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Electricity Cost-Sharing in Energy Communities Under Dynamic Pricing and Uncertainty

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ABSTRACT Most of the prosumers nowadays are constrained to trade only with the supplier under a flat tariff or dynamic time-of-use price signals. This paper models and discusses the cost-saving benefits of flexible prosumers as members of energy communities who can exchange electricity among peers and on the wholesale markets through a community manager. Authors propose a novel centralized post-process sharing method by introducing a two-stage mechanism which, unlike the existing methods, guarantees benefits for prosumers joining the energy community. The first stage assesses internal price calculation in three different methods: Bill Sharing Method Net (BSMN), Mid-Market Rate Net (MMRN), and Supply-Demand Ratio Net (SDRN). In their original form, prices are calculated in a single stage and the comprehensive analyses in the paper show that some members face increased cost. To solve this issue, the paper improves the methods by introducing the second stage in which the compensation methodology is defined for the distribution of savings which ensures that all community members gain benefits. Results investigate the value of inner technical flexibility of the prosumer (flexible preferences of the final consumer can reduce the cost from 3% up to 20 %). Moreover, incentives/penalties encourage the utilization of a flexible behavior to adjust the real-time consumption of prosumers' appliances to a predefined day-ahead schedule. This type of pricing results in a lower amount of benefits sharing in the community (the reduction of 18-47% in MMRN and 49-114% in SDRN compared to existing pricing) which makes this incentives/penalties pricing more preferable. The paper concludes that prosumers with an excess PV production would not benefit from the internal energy exchange in the community under BSMN due to free energy exchange between members.

INDEX TERMS Cost-sharing, day-ahead market, demand response, energy community, peer-to-peer trading.

I. NOMENCLATURE

Stochastic and non-stochastic parameters are presented as **bold** text, while variables are a regular type of text. Where augmented with the subscripts s and t, they refer to the values they take on in scenario s and time period t, while the subscript d stands for a household and ap for a different uninterruptible flexible appliance. If not stated differently, variables and parameters are positive.

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Indices and Sets

$ap \in A$	Uninterruptible flexible appliances
$d \in D$	Households
$d \in D^{+}$	Community members with decreased cost in the first stage
$d \in D^{-}$	Community members with increased cost in the first stage
$t \in T$	Time steps
$s \in S$	Scenarios

Parameters

$\boldsymbol{\pi_s}$	Probability of scenario s

$\lambda_t^{DAB/S}$	Day-ahead (DA) buying/selling price [DKK/kWh]
$\underline{E}_d$	Minimum state of energy of EV at the end of a charging cycle [kWh]
$\overline{E}_d$	The battery capacity of EV [kWh]
$\overline{P}_d$	Maximum charging power of EV [kW]
P^{uniap}	Power of uninterruptible appliance [kW]
L^{ap}	Cycle length of uninterruptible appliance [h]
$H_d^{a/l}$	The hour when a car arrives/leaves at home [h]
Δt	Time interval [1h]
$\lambda_t^{DOWN/UP}$	Down/up incentive price [DKK/kWh]
$\lambda^{BALB/S}$	Balancing cost for bought and sold energy [DKK/kWh]
λ^{NET}	Network charges [DKK/kWh]

Stochastic parameters

$P_{d,s,t}^{ms}$	Must-serve load [kW]
$PV_{d,s,t}$	PV production [kW]

Variables

$cost_{s,t}^{pen}$	penalization cost [DKK]
C_d^{ind}	Individual cost under supplier [DKK]
C_d^{comm}	Cost of a community member in the first stage under cost-sharing mechanism m [DKK]
C_d^{new+}	Cost of a community member in the second stage who was better off in the community in the first stage [DKK]
C_d^{new-}	Cost of a community member in the second stage who was worst off in the community in the first stage [DKK]
C^+	Sum of the cost reduction of community members compared to individual trading with supplier [DKK]
C^-	Sum of the cost increase of community members compared to individual trading with supplier [DKK]
min *bound*	The minimum value of benefits for sharing among community members
$P_{d,s,t}^{HD}$	Power imported (positive) /exported (negative) from/to supplier by household [kW]
$P_{s,t}^{GRID}$	Power imported (positive) /exported (negative) by the energy community [kW]
$P_{d,s,t}^{HDB/S}$	Imported/exported power of each household [kW]
$P_{s,t}^{UP/DOWN}$	The community's up/down regulation [kW]
$P_{d,s,t}^{HDB/S}$	Buying/selling power of household [kW]
$P_t^{DAB/S}$	DA community's contracted buying/selling power [kW]
$P_{d,s,t}^{net}$	Net-load (negative if PV production excesses load) [kW]
$P_{d,s,t}^{uniap}$	Consumption of uninterruptable appliance [kW]
$P_{d,s,t}^{EV}$	EV charging power [kW]
$P_{d,s,t}^{th}$	Thermal load [kW]
$P_{d,s,t}^{ch/dis}$	Battery charging/discharging [kW]
$P_{s,t}^{netpos/neg}$	Sum of positive/negative net-load in the community [kW]
$\lambda_{s,t}^{mB/S}$	Internal buying/selling price under cost-sharing mechanism m
$\lambda_{s,t}$	Compensation rate under SDRN [DKK/kWh]
$\lambda_{s,t}^{unit}$	The average cost of energy [DKK/kWh]
$SDR_{s,t}$	Supply-demand ratio
Δ_d	Difference between individual cost and community member cost in the first stage

Binary variables

$x_{d,s,t}^{def}$	1 if EV is being charged and 0 otherwise
$x_{d,s,t}^{uniap}$	1 if the uninterruptable load starts the cycle and 0 otherwise

II. INTRODUCTION

A. MOTIVATION

The latest package of measures in the European Union (EU) for a clean energy transition, 'Clean Energy for all Europeans', puts the end-user into the focus by requiring, among other things, integration of more renewable energy sources (RES) and the market empowerment of final consumers [1]. To achieve this, new models and tools for end-consumers are needed, to give them the chance to find an alternative business model in order to reduce their electricity bill [2]. This is important since the survey conducted in [3] suggests there was a significant increase in the electricity retail price despite market liberalization. Moreover, many EU member states still regulate end-user electricity prices and have a single dominant supplier [4]. To enable the transition and utilize demand-side flexibility, it is crucial to have a retail-level competition and to offer market participation through innovative business models [5], [6]. In this context, energy communities have emerged as new entities providing the end-users novel platforms to invest into low carbon assets, but also as operational market entities with capabilities to exchange the surplus (deficit) of energy among their peers. Their main goal is to incentivize consumers to produce and consume energy locally, reducing the electricity cost and increasing the self-consumption of RES.

B. LITERATURE REVIEW

The community manager (CM) is a new market entity participating in the wholesale markets on behalf of its members, but it also coordinates the electricity trade and transactions within the community [7]. Different aspects and benefits of this concept have been researched, such as adjusting peak-hour load, reducing the grid losses [8] and congestions [9], and improving self-balancing to enable further integration of RES [10]. In general, the CM optimizes flexible assets of the community in order to achieve a better market position by incentivizing its members to trade within the community or with the market whenever more convenient. The savings are shared among community members and the challenge is to find a cost-sharing method that fairly awards the peers depending on their contribution to the entire community's wellbeing. CM is an entity essentially different from a regular supplier and does not gain any profit. Indeed, the CM is, all in all, a platform for providing prosumers with multiple options for monetizing their flexibility, but also exposing them to risks of uncertainties traditionally hedged by the supplier. CM is in charge of scheduling the operation of the flexible appliances in the energy community in order to achieve the lowest electricity cost for the entire community. CM is a virtual entity managed and owned by the members of the community, meaning that, in the end, any profit made by the CM is divided among the community members.

A motivational psychology framework is proposed in [11] to describe the different motivational stages that encourage prosumers to join p2p energy trading. Their interaction is modelled as the canonical coalition game. The social cooperation between prosumers is modelled as a coalition formation game in [12] enabling prosumers to decide should they use battery storage in p2p trading. P2p trading can also be modelled through a bidding process or by way of a game-theory approach. The authors in [13], [14], and [15] present an auction-based p2p trading mechanism, where different bidding strategies for prosumers are analyzed. Several papers are based on game-theory (Stackelberg game, Nash bargaining, a non-cooperative game) to model the negotiation between prosumers or between prosumers and a central entity responsible for p2p trading. P2p energy trading based on a Stackelberg game in which the renewable and non-renewable producers lead, while prosumers and consumers follow is presented in [16] showing higher social welfare of consumers and prosumers compared to conventional p2p trading. The authors in [17] study the energy trading based on a Stackelberg game between prosumers who share energy storage. The energy sharing provider leads the game setting the internal trading prices, while the prosumers follow optimizing their energy profile. Two sharing modes are distinguished: directly sharing in which the energy sharing provider acts as an intermediator between prosumers with energy excess and deficit without the storage and buffered sharing in which the energy sharing provider uses a shared battery for matching the demand in different periods. The price competition on the upper level between the sellers is modelled as a noncooperative game, while the seller selection competition on the lower levels among buyers is modelled with an evolutionary approach. The interaction between upper and lower levels in p2p trading is based on a Stackelberg game [18] in which sellers are leaders and buyers are followers. A two-stage real-time (RT) energy sharing optimization model is presented in [19]. A cluster of buildings consisting of offices, industrial, and commercial buildings firstly minimizes the total energy cost and then shares the energy in a non-cooperative game with transparent energy sharing profiles. The model deals with the uncertainty by adjusting the energy schedule traded with the retailer and keeping the predefined day-ahead (DA) energy exchange profile with other buildings. The bilevel objective model in [20] minimizes the cost and ensures fairness for all p2p members involved in energy trading based on the Nash barging solution taking into account network constraints and energy scheduling in both DA and RT markets. The privacy issue regarding p2p trading has been addressed in [15] and [21]. The distributed approach developed in [15] describes a method for local optimal energy scheduling and sharing that guarantees data confidentiality, while in [21] the prices provided from a p2p platform agent are calculated based on a multiclass energy management problem considering the wholesale energy price, the energy demand of each prosumer and the expected losses in an iterative process. A convex formulation of the model is proposed to reduce the computational burden and to implement it in RT. The model in this paper proposes a different approach in which the prices are not calculated in RT, i.e., they are calculated the day after energy delivery and therefore, the model does not require a fast optimization algorithm. Moreover, the paper precisely defines internal prices based on the amount of shared energy and both DA prices and incentives for flexibility. The authors in [22] compare cost-sharing-methods among community members, namely Bill Sharing Method (BSM), Mid-Market Rate (MMR), and Auction-based Pricing Strategy (APS) with flat buying and selling prices and without any demand response program. The work in [23] describes cost savings in an energy community with and without p2p trading. The results show that the community is always better off by performing p2p trading, however, the paper does not include a sharing mechanism that guarantees cost savings for all the community members and only focuses on the optimum for the entire community. The paper in [24] compares the outcome of BSM, MMR, and Supply Demand Ratio (SDR) cost-sharing mechanisms in an energy community using heuristic methods. To facilitate the convergence of the proposed algorithm, their model uses step-length control and includes a learning process. An innovative iterative p2p trading mechanism called ECO-Trade is described in [25], where the authors consider an energy community with different percentages of households equipped with PV and batteries to demonstrate that ECO- trade, which is based on a near-optimal algorithm, provides better solutions in terms of accuracy and computational time than that provided in [26]. The work in [27] proposes a SDR cost-sharing method within a p2p trading framework that takes into account consumers' preferences with respect to their desired level of participation. The model in [28] introduces a SDR-based profit-sharing scheme with a compensation rate that incentivizes all consumers to join the energy community by ensuring them lower electricity costs. The energy community is exposed to dynamic buying and selling prices, but there is no uncertainty related to the price or PV production and demand or discussion on the optimal cost-sharing method. As an upgrade of [28], this paper precisely models demand flexibility, considers the stochastic nature of PV production and consumers' load, and investigates the value of flexibility incentives to adjust the RT operation schedule of household appliances to a predefined DA schedule. A multi-energy retailer (MER) aims to maximize its profit from selling electricity, gas, and heat demands to the multi-energy consumer [29]. MER participates in the electricity, gas, and heat market and operates tri-state compressed air energy storage (tri-CAES) and combined heat and power (CHP) technologies in order to satisfy the demand of final consumers. Final consumers are encouraged with incentive compensation to participate in load shifting when market prices are high resulting in reduced cost of MER. A multi-objective two-stage stochastic problem considering uncertainties related to electric and gas load and wind power plant (WPP) production is modeled in [30]. The benefits of employing demand response programs in electrical and gas networks are investigated, together with a reduction of CO2 emissions resulting in no curtailment of WPP production and reduction of both gas and electrical network operational cost. Different models of community energy trading are compared in [31]. The first one does not consider any energy exchange between microgrids and is individually oriented. The second one proposes a collective benefit without considering individual interests. The third one focuses on a collective and a satisfactory level of individual interests, although the individual benefits of some microgrids are not accomplished in this model. The fourth one brings both collective and individual benefits with the same percentage of cost savings for each microgrid and presents the best solution of proposed models. A two-level optimization problem for cost minimization and peak shaving of neighboring energy hubs is presented in [32]. The lower level focuses on individual household (home energy hub HEH) energy supply, while the upper level forms the coalition giving HEHs and conventional buildings financial compensation to facilitate trading in the local market. Virtual energy hub supplies their heat and electricity demand from CHP, boilers, and local markets taking into account risk-constrained self-scheduling of battery and thermal storage to reduce the purchase cost of electricity and heat [33]. The results show almost 70% of cost reduction for electricity imported from local markets. The interaction of microgrids with 100% renewable power in the transactive energy markets is proposed in [34]. The case with local energy exchange brings 18.34 % cost reduction for each microgrid which highly motivates them for local energy sharing due to high energy prices for energy exchange with the main grid.

Based on the literature review shown in Table 1, the following research gaps have been identified:

- Relevant literature on cost-sharing methods recognizes three main categories: i) game-theory methods which are rather complex to deploy, such as [8], [16]–[18], ii) coalition games ([11], [12], [20]) and iii) post-event methods which guarantee model convergence (such as BSM, MMR, SDR [22], [28], [37]). Game-theory cost-sharing methods are computationally demanding and this complexity increases exponentially with the number of peers. Coalition games are sometimes restricted with the number of prosumers per coalition, preventing the formation of a grand coalition (which brings the highest savings) and potentially leading to economic dissatisfaction of prosumers. All known post-processing cost-sharing methods are easily implementable and guarantee model convergence. However, and as the results in this paper will show, they are defined so that they do not guarantee economic benefits to all community members as opposed to staying in traditional supplier-household contracts. To bridge this gap the paper defines a new two-stage post-processing cost-sharing method that guarantees lower costs for all energy community members.
- The flexibility of the end-users is often neglected or is not sufficiently modelled. Only a few papers focus on this and model both the household level batteries and controllable smart home devices, such as [8], [19], [20], [24]. Other papers either model only the battery storage or focus more on MES aspects [28]–[34]. However, none of them considers post-processing cost-sharing methods in their analyses.
- Although some papers include uncertainty aspects in their modeling, none of them models static, post-event cost-sharing methods to deal with this important feature of low-carbon energy systems. Additionally, to the authors' knowledge, none of the papers models flexibility incentives for the end-users which award those ready to change their consumption to benefit the power system.

According to [42], an energy community is a legal entity based on voluntary participation with the primary purpose of providing environmental, economic, or social community benefits for its members or the local areas, rather than solely financial profits. Real-world examples of energy communities are Bioenergy Village Jühnde, Brixton Energy, Energy Cooperative of Karditsa, Green Energy Cooperative (ZEZ) [43], etc. The work in this paper considers an energy community operated by a CM whose members have the possibility of p2p energy trading with internal prices determined based on both DA prices and flexibility incentives reflecting regulating power costs.

This paper seeks to investigate the financial benefits arisen from participating in an energy community and demonstrates under which conditions the new market concepts enable cost savings for prosumers. Nowadays, trading with the supplier solely is the most realistic choice for energy procurement. However, due to the growing integration of distributed RES and the liberalization of the retail energy market, energy communities are becoming more and more popular. Community members are becoming active market participants with multiple choices for energy purchase/sale, instead of only one dominant supplier, which is, for example, one of

TABLE 1. Comparison of literature review.

Reference	Battery	Other flexibility	Direct optimization	Uncertainty	Cost-sharing method
[7]	No	No	No	No	min-max import share
[8]	Yes	Yes	No	No	a game theory-based approach, no negotiation between peers
[11]	No	No	No	No	MMR based on a canonical coalition game
[12]	Yes	No	No	No	a coalition formation game
[22]	No	No	Yes	No	BS, MMR, APS
[23]	Yes	No	Yes	No	Not investigated
[13]	Yes	Controllable load	No	Yes	continuous double auction market
[14]	No	No	No	No	double auction market
[15]	Yes	Electric vehicle	No	No	continuous double auction market
[16]	No	No	No	Yes	a game theory-based approach Stackelberg game
[17]	Yes, shared one	No	No	Yes	a game theory-based approach Stackelberg game
[18]	Yes	No	No	No	a game theory-based approach Stackelberg game
[19]	Yes	HVAC Units, Shiftable Electrical Appliances, Flexible Commercial Services	No	Yes	a non-cooperative game
[20]	Yes (EV)	EV, shiftable and adjustable load	No	Yes	Nash bargaining
[21]	Yes	No	No	No	a centralized price setting mechanism to balance supply and demand, ADMM performed by p2p platform agent
[24]	Yes	Non-interruptible appliances, thermostatically controlled appliances, EV	No	No	heuristic
[25]	Yes	Uninterruptible appliance	No	No	ECO-Trade Algorithm
[27]	No	Shiftable load	No	Yes	iterative SDR
[28]	Yes	No	Yes	No	SDR
[29]	Power to gas storage, power to heat storage	CHP, tri-CAES system, demand response	Yes	Yes	no
[30]	Gas storage	Demand response	ε- constraint technique	Yes	no
[31]	Battery and thermal storage	CCHP	Yes	Yes	different models ensuring collective or individual interest
[32]	Yes	EV, CHP, demand response	No	No	bidding strategy based on weighted distributing of excess power among consumers
[33]	Battery and thermal storage	CHP, boiler	No	Yes	cost minimization for heat and electricity supply from local markets, no cost-sharing
[34]	Battery and thermal storage	Load shifting	Yes	Yes	the same percentage of cost savings for each microgrid
[35]	Yes	No	Yes	No	bilevel-approach, local market clearing
[36]	Yes	No	Yes	No	p2p market, p2p prices calculated based on desired margin and p2p trader margin
[37]	Yes	No	Yes	No	SDR
[38]	No	No	Yes	No	monthly electricity consumption and self-consumption rate
[39]	Yes	No	No	No	no
[40]	Yes	Load-shifting	Yes	Yes	no
[41]	Yes	No	Yes	Yes	no
This paper	Yes	EV, uninterruptible appliances, thermostatically controllable load,	Yes	Yes	a novel centralized two-stage cost-sharing method

the main objectives of the Clean Energy Package (providing better deals to all end users) established by the European Union [1], [42].

C. CONTRIBUTIONS

Against this background, the contributions of the paper are the following:

1. The proposal of a novel two-stage cost-sharing model that guarantees individual welfare for each community member. After running multiple simulations with different types of prosumers in the energy community, this paper shows that the centralized formulation of the existing/well-known cost-sharing mechanisms (described in [22], [28]) cannot always guarantee that all prosumers are better off in the community. The authors introduce a second stage which defines the minimum bound of cost savings in the community to be shared among community members who are worst off in the community in the first stage which results in lower electricity cost for all community members compared to individual trading with the supplier. The prices are calculated ex-post, the day after energy delivery. In the proposed approach peers do not need to negotiate about the trading volumes and prices and thus the model guarantees the convergence. Both stages in this cost-sharing approach do not interfere with the optimization algorithm, which makes it simple and fast to solve (0.031 seconds for a small test case and 0.172 seconds for the bigger one with 100 prosumers). Although the methods are discussed in previous publications, such as BSM in [22] and [24], this paper provides a systematic analysis and proves the disadvantages of applying the BSM cost-sharing method for prosumers with excess PV production. This is analyzed and evaluated on a small test case with three community members and a realistic test case involving 100 participants (and different configurations regarding the percentage of households equipped with PV, battery storage, and flexible appliances).
2. Unlike papers not considering any kind of flexible behavior [7], [11], [14], [22] or focusing only on battery storage [12], [17], [18], [21]–[23], [28]–[37], [39], this paper investigates the monetary value of several flexible appliances in terms of cost reduction for all community members. The model analyses the impact of different flexible appliances on electricity cost reduction compared to the case with fixed consumption. The existing literature body considers the effect of uncertainty of demand or RES production on the cost [16], battery scheduling in DA and RT optimization [17], adjusting the energy schedule with RT trading with the retailer in order to keep the predefined agreed p2p volume [19], dealing with forecasting error [20], [40], the uncertainty of market prices and demand on the profit due to contract violations between the local energy system and consumers [27], optimal size of battery and PV modules [41]. However, this paper looks into pricing mechanisms stimulating final prosumers equipped with PV and flexible appliances to adjust their RT operational points to predefined DA schedules by explicitly modelling their uncertainty aspects. This creates a proper award system for a flexible and responsive prosumer reflected in a higher cost reduction compared to the current pricing scheme.

D. ORGANIZATION OF THE PAPER

The rest of the paper is organized as follows: Section III describes the differences between individual directly trading with the supplier and collective trading within an energy community represented by the CM. Section IV introduces the two-stage cost-sharing algorithm together with three cost-sharing methods: MMRN, SDRN, and BSMN. Section V describes the case study, while results are analyzed in Section VI. Finally, Section VII concludes the paper.

III. INDIVIDUAL AND COMMUNITY ENERGY SUPPLY

Prosumers today are not responsible for their PV or load forecasting and do not trade directly on the electricity market. Instead, they have a contract signed with the supplier providing them fixed prices, which the supplier offers considering its exposure to both market and its portfolio uncertainties. Together with energy cost, consumers pay network tariffs and balancing costs for each consumed or injected kWh of energy [46]. In recent years, feed-in-tariffs and incentives for household PV integration have been reduced [44]. Consumers are supplied at a higher buying price compared to the price at which they can sell their PV production [8], [23], and [28]. This difference in the buying and selling pricing creates opportunities for consumers to join in an energy community represented by a CM. In the same way, as leaders of balancing groups are responsible for their deviation, the CM also faces balancing costs for the entire community and creates incentive signals to stimulate prosumers to fully utilize their flexibility. Two different approaches of retail market operation are analyzed and compared in this paper. In the first one, each consumer independently trades directly with the supplier, without any interaction with other consumers. In the second approach, consumers join in an energy community represented by a CM who is in charge of trading in the power exchange on their behalf.

A. INDIVIDUAL TRADING WITH THE SUPPLIER

Fig. 1 illustrates the relationship between the supplier and the individual consumers. It is assumed that consumers are not competing against each other or against the supplier.

Consumers are individual entities who sign the contract with their supplier and in this case cannot exchange energy internally. The supplier provides DA buying and selling prices to consumers, while the national transmission system operator charges network and balancing fees (grey one-way arrows). Black, two-way arrows represent power flows (supplier procures energy for prosumers, but also buys excess energy from them).

Each consumer's goal is to minimize their energy procurement cost formulated in (1). They purchase energy from or sell it to the supplier and face a balancing cost for each kWh of procured or sold energy together with the cost for the network usage for procured energy. According to [46], injected energy from PV is not charged with the network fees.

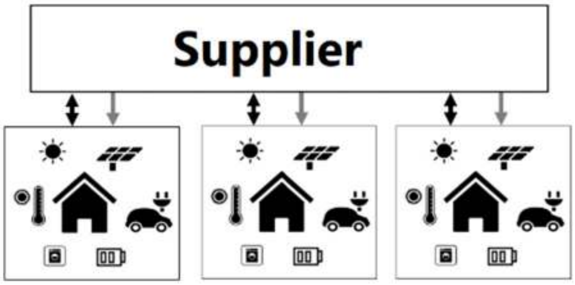

FIGURE 1. Energy and financial flow in directly trading with supplier.

All the scenarios are considered equiprobable.

$$\min C_d^{ind}$$
$$C_d^{ind} = \sum_{t\in T} \Delta t \sum_{s\in S} \pi_s [\left(\lambda_t^{DAB} + \lambda^{BALB} + \lambda^{NETB}\right) \cdot P_{d,s,t}^{HDB} - (\lambda_t^{DAS} - \lambda^{BALS}) \cdot P_{d,s,t}^{HDS}] \tag{1}$$

In scenario s, each consumer net load is divided in imported $P_{d,s,t}^{HDB}$ and exported $P_{d,s,t}^{HDS}$ at time step t (2). The variables representing trading power are greater than zero (3).

$$P_{d,s,t}^{HD} = P_{d,s,t}^{HDB} - P_{d,s,t}^{HDS} \tag{2}$$
$$P_{d,t}^{HDB}, P_{d,t}^{HDS} \geq 0 \tag{3}$$

The power balance equation for consumer d is formulated in (4). The demand of each consumer is composed of must-serve load, flexible uninterruptible appliances (*ap* stands for washing machine, dishwasher, and dryer), flexible charging of EV, flexible thermal load, and a small battery. The demand can be supplied from rooftop PV or bought from the supplier. If there is an excess PV production, it is sold to the supplier ($P_{d,s,t}^{HD} < 0$).

$$P_{d,s,t}^{HD} + \boldsymbol{PV_{d,s,t}} = \boldsymbol{P_{d,s,t}^{ms}} + \sum_{ap\in A} P_{d,s,t}^{uniap} + P_{d,s,t}^{EV} + P_{d,s,t}^{th} + P_{d,s,t}^{ch} - P_{d,s,t}^{dis} \tag{4}$$

The flexible charging of EVs is modelled by inequality constraints (5)-(6):

$$\underline{\boldsymbol{E_d}} \leq \sum_{t\epsilon T} \boldsymbol{\Delta t} \cdot P_{d,s,t}^{EV} \leq \overline{\boldsymbol{E_d}} \tag{5}$$
$$P_{d,s,t}^{EV} \leq \overline{\boldsymbol{P_d}}, \; if \quad \boldsymbol{H_d^a} \leq t \leq \boldsymbol{H_d^l}$$
$$P_{d,s,t}^{EV} = 0, \quad otherwise \tag{6}$$

EVs' state of energy when leaving the home is defined by consumers' preferences and modelled by way of (5), while the maximum charging power is enforced by (6). Charging is allowed only during the hours when the car is parked at home.

The supply of flexible uninterruptible appliances is modelled with (7)-(8). The sum of all binary variables indicating when the appliance is started is equal to 1, which ensures that the appliance is started once a day in (7).

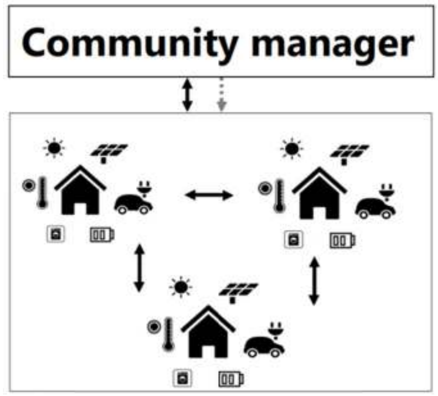

FIGURE 2. Energy and financial flow in energy community trading.

Equation (8) guarantees that, when the appliance is started, the cycle cannot be interrupted.

$$\sum_{t=1}^{T-\boldsymbol{L^{ap}}} x_{d,s,t}^{uni\ ap} = 1 \tag{7}$$
$$P_{d,s,t}^{uni\ ap} = \sum_{l=0}^{\boldsymbol{L^{ap}}-1} x_{d,s,t-l}^{uni\ ap} \cdot \boldsymbol{P^{uni\ ap}} \tag{8}$$

Flexible thermal loads are modelled as in [47]. Outside temperature is considered as an input parameter, while room, floor, and water temperature inside a water tank connected to a heat pump are variables used for modelling heating dynamics. Minimum and maximum bounds of room temperature are described in Section V.

Each household is equipped with battery storage modelled with a non-constant charging ability depending on the battery state of energy. The resulting non-linear charging curve piecewise approximated with three segments of decreasing slope as the battery state of energy increases. The reader is referred to [48] for a precise mathematical formulation of batteries.

B. ENERGY COMMUNITY

In the energy community, consumers exchange surplus of energy among themselves. The difference in the buying and selling prices offered by the supplier creates opportunities for the consumers to benefit from joining an energy community. They are represented by the CM who buys and sells energy from the supplier and faces balancing costs for deviations of end-consumers' announced profiles. CM uses a centralized approach to determine the behavior of all the consumers' flexible appliances in RT in order to reduce the electricity cost of the whole community and thus, of each consumer.). The consumers within the community exchange their surplus of electricity with their peers and do not negotiate about trading volume and prices. The grey arrow in Fig. 2 represents the buying and selling prices sent out by the CM to the consumers *ex-post* (that is, the day after the actual exchange of energy. Trading between communities is outside the scope of this paper.

The mathematical model that determines community' cost is given by (9)-(12). The CM minimizes the energy procurement cost for the entire community (minus the profit from selling PV excess) and faces the penalization cost for the energy deviations incurred by the cooperative (9)-(11) and network charges. The community is treated as one single entity (12).

$$\min \sum_{t\in T} \Delta t[\boldsymbol{\lambda}_t^{\boldsymbol{DAB}} \cdot P_t^{DAB} - \boldsymbol{\lambda}_t^{\boldsymbol{DAS}} \cdot P_t^{DAS} + \sum_{s\in S} \boldsymbol{\pi}_s \left(\boldsymbol{\lambda}_t^{\boldsymbol{UP}} \cdot P_{s,t}^{UP} - \boldsymbol{\lambda}_t^{\boldsymbol{DOWN}} \cdot P_{s,t}^{DOWN}\right) + \boldsymbol{\lambda}^{\boldsymbol{NETB}} \cdot P_{s,t}^{+}] \tag{9}$$

$$P_{s,t}^{GRID} = P_t^{DAB} - P_t^{DAS} + P_{s,t}^{UP} - P_{s,t}^{DOWN} \tag{10}$$

$$P_t^{DAB}, P_t^{DAS}, P_{s,t}^{UP}, P_{s,t}^{DOWN}, P_{s,t}^{net\ pos}, P_{s,t}^{net\ neg} \geq 0 \tag{11}$$

$$P_{s,t}^{GRID} = P_{s,t}^{net\ pos} - P_{s,t}^{net\ neg} = \sum_{d\in D} (\boldsymbol{P}_{\boldsymbol{d,s,t}}^{\boldsymbol{ms}} + \sum_{ap\in A} P_{d,s,t}^{uni\ ap} + P_{d,s,t}^{EV} + P_{d,s,t}^{th} + P_{d,s,t}^{ch} - P_{d,s,t}^{dis} - \boldsymbol{PV}_{\boldsymbol{d,s,t}}) \tag{12}$$

Furthermore, optimization problem (9)-(12) also includes the consumers' constraints (5)-(8), as well as thermal heating and battery storage.

IV. COST-SHARING MECHANISMS

The optimization algorithm in this approach is a centralized one, i.e., the CM schedules the flexible appliances of community members to achieve lower electricity costs. The excess PV production in the community is firstly shared among community members and the rest is traded on the central power exchange. The main advantage of this approach is that final consumers do not need to negotiate about the trading volumes and prices or individually schedule their appliances. The CM is in charge of scheduling flexible appliances and computes the prices based on their net-load and defined cost-sharing methods. The internal trading prices are calculated outside the optimization algorithm, the day after energy delivery, which makes the optimization algorithm simple to solve and it guarantees the convergence which will ensure the broad integration of this cost-sharing approach. The electricity procurement cost of the energy community is shared among its members based on their net-load in hour t and scenario s. The cost allocation is conducted when the daily operation is completed (that is, at the beginning of the day n, the cost incurred in day n-1 is allocated). Therefore, the cost-sharing process does not interfere with the optimization problem, which makes it simple and fast to solve. The only information needed for the cost allocation among the community members is their net-load measured at the end-consumers' smart meter (13):

$$P_{d,s,t}^{net} = \boldsymbol{P}_{\boldsymbol{d,s,t}}^{\boldsymbol{ms}} + \sum_{ap\in A} (P_{d,s,t}^{uni\ ap} + P_{d,s,t}^{EV} + P_{d,s,t}^{th} + P_{d,s,t}^{ch} - P_{d,s,t}^{dis} - \boldsymbol{PV}_{\boldsymbol{d,s,t}}) \tag{13}$$

As the CM faces a penalization cost due to imperfect net-load forecasts, the average cost of energy in time step t and scenario s $\boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}}$ is given by (14):

$$\boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} = \frac{\boldsymbol{\lambda}_t^{\boldsymbol{DAB}} \cdot P_t^{DAB} - \boldsymbol{\lambda}_t^{\boldsymbol{DAS}} \cdot P_t^{DAS}}{P_{s,t}^{GRID}} + \frac{\boldsymbol{\lambda}_t^{\boldsymbol{UP}} \cdot P_{s,t}^{UP} - \boldsymbol{\lambda}_t^{\boldsymbol{DOWN}} \cdot P_{s,t}^{DOWN}}{P_{s,t}^{GRID}} \tag{14}$$

The first stage redefines existing cost-sharing mechanisms and bases them on consumers' net-load and their technical characteristics. Nowadays, when feed-in tariffs for PV are gradually decreasing, the installation and implementation of net-metering (single four-quadrant meter) are perfectly viable [44] and [45]. Unlike [22] and [24], where internal community prices in MMR and BSM (similar is the case for SDR in [28]) are computed based on the total community's consumption and generation, in the proposed approach the consumers pay or get paid based on their net-load in scenario s and time period t. This means that consumers only sell surplus or buy deficit of energy, differently from the existing research, where they sell their entire PV production and buy their entire demand (not deficit). The second stage describes the benefit reallocation if any of the community members face higher costs in the community.

A. PRICES CALCULATION IN THE FIRST STAGE

1) BILL SHARING METHOD NET

The Bill Sharing Method Net (BSMN) is based on allocating the electricity cost among consumers based on their contribution to the total community cost. In each time period t and scenario s, the community cost is divided among consumers who contribute to energy purchase. It uses the ratio between the total community electricity import and the sum of all the individual positive net-loads if the community purchases energy, and on the ratio between the total community export and the sum of the all individual negative net-loads if the community sells energy. As an upgrade of [22], this paper uses dynamic pricing and flexible appliances and reformulates the mechanism in terms of net-load unlike [24]. Furthermore, for the first time, the disadvantage of BSMN for consumers with an excess PV production is explained.

The total net import (15) and export (16) of the community are calculated *ex-post* as follows:

$$P_{s,t}^{net\ pos} = \sum_{d\in D} P_{d,s,t}^{net},\ if\ P_{d,s,t}^{net} > 0 \tag{15}$$

$$P_{s,t}^{net\ neg} = \sum_{d\in D} P_{d,s,t}^{net},\ if\ P_{d,s,t}^{net} < 0 \tag{16}$$

If the community purchases energy in hour t, the price for consumers who have a deficit of energy is calculated as (17):

$$\lambda_{s,t}^{BSMN\ B} = \boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} \cdot \frac{P_{s,t}^{GRID}}{P_{s,t}^{net\ pos}} \tag{17}$$

It can be noticed that consumers who have an excess of electricity are not remunerated if that electricity is shared/consumed within the community. Since the community in the above case has a deficit of energy, the cost of procuring energy is shared among consumers who contribute to the deficit. If, on the contrary, the community sells energy in hour *t*, the price for consumers who have excess energy is computed as (18):

$$\lambda_{s,t}^{BSMN\ S} = \boldsymbol{\lambda_{s,t}^{unit}} \cdot \frac{P_{s,t}^{GRID}}{P_{s,t}^{net\ neg}} \tag{18}$$

In this case, consumers who have a deficit of energy are supplied at zero cost. Finally, if the community is in balance, the electricity procurement cost is 0 (the community neither needs to sell or buy) and consumers do not pay or do not get paid.

2) MID-MARKET RATE NET SCHEME

In the case of the Mid-Market Rate Net (MMRN) scheme, the internal buying and selling prices are affected by the amount of energy exchanged within the community. Consumers with a deficit of energy pay and the ones with excess energy are getting paid at a price that is determined based on how much of the energy is consumed within the community and how much from the supplier. Unlike [22], in this paper consumers are exposed to dynamic prices to fully exploit their flexibility. Moreover, MMR is redefined from [22] and [24] and the internal price calculation is based on the individual net-load of consumers. Three different cases are considered, depending on whether the community is in balance, buys or sells energy.

1) The community is in balance ($P_{s,t}^{GRID} = 0$).

In the case that the community is in balance and, hence, there is no exchange of energy with the grid, the internal buying and selling prices in hour *t* are the same. More specifically, they are equal to the average value between the DA buying and selling prices (19):

$$\lambda_{s,t}^{MMRN\ B} = \lambda_{s,t}^{MMRN\ S} = \frac{\boldsymbol{\lambda_t^{DAB}} + \boldsymbol{\lambda_t^{DAS}}}{2} \tag{19}$$

Additionally, as $P_{s,t}^{GRID}$ is equal to zero, the average cost of energy cannot be calculated as in (14). The penalization cost associated with the realization of scenario *s* is given by (20):

$$\begin{aligned} cost_{s,t}^{pen} = \boldsymbol{\lambda_t^{DAB}} \cdot P_t^{DAB} - \boldsymbol{\lambda_t^{DAS}} \cdot P_t^{DAS} \\ + \boldsymbol{\lambda_t^{UP}} \cdot P_{s,t}^{UP} - \boldsymbol{\lambda_t^{DOWN}} \cdot P_{s,t}^{DOWN} \end{aligned} \tag{20}$$

An equal amount of cost is allocated to each community member (that is, the cost is divided according to the number of consumers in the community).

2) The community buys energy ($P_{s,t}^{GRID} > 0$).

If the community takes energy from the grid, the consumers who have excess energy $\left(P_{d,s,t}^{net} < 0\right)$, are paid at the price (21):

$$\lambda_{s,t}^{MMRNS} = \frac{\boldsymbol{\lambda_{s,t}^{unit}} + \boldsymbol{\lambda_t^{DAS}}}{2} \tag{21}$$

In contrast, consumers who have a deficit of energy pay a price based on the ratio of the total community import and the total positive and negative net-loads in the community (22):

$$\lambda_{s,t}^{MMRN\ B} = \frac{\boldsymbol{\lambda_{s,t}^{unit}} \cdot P_{s,t}^{GRID} + \lambda_{s,t}^{MMRNS} \cdot \left|P_{s,t}^{net\ neg}\right|}{P_{s,t}^{net\ pos}} \tag{22}$$

Notice that the community energy deficit $P_{s,t}^{net\ pos}$ is covered with the purchase of energy from the supplier $P_{s,t}^{GRID}$ and/or with the excess PV production within the community $P_{s,t}^{net\ neg}$. As the internal selling price $\lambda_{s,t}^{MMRN\ S}$ is lower than the average cost of energy from the supplier $\boldsymbol{\lambda_{s,t}^{unit}}$ (see (21)),the larger the amount of energy exchanged within the community, the lower the internal buying price $\lambda_{s,t}^{MMRN\ B}$.

3) The community sells energy ($P_{s,t}^{GRID} < 0$).

If the community sells energy, the consumers who have a deficit of energy $\left(P_{d,s,t}^{net} > 0\right)$, pay the average price (23):

$$\lambda_{s,t}^{MMRN\ B} = \frac{\boldsymbol{\lambda_t^{DAB}} + \boldsymbol{\lambda_{s,t}^{unit}}}{2} \tag{23}$$

On the other hand, consumers who have excess energy get paid based on the ratio of the total community export and the total positive and negative net-loads in the community (24):

$$\lambda_{s,t}^{MMRN\ S} = \frac{\boldsymbol{\lambda_{s,t}^{unit}} \cdot \left|P_{s,t}^{GRID}\right| + \lambda_{s,t}^{MMRNB} \cdot P_{s,t}^{net\ pos}}{\left|P_{s,t}^{net\ neg}\right|} \tag{24}$$

The summation of all the surpluses of PV production $P_{s,t}^{net\ neg}$ is sold to the supplier $P_{s,t}^{GRID}$ or exchanged with the community members $P_{s,t}^{net\ pos}$. As the internal buying price $\lambda_{s,t}^{MMRN\ B}$ is higher than the average selling price provided by the supplier $\boldsymbol{\lambda_{s,t}^{unit}}$,the larger the amount of energy exchanged within the community, the higher the internal selling price $\lambda_{s,t}^{MMRN\ S}$.

3) SUPPLY DEMAND RATIO NET SCHEME

The Supply-Demand Ratio ($SDR_{s,t}$) is defined as the ratio between the negative and positive net-loads in the community (25):

$$SDR_{s,t} = \frac{\left|P_{s,t}^{net\ neg}\right|}{P_{s,t}^{net\ pos}} \tag{25}$$

Differently from [18], this paper considers the stochastic nature of demand, PV production, and outside temperature, and therefore, SDRN is based on consumers' net-load instead. Five possible situations may occur:

1. $P_{s,t}^{net\ pos} = 0$ and $SDR_{s,t} = \infty$.

Each consumer in the community has a surplus of PV production. In that situation, the selling price under the SDRN scheme is equal to the average cost of energy in scenario *s* and time *t* (26):

$$\lambda_{s,t}^{SDRN\ S} = \boldsymbol{\lambda_{s,t}^{unit}} \tag{26}$$

2. $SDR_{s,t} = 0$.

Each consumer in the community has a deficit of energy. The community has to buy energy from the supplier and each consumer pays the average cost of energy in scenario s and time step t (27):

$$\lambda_{s,t}^{SDRN\ B} = \boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} \tag{27}$$

3. $SDR_{s,t} = 1$.

If the community self-balances and does not procure or sell energy from the grid in time step t and scenario s, the internal buying and selling prices are both the same (28):

$$\boldsymbol{\lambda}_{s,t}^{SDRN\ S} = \boldsymbol{\lambda}_{s,t}^{SDRN\ B} = \boldsymbol{\lambda}_{t}^{DAS} + \lambda_{s,t} \tag{28}$$

where $\lambda_{s,t}$ is a compensation rate guaranteeing that the consumers are always better off in the community. Its value can be in the range $[0, \boldsymbol{\lambda}_{t}^{DAB} - \boldsymbol{\lambda}_{t}^{DAS}]$ [28]. This value will be defined in the case study.

4. $SDR_{s,t} > 1$.

If the community has a surplus of energy and some consumers have positive net-load, the internal selling and buying prices determined by the CM in time step t and scenario s are (29)-(30):

$$\boldsymbol{\lambda}_{s,t}^{SDRN\ S} = \boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} + \frac{\lambda_{s,t}}{SDR_{s,t}} \tag{29}$$

$$\boldsymbol{\lambda}_{s,t}^{SDRN\ B} = \boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} + \lambda_{s,t} \tag{30}$$

5. $0 < SDR_{s,t} < 1$.

If the community has a deficit of energy (which must be purchased from the supplier), but some consumers have a surplus of PV production that is consumed locally, the internal selling and buying prices are calculated as follows (31)-(32):

$$\boldsymbol{\lambda}_{s,t}^{SDRN\ S} = \frac{\boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} \cdot \left(\boldsymbol{\lambda}_{t}^{DAS} + \lambda_{s,t}\right)}{\left(\boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} - \lambda_{t}^{DAS} - \lambda_{s,t}\right) \cdot SDR_{s,t} + \lambda_{t}^{DAS} + \lambda_{s,t}} \tag{31}$$

$$\boldsymbol{\lambda}_{s,t}^{SDRN\ B} = \boldsymbol{\lambda}_{s,t}^{SDRN\ S} \cdot SDR_{s,t} + \boldsymbol{\lambda}_{\mathbf{s,t}}^{\mathbf{unit}} \cdot \left(1 - SDR_{s,t}\right) \tag{32}$$

B. BENEFIT REALLOCATION IN THE SECOND STAGE

The results presented in this paper have shown that the mathematical formulation of existing direct cost-sharing methods does not always favor participation in the energy community, but rather result in lower cost if the prosumer individually signs a dynamic price contract with the supplier. For this reason, the paper proposes the second stage for the existing direct cost-sharing methods. This second stage is executed in case any of the prosumers face higher cost $C_{d}^{com\,m}$ when being a member of the community compared to the individual supplier cost C_{d}^{ind}. The logic of the improved direct cost-sharing concept is as follows:

1. The first stage is conducted as described in Section IV A.
2. Each community member allocated cost (under m cost-sharing method) is compared to the cost it would receive if staying with the supplier (33). C_{d}^{ind} can easily be calculated as all price parameters are transparent and publicly available on a DA base.

$$\Delta_{d} = C_{d}^{ind} - C_{d}^{com\,m}, \quad \forall d \in D \tag{33}$$

3. If all community members are paying less compared to staying with the supplier, the algorithm stops. If any community member is worst off in the community, the second stage is initiated.
4. The sum of the positive cost difference C^{+} is calculated in (34), i.e., for all prosumers who are better off in the community. The sum of the negative cost difference C^{-} is calculated in (35), i.e., for all prosumers who are worst off in the community.

$$C^{+} = \sum_{d \in D^{+}} \Delta_{d} \quad if\ \Delta_{d} \geq 0 \tag{34}$$

$$C^{-} = \left| \sum_{d \in D^{-}} \Delta_{d} \right| \quad if\ \Delta_{d} < 0 \tag{35}$$

5. If $C^{+} \geq C^{-}$, the benefits are distributed between community members as described in (36) and (37). This ensures that they are at least equally well off as they would be in the traditional supplier contracts. The logic of this distribution is based on the concept of *minimum bound*. This minimum bound, defined by a range in (36), is a concept that guarantees that for the values between the lower and the upper limit each end-user will have at least the same cost as in the case of having the contract with the supplier. For any value in between the end-user will be better off in the community. The same value of minimum bound has to be chosen for each consumer in benefit reallocation. The cost of community members in the second stage is calculated in (37a) and (37b).
if $C^{+} \geq C^{-}$:

$$\frac{C^{-}}{C^{+}} \leq \min\ bound \leq 1 \tag{36}$$

if $\Delta_{d} \geq 0$:

$$C_{d}^{new+} = C_{d}^{com\,m} + \min\ bound \cdot \Delta_{d}, \tag{37a}$$

if $\Delta_{d} < 0$:

$$C_{d}^{new-} = C_{d}^{com\ m} - \frac{|\Delta_{d}|}{C^{-}} \cdot \sum_{d \in D^{+}} \left(C_{d}^{new+} - C_{d}^{com\ m}\right), \tag{37b}$$

6. If $C^{+} < C^{-}$, the benefits cannot be reallocated under m cost-sharing method which makes it a non-preferable cost-sharing method.

V. CASE STUDY

For the analyses that follow, two prosumers and a flexible consumer are considered. All three have flexible thermal heating, flexible uninterruptible appliances (washing machine, dishwasher, and dryer), a battery (4kWh), and a smart EV charger (3.7 kW) with the same EV battery capacity

(30 kWh). The power of the washing machine, the dryer, and the dishwasher is 2 kW, 2.5 kW, and 1.9 kW, respectively, while the cycle length of each appliance is 3 h, 2h, and 1h, in that order. For the modeling of the thermal heating, an upper temperature bound is set at 25 °C for each household, while the lower bound depends on the consumers' preferences on the assumption that they allow for a lower temperature at night or when not at home.

Prosumer 1: Car 1 is parked at home between hour 23 and hour 6 in the morning, while $\underline{\boldsymbol{E}}_{\mathbf{1}}$ at the end of the charging period is set at 25.9 kWh ($\boldsymbol{H}_{\mathbf{1}}^{a} = 23, \boldsymbol{H}_{\mathbf{1}}^{l} = 6$). Consumer 1 sets the lower temperature bound at 19°C from hour 21 to 6 in the morning, and 22 °C for the rest of the day.

Consumer 2: Car 2 is parked at home between hour 18 and 7 ($\underline{\boldsymbol{E}}_{\mathbf{2}} = 22.2kWh$). Consumer 2 sets the lower temperature bound at 20°C during hours 23-9, and at 23 °C during the rest of the day.

Prosumer 3: Car 3 is connected to the charger between hours 17 and 8 ($\underline{\boldsymbol{E}}_{\mathbf{3}} = 29.6kWh$). Consumer 3 requires an indoor temperature of at least 18°C from hour 23 to 13, while 21°C is set as the lower bound during the rest of the day.

Albeit the minimum and maximum temperature bounds are set as fixed parameters, uncertainty related to thermal heating is considered through different scenarios of the outside temperature. Three different cases of PV production are considered with six possible scenarios each: high (black discontinuous line), medium (dark grey dotted line), and low (light grey color) as depicted in Fig. 3. PV and temperature measurements are taken from a PV panel placed on the rooftop of a laboratory in Zagreb and grouped to fit in the three previously mentioned cases.

DA buying (black) and selling (grey) prices, as well as up (black dotted) and down incentive prices (grey dotted) are presented in Fig. 4. The difference in the buying and selling prices offered by the supplier actually represents the real situation in some countries like Denmark. The Danish supplier Orsted offers dynamic selling prices to the final consumers [49], while the surplus of PV production is sold at the market price (Nordpool [50]). According to the proposal of the market design in the European directive [42], more transparent RT price signals (which reflect the DA market prices) stimulate consumers to change their consumption, either individually or through aggregation. This results in increased flexibility that facilitates the transition towards a carbon-neutral power system. Danish prices are taken as an example due to data availability, however other countries in the EU have already implemented dynamic tariffs for end-users (such as Red Eléctrica in Spain [51] or 7H Kraft in Sweden [52]). The approach used in this paper is not country-specific, but rather general enough for the entire EU. Network charge for supplied kWh is set at 9.7 ORE/kWh while balancing cost in directly trading with the supplier is set at 0.197 ORE/kWh for purchased energy and 0.112 ORE/kWh for sold energy [46]. Up and down incentive prices encourage prosumers in the energy community to follow their

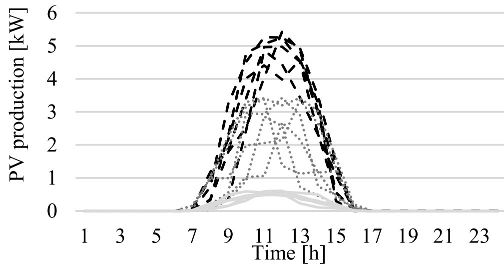

FIGURE 3. **Aggregated PV production.**

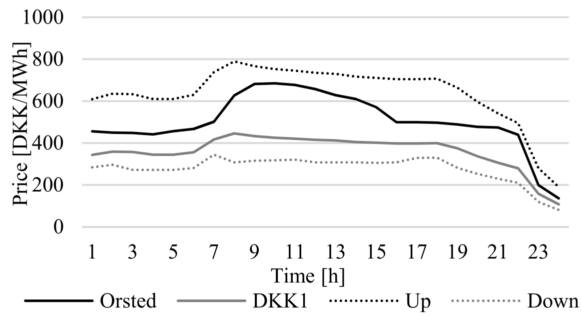

FIGURE 4. **DA buying/selling prices, up /down flexibility incentives.**

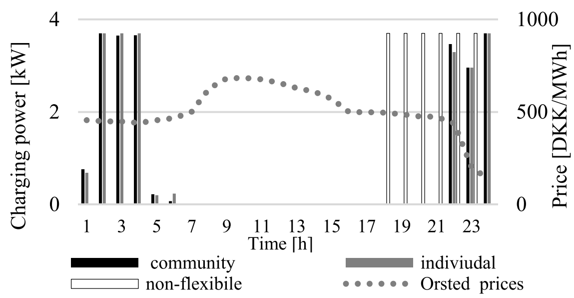

FIGURE 5. **Flexible and non-flexible charging of EV – consumer 2.**

predefined DA schedule instead of paying the balancing cost for each bought or sold kWh of energy.

If the energy community has a deficit of energy with respect to the committed DA schedule, it will pay the difference at the up price, which is higher than the DA buying price. On the other hand, if a consumer has a surplus of energy, they will sell the difference from the scheduled amount at the down-price, which is lower than the DA selling price.

VI. RESULTS

In this section, the monetary value of implementing a flexible EV charging and a flexible start-up time of uninterruptible appliances is assessed. Further, the analysis shows for which case of PV production consumers are always better off in the community and elaborates which cost-sharing scheme is preferable for different types of consumers.

A. BENEFITS OF FLEXIBILE PROSUMPTION

The flexible scheduling of domestic appliances results in a significant cost reduction compared to the case when the

TABLE 2. Averaged cost reduction (in %) (computed over the set of scenarios) in the case of a high PV production with flexible appliances.

	Consumer	1	2	3
	Supplier	-8.18	-11.32	-10.34
Community	MMRN	-8.62	-11.00	-10.89
	SDRN	-8.71	-11.37	-10.39
	BSMN	-6.99	-19.72	-3.66

EV charging and the start of uninterruptible appliances are not flexible. In the non-flexible scenario, it is supposed that the charging of the EV is started from the very moment the car arrives home. The car is being charged at maximum charging power until the desired battery state of energy is reached. Besides, the starting times of the washing machine, the dryer, and the dishwasher are fixed to 18 h, 21 h, and 23 h, respectively. On the other hand, in the flexible regime, the operation of each appliance is determined by the CM scheduling algorithm in accordance with the predefined comfort zones of consumers. The average cost reduction in percentage for each consumer in the case of high PV production is shown in Table 2. The first row in this table provides the cost reduction for the instance in which each consumer trades directly with the supplier, while the remaining rows in the table pertaining to the different cost-sharing mechanisms in the community that have been described in Section IV. As can be seen in Table 2, smart charging of EV and flexible starting time of uninterruptible appliances can significantly reduce the end-user cost (from 3% to almost 20% cost reduction in flexible regime). The highest cost reduction achieves consumer 2 who does not have PV installed.

Average (over the observed set of scenarios) charging powers of EVs under the flexible and non-flexible case studies are compared in Fig. 5 for consumer 2. Non-flexible charging is set from hour 18. The car is being charged at the maximum power of 3.7 kW for 6 hours to reach the desired state of charge, which is set at 22.2 kWh. Compared to flexible charging, which considers prices, one can notice that cost reduction in the flexible case is achieved by charging the EV in hour 24 and during the morning hours from 0 to 6 am when the prices are lower compared to the early evening prices from hour 18 to 21.

Moreover, in the flexible regime, the start-up time for washing machine, dryer, and dishwasher is at hour 21h, 22h, and 23h, while in non-flexible is set at 18h, 21, and 23h. The biggest cost reduction is achieved by the scheduling of washing machine where the whole washing period of 3 hours is moved to less expensive hours.

B. ANALYSIS OF THE BEST COST-SHARING MECHANISM

Table 3 compares the average cost of procuring electricity by the energy community under the different cost-sharing methods for the three considered cases and the cost linked to individually trading with the supplier. A fair cost-sharing mechanism is the one that makes all consumers better off within the energy community compared to the individual trading approach with the supplier. As can be seen from Table 3, all community members are better off in the energy community with SDRN and MMRN for the cases of medium and high PV production. In the case of low PV production, prosumer 3 is not always better off within the energy community. Their cost reduction can, in case of high PV production, reach 20% with community trading and cost-sharing under BSMN. In MMRN, if the energy community self-balances, consumers with excess energy get paid more than in the individual trading strategy. In particular, they are paid at the average of the buying and selling prices offered by the supplier, which is higher than the selling price. Likewise, consumers who need to buy get the same average price, which is lower than the buying price. Under SDRN, those consumers with excess energy get a compensation, which is set at $(\lambda_t^{DAB} - \lambda_t^{DAS})/2$. The result is that all the members in the cooperative are awarded for supporting the self-sufficiency of the community.

Table 4 shows the attained cost reduction (if negative) or cost increase (if positive) in percentage under the six scenarios of high PV production. It can be noticed that all consumers are better off in the energy community under SDRN and MMRN. The exception is prosumer 1 in scenario 5, consumer 2 in scenario 4 under MMRN and prosumer 3 in scenario 2 under SDRN (the benefit reallocation in the second stage will be explained further in the text). However, BSMN is only favorable for the consumer without PV as they profit from prosumers with an excess PV production. The energy deficit of consumer 2 is supplied at zero cost from excess PV production from other prosumers resulting in the biggest cost savings. Cost savings for prosumers 1 and 3 under MMRN and SDRN are very similar because they reward excess PV production with higher internal selling prices compared to that of the supplier. The optimal contracts that lead to a win-win situation for all stakeholders are both MMRN and SDRN. For high PV production, prosumers 1 and 3 incur higher electricity costs under BSMN. To further illustrate the disadvantages of BSMN for prosumers with a surplus of PV production, Table 5 shows the electricity procurement costs in DKK for all consumers in hour 10 of scenario 6, under the individual trading setup and the BSMN cost-allocation method that is based on net-load (note that a negative cost represents a profit from selling energy). In this hour, the community does not exchange energy with the grid, while the consumers' net-loads are -0.24kW, 2.4 kW, and -2.16 kW. Consumer 2 takes advantage of the excess PV production from prosumers 1 and 3. Moreover, in the hours when the total net-load of the community is negative, the consumers who contribute to the profit of the community share only the profit for the energy exported outside the community, but not for the energy shared among other community members. In contrast, a consumer with a positive net-load is the one benefiting the most because they do not pay anything for

TABLE 3. Average cost (IN DKK and computed over the respective set of scenarios) of individual vs. community trading under the different cost-sharing methods in the first stage.

Case	High PV			Low PV			Medium PV		
Consumer	1	2	3	1	2	3	1	2	3
Supplier	18.89	22.72	19.74	24.84	22.72	24.08	22.18	22.72	21.71
MMRN	18.61	22.53	19.44	24.83	22.67	24.11	21.91	22.33	21.42
SDRN	18.76	22.31	19.60	24.83	22.66	24.12	21.91	22.24	21.51
BSMN	20.22	18.06	21.76	24.92	22.42	24.27	21.99	20.51	23.16

TABLE 4. Cost comparison (in %) under six scenarios of high pv production in the first stage.

Consumer	1			2			3		
Method	MMRN	SDRN	BSMN	MMRN	SDRN	BSMN	MMRN	SDRN	BSMN
1	-0.95	-0.84	5.69	-0.17	-1.24	-20.15	-1.68	-0.66	13.15
2	-2.35	-1.92	9.26	-0.28	-2.04	-23.76	-1.56	0.02	14.07
3	-0.83	-0.54	5.79	-1.96	-2.39	-9.63	-1.15	-0.93	1.33
4	-2.89	-2.51	3.90	0.23	-1.01	-23.84	-2.56	-1.42	20.12
5	0.30	0.32	3.91	-1.66	-2.22	-10.29	-0.69	-0.06	5.78
6	-2.25	-1.55	14.40	-1.08	-1.98	-21.46	-1.71	-1.29	7.16

TABLE 5. Cost comparison in individual and bsmn approach.

Consumer	1				2				3			
Type	Supplier		BSMN		Supplier		BSMN		Supplier		BSMN	
	Netload [kW]	Cost [DKK]	Netload [kW]	Cost [DKK]	Netload [kW]	Cost [DKK]	Netload [kW]	Cost [DKK]	Netload [kW]	Cost [DKK]	Netload [kW]	Cost [DKK]
Hour 10	-0.08	-0.03	-0.24	0	0.18	0.14	2.4	0	-0.90	-0.38	-2.16	0

their energy deficit. The amount of energy consumed within the community reduces the selling price (see Equation (18)), and thus reduces the profit for those consumers with an excess PV production. When the community sells energy, the so-obtained profit is shared among prosumers 1 and 3 (that is, between the consumers who have excess energy). However, prosumers 1 and 3 are paid only for the surplus of PV production that is sold by the CM to the supplier and not for that part of the surplus that is consumed within the community. This means that consumer 2 (without PV) covers their deficit of energy at zero cost.

C. SENSITIVITY STUDIES

The results in Table 6 below show daily costs for each consumer in DKK, under different cost-sharing mechanisms, for a case where all three consumers have a PV panel installed. It can be noticed that regardless of all community members have PV installed and excess PV production, they are better off with MMRN and SDRN, while consumer 2 is worse off with BSMN due to the highest excess PV production. The average of PV production excess during the day for consumer 1 is 2.58 kWh, for consumer 2 is 3.33 kWh, and for consumer 3 is 2.30 kWh.

Furthermore, an additional study is conducted for an energy community consisting of 100 participants. Fig. 6 presents the ratios between the energy cost in the community and the cost in the individual approach, for different percentages of PV share and customer flexibility potential. A lower ratio means that trading within the community is more profitable for the consumer. More specifically, if the ratio is below 1, the consumer is better off within the community, while a ratio bigger than 1 involves the existence of consumers who are better off under the individual trading scheme. Simulations are performed for four cases:

TABLE 6. Average cost comparison when all prosumers have PV (DKK).

Consumer	1	2	3
supplier	20.55	16.30	21.69
MMRN	20.47	16.28	21.44
SDRN	20.50	16.29	21.40
BSMN	20.53	16.85	20.81

1) all community members have PV, battery storage, and the flexible start of uninterruptible appliances (denoted as *flexi uni* in Table 7),
2) all community members have PV, 50% of all consumers do not have battery storage or capability to flexibly start uninterruptible appliances,
3) 50% of community members have PV, none has a battery and 50% have the flexible start of uninterruptible appliances,
4) 50% of community members have PV, battery, and the flexible start of uninterruptible appliances (not necessarily the consumer with PV has flexible appliances as well).

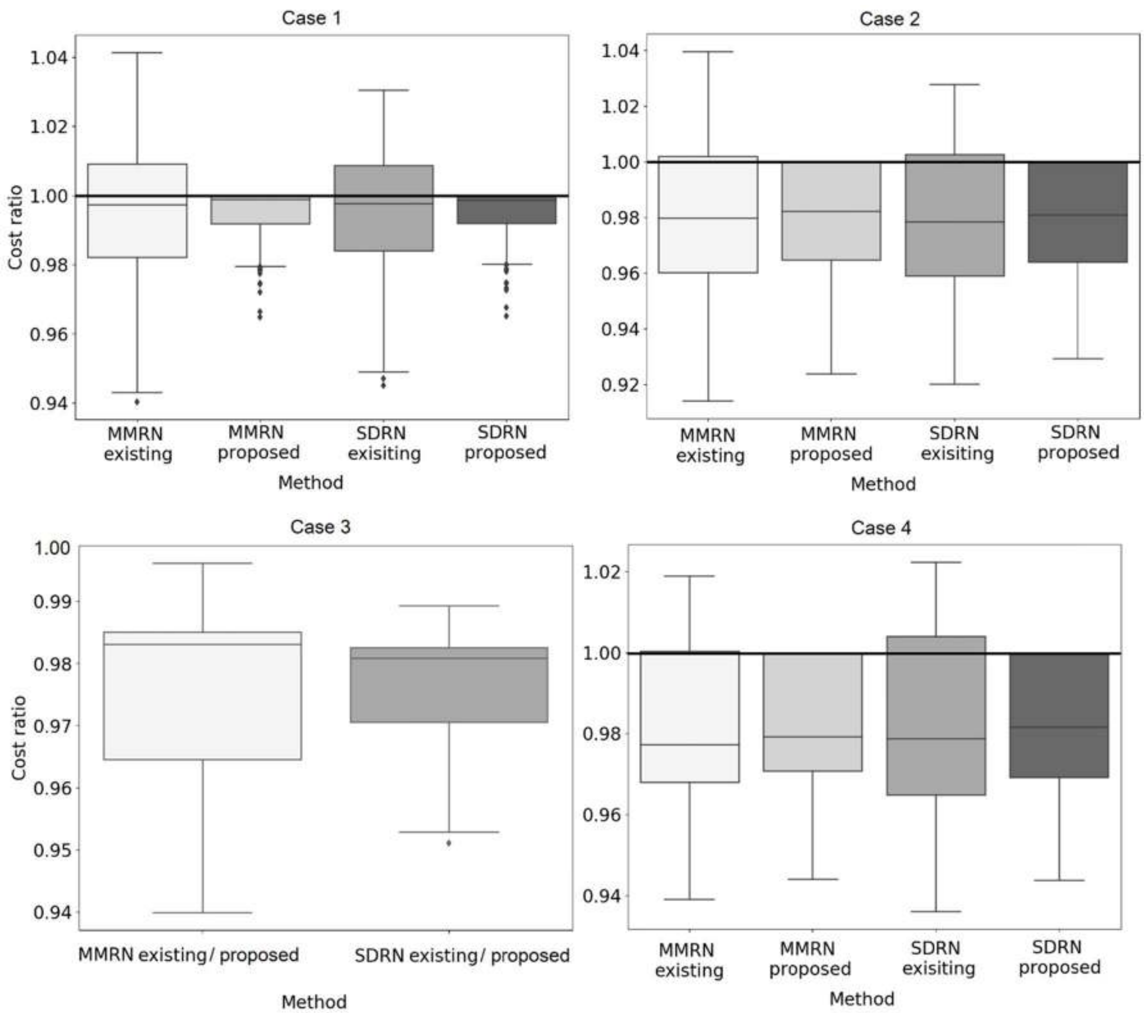

FIGURE 6. Comparison of cost ratios under different pricing mechanism.

TABLE 7. Comparison of cost reduction and cost increase in current and proposed pricing scheme in %.

Method	MMRN		SDRN		BSMN	
Pricing	Current	Proposed	Current	Proposed	Current	Proposed
Cost reduction	5.97 – 8%	3.52 – 7.61%	4.88 – 7.97%	3.52 – 7.07%	30.16 – 32.43%	30.16 – 32.43%
Cost increase	1.90 – 4.14%	0	2.24 – 3.05%	0	19.78 – 25.37%	19.78 – 25.37%

For consumers without the flexible start of uninterruptable appliances, the start-up time is set as explained in Section VI A. In the first stage of the cost-sharing, the internal buying and selling prices according to the three cost-sharing schemes are calculated. The second stage determines the lower value of the benefit reallocation if any of the community members face higher costs in the community. In Case 3 all community members are at least the same or better off in the first stage under the existing MMRN and SDRN. The cost ratio is 1 or lower than 1 which means that there is no need to run the proposed stage 2 of the cost-sharing allocation. On the other hand, one can notice from Fig. 6 in Cases 1, 2, and 4, some community members are worst off in the energy community under the existing pricing mechanisms (a white boxplot for MMRN and a gray boxplot for SDRN), i.e., their ratio is higher than 1. In these two cases, the second stage is executed ensuring the distribution of benefits as described in Section IV. B. and the results in Fig. 6 show that now all community members face at least the same or lower cost compared to the individual trading with the supplier in all scenarios. Graphs are plotted for the lower limit of the minimum bound which defines the minimum value of cost reduction sharing. All community members have a ratio equal to 1 or lower than 1 in light gray boxplots (MMRN) and dark

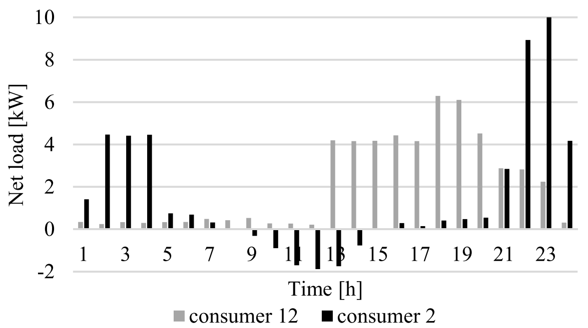

FIGURE 7. Net-load of consumers 2 and 12.

TABLE 8. Reduction in lower bound in % of benefit reallocation in case 4.

Scenario	MMRN	SDRN
1	18.94	49.56
2	37.07	65.59
3	35.50	59.88
4	30.07	48.92
5	32.38	61.53
6	47.43	114.29

gray boxplots (SDRN). Interestingly, it can again be noticed that BSMN is not a preferable method for community trading. BSMN underperforms in all analyzed cases, suggesting this is not a desirable method to be used for cost-sharing in energy communities. The proposed improvements of the original method cannot be applied because $C^+ < C^-$, concluding that the prosumers with excess PV will not be attracted to join the energy community under the BSMN method as their over-production is treated as free electricity for other community members. The total cost increase for prosumers is higher than the total cost reduction in the community, making it impossible to reallocate the benefits among community members to achieve the lower cost for all members. To explain the reason why the BSMN method is not a preferential method in the community participation, the net loads of consumers 2 and 12 in case 4 and under BSMN cost-sharing mechanism are compared. Fig. 7 represents the net-load during the day of consumer 2 and 14 in case 4. It can be noticed in Fig. 7 that consumer 2 has a surplus of PV during the day, which is shared among other community members for free. The total community export in hours 8,9, 14 is zero, whereas consumer 2 is not getting paid at all in hours 9 and 14.

D. THE VALUE OF FLEXIBILITY INCENTIVES

In the current trading with the supplier, consumers pay the balancing cost for each consumed or injected kWh of energy [46] as described in (1). This paper proposes flexibility incentives that encourage the prosumers to follow the predefined DA schedule and minimize paying for regulating up and down power deviations. Additional simulations were run to demonstrate the benefits of the proposed community pricing with flexibility incentives compared to the current pricing scheme when final prosumers are engaged in the energy community. The results in Table 7 clearly show that under the current cost-sharing calculation of MMRN and SDRN some community members will end up with higher energy bills compared to the individual trading with their supplier. On the other hand, the proposed two-stage method guarantees this will not happen as it evenly distributes the welfare among members. Although in the proposed approach individual cost reduction is lower (5.97 – 8% compared to 3.52 – 7.61%), none of the community members face higher costs. On the other hand, in the current community trading, some community members face up to 4% of a cost increase under MMRN. The results also clearly show that BSMN should not be used as the community cost-sharing method. Table 8 shows the change in minimum bound value between the case in which the energy community pays the balancing cost and the proposed pricing method based on flexibility incentives. Interestingly, this minimum bound cannot be calculated for Case 1 and 2 when the community pays the balancing cost for each kWh of consumed or injected kWh of energy ($C^+ < C^-$). This means that some community members will be worst off in the community. In Case 3, all community members are better off in the community in both types of community pricing. In Case 4 consumers who are better off in the first stage will need to share a lower amount of their cost reduction with other community members. This lower value of minimum bound is reduced by 18-47% in MMRN and 49-114% in SDRN in the proposed pricing which makes it more preferable compared to the current pricing scheme.

VII. CONCLUSION

To raise awareness about energy efficiency, it is important to encourage prosumers and energy communities to consume energy locally and to utilize their flexibility by following price incentives. In order to reduce prosumers' electricity costs, this paper describes an energy community driven by price signals from a CM. The CM contracts buying and selling energy from a DA market and encourages flexible behavior of its community members with incentives that capture the regulating power costs linked to errors in the forecast load and PV production. The allocation of those costs within the community is carried out ex-post (in particular, the day after energy delivery) based on individual net-load measurements and both DA market prices and incentives from the CM. In this approach, consumers do not need to negotiate the exchanged electricity volumes and prices between each other. They share the surplus of energy, while the CM determines the transaction prices the day after. Firstly, the monetary value in terms of decreasing electricity costs with domestic flexible appliances is assessed. The case with fully flexible uninterruptable appliances and EV charging is compared with a non-flexible setup with a predefined starting time of EV charging and uninterruptible appliances resulting in savings between 3 and 20%. Secondly, the paper investigates the differences and advantages of various cost-sharing mechanisms for prosumers with PV generation and explains the main disadvantages of the BSMN method for prosumers with excess PV production. Excess PV production in the energy community under BSMN is shared at zero cost which benefits only consumers with an energy deficit, while sellers are at a loss. Thirdly, the paper demonstrated that some community members are not always better off with existing MMRN, SDRN, and BSMN cost-sharing methods compared to the individual trading with the supplier. To overcome this issue, the authors propose the second stage in the centralized cost-sharing process which provides the lower bound of cost reduction reallocation to be shared among peers to achieve lower energy cost under MMRN and SDRN. The results show that none of the community members will face increased cost compared to individual trading with the supplier (unlike in current community trading where some members face up to 4% of cost increase in the community). Furthermore, the paper introduces flexibility incentives, reflecting balancing market costs, with the goal to encourage consumer's RT flexible behavior to follow a predefined DA schedule. This results in lowering the value of the minimum bound in benefit reallocation by 18-47% in MMRN and 49-114% in SDRN.

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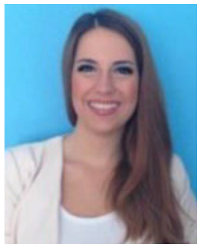

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