

$$C_j^{max} - C_j^t + uA_j^t M \geq 0, \quad t \in [arr_j, dep_j] \tag{20}$$

$$C_j^{max} - C_j^t - (1 - uA_j^t) M \leq 0, \quad t \in [arr_j, dep_j] \tag{21}$$

$$C_j^t - C_j^{min} + uB_j^t M \geq 0, \quad t \in [arr_j, dep_j] \tag{22}$$

$$C_j^t - C_j^{min} - (1 - uB_j^t) M \leq 0, \quad t \in [arr_j, dep_j] \tag{23}$$

$$uA_j^t = 0, \quad t \notin [arr_j, dep_j] \tag{24}$$

$$uB_j^t = 0, \quad t \notin [arr_j, dep_j] \tag{25}$$

while u_j^t becomes 1, if the temperature is either above or below limits:

$$u_j^t \geq uA_j^t + uB_j^t \tag{26}$$

Finally, the min-max objective is reformulated by introducing slack variable z, and the final mixed-integer linear program, is written as:

$$\begin{aligned} & \min\{z\} \\ \text{s.t} \quad & z \geq \theta_{f(n)}(\boldsymbol{x_n}), \quad \forall n \in N \\ & (2) - (6), (8) - (11), (13), (16), (17), (20) - (26) \end{aligned} \tag{27}$$

We also formulate the standard social cost minimization objective in order to showcase the different behavior stemming from the two approaches:

$$\begin{aligned} & \min\{\sum_{n \in N} \theta_{f(n)}(\boldsymbol{x_n})\} \\ & \text{s.t}(2) - (6), (8) - (11), (13), (16), (17), (20) - (26) \end{aligned} \tag{28}$$

IV. Simulation Results

In this section we present simulation results to demonstrate the behavior of the proposed framework.

A. Illustrative example

For the purpose of demonstrating the system's behavior, we present a small example setup with 2 TCL units: $N_{TCL} = \{A, B\}$ and 4 SCLs: $N_{SCL} = \{a, b, c, d\}$. For a horizon of 9 timeslots we set the available energy and outdoor temperature (in Fahrenheit) as shown in Table I. For the two TCLs, the parameters are set as in Table II, while for the four SCLs, the parameters are shown in Table III. The TCLs initial temperature (at timeslot 1) is assumed to be equal to the environment's temperature C^1_{env} and the comfort interval $[C_i^{min}, C_i^{max}]$ was set to [73, 79].

For this example setup, Fig. 1 shows the power that each agent consumed in each timeslot. A green car signifies the arrival timeslot of an SCL. Yellow cells signify the timeslots that the SCL would need to fully satisfy its demand, if resource constraints did not apply, while an hourglass signifies a timeslot that the SCL is waiting due to resource constraints.

TABLE II: Illustrative example TCL parameters

TCL	x_j^{min}	x_j^{max}	con_j	ins_j	arr_j	dep_j
A	0	4	0.05	3.5	1	9
B	0	4	0.05	3.5	1	9

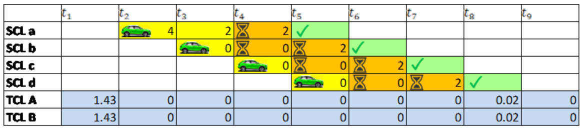

Fig. 1: Min-Max solution for the illustrative example

SCL a waits for one timeslot and the other SCLs for two timeslots. The TCLs remain within comfortable temperatures the whole time. Figure 2 shows the respective outcome of our benchmark for the same setting. The evident difference is that the Social Cost minimization approach sacrifices SCL a (with 4 waiting timeslots) for the benefit of the rest, while the Max-Min fairness approach leaves no agent waiting for long at the cost of all agents experiencing a limited delay.

The behavior of the TCLs is the same for both cases. They consume energy in timeslot 1, so as to leave room for the SCLs to consume energy in later timeslots. Their temperature across time is depicted in Fig. 3. The TCLs' temperatures in the first two timeslots would be within comfort levels (78 F) even without consuming power at timeslot 1. However, as SCLs are going to arrive in later timeslots, the TCLs bring their temperature down to the minimum level so that they will not require consuming energy at the same time with the SCLs.

B. Case Study

In this subsection we present more general results for a larger setting with parameters that are probabilistically set. A system of 70 TCLs and 30 SCLs was simulated for a horizon of 28 timeslots, where each timeslot represents a 15-minute interval ($\Delta t = 15min$). The horizon represents the interval from 05.00 in the morning, until 12.00. The average outside temperature $C_{env}^t(average)$ was assumed to follow the temperature of a typical summer day in southern Europe, starting at 78.1 degrees Fahrenheit at 05.00 and gradually reaching 97 at 12.00.

The system was simulated in a 3-GHz (24 cores) workstation (RAM: 128 GB) using Matlab 2018b. The big-M values where set as $M = |N_{SCL}| max_{i \in N_{SCL}} E_i + |N_{TCL}| max_{j \in N_{TCL}} C_j^{max}$ so as to make sure that it is always big enough to properly enforce the constraints. Solution times for one experiment under this setup were observed to be

TABLE III: Illustrative example SCL parameters

SCL	x_i^{min}	x_i^{max}	arr_i	η_i	E_i
a	0	4	2	1	8
b	0	2	3	1	2
c	0	2	4	1	2
d	0	2	5	1	2

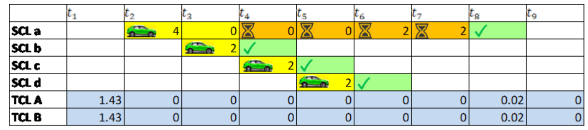

Fig. 2: Benchmark solution for the illustrative example

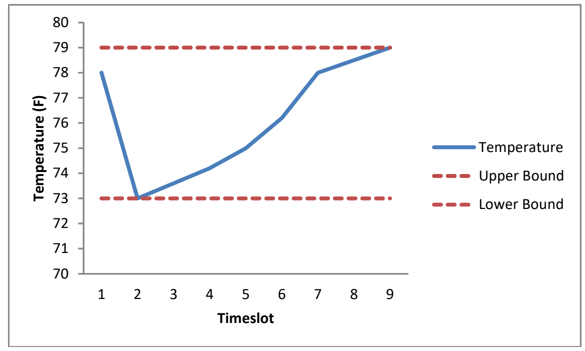

Fig. 3: Temperature of the TCLs for the illustrative example

between 1 and 7 seconds, depending also on the tightness of each problem instance.

In the experiments, the temperature of a timeslot C_{env}^t was assumed to be uniformly distributed between $C_{env}^t(average) - 2.5$ and $C_{env}^t(average) + 2.5$. Lower bounds on power consumption were set to $x_n^{min} = 0, \forall n \in N$. Upper bounds $x_i^{max}, i \in N_{SCL}$, for the power consumption of SCLs, were assumed to follow a normal distribution with an average value of $x_i^{max}(average) = 10kW$ and a standard deviation of $1kW$. The arrival times of the SCLs were set to follow a normal distribution around 7:30 (timeslot 10) in the morning (with $\sigma = 4$) in order to capture the peak of en-route charging electric vehicles on their way to work. The SCLs efficiency of charging, η_i, follows a uniform distribution between 90% and 100%, whereas the energy required E_i has an average value of $20kW\Delta t$ (which on average corresponds to two timeslots of charging at full power capacity) and a σ of 3.33.

For the TCLs, upper bounds $x_j^{max}, j \in N_{TCL}$, follow a normal distribution with average $x_j^{max}(average) = 5kW$ and standard deviation $0.5kW$. Parameter con_j was randomly sampled from the interval [3, 4], whereas parameter ins_j has an average of 0.05 and a standard deviation of 0.01. TCL loads were assumed to have an arrival peak at 08:00 with $\sigma = 4$, and staying ON for the whole horizon.

Minimum comfortable temperatures C_j^{min} were set around 72 degrees, whereas C_j^{max} were set around 80, both with a small σ of 0.5. RES production was assumed to come from solar and wind energy: $L^t = L_{solar}^t + L_{wind}^t$. Solar energy for timeslot t follows a normal distribution around $L_{solar}^t(average)$. For 12:00, parameter $L_{solar}^{28}(average)$, which is the average solar generation at time 12:00 was set to: $L_{solar}^{28}(average) = percentage \times x_{system}$, where $x_{system} = |N_{TCL}| x_j^{max}(average) + |N_{SCL}| x_i^{max}(average)$ and $percentage \in [0, 1]$. That is, the average solar generation at 12:00 was derived as a percentage of the maximum system

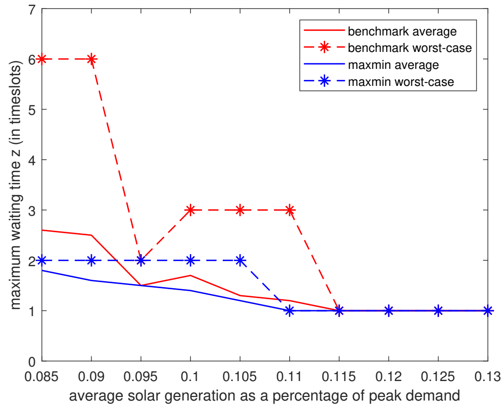

Fig. 4: Average and worst-case z for (1) and benchmark (2) as a function of $percentage$

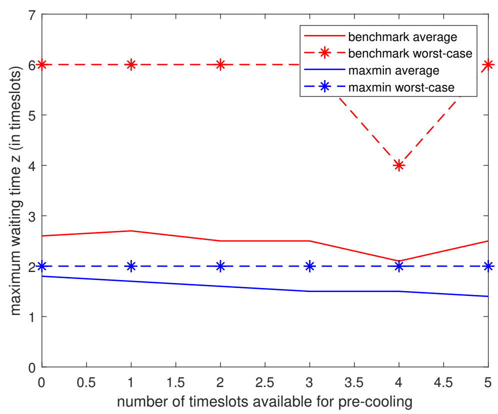

Fig. 5: Average and worst-case z for (1) and benchmark (2) as a function of t_{prec}

power consumption which would occur if all devices in N consumed simultaneously at their maximum power capacity. The earlier the timeslot, the lower the average solar generation: $L^t_{solar}(average) = L^{28}_{solar}(average) - 0.04 \times (28 - t)$.

Given these averages, the actual L^t_{solar} for the experiments was normally distributed with a standard deviation of $\sigma^t = 0.1 L^t_{solar}(average)$. Wind generation was selected to vary randomly between 0 and $0.5 L^{28}_{solar}(average)$. We present a study about the maximum waiting time z of the system for various values of $percentage$. Naturally, the lower the value of $percentage$, the more tight the scenario. A number of ten experiments were conducted for each value of $percentage$. Figure 4 depicts the averaged and the worst-case results for both algorithms (the min-max fair and the benchmark).

Next, we assume a functionality of pre-cooling the temperature of each TCL. Each TCL is able to start its power consumption, t_{prec} timeslots before arrival. More formally, (4), was generalized to:

$$x^t_j = 0, \qquad t < arr_j - t_{prec}, \quad t > dep_j \tag{29}$$

For $percentage = 0.085$, and for different values for parameter t_{prec}, the results for the maximum waiting time z are depicted in Fig. 5. Naturally, for the maxmin algorithm, z diminishes as the precooling capability grows higher. This is not necessarily the case for the benchmark, since minimizing z is not the algorithms objective.

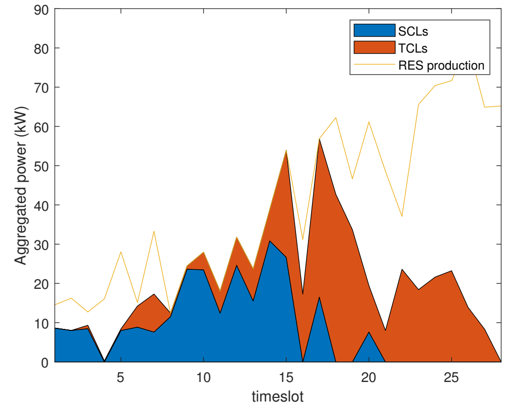

Fig. 6: Aggregated consumption profile with (1) and $t_{prec} = 0$

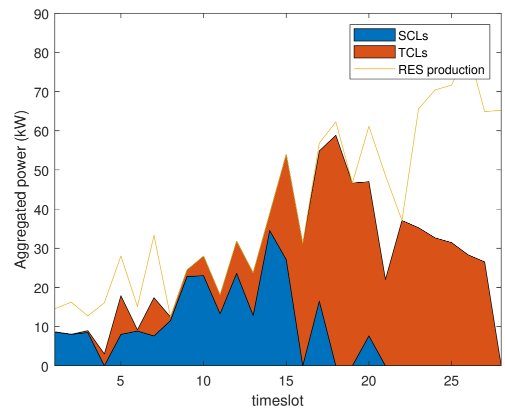

Fig. 7: Aggregated consumption profile with (2) and $t_{prec} = 0$

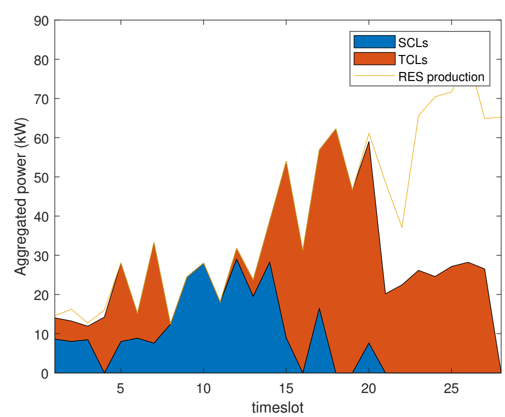

Fig. 8: Aggregated consumption profile with (1) and $t_{prec} = 5$

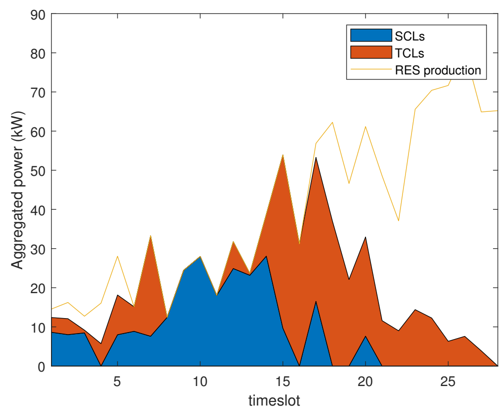

Fig. 9: Aggregated consumption profile with (2) and $t_{prec} = 5$

For $t_{prec} = 0$, the resulted aggregated profiles of power consumption for SCLs and TCLs are depicted in additive graphs together with the RES production at each timeslot. Figure 6 depicts the min-max case and Fig. 7 depicts the benchmark case. For $t_{prec} = 5$, the corresponding profiles are modified as in Figs. 8 and 9. From the figures it can be observed how in the case of the pre-cooling functionality, the TCLs move part of their load in earlier timeslots in order to facilitate the SCLs charging during peak demand timeslots.

V. Conclusions and Future Work

We considered a RES-based energy community. We formulated the min-max fair allocation problem so that the disutility of the worst-off user is minimized. We modeled the utility functions of the devices such that they do not depend on a self-reported user valuation for energy, but rather on measurable factors. The optimization problem was efficiently solved and the results demonstrate the difference in the worst-off user's utility between the proposed formulation and the standard formulation that minimizes the average user's disutility.

Future studies can extend this work in various directions. The interaction with a supplier and the wholesale electricity prices can be incorporated in the model. A decentralized optimization framework would be valuable towards preserving users' privacy, and could be configured with a pricing scheme. With respect to the ownership of RES facilities, different business models and their implications can be studied. Also, the effect of uncertainty on system parameters (e.g. RES generation) should be thoroughly studied.

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