Optimal Prosumer Scheduling in Transactive Energy Networks Based on Energy Value Signals

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***Abstract*— We present a novel fully distributed strategy for joint scheduling of consumption and trading within transactive energy networks. The aim is maximizing social welfare, which itself is redefined and adapted for peer-to-peer prosumer-based markets. In the proposed scheme, hourly energy values are calculated to coordinate the joint scheduling of consumption and trading, taking into consideration both preferences and needs of all network participants. Electricity market prices are scaled locally based on hourly energy values of each prosumer. This creates a system where energy consumption and trading are coordinated based on the value of energy use throughout the day, rather than only the market price. For each prosumer, scheduling is done by allocating load (consumption) and supply (trading) blocks, maximizing the energy value globally and locally within the network. The proposed strategy was tested using a case study of typical residential prosumers. It was shown that the proposed model could provide potential benefits for both prosumers and the grid, albeit with a user-centered, fully distributed management model which relies solely on local scheduling in transactive energy networks.**

Keywords — decentralized energy management, prosumers, transactive energy, social welfare, distributed optimization.

NOMENCLATURE

Sets

$\mathbf{A}$	Set of schedulable appliances
$\mathbf{S}$	Set of all available energy suppliers (including grid)
$\mathbf{\Psi}$	Set of all available energy suppliers - prosumers only
$\mathbb{R}$	Set of all real numbers
$\mathbb{Z}$	Set of all integers

Indices

α	Index of schedulable appliances
σ	Index of available energy suppliers (including grid)
ψ	Index of available energy suppliers - prosumers only
t	Index of time slot

Variables

A_t^α	Allocation of appliance α at time t (binary)
P_t^G	Energy price offered by the grid at time t
P_t^{IEP}	Indexed Electricity Price (IEP) at time t
ϕ_t^{IEP}	Ratio of IEP to grid price at time t
P_t^ψ	Energy price offered by prosumer ψ at time t
R	Rigidity factor for reference prosumer
κ_t^ψ	Competitiveness index of prosumer ψ at time t
γ	Scaling factor to calculate energy value
γ_b	Scaling factor to calculate energy value (base value)
μ_t^α	Preference to schedule appliance α at time t (normalized)
ζ_t^α	Energy value of appliance α at time t
τ_t^σ	Transacted energy from supplier σ for time t
ω_t^σ	Maximum transactable energy from supplier σ for time t
N_t	Number of timeslots in the decision-making horizon
N_ψ	Number of prosumers in the transactive energy network
N_α	Number of schedulable appliances for reference prosumer

I. INTRODUCTION

It is no secret that energy systems are undergoing a substantial paradigm shift, unleashing societal and economic chain reactions rivaled in magnitude by no less than those of the 18th Century industrial revolution. Three centuries and three industrial revolutions later, engineers and policymakers find themselves facing a wave of unprecedented technical breakthroughs and societal changes to which existing structures and mechanisms need to be adapted. The ability to harness and use energy has been the backbone of human development ever since discovering the controlled use of fire. With human civilization now taking a similar leap into advancing the way energy is harnessed and used, it is necessary to revisit energy quantification as a resource, and the way it is managed and traded [1], [2].

A. State-of-the-Art

The rise of "prosumers" (producers and consumers of energy, simultaneously), was driven by the many recent technological advancements for energy generation (primarily electrical) from local resources, and those to store it, both of which were seldom possible at an economically adequate level of conversion efficiency for small-scales before the current decade [3]. Simultaneously, the increased attention towards the "demand"-side by means of the development of new enabling technologies, and more importantly by the enactment of legislation to direct demand-side management (DSM) and demand response (DR) policies, has inspired the mindset of moving towards more user-centric and decentralized energy systems [4]. This was further enabled by the rise of the Internet of Things (IoT), and strengthened information infrastructures which allow for real-time communication, data analysis, and decision-making to take place in modern smart grids [5]. The most pressing issue is adapting existing structures and frameworks to this proliferation of small-scale resources. This gives more power to prosumers, dismantling established structures of energy markets, especially with regards to the relationship between the grid and the prosumer sides [6].

With prosumer-centered energy trading emerging as a disruptive scenario, there is little literature available with concrete solutions to this paradigm shift. Most offered solutions are based on traditional approaches such as the Feed-in-Tariff (FiT) or Energy Premiums (EP). These models are vastly outdated and were initially meant as incentives in the early days of distributed energy resources (DER) penetration, and never meant as a permanent approach upon which new management tools are to be developed [3], [7]. The proposed solutions so far can be said to exist between two extremes.

The first, more outdated, extreme is where prosumers with installed local generation either store any surplus generation or feed it into the grid, either for no payment at all (especially in the case of EPs or DER-subsidy programs) or in exchange for a flat-rate (the case of FiT). In all cases, this class of solutions is economically unfair for the prosumers as they are seldom compensated for services they provide to the grid [6].

The other, recently more popular, extreme is referred to as net-metering (NM) in which the grid pays prosumers the full grid price for feeding-in their surplus generation, acting as their "battery" [8]. This approach is inherently interlinked with the implementation of price-based DR programs, particularly real-time pricing (RTP), which is the only current framework of establishing a link between market conditions and the prosumers [9].

Many DR programs are already implemented in different markets around the world. Although DR was not originally established for this purpose, it can temporarily suffice as a way of managing this sudden proliferation of prosumers in order to ensure an economic benefit for both sides. Moreover, almost all currently implemented DR programs are based on centralized or hierarchical structures in which the grid-side operator is in control [4], [7], [10]. However, a shift towards more user-centric systems with fully distributed management is inevitable in case of prosumer-dominated energy networks. As such, the use of DR as a temporary solution will have to be replaced soon by a more permanent energy management framework. One solution rapidly gaining interest is peer-to-peer trading, which is now enabled by distributed ledger and optimization technologies [6], [11]–[13].

B. Contributions

In this study we propose and test a novel framework for distributed management of transactive energy networks. Rather than minimizing energy costs as traditional models do, in this case we maximize energy value which we propose as a new way of quantifying social welfare for prosumer networks.

The proposed framework is fully distributed, in which only local computation is needed and no private data exchange between the prosumers is required to achieve coordinated scheduling of consumption and trading.

C. Paper Organization

The remainder of this manuscript is organized as follows: Section II presents the methodology and formulation of the proposed model. First, traditional models of quantifying social welfare in power systems are defined (II.A), followed by a discussion of the concept in the case of prosumers (II.B). Energy value signals are then proposed as an alternative quantification thereof (III.B), and their use in the proposed distributed scheduling model is presented (IV.B). In Section III, a case study is demonstrated to test this model. In Section IV, the results are shown along with a discussion of the proposed model's effectiveness. Finally, Section V presents the conclusions of this study in addition to future work.

II. Methodology and Formulation

Being inherently a "social" concept, it is important to re-establish the underlying definition of social welfare before proceeding to quantify it mathematically or incorporate it in any model. The Oxford dictionary defines social welfare as:

"The well-being of a community or society, especially with regard to health and economic matters" [14]

From there, the concept is extended to the definition used in the domain of economics:

"The well-being of the entire society. Social welfare is not the same as standard of living but is more concerned with the quality of life." [15]

Here we can establish that social welfare emphasizes the way in which resources are allocated and used within a society, i.e. quality, rather than the collective availability or cost of this resource i.e., quantity or total standard of living. This is important to establish before proceeding to mathematically modeling and quantifying social welfare for application in the context of electrical power systems.

A. Status-Quo of Social Welfare Models

In power systems scientific research, a vast majority of the literature uses the Bergson-Samuelson function [16] (or an adaptation thereof) to quantify social welfare [17]–[19]. In this model, a number of individuals in a society ($i=1,2,\ldots,n$) require some commodity (x) which is allocated in different amounts to each of them (x_i). The desire or need of each individual to this utility (i.e., how much they would be willing to pay for every additional unit of this utility) can be expressed using a utility function for each individual and their allocation: $u_i(x_i)$. The opposite applies for the supplier of a utility: the utility function in this case represents how much it would cost for them to generate an additional unit of the commodity (in this case the value is negative) The Bergson–Samuelson model thereby defines social welfare as a function of all individual utility functions in the society: [16]

$$W_{BS} = f\big(u_1(x_1),\, u_2(x_2), \ldots u_n(x_n)\big) \tag{1}$$

This general definition was adapted for double-sided bidding competitive electricity markets by the majority of literature, to obtain the form shown in Eq. (2).

$$W_{BS} = \sum_i U_i\big(Q_2(i)\big) - \sum_j C_j\big(Q_0(j)\big) - C_T \tag{2}$$

In this case, the social welfare function represents the sum of utility functions of consumers and generators of energy, in addition to the transmission and/or grid costs (C_T). The benefit of a consumer to use purchased energy is incorporated by means of their utility function. [16]

B. Social Welfare of Prosumers

It is clear that the existing approach of quantifying this benefit of energy use does not apply to the newly emerging paradigm of prosumer-based transactive energy networks. First, in this paradigm, there is no clear distinction between the supply and demand sides in the same manner quantified by the utility functions.

Secondly, a prosumer's benefit of using energy may not always depend only on their desire to use their loads/appliances, but may depend also on current market conditions which may make it more profitable for them to transact their generated energy rather than use it, or vice versa.

C. Energy Value Signals

Consider a residential prosumer that has a varying number of schedulable appliances α_i. These loads are scheduled for different timeslots t of each day. The scheduling of the appliances can be mathematically represented by means of an allocation matrix A, described as follows:

$$A_t^\alpha \coloneqq A(t,\alpha) = \begin{cases} 1, & \text{if } \alpha \text{ is on in } t. \\ 0, & \text{if } \alpha \text{ is off in } t. \end{cases} \tag{3}$$

Based on their preferences, the prosumer can control an energy value signal for each load, which reflects the value of allocating energy consumption to this load during various timeslots of the day. In our proposed model, we define this energy value signal, ζ, as follows:

$$\zeta_t^\alpha = \mu_t^\alpha \cdot \gamma + P_t^G \tag{4}$$

In this case, the prosumer's value of allocating energy to an appliance α during timeslot t is obtained by scaling the current price of electricity from the grid (P_t^G) by means of a user-defined preference of (μ_t^α) and a rigidity factor R. The energy value matrix can then be compiled as follows, with the same dimensions as the allocation matrix.

$$\mathrm{Z}_{t,\alpha} \coloneqq \mathrm{Z}(t,\alpha) = \zeta_t^\alpha \tag{5}$$

The preference μ_t^α is defined as a real number between zero and one:

$$\mu_t^\alpha \in \mathbb{R} \cap [0,1] \tag{6}$$

The rigidity R is defined as an integer between one and a maximum value of R_{max}:

$$R \in \mathbb{Z} \cap [1, R_{max}] : 2 < R_{max} \tag{7}$$

This rigidity factor determines a prosumer's flexibility to allocate a load to different hours. A scaling factor is then used:

$$\gamma = f(\gamma_b, R, P_t^G) \coloneqq \frac{(R-1)}{(R_{max}-1)} \cdot \gamma_b \cdot P_t^G \tag{8}$$

On the other hand, the total energy supply available throughout the day consists of contracted power the grid and all prosumers making offers for the decision-making window:

$$\sigma \in \mathrm{S} = \{G, \Psi\} \tag{9}$$

And the set of prosumers is defined accordingly:

$$\psi \in \Psi = \{\psi_1, \psi_2, \dots, \psi_{N_\psi}\} \tag{10}$$

Each prosumer offers a price to supply electricity for every hour. In our proposed framework, this price needs to be less than the grid price, but also higher than the price to feed-in to the grid. Operating between both extremes of FiT and NM, we choose a more moderate indexed electricity price (IEP).

$$P_t^\psi = \kappa_t^\psi \cdot P_t^G \tag{11}$$

The competitiveness coefficient κ reflects the "greediness" of each prosumer when making their offers. I.e., the higher the offer, the greater the profit made by this prosumer albeit with a greater risk of not selling their energy due to better offers. This value drives the competitiveness between prosumers in the proposed transactive energy market model.

$$\kappa_t^\psi \in \mathbb{R} \cap (\phi_t^{IEP}, 1) \tag{12}$$

This limitation is based on the IEP as a fraction of the grid price. In this sense, if the competitiveness of a prosumer is too high and fails to transact their energy offer, the alternative is feeding their surplus energy to the upper level of the grid.

$$\phi_t^{IEP} = \frac{P_t^{IEP}}{P_t^G} \tag{13}$$

Looking back to the reference prosumer, the amount of energy transacted from a supplier (prosumer or the grid) is expressed as:

$$\tau_t^\sigma \in \mathbb{R} \cap [0, \omega_t^\sigma] \tag{14}$$

As such, partial transactions from each supplier can be made with a maximum amount equal to the offered quantity ω_t^σ from that prosumer for that timeslot.

An important aspect of this model is that the reference prosumer enters the market themselves by making energy offers from locally generated energy. The self-consumption of the prosumer is thereby a result of them self-transacting the energy. I.e., there is no discrimination between the prosumers offering energy supply in the scheduling model; it is only based on the offered prices for each timeslot.

D. *Prosumption Scheduling*

With all relevant definitions now established, it is possible to implement a tool for coordinated scheduling between energy consumption and trading scheduling which can be summarized in threes steps as follows:

Step 1: Sort incoming offers from suppliers in ascending order of cost for each timeslot.

Step 2: Schedule consumption blocks based on defined energy value of each block for each timeslot, such that the maximum energy value is achieved for the day, constrained by the maximum available power supply.

Step 3: Transact energy from suppliers in descending order of cost based on calculated consumption schedule.

III. Case Study and Analysis

To demonstrate the proposed framework, we consider a typical household with the schedulable loads listed in Table I. The scheduling is performed for a 24-hour-ahead period with hourly timeslots for energy consumption and transaction scheduling. In Figure 1, the total available energy offered from the grid or prosumers for each hour is shown. The prosumer is assumed to have a contracted power of 10.35 kWh with the grid, which sets their maximum hourly load. The green bars show the energy offers made from different prosumers connected to the transactive energy network for this decision-making horizon.

TABLE I. Schulable loads in the reference prosumer's residential household.

α - Load Description	***Consumption (kW)***	***Duration (h)***
α_1 - Space Heaters	3.0	6
α_2 - Oven and Stove	2.0	2
α_3 – Clothes Iron	1.0	1
α_4 - Clothes Dryer	3.0	3
α_5 - Clothes Washer	1.0	3
α_6 - Dishwasher	2.0	1
α_7 - Refrigerator	0.5	20
α_8 - Entertainment (TV / PC)	0.4	4
α_{10} - Base Load	2.0	24

TABLE II. Hourly prices for energy offers from the grid and prosumers in the transactive energy network.

t	**G**	**ψ_1**	**ψ_2**	**ψ_3**	**ψ_4**	**ψ_5**	**ψ_6**	**ψ_7**	**ψ_8**	**ψ_9**
1	0.057	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2	0.051	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	0.050	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
4	0.048	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5	0.047	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
6	0.049	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
7	0.048	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
8	0.050	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
9	0.053	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
10	0.054	0.049	0.050	0.051	0.053	0.051	0.052	0.054	0.051	0.050
11	0.058	0.053	0.058	0.058	0.053	0.058	0.053	0.055	0.057	0.055
12	0.059	0.057	0.056	0.057	0.058	0.058	0.055	0.054	0.058	0.059
13	0.060	0.054	0.057	0.057	0.057	0.059	0.054	0.056	0.057	0.059
14	0.059	0.057	0.059	0.054	0.059	0.056	0.057	0.059	0.055	0.058
15	0.059	0.057	0.058	0.054	0.055	0.054	0.054	0.059	0.056	0.056
16	0.053	0.052	0.052	0.053	0.053	0.052	0.053	0.051	0.051	0.049
17	0.053	0.050	0.051	0.053	0.052	0.051	0.051	0.052	0.053	0.052
18	0.060	0.057	0.059	0.055	0.054	0.056	0.058	0.054	0.059	0.055
19	0.068	0.062	0.067	0.067	0.067	0.063	0.062	0.067	0.066	0.062
20	0.070	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
21	0.070	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
22	0.067	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
23	0.067	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
24	0.066	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

In this case, nine prosumers are making offers with different maximum energy quantities and prices for each hour. Different prices (including transmission costs) offered by each supplier are shown in Table II, with the reference prosumer (the one doing the scheduling) is personally participating in this market, being represented as prosumer one, or ψ_1. The hourly prices from the grid are shown in red, with darker values being higher. For each hour, the prices offered by prosumers are shaded from lightest to darkest, relative to how much less they are compared to the grid price of that hour.

It is obvious that all prosumers have solar-based generation. Different generation scenarios, in addition to different randomized uncertainties have been modeled for each prosumer to reflect a realistic case.

As previously elaborated in Section II.C, the values in Table II show that the prosumers offer energy at hourly prices, which are between the grid price and the IEP: refer to (9) and (10). In this case, we assume the IEP to be 10% of the grid price. Different prosumers make more or less competitive offers each hour based on their strategy.

In this case, study, we assume the hourly competitive coefficient, κ, for each prosumer to vary randomly. The hourly energy offers are visualized in Figure 2, which clearly shows multiple aspects of the considered transactive energy market.

First, the grid hourly prices reflect the implementation of some real-time pricing (RTP) DR program, reflecting higher prices in times of higher demand for residential consumption. This will be re-emphasized shortly with the introduction of the prosumer preferences for appliance scheduling.

As such, the existence of both a fully decentralized transactive energy market for prosumers and a market for large utilities will be shown to not be mutually exclusive. Rather, the interaction between the two may very well lead to more efficient systems. While this is out of the scope of this study, this interaction will be the focus of future studies on this proposed framework, in which this model can be scaled to what is sometimes referred to as "fractal" energy systems.

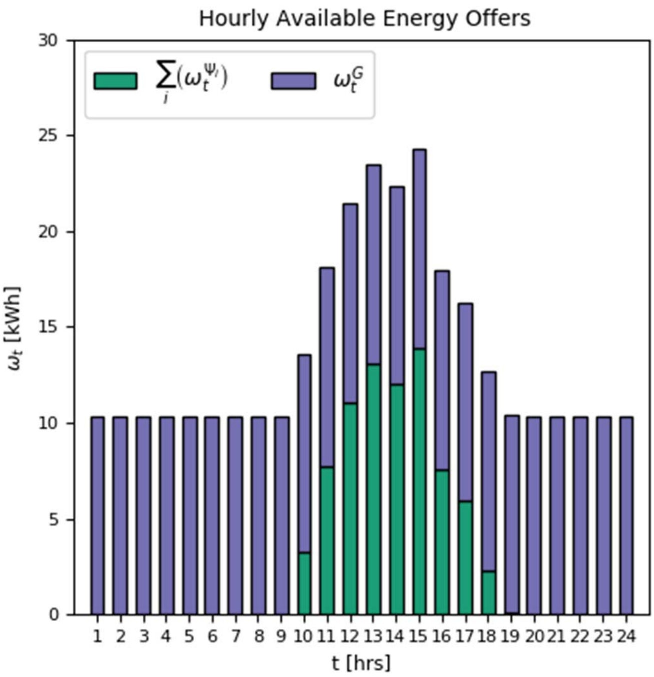

Fig. 1. Hourly available energy from suppliers in the transactive network: Grid (purple) and Prosumers (Green).

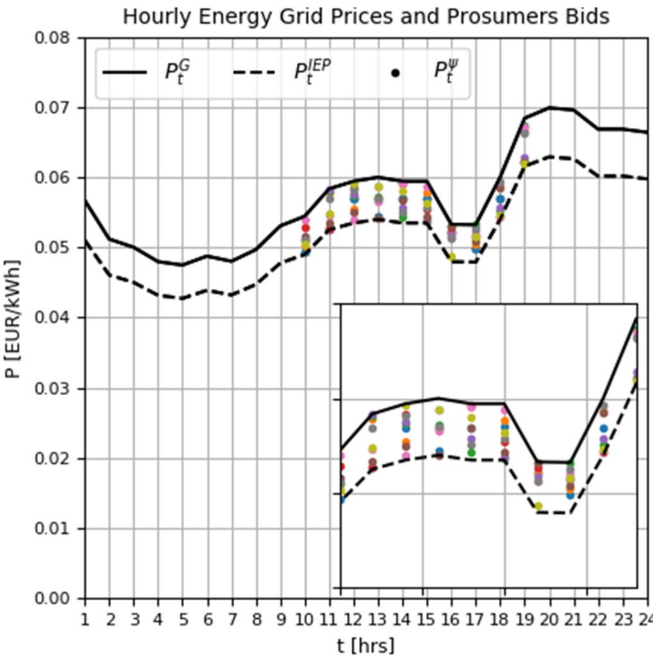

Fig. 2. Hourly values of energy price corresponding to: grid supply (solid black line), grid-indexed electricity price (dashed black line), and prosumers in the transactive network (different colored dots corresponding to different prosumers). Hours with prosumer offers (during the day hours due to reliance on solar generation) are zoomed in on the bottom-right corner.

This brings up the second aspect to infer from Figure 2. A prosumer's bidding strategy can have a significant effect on market dynamics, including strategies of other prosumers. This dynamic interaction is not only confined within the prosumers transactive network, but extends to the grid. The main motive of DR programs and RTP was to incentivize active participation from consumers. This idea can be extended to this prosumer-based model, with the prosumers' bidding strategies within their network having a significant effect on grid prices, enabling a two-way interaction between grid prices, prosumer prices, and a dynamically changing IEP index, resulting in a varying bidding margin for prosumers. This will be addressed in future studies on this framework.

The final step to setup up the case study is for the reference prosumer to indicate their preference for the allocation of the appliances. This is shown in Table III, in which these values are normalized and transformed to calculate the value signals.

IV. Results and Discussion

The optimal schedule is obtained using the approach highlighted in Section III.D. In this study, an exhaustive search code implemented using Python was used. The model takes a fraction of a second to run, showing that by employing a more superior optimization algorithm it can run in real-time. Table IV shows the resulting allocation matrix A(t,α).

It can be seen that the scheduling tool attempted as much as possible to adhere to user preferences, subject to also minimizing the energy cost and thereby maximizing the total value of energy for each hour (the objective function of the optimization model).

For instance, the space heater (α_1) was scheduled two hours before the preferred hours for the prosumer, due to the significantly higher availability of (cheaper) energy supplied through other prosumers in the transactive network. The same applies to the refrigerator (α_7), scheduled at 1:00. This can be seen in Figure 3.

TABLE III. REFERENCE PROSUMER PREFERENCES FOR APPLICANCE ALLOCATION (1→LOWEST, 3→HIGHEST).

t	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1
7	1	1	1	2	1	1	1	1	1
8	1	1	1	2	1	1	1	1	1
9	1	1	1	2	1	2	1	1	1
10	1	1	1	2	1	3	1	1	1
11	1	1	1	2	1	3	1	1	1
12	1	1	1	2	1	3	1	1	1
13	1	1	1	2	1	3	2	1	1
14	1	1	1	2	1	3	3	1	1
15	1	1	1	2	1	2	3	1	1
16	2	1	1	2	1	1	3	1	1
17	2	1	1	1	1	1	1	1	1
18	2	1	2	1	1	1	1	1	1
19	2	2	3	1	2	1	1	3	1
20	2	3	2	1	3	1	1	3	1
21	2	2	1	1	3	1	1	3	1
22	1	1	1	1	2	1	1	3	1
23	1	1	1	1	1	1	1	3	1
24	1	1	1	1	1	1	1	3	1

TABLE IV. OBTAINED ALLOCATION MATRIX FOR APPLIANCES.

t	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
1	0	0	0	0	0	0	1	0	1
2	0	0	0	0	0	0	1	0	1
3	0	0	0	0	0	0	1	0	1
4	0	0	0	0	0	0	1	0	1
5	0	0	0	0	0	0	1	0	1
6	0	0	0	0	0	0	1	0	1
7	0	0	0	1	0	0	1	0	1
8	0	0	0	1	0	0	1	0	1
9	0	0	0	1	0	0	1	0	1
10	0	0	0	0	0	1	1	0	1
11	0	0	0	0	0	0	1	0	1
12	0	0	0	0	0	0	1	0	1
13	0	0	0	0	0	0	1	0	1
14	1	0	0	0	0	0	1	0	1
15	1	0	0	0	0	0	1	0	1
16	1	0	0	0	0	0	1	0	1
17	1	0	0	0	0	0	1	0	1
18	1	0	0	0	0	0	1	0	1
19	1	1	1	0	0	0	1	0	1
20	0	1	0	0	1	0	1	0	1
21	0	0	0	0	1	0	0	1	1
22	0	0	0	0	1	0	0	1	1
23	0	0	0	0	0	0	0	1	1
24	0	0	0	0	0	0	0	1	1

It can be seen that from 11:00 to 15:00, the energy is 100% supplied from the prosumers in the transactive network. This corresponds to a significant reduction of energy cost during those hours, as shown in Figure 4.

Concerning energy trading, it can be seen that while energy cost was minimized as much as possible, this did not come at the cost of sacrificing the reference prosumer's welfare, with the peak load occurring at 19:00, when there was in fact no supply from the transactive network of prosumers. However, the maximum possible utilization of cheaper energy from the transaction energy was achieved as can be seen in Figure 3. This can also be seen in Figure 4, where the maximized energy value signal can be compared to the energy hourly energy cost.

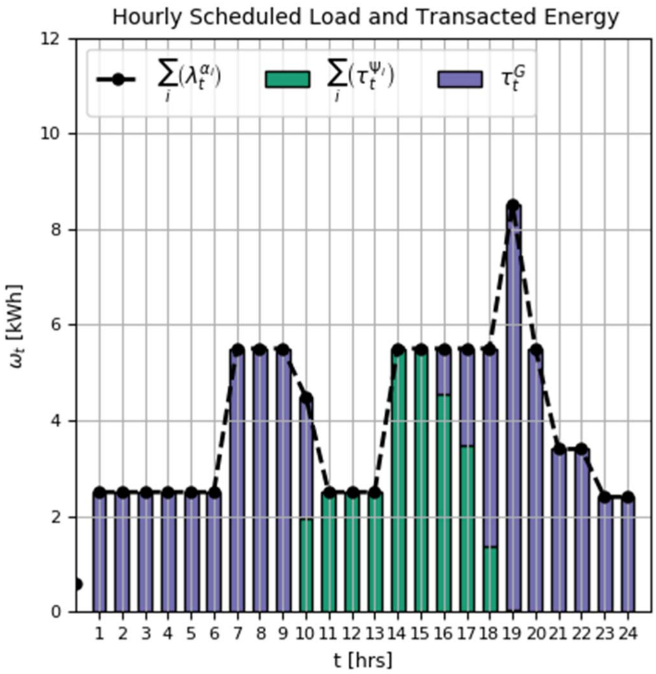

Fig. 3. Hourly scheduled load and transacted energy. The total hourly load is shown using the black dotted line, the energy purchased from the grid is shown using the purple bars, and the total transacted energy from the prosumers in the transactive network is shown using the green bars.

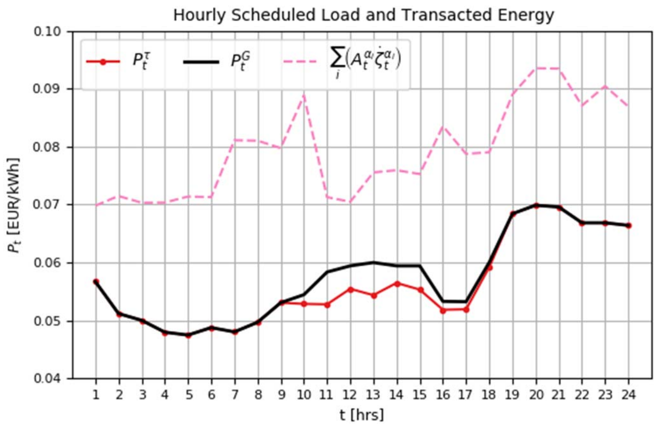

Fig. 4. Hourly energy price paid by reference prosumer (red line), electricity price from the grid (black) and the maximized energy value signal (pink dashed line).

By being more flexible in their consumption preferences (refer to Table III), the reference prosumer can guide the scheduling tools to give more weight to cost reduction, and vice versa.

Finally, we can now compare our proposed framework with the traditional approaches existing on both extremes as discussed in Section I. By comparison with the case of net metering, our model exhibits a potential benefit for the upstream grid as it does not have to pay for energy generated locally by the consumers as they pay each other locally within the transactive network. In addition, our framework provides the coordinated scheduling of prosumers in a fully distributed manner, without the need of a central operator, while always providing a guarantee that the generated electricity will be paid for regardless of the "presumption" schedules of the users in the network. The only thing that varies (maximized) is the global value of energy, but in all cases, any locally generated energy will be paid for, with the worst-case scenario corresponding to the lower bidding margin of the IEP. On the other hand, comparison with systems where the prosumers are not paid for fed-in energy, it is obvious that this framework provide a benefit for the prosumers. In fact, the proposed framework can be directly applied to such systems, as an extreme case of having a zero-valued IEP bidding margin. All in all, the proposed model can provide potential economic benefits to both the grid and prosumer, while being user-centric and fully distributed.

An important aspect to note is that the reference prosumer themselves is participating in the transactive energy market, and with no discrimination between buying energy from themselves or other prosumers. The only deciding factor is offered price from each prosumer. This is important for the market dynamics, as there are hours when the prosumer can profit more by selling it to another rather than self-consuming (or in this case, self-transacting) it. In this study, we consider all the offered prices already including the transmission and grid connection costs. However, the transactive network can be a virtual one rather than physical, and a future study can investigate the effect of the presence of prosumers from different low-voltage networks.

V. CONCLUSION

In this study, we propose and test a novel framework for distributed management of transactive energy networks. Energy value signals are proposed as an alternative means of quantifying social welfare for prosumer-centered networks. Afterwards, a coordinated scheduling algorithm for joint scheduling of energy consumption and trading is formulated. The scheduling tool runs locally at each prosumer in order to achieve a maximum global energy throughout the network. Rather than minimizing energy costs as traditional models do, in this case we maximize energy value, which we propose as a new way of quantifying social welfare for prosumer networks, simultaneously leveraging comfort levels and minimizing costs. Energy value reflects the value set by the user of allocating energy for a certain usage at a certain time. These user preferences are input locally resulting in the optimal schedule of each prosumer, which in turn affects the price of energy globally in a similar manner to demand response programs. The local energy transactions are guided within a margin relative to the upstream grid prices. It was shown that the proposed model could provide potential benefits for both prosumers and the grid, albeit with a user-centered, fully distributed approach to schedule energy consumption and trading in transactive energy networks of prosumers. Since all calculations run locally at each prosumer, no exchange of private information is needed to achieve fully distributed management of the network. For future work, the effect of employing such a model on power flow and grid connection costs should be investigated in detail in order to confirm the applicability of this approach on existing power systems. Moreover, investigation of the effect of employing different bidding strategies by the prosumers should be performed, in order to ensure transparency and verification can be guaranteed between the prosumers.

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