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# Cost allocation in integrated community energy systems — Performance assessment

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ABSTRACT

Integrated community energy systems (ICESs) are a modern development of local energy systems by integrating distributed energy resources and local communities. Cost allocation is one of the key issues affecting the success of ICESs. Costs should be allocated to those who cause them, and benefits to those who make the investments. A well-designed cost allocation approach will therefore contribute to a successful implementation and sustainable development of ICESs. This paper presents a general framework for designing cost allocation schemes in ICESs. Various cost allocation methods are proposed to compute the energy bills for local community members in an ICES. In addition, the cost reflectiveness of different cost allocation methods has been computed based on a case study of an ICES to gain insights into how well the costs are allocated. Next to this, the same is also done for the cost predictability to investigate how the energy costs would change in the long term. The results showed that methods with a single energy charging component perform the best in terms of the two criteria. Our assessment can facilitate local community members in selecting a method that satisfies their requirements. Overall, this research contributes to a successful implementation of cost allocation in an ICES.

## 1. Introduction

### 1.1. Background and motivation

Integrated community energy systems (ICESs) emerge in the development of local energy systems by integrating local distributed energy resources (DERs) and local communities [1,2]. ICESs utilize the technical values of community microgrids and the social and economic values of integrated energy systems to create systems that are robust, reliable, and secure [1]. ICESs emphasize the engagement of local community members to participate in the decision-making process, on such matters as making investments in community DERs and selecting a socially acceptable cost allocation method, so that they take full control of the energy system [3]. Individual households are the basic units of local communities; they can choose whether or not to invest in an individual DER. In doing so they are changing their role from being consumers to prosumers thanks to local generation, demand response, and energy efficiency measures. They are interconnected and can also consume or share energy within an ICES, once they agree to join. Similar to any local energy system, an ICES can work in both grid-connected and off-grid mode [4]. Off-grid ICESs aim to achieve self-sufficiency by reducing dependence on the grid, exchanging energy with it only when necessary. This is the future trend [5]. Compared to a large number of individual grid-connected DERs, ICESs reduce the effects on the distribution grid through collective generation, consumption, purchasing, and local energy management [3]. ICESs have a significant role to play in the transition to future energy systems.

One of the novel aspects of ICESs lies in their ability to enable community control of energy generation and consumption, which is a big step forward in social innovation in the management of energy systems. Various actors can involve themselves in ICESs, with different interests. Local community members can generate and consume affordable and green energy. They are also offered the opportunity to become investors and have the right to make decisions. External investors can invest in community DERs, too, to pursue profits. Energy service companies make profits by providing related services, such as energy efficiency improvement, system operation, and the management of local generation and delivery. A strong sense of community is essential for an ICES, since local community members are involved in the planning, development, and administration of the energy system as well as the allocation of its costs and benefits [6,7].

Earlier studies on ICESs have mostly concentrated on technical aspects, such as hierarchical management [8], optimal scheduling and dispatching with the objective of minimizing operational costs [9–11]. The available tools for optimization planning and analysis of ICESs are comprehensively reviewed in [1]. The study in [12] presents an assessment framework for the value of ICESs in terms of costs and benefits for

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**Nomenclature**

| | |
|---|---|
| $B_e$ | Charging and discharging efficiency of storage |
| $C1_{i,j}$ | Annual cost for user $i$ under method $j$ in year 1 (€) |
| $C2_{i,j}$ | Annual cost for user $i$ under method $j$ in year 2 (€) |
| $C$ | Energy cost per customer (€/customer) |
| $C_{base}$ | Costs in off-peak hours (€) |
| $C_{i,DER}$ | Annual cost for user $i$ for its individual energy system (€) |
| $C_{i,j}$ | Annual cost for user $i$ under method $j$ (€) |
| $C_i(t)$ | Energy cost at hour $t$ for user $i$ (€) |
| $C_{peak}$ | Costs in peak hours (€) |
| $CPI_{i,j}$ | Cost predictability index for user $i$ under method $j$ |
| $CRI_{i,j}$ | Cost reflectiveness index for user $i$ under method $j$ |
| $CS_i$ | Subscribed capacity of DERs by household $i$ (kW) |
| $D(t)$ | Total energy consumption for all users at hour $t$ (kWh) |
| $D_i(t)$ | Energy consumption for user $i$ at hour $t$ (kWh) |
| $E(t)$ | Total energy consumption at hour $t$ (kWh) |
| $E_{ave}(t)$ | Energy consumption below the threshold (kWh) |
| $E_{B\_max}$ | Maximal energy state of storage (kWh) |
| $E_{B\_min}$ | Minimal energy state of storage (kWh) |
| $E_{base}(t)$ | Energy consumption in off-peak hours (kWh) |
| $E_B(t)$ | Energy state of storage at hour $t$ |
| $E_B(t+1)$ | Energy state of storage at hour $t+1$ |
| $E_{dif}(t)$ | Energy difference between generation and demand at hour $t$ (kWh) |
| $E_{ex\_grid}(t)$ | Energy exchange with the grid at hour $t$ (kWh) |
| $E_{exc}(t)$ | Energy consumption exceeds the threshold (kWh) |
| $E_i(t)$ | Energy consumption at hour $t$ of user $i$ (kWh) |
| $E_{peak}(t)$ | Energy consumption in peak hours (kWh) |
| $E_{RES}(t)$ | Energy generation from RESs at hour $t$ (kWh) |
| $E_{th}$ | Threshold value (kWh) |
| $f$ | Allocation coefficient |
| $f_{1,i}$ | The first allocation factor for user $i$ |
| $f_{2,i}$ | The second allocation factor for user $i$ |
| $IC_{PV}$ | Installed capacity of PV (kW) |
| $IC_{WT}$ | Installed capacity of wind turbine (kW) |
| $lf$ | Load factor |
| $N$ | Number of customers |
| $P_{ave,i}$ | Average demand of user $i$ (kW) |
| $P_{ave}$ | Energy price for consumption below the threshold (€/kWh) |
| $P_{base}$ | Energy price in off-peak hours (€/kWh) |
| $P_{CP,i}$ | Coincident peak demand of user $i$ (kW) |
| $P_{CP}$ | Coincident peak capacity price (€/kW) |
| $P_{CP}$ | Coincident peak price (€/kW) |
| $P_{CS}$ | Subscribed capacity price (€/kW) |
| $P_C$ | Capacity price (€/kW) |
| $P_{exc,i}$ | Excess demand of user $i$ (kW) |
| $P_{exc}$ | Energy price for consumption exceeds the threshold (€/kWh) |
| $P_E$ | Average energy price (€/kWh) |
| $P_f$ | Flat energy price (€/kWh) |
| $P_{NCP,i}$ | Non-coincident peak demand of user $i$ (kW) |
| $P_{NCP}$ | Non-coincident peak capacity price (€/kW) |
| $P_N$ | Customer service price (€/customer/year) |
| $P_{peak,i}$ | Peak demand of user $i$ (kW) |
| $P_{peak}$ | Energy price in peak hours (€/kWh) |
| $P_{PV}(t)$ | PV generation per capacity at hour $t$ (kWh/kW) |
| $P_{WT}(t)$ | Wind turbine generation per capacity at hour $t$ (kWh/kW) |
| $T_{ave}$ | Hours for consumption below the threshold (h) |
| $T_{base}$ | Off-peak hours (h) |
| $T_{exc}$ | Hours for consumption exceeds the threshold (h) |
| $T_{peak}$ | Peak hours (h) |
| $TC$ | Total costs (€) |
| $TC_C$ | Costs allocated to capacity component (€) |
| $TC_{E+C}$ | Costs allocated to energy and capacity components (€) |
| $TC_E$ | Costs allocated to energy component (€) |
| $TC_S$ | Costs allocated to customer service component (€) |
| $TC_T$ | Total costs in time period $T$ (€) |
| DERs | Distributed energy systems |
| EMS | Energy management system |
| ICESs | Integrated community energy systems |
| RESs | Renewable energy sources |
| ToU | Time of use |

local communities. Another assessment framework is presented in [4], to evaluate the value of ICESs in terms of total energy costs and $CO_2$ emissions in grid-connected and off-grid operation modes. These works thus focus on technical optimization problems driven by economic incentives to reduce operation and energy costs, and on environmental concerns with a view to reducing $CO_2$ emissions.

The review in [3] provides a good overview of the key issues and trends shaping the development of ICESs. One of those key issues that requires further study is the fair allocation of costs and benefits among local stakeholders. Costs should be allocated to those who cause them and benefits should accrue to those who make the investments. Fair cost allocation is the main factor that affects the success of an ICES [2]. It helps to avoid free-rider behavior, contributes to the cooperation of local community members, and promotes social acceptance of the cost allocation results [5]. However, the work associated with cost allocation in the application of ICESs has not been studied in the existing research. It will therefore be of great value to investigate this aspect in depth in order to facilitate the successful implementation of ICESs in the short-term, as well as to ensure their long-term development. Cost allocation for an energy system is often discussed in another field of study, namely tariff design in large power systems; it shows how the costs in those systems are allocated to the end-users. The study in this paper focuses on cost allocation methods and their performance assessment. To this end, the tariff design framework and widely used cost allocation methods are reviewed in the next section.

### 1.2. Review of tariff design

Tariff is the interface between a utility grid and its end-users under regulation [13]. It is used to charge customers for the electricity service they receive. Tariffs are basically a group of charges, with each charge serving a particular component of the tariff. The electricity tariff consists of: distribution network charges, transmission network charges, energy prices, and regulated taxes [14,15]. In a liberalized electricity market, energy prices are determined by the competitive market, while distribution and transmission network charges remain regulated [16].

Tariffs need to achieve two main objectives: the first is to recover the total allowed costs, while the second is to send economic signals to consumers to ensure that the system is used in the most efficient way [13,17]. Tariffs are designed to follow regulatory principles, which are frequently in conflict with each other. These principles are often used to coordinate the relationship between the energy sector and its customers, and in general they are categorized into three groups, namely system sustainability principles (which include cost recovery and additivity) [18,19], economic efficiency principles (which include cost causality, productive efficiency, and allocative efficiency) [20–22], and customer protection principles (which include non-discrimination, transparency, predictability, and simplicity) [23–25]. Detailed explanations of these principles can be found in [26,27]. In practice, tariff design should consider the practical situation, to ensure its successful implementation, should prioritize some of the above principles over others.

Generally, tariff design is divided into two steps [13,26]. The first is to define the allowed revenues that need to be recovered in each activity. The second is to allocate these costs to each activity, based on cost allocation methods. The final tariffs are computed by adding all those individual ones calculated for each activity. Cost allocation is a very important procedure in tariff design, since it conveys information about how the costs are allocated. The cost allocation methods in tariff design are usually applied to the utility grid and used in transmission and distribution networks. Most of the network costs are fixed; they are mainly capital, and operation and maintenance (O&M) costs, representing investment in electricity transmission infrastructures. The capacity of the network should be large enough to satisfy load demand in peak hours.

Tariffs may be fixed or variable. According to [27], they are classified into fixed, capacity usage-based, and energy usage-based tariffs. Many methods can be adopted to allocate distribution network costs to the end users; those most widely used methods and their applicability to ICESs are reviewed and discussed comprehensively in [5]. Power flow-based methods, such as contract path [28,29], distance-based-MW-mile [30], and power-flow-based-MW-mile methods [31,32], allocate costs based on the distance and the magnitude of power flow. They are not applicable in the context of cost allocation in ICESs, since ICESs are low voltage and include no transmission and distribution networks. The costs in ICESs are almost fixed and are capex intensive, that capital being used to invest in renewable energy sources (RESs). The marginal cost for RESs is almost zero [33,34]. In addition, in the case of a grid-connected ICES, the investment in DERs accounts for the majority of costs, while energy exchange cost with the grid represents a portion so small that it can be disregarded. For this reason, the marginal cost pricing method is not applicable in the context of cost allocation in ICESs. The Ramsey method is based on marginal cost pricing [35,36], so it cannot be used for allocating costs in ICESs, either. According to the analysis in [5], however, some methods, such as flat energy pricing [37], time-of-use (ToU) [38], and the like, can be used to allocate cost in ICESs. Overall, the cost allocation methods adopted in large power systems provide some possible options to allocate costs in ICESs. Ideally, however, new tailored methods should be developed in order to fit their specific context.

### 1.3. Scope and research objectives

The ICESs considered in this study are at a community level. The power generated by local DERs is fed to the local members directly, without using a transmission or distribution network, and all the customers are at the same voltage level. The system configuration is thus different from that of large power systems. Currently, there are no guidelines or statutory regulations on how to allocate costs in ICESs. Our first objective, therefore, is to develop a systematic framework in order to ensure the successful implementation of cost allocation in ICESs.

Our literature review shows that some methods adopted in network cost allocation can be applied in ICESs, and some cannot. However, no detailed information about how they are implemented in the context of ICESs is presented. For instance, what data is required and how it is calculated. In addition, there is no one-size-fits-all solution; new methods will thus have to be developed in order to provide more options. Consequently, the second objective of this study is to derive cost allocation methods from those used in tariff and to develop more options to allocate costs in ICESs.

Many possible cost allocation methods can be used in ICESs. Each has its own characteristics and may perform differently, and there is no consensus on which is the best. Therefore, the third objective of this paper is to evaluate their performance in order to draw clear distinctions among them all. Thus, it can better assist the local community members in selecting a satisfying cost allocation method.

### 1.4. Contributions of this paper

The main contributions made by this paper are as follows.

- A cost allocation design framework specifically for ICESs is developed. Furthermore, that framework can also be used both in any local energy system with characteristic similar to an ICES.
- Tailored cost allocation methods are derived and formulated, based on the methods applied for tariff design in large power systems.
- The performance of the proposed cost allocation methods is assessed quantitatively, using two essential criteria: cost reflectiveness and cost predictability.
- The impact of abnormal conditions (sudden changes in generation and consumption) on the performance of cost allocation methods in terms of cost reflectiveness and predictability is presented to show the consequences brought by these changes.
- A sensitivity analysis is presented to assess the impact of the size of the community on the performance of the proposed cost allocation methods in terms of the two criteria. And the impact of different number of prosumers in the community is analyzed to see how well the methods handle this variable in respect of the two criteria.

### 1.5. Structure of this paper

The remainder of this paper is organized as: Section 2 illustrates cost allocation framework in ICESs. Section 3 presents cost allocation methods. A model of an ICES is presented in Section 4. Section 5 conceptualizes cost reflectiveness and predictability which are used to assess the performance of the proposed cost allocation methods. Section 6 presents a case study and results analysis with a discussion. Finally, a conclusion as well as future work recommendations are illustrated in Section 7.

 

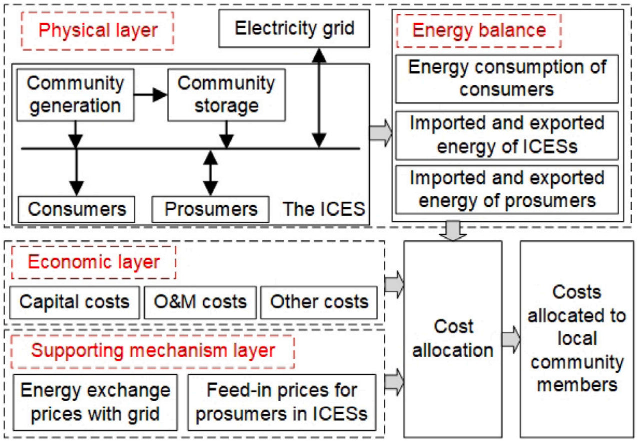


**Fig. 1.** Framework for cost allocation in ICESs.

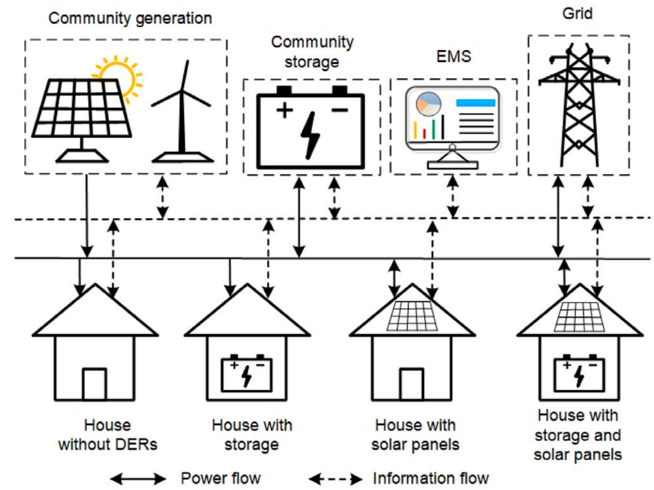


**Fig. 2.** A physical ICES system.

## 2. Framework for cost allocation in integrated community energy systems

A clear and concise framework is required to ensure successful cost allocation in ICESs, since they are different from general power systems. Fig. 1 shows the cost allocation framework in ICESs. This comprises several layers: the physical, the economic, and the supporting mechanism. Each of these layers focuses on different aspects of the design and provides essential inputs to the cost allocation model. They are therefore described in turn in the following sections.

### 2.1. Physical layer

The physical layer presents how the energy system works: specifically, how power and information flow among the different actors in the system. A basic framework of the physical system of the ICES under consideration is shown in Fig. 2. Community generation (solar panels and wind turbines) produces energy and supplies it to local community members (consumers and prosumers). Community storage is used to dispatch energy within the community, being charged from surplus generation and discharged when generation is not sufficient. Local community members can invest in DERs (storage, solar panels or both) to become prosumers. The local community forms a cooperative to exchange energy with the grid. In addition, even though the ICES considered in this paper is grid-connected, the objective of the community is to be self-sufficient. Therefore, energy exchange with the grid is very limited. The whole energy system is controlled by a community energy management system (EMS). The outputs of this physical layer are energy consumption and exchange data, collected at the individual and community levels. This data is necessary information for allocating costs in an ICES. Furthermore, these outputs are considered as the inputs of cost allocation.

### 2.2. Economic layer

The economic layer includes the various costs that are used to purchase infrastructures and cover management fees. These costs plus the energy exchange costs with the grid are the total costs required to be recovered from cost allocation. Principally, they comprise capital, O&M, and other costs. Capital costs are the investment in purchasing and installing DERs. O&M costs are mainly expenses for infrastructure maintenance. These two kinds of costs vary with the overall capacity of the DERs. Other costs are mainly customer management expenses, such as metering, grid connection, and energy billing.

### 2.3. Supporting mechanism layer

The supporting mechanism layer comprises the arrangements needed to ensure successful energy exchange within an ICES and with the grid. Such a mechanism can be regarded as the rules that local community members should follow once they agree to join an ICES. Specifically, these mechanisms are defined as follows.

1. Prosumers are required to pay for their own investments in individual DERs. This cost is incurred through personal action, and so is not considered part of the cost of the system as a whole. The objective of an ICES is to satisfy local demand from local generation by building a local energy system. The costs requiring allocation are common costs of providing electricity to local community members, which includes costs of community DERs and the community energy management system, energy purchases and other related costs.

2. Consumers and prosumers are required to consume energy within the community. Moreover, prosumers are required to sell surplus energy to the community in order to achieve efficient utilization of local generation. The ICES in this study acts as an aggregator, purchasing energy from and selling it to the grid on behalf of the whole community as a collective.

3. The feed-in price for prosumers is determined by the mechanism adopted; for instance, periodic compensation, net energy exchange [39], full peer-to-peer (P2P) energy trading, and community-based P2P energy trading [40,41]. Each trading mechanism has its advantages and disadvantages; which is selected depends on the local situation and the practical complexity of implementation. This study takes community-based P2P energy trading as the energy exchange mechanism used. In order to ensure benefits for local community members and provide incentives for them to stay in the ICES in the long-term, the supporting mechanism of energy exchange must satisfy the following criteria: (1) from the prosumer perspective, the energy selling price to the community is at least equal to the feed-in price to the grid; and (2) from the consumer perspective, the energy selling price is no higher than the price of purchasing energy directly from the grid.

## 3. Cost allocation methods

This section presents methods that can be used to allocate costs in ICESs. Some of these methods have already been adopted in tariff design, but the implementation mechanism may not be the same due to the differences between large power systems and ICESs. Each method is explained in detail to show how its concepts are translated from tariff design and how it is derived from underlying principles. The methods are also formulated mathematically, to show how they are implemented and what data are required.

### 3.1. M1: cost allocation based on number of users

In this method, costs are allocated based on the number of users in the community. It is the method adopted in [42], where it is considered the simplest method to allocate the total costs evenly to each building. Every local member pays exactly the same. It is formulated as:

$$C = \frac{TC}{N} \tag{1}$$

where $C$ (€/customer) is the cost allocated to each customer in the community, $TC$ (€) is total costs, and $N$ is the number of households. The only two required data items are the total cost of the ICES and the number of community members. This approach can thus be implemented without requiring any kind of measuring equipment. It is straightforward to understand and simple to compute. The biggest disadvantage is that it does not take actual consumption into account so that, especially in cases where some households consume a lot of energy and other very little, it is unfair on the latter because they pay the same as everyone else. Nevertheless, it still makes sense if all the households involved have similar energy consumption behavior. Technically speaking, it is easy to implement this method in any energy system.

### 3.2. M2: flat energy pricing

In this approach, the cost is allocated based on total energy consumption within a predefined time period, such as one month or one year. The energy price is fixed during that specific period [43,44]. Consumers pay for their electricity at a flat rate per kWh [45]. The energy price $P_f$ (€/kWh) is calculated as:

$$P_f = \frac{TC_T}{\sum_{i=1}^{N} \sum_{t=1}^{T} E_i(t)} \tag{2}$$

where $TC_T$ (€) is the total costs during the time period $T$, and $E_i(t)$ (kWh) is the hourly energy consumption of household $i$. The required data items are total costs and hourly energy consumption, which can be measured by smart meters. The energy price is time-independent; local community members are all charged the same rate during the predefined time period.

### 3.3. M3: time of use energy pricing

Time of use (ToU) energy pricing is aimed at differentiating energy prices between peak and off-peak hours [18,46]. The price in each time period is fixed, and is higher in peak hours and lower in off-peak hours [38]. According to [47], the rules for cost allocation are that costs of satisfying base demand are allocated to the two periods and the costs of satisfying peak demand are allocated to peak hours only. In large power systems, generators are dispatched according to load demand at different times. It is therefore easy to calculate the costs incurred in different time periods from the actual operational situation. In an ICES, however, it is not easy to differentiate costs during the two periods, because energy generation by RESs is non-dispatchable. In this paper, it is proposed that the costs be allocated to the two periods by taking into account load factor and peak and off-peak time blocks. The two resulting prices (€/kWh) are formulated as:

$$P_{base} = \frac{C_{base}}{\sum_{t=1}^{T_{base}} E_{base}(t)} \tag{3}$$

$$P_{peak} = \frac{C_{peak}}{\sum_{t=1}^{T_{peak}} E_{peak}(t)} \tag{4}$$

$$C_{base} = TC_T \times lf \times \frac{T_{base}}{T} \tag{5}$$

$$C_{peak} = TC_T \times \ lf \times (1 - \frac{T_{base}}{T}) + TC_T \times (1 - lf) \tag{6}$$

$$TC_T = C_{base} + C_{peak} \tag{7}$$

where $P_{base}$ and $P_{peak}$ (€/kWh) are the energy prices in off-peak and peak hours respectively, $C_{base}$ and $C_{peak}$ (€) are the costs in off-peak and peak hours during time period $T$, $T_{base}$ and $T_{peak}$ (hours) are the total off-peak and peak hours during time period $T$, and $E_{base}(t)$ and $E_{peak}(t)$ (kWh) are energy consumption in the ICES in off-peak and peak hours. $lf$ is the load factor, defined as the ratio between average energy consumption and peak demand [48]:

$$lf = \frac{\frac{1}{T}\sum_{t=1}^{T} E(t)}{P_{peak}} \tag{8}$$

where $E(t)$ (kWh) and $P_{peak}$ (kW) are the hourly energy consumption and peak demand in the ICES during time period $T$. The hourly energy cost $C_i(t)$ (€) for customer $i$ is:

$$C_i(t) = \begin{cases} P_{base} \times E_i(t) & t \in T_{base} \quad \text{(a)} \\ P_{peak} \times E_i(t) & t \in T_{peak} \quad \text{(b)} \end{cases} \tag{9}$$

The data required for this method, so as to calculate total energy consumption in peak and off-peak hours, includes total costs, off-peak hours, peak hours, hourly energy consumption. Smart meters are required to gather the hourly energy consumption data. This pricing mechanism incentivizes users to reduce energy consumption in peak hours or to shift it to off-peak hours by charging a higher price during peak hours. From a technical perspective, the energy prices can be provided ex ante by using historical data or ex post (for instance, at the end of the month) by using real data. This depends on the strategy adopted by the local community, although the pricing mechanism used should always be clear to its members.

### 3.4. M4: capacity subscription

The idea behind this method is that each consumer subscribes to a certain amount of DER capacity according to their consumption levels. The total generation from the DERs is determined by the capacity installed. This installed capacity is calculated by the simple rule that annual generation equals annual energy consumption [49]. The capacity price $P_{CS}$ (€/kW) is formulated as:

$$P_{CS} = \frac{TC}{\sum_{i=1}^{N} CS_i} \tag{10}$$

where $CS_i$ (kW) is the capacity of DERs subscribed by household $i$, $P_{CS}$ is the subscribed capacity price (€/kW). The two required data items are total costs and the DER capacity subscribed to by each household, which can be estimated at the beginning of the project by means of historical consumption data. This method simplifies the process of allocating costs and is easy to implement in practice.

### 3.5. M5: coincident peak pricing

In this approach, the costs are allocated based on the peak demand contribution of each household to the total system peak demand within the predefined time period, such as one month, one season or one year [47,50]. The capacity price $P_{CP}$ (€/kW) is formulated as:

$$P_{CP} = \frac{TC_T}{\sum_{i=1}^{N} P_{CP,\ i}} \tag{11}$$

where $P_{CP,\ i}$ (kW) is the peak demand by household $i$, which is coincident with the system peak demand in time period $T$. The required data items are total costs and the peak demand of each household that happened at the system peak time. It is possible to obtain individual peak demand data using smart meters. The pricing signal indicates how consumers' peak demand affects their energy bills and incentivizes them to reduce peak demand.

### 3.6. M6: non-coincident peak pricing

The principle underlying non-coincident peak pricing is to allocate costs based on individual peak demand [51,52]. The difference between this method and the coincident peak pricing is that individual peak demand may not coincide with system peak demand. The capacity charge $P_{NCP}$ (€/kW) is formulated as:

$$P_{NCP} = \frac{TC_T}{\sum_{i=1}^{N} P_{NCP,\ i}} \tag{12}$$

where $P_{NCP,\ i}$ (kW) is the individual peak demand by household $i$. The required data items are total costs and individual household peak demand. The pricing signal indicates how consumers' peak demand influences their energy bills. This is an effective way to incentivize consumers to reduce their individual peak demand, no matter when system peak demand occurs.

### 3.7. M7: segmented energy pricing

The idea of segmented energy pricing is that electricity is sold at different prices for different consumption levels [53]. Consumers are charged at the base price when their consumption level is below a defined threshold, and at another price for any consumption exceeding that. The excess component is the difference between individual peak and average energy consumption (or demand). The threshold is determined using the hourly average energy consumption by households. The total costs in time period $T$ are classified based on load factor. Segmented energy pricing is formulated as:

$$P_{ave} = \frac{TC_T \times lf}{\sum_{i=1}^{N} \sum_{t=1}^{T_{ave}} E_{ave}(t)} \tag{13}$$

$$P_{exc} = \frac{TC_T \times (1 - lf)}{\sum_{i=1}^{N} \sum_{t=1}^{T_{exc}} E_{exc}(t)} \tag{14}$$

$$T = T_{ave} + T_{exc} \tag{15}$$

where $P_{ave}$ (€/kWh) is the energy price when consumption is below the base threshold, $P_{exc}$ (€/kWh) is the energy price for the component of energy consumption exceeding that threshold, $T_{ave}$ and $T_{exc}$ (hours) are the hours of consumption below and exceeding the threshold, respectively, and $E_{ave}(t)$ and $E_{exc}(t)$ (kWh) are consumption below and exceeding the threshold.

The hourly energy bill structure for user $i$ is:

$$C_i(t) = \begin{cases} P_{ave} \times E_i(t) & E_i(t) \le E_{th} \quad \text{(a)} \\ P_{ave} \times E_{th} + P_{exc} \times (E_i(t) - E_{th}) & E_i(t) > E_{th} \quad \text{(b)} \end{cases} \tag{16}$$

Where $E_i(t)$ (kWh) is the hourly energy consumption by household $i$, and $E_{th}$ (kWh) is the threshold value. The required data items for this method are total costs, hourly energy consumption by each household, which are easy to obtain using smart meters. This method focuses on consumption level, regardless of the time of consumption. Customers are incentivized to pay attention to their energy consumption all the time and try to keep this below the threshold in order to minimize its cost. It thus provides a good incentive to adjust consumption behavior. Similar to the ToU energy pricing method, the price signal can be provided either ex ante or ex post, according the strategy adopted by the local community.

### 3.8. M8: average and excess pricing

The underlying principle of the average and excess method is to allocate costs directly to users by means of two factors [47,51]. The first of these presents average consumption by each customer in relation to the average for the entire system. The second shows excess energy consumption by each customer in relation to excess energy consumption in the system as a whole (which equals peak demand minus average energy consumption). The two factors and the energy bills are formulated as:

$$f_{1,\ i} = \frac{P_{ave,\ i}}{\sum_{i=1}^{N} P_{ave,\ i}} \times lf \tag{17}$$

$$f_{2,\ i} = \frac{P_{exc,\ i}}{\sum_{i=1}^{N} P_{exc,\ i}} \times (1 - lf) \tag{18}$$

$$P_{exc,\ i} = P_{peak,\ i} - P_{ave,\ i} \tag{19}$$

$$C_i = (f_{1,\ i} + f_{2,\ i}) \times TC_T \tag{20}$$

where $f_{1,\ i}$ and $f_{2,\ i}$ are the two-part allocation factors for customer $i$, $P_{ave,\ i}$ (kW) , $P_{exc,\ i}$ (kW) and $P_{peak,\ i}$ (kW) are the average demand, excess demand, and peak demand by user $i$, respectively. The required data items are total costs and the hourly energy consumption by each household. The two factors indicate to consumers how their consumption levels affect their energy bills. The primary focus should be on the second factor, as it reflects the gap between peak and average demand. The smaller the second factor, the better: that indicates that customers are contributing less to the system's peak demand. The pricing signal provided by this method is that it is better for consumers to avoid high peak demand and instead to maintain flat and stable energy consumption.

### 3.9. M9: two-part pricing

The two-part tariff is first proposed in [54]. The first part of the price is linked to marginal cost, the remainder to fixed cost. That is used to recover those costs the marginal-cost-based price is unable. As many studies have shown [34,55], however, the marginal cost for RESs is almost zero. The ICES considered in this paper is a grid-independent energy system that only exchanges energy with the grid when necessary, and therefore the costs thereof are just a small portion of the total, so we do not take its marginal cost into consideration in the context of this research. Costs in an ICES are mostly fixed, and do not vary with energy generation. In this method, the fixed costs are translated into variable ones using a coefficient. It classifies the total costs as either energy-related or capacity-related costs. They are then allocated to the end-users based on two charges: an energy charge and a capacity charge. This approach is formulated as:

$$P_E = \frac{TC_E}{\sum_{i=1}^{N} \sum_{t=1}^{T} E_i(t)} \tag{21}$$

$$P_C = \frac{TC_C}{\sum_{i=1}^{N} P_{CP,\ i}} \tag{22}$$

$$TC = TC_E + TC_C \tag{23}$$

$$TC_E = TC \times f \tag{24}$$

$$TC_C = TC \times (1 - f) \tag{25}$$

where $P_E$ (€/kWh) is average energy price, $P_C$ (€/kW) is coincident peak price, $TC_E$ (€) is the cost allocated to energy component, $TC_C$ (€) is the cost allocated to capacity component, and $f$ is the coefficient that divides the total costs between energy-related and capacity-related costs. The required data items are total costs, hourly energy consumption and peak demand by each household, and a coefficient. The energy bills of end-users are determined by their energy consumption and peak demand. The principle underlying this method is to translate fixed costs into variable ones by using a coefficient. These costs are then allocated according to the two cost drivers, energy and capacity, which reflect cost-causality.

### 3.10. M10: multi-part pricing

This method is derived from cost allocation based on the cost-causality principle. Its name refers to the fact that the system costs are allocated to the agents or elements (also referred to as cost drivers) that

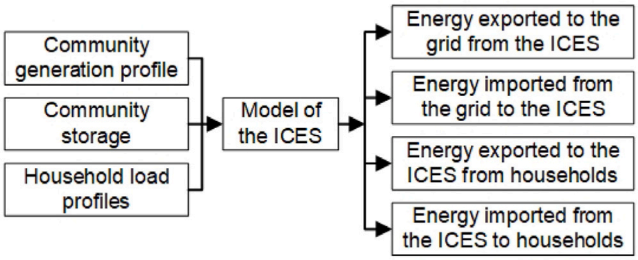


**Fig. 3.** Inputs and outputs of mathematical model of the ICES.

cause them, thus giving a highly efficient signal [17,56]. According to the study reported in [57–59], the most commonly used cost drivers are energy (kWh), capacity (kW), and customer service (customer number). In this approach, the first step is to classify customer service-related costs, which are generated by metering, meter reading, billing, bill collection, and other related activities. The remaining cost is then classified by using a coefficient, which is similar to that used in two-part pricing. The method is formulated as:

$$P_E = \frac{TC_E}{\sum_{i=1}^{N}\sum_{t=1}^{T} E_i(t)} \tag{26}$$

$$P_C = \frac{TC_C}{\sum_{i=1}^{N} P_{CP,\ i}} \tag{27}$$

$$P_N = \frac{TC_S}{N} \tag{28}$$

$$TC_{E+C} = TC_T - TC_S \tag{29}$$

$$TC_E = TC_{E+C} \times f \tag{30}$$

$$TC_C = TC_{E+C} \times (1 - f) \tag{31}$$

Where $P_N$ (€/household/year) is the customer service price, $TC_{E+C}$ (€) is the sum of energy-related and capacity-related costs, and $TC_S$ (€) is the cost of customer service. The required data items are total costs, customer service costs, peak demand, hourly energy consumption, number of households, and allocating coefficient. This approach emphasizes allocating costs to the drivers that cause them, in order to link cost and causality. The costs drivers are reflected in the structure of the final energy bill. This method is easy to implement with the help of smart meters and the pricing strategy is similar to ToU energy pricing either, ex ante or ex post.

## 4. Models of the integrated community energy system

### 4.1. Problem formulation

A model of the ICES is required in order to implement cost allocation. Energy, peak demand, and DER costs are the essential parameters used to allocate the costs to the local community members. For this paper, two such models have been designed: a mathematical and an economic one. The former provides data necessary for cost allocation in the latter, as elaborated below.

### 4.2. Mathematical model of the integrated community energy system

The objectives of the mathematical model are: (1) to ensure the balance of energy supply and demand in the ICES; and (2) to calculate the energy data required by the economic model. The inputs and outputs for the mathematical model are shown in Fig. 3. This model incorporates energy generation, storage, and consumption at the community and the individual household levels.

#### 4.2.1. Load profile of households

Individual households are the fundamental components of an ICES. In our research, the community consists of several households. These can also become prosumers by investing in DERs. The hourly energy demand of each household is denoted as $D_i(t)$ (kWh). A positive value indicates that energy is required from the community, for which the household needs to pay. A negative value indicates that surplus energy is delivered to the community, and from which the household can benefit. The total hourly energy demand by households $D(t)$ (kWh) is:

$$D(t) = \sum_{i=1}^{N} D_i(t) \tag{32}$$

#### 4.2.2. Energy generation from renewable energy sources

Energy generation from RESs depends on the installed capacity. The installed photovoltaic (PV) and wind turbine capacities are $IC_{PV}$ and $IC_{WT}$ (kW), respectively. The hourly generated power per capacity from PV and wind turbine is $P_{PV}(t)$ and $P_{WT}(t)$ (kWh/kW), respectively. Therefore, the hourly energy generation from RESs $E_{RES}(t)$ (kWh) is calculated as follows:

$$E_{RES}(t) = IC_{PV} \times P_{PV}(t) + IC_{WT} \times P_{WT}(t) \tag{33}$$

Calculating the optimum installed capacity in order to minimize the total costs is usually an optimization problem but not an energy system planning problem, which puts it beyond the scope of this research. Our objective is to allocate costs to customers once the energy system is in place. In this paper we use the following rule to calculate the installed capacity: the yearly energy generation from RESs equals the yearly energy demand. In practice, however, energy generation from RESs may not be enough to meet demand at all times. And there are also periods when energy generation exceeds demand. The hourly energy difference $E_{dif}(t)$ (kWh) is calculated as:

$$E_{dif}(t) = E_{RES}(t) - D(t) \tag{34}$$

#### 4.2.3. Energy storage

Energy storage is used to retain surplus energy from generation for later supply to households when there is a shortage from generation. Energy generated by RESs is first delivered to households, then the surplus generation is transferred to storage. Once the storage system is full, any further surplus is sold to the grid to earn revenue. When generation by RESs falls short of current demand, stored energy is used first to make up the shortfall. When that runs out, the community energy system purchases the extra energy it needs from the grid. The energy state of the battery always satisfies the following formula:

$$E_B(t+1) = \begin{cases} E_{Bmax} & E_B(t) + E_{dif}(t) \times B_e \geq E_{Bmax} & \text{(a)} \\ E_B(t) + E_{dif}(t) \times B_e & E_{Bmin} < E_B(t) + E_{dif}(t) \times B_e < E_{Bmax} & \text{(b)} \\ E_B(t) + E_{dif}(t)/B_e & E_{Bmin} < E_B(t) + E_{dif}(t)/B_e < E_{Bmax} & \text{(c)} \\ E_{Bmin} & E_B(t) + E_{dif}(t)/B_e \leq E_{Bmin} & \text{(d)} \end{cases} \tag{35}$$

where $E_B(t+1)$ and $E_B(t)$ (kWh) is the energy state of the storage system at hours $t+1$ and $t$, respectively, $E_{Bmax}$ and $E_{Bmin}$ (kWh) are its maximal and minimal energy state, and $B_e$ is its charging and discharging efficiency.

Following the energy system operation rule, it is easy to calculate the energy exchange with the grid for the whole community. The hourly energy exchange with grid $E_{ex\_grid}(t)$ (kWh) is as follows:

$$E_{ex\_grid}(t) = \begin{cases} E_{dif}(t) - (E_{Bmax} - E_B(t))/B_e & E_B(t) + E_{dif}(t) \times B_e \geq E_{Bmax} & \text{(a)} \\ 0 & E_{Bmin} < E_B(t) + E_{dif}(t) \times B_e < E_{Bmax} & \text{(b)} \\ 0 & E_{Bmin} < E_B(t) + E_{dif}(t)/B_e < E_{Bmax} & \text{(c)} \\ E_{dif}(t) + (E_B(t) - E_{min}) \times B_e & E_B(t) + E_{dif}(t)/B_e \leq E_{Bmin} & \text{(d)} \end{cases} \tag{36}$$

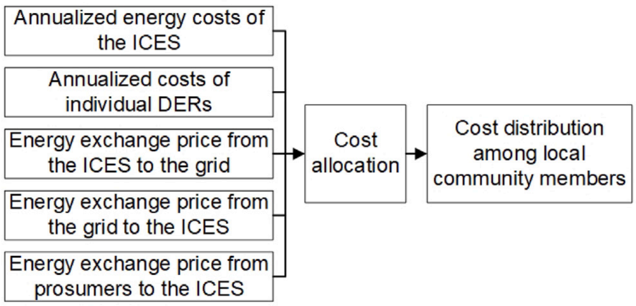


**Fig. 4.** Inputs and outputs of economic model of the ICES.

### 4.3. *Economic model of the integrated community energy system*

The economic model aims to calculate the annualized energy cost for the whole community, in order to facilitate cost allocation during the next step. The inputs and outputs of the economic model are presented in Fig. 4. The annual energy costs at the community level include the annualized cost of DERs, which consist of capital costs, O&M costs, and other costs caused mainly by providing customer services. These costs are typically fixed. Energy exchange prices between the ICES and the grid determine the energy exchange costs, which generally vary with the amount of energy exchange. The annualized costs are then allocated according to the method selected by the local stakeholders.

## 5. Assessment of cost allocation methods in the integrated community energy system

### 5.1. *Cost reflectiveness*

No matter what energy system is used, the ultimate goal of cost allocation is cost reflectiveness. This topic has been addressed in many studies [24,39]. A cost-reflective allocation mirrors the contribution made by consumers to the energy system and incentivizes them to utilize energy in a cost-efficient manner. In order to evaluate how close the energy bills actually paid by local community members in the ICES are to the amounts they should be paying, the cost of investing in DERs by the individual is used as the benchmark to indicate whether the specific cost allocation method is cost-reflective. To provide a quantitative method to measure cost reflectiveness, in this paper, it is defined as the ratio of the difference between the cost local community members pay in the ICES and the cost of their own investments in DERs, divided by that latter investment cost. Cost reflectiveness is expressed as follows:

$$CRI_{i,j} = \frac{C_{i,j} - C_{i,DER}}{C_{i,DER}} \quad (37)$$

where $CRI_{i,j}$ is the cost reflectiveness index for household $i$ under method $j$, $C_{i,j}$ (€) is the annual cost to household $i$ under method $j$, and $C_{i,DER}$ (€) is the annual energy costs to household $i$ of its individual energy system, including investments in DERs and the costs of energy exchange with the grid. If the result is positive, that indicates that the household is paying more than it should. Zero means that it is paying exactly the right amount and a negative result indicates it is paying less and so saving on its energy bills by being part of the ICES. It also indicates that the household benefits from its ICES participation, compared to investing individually in DERSs.

### 5.2. *Cost predictability*

A sustained commitment by local community members is an essential factor that affects the long-term development of ICESs, and that commitment is greatly influenced by the way their energy bills evolve. Customers will leave the energy system if their energy costs increase a lot year on year, and that is likely to trigger a vicious circle of ever-higher bills forcing out more and more customers. Which, eventually, will lead to a complete collapse of the energy system. As for investors, their objective is to ensure cost recovery. Cost predictability helps them evaluate the extent to which they can do this. For this reason, it is necessary to compare the long-term differences in energy bills.

Cost predictability is all about changes in energy bills [24]. Local community members can evaluate if the selected method provides a long-term incentive by comparing their energy costs in two consecutive years. If the change is small or close zero, it indicates that the selected method provides a strong long-term incentive. It is thus a good indicator that local members will remain in the ICES in the long-term. It also contributes to the stable development of the energy system. In this paper, cost predictability is defined as the difference between costs in two consecutive years, formulated as:

$$CPI_{i,j} = \frac{C2_{i,j} - C1_{i,j}}{C1_{i,j}} \quad (38)$$

where $CPI_{i,j}$ is the cost predictability index for household $i$ under method $j$ , and $C1_{i,j}$ and $C2_{i,j}$ (€) are its energy costs in years 1 and 2 under method $j$, respectively. A positive result indicates that the household pays more in the second year, zero that it pays the same in both years, and a negative value that it pays less in the second year. Ideally, any difference should be minimized so that the amount of the household's annual energy bill does not change much over the lifetime of the energy system. That attracts customers to stay in the ICES in the long-term.

## 6. Case study and results analysis

### 6.1. *Case study set up*

This case study investigates the performance of cost allocation methods in respect of cost reflectiveness and predictability for a group of 100 households. This section explains the background of the input data.

#### 6.1.1. *Hourly energy demand*

The case study makes use of household electricity consumption data from the UK Power Networks project (half-hourly measurements over two years in 2012 and 2013) [60].

#### 6.1.2. *Hourly PV power generation*

For this case study, the only RESs taken into consideration are PV panels in the local community. The hourly metered data for RES generation is obtained from the open data platform Renewables.ninja [61].

#### 6.1.3. *Techno-economic parameters*

Table 1 presents the techno-economic parameters used in the case study. They include capital costs, O&M costs, and the lifetimes of the PV panels and battery. Table 2 shows the energy exchange prices between the different parties: from the grid to the ICES, from the ICES to the grid, and from households to the ICES.

**Table 1**
Techno-economic parameters.

| | Capital costs(€/kW) | O&M costs(€/kW/year) | Lifetime(years) | Source |
|---|---|---|---|---|
| PV | 1100 | 5.5 | 25 | [62] |
| Battery | 200 | 2 | 10 | [63] |

**Table 2**
Energy exchange prices.

| | From the grid to ICES | From ICES to the grid | Households to ICES |
|---|---|---|---|
| EnergyL exchange price (€/kWh) | 0.21 | 0.10 | 0.10 |

**Table 3**
Descriptive statistics for cost reflectiveness under different cost allocation methods.

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Median | −0.183 | −0.165 | −0.171 | −0.165 | −0.391 | −0.212 | −0.206 | −0.206 | −0.199 | −0.194 |
| Variance | 0.075 | 0.007 | 0.010 | 0.007 | 0.508 | 0.110 | 0.035 | 0.047 | 0.037 | 0.029 |
| 5th percentile | −0.500 | −0.340 | −0.350 | −0.340 | −0.910 | −0.590 | −0.550 | −0.460 | −0.440 | −0.390 |
| 95th percentile | 0.470 | −0.050 | 0.000 | −0.050 | 1.120 | 0.360 | 0.130 | 0.190 | 0.150 | 0.110 |

**Table 4**
Descriptive statistics for cost predictability under different cost allocation methods.

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Median | – | 0.027 | 0.029 | 0.027 | 0.056 | 0.017 | 0.035 | 0.022 | 0.034 | 0.031 |
| Variance | – | 0.032 | 0.033 | 0.032 | 14.104 | 0.216 | 0.055 | 0.073 | 0.058 | 0.036 |
| 5th percentile | – | −0.260 | −0.280 | −0.260 | −0.910 | −0.370 | −0.320 | −0.270 | −0.250 | −0.220 |
| 95th percentile | – | 0.220 | 0.230 | 0.220 | 2.000 | 0.580 | 0.350 | 0.380 | 0.360 | 0.300 |

### *6.2. Results analysis*

#### *6.2.1. Analysis of cost reflectiveness*

The results of the calculations of cost reflectiveness for the ten cost allocation methods are shown below. Fig. 5 shows the probability density of the distribution of cost reflectiveness under the ten cost allocation methods for a group of 100 households consuming electricity in an ICES. These distributions indicate how cost-reflective a cost allocation method is. For each sub-figure, a higher peak around zero indicates more consumers with perfect cost reflectiveness, while a thinner tail near the horizontal axis indicates that fewer consumers are paying more or less than they should be. These are desirable characteristics for the cost allocation methods. In order to gain more insight into the results, the median, the variance, and the 5th and 95th percentile values of the distribution are also calculated, these are listed in Table 3.

From Table 3 and Fig. 5, a number of conclusions can be drawn. First of all, the ten cost allocation methods all have a median value less than zero, which implies that the majority of the consumers pay less in the ICES than if they were to invest individually. Secondly, methods 2 and 4 have the lowest variance (equal in this case), and both the 5th and 95th percentile values are closest to zero. This implies that these two methods are the most cost reflective of the ten cost allocation methods. Methods 2 and 4 have the same performance because the subscribed capacity in method 4 is calculated by dividing annual energy consumption by annual generation per capacity. This means that energy bills are determined by the volume of electricity consumption, which is the same strategy as used in method 2. Method 3's performance is comparable to that of method 2 (or 4); they have the same pricing mechanism, with energy for the charging component, although method 3 also considers time differences. Method 5 shows the poorest cost reflectiveness since it has the highest variance: about 5% of consumers are paying 91% less than what is considered cost-reflective and about 5% of are paying 112% more. The reason for this bad performance is that coincident peak pricing allocates costs based on the peak demand contribution by each consumer to the total system peak demand, even though these two peaks do not always coincide. Method 10 performs similarly to method 9, but slightly better. It subdivides total costs into three components - those related to energy, capacity, and customer services, respectively. Whereas method 9 is confined to two-part pricing, with only energy and capacity components.

#### *6.2.2. Analysis of cost predictability*

Cost predictability is another essential factor that affects the performance of cost allocation methods. Local community members can predict the extent to which their energy bills change year on year. And investors can predict the extent to which they are likely to recover their investment. As with cost reflectiveness above, Fig. 6 shows the probability density of the distribution of cost predictability under the ten cost allocation methods for a group of 100 households consuming electricity in an ICES in two consecutive years. Moreover, the median, the variance, and the 5th and 95th percentile values of the distribution are also calculated; these are shown in Table 4. Method 1, allocating costs based on the number of users, is omitted as its predictability is perfect. The reason for this is that the annual costs to be recovered consist of two parts: fixed costs for DERs, which are the same each year, and variable costs for energy exchange with the grid and the household. The variable costs are determined by the volume of energy exchanged and the energy exchange price. In this case study, the ICES is grid-connected, but for the most part independent of the grid, since the great majority of the energy consumed comes from community generation. The energy exchange costs in years 1 and 2 are € 13442 and € 14148, respectively. In other words, there is almost no change in costs and so the cost predictability of method 1 is assumed to be perfect.

From Table 4 and Fig. 6, we can draw the following conclusions. The differences between the ten methods are apparent. They can be classified into two categories. In the first of these, methods 5 and 6 have a lower peak around zero and a fatter tail, which indicates that a substantial year-on-year change in energy bills is more likely. This can also be seen from the percentile values in Table 4. In the second category are the remaining methods, all with a high peak around zero, indicating that their cost allocations in the two consecutive years remain constant for many customers in the local community. This high predictability also shows up in Table 4 for these methods: their median and variance values are close to zero. Methods 2 and 4 produce the same performance, for the same reason as they do with cost reflectiveness. Methods 2, 3, 4, and 10 all have a similar, better performances, with a lower variance, the median near zero, and both their 5th and their 95th percentile values closest to zero. Methods 7, 8, and 9 display performances comparable to methods 2, 3, 4 and 10. A method includes an energy charging component shows a better performance with respect to cost predictability.

#### *6.2.3. Abnormal conditions analysis*

In the cases above, community energy generation and consumption in the second year do not change significantly. It is easy to conclude that each method has a similar performance in different years in the lifetime of the energy system, since the common costs of community DERs are fixed and energy exchange costs accounts for a small portion

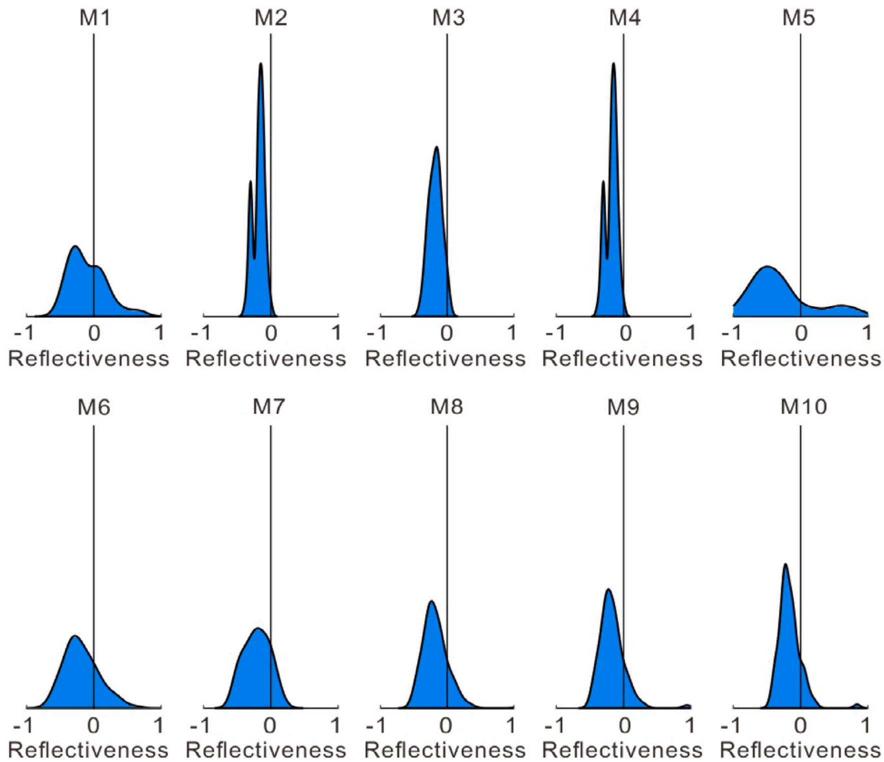


**Fig. 5.** Probability density of the distribution of cost reflectiveness under the ten cost allocation methods for households.

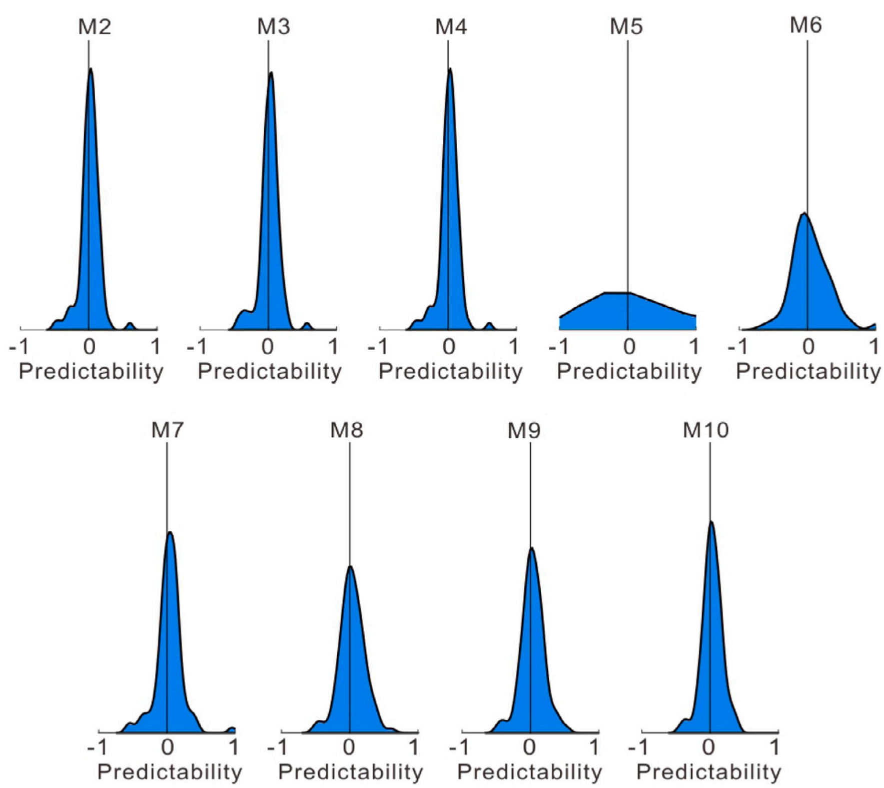


**Fig. 6.** Probability density of the distribution of cost predictability under the ten cost allocation methods for households.

of total common costs. The cases analyzed above are in an ideal and normal situation, however, it is also interesting to see how cost reflectiveness and predictability might change following a sudden change in energy generation and consumption. A comprehensive analysis has therefore been carried out to do just that. For this, it is assumed that both energy generation from solar panels and household consumption either increase or decrease by one-third in the second year, in this case study, that is the year 2013 - thus producing four scenarios for

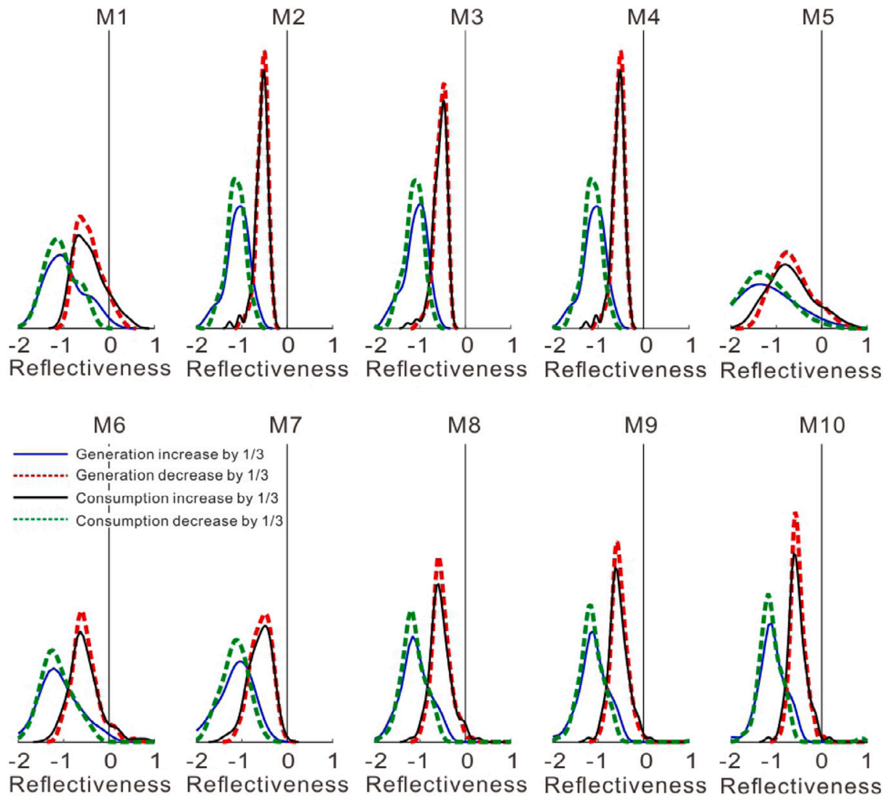


**Fig. 7.** Probability density of the distribution of cost reflectiveness under the ten cost allocation methods for households in abnormal conditions.

the analysis of each indicator. The corresponding results in terms of the probability density of the distribution of cost reflectiveness and of cost predictability for the ten methods are shown in Figs. 7 and 8, respectively.

From these two figures, it is apparent that both cost reflectiveness and predictability decline in abnormal conditions, no matter which method is applied. The effect of energy generation increasing and energy consumption decreasing shows a similar performance, which is the same for the case of energy generation decreasing and energy consumption increasing. Furthermore, local communities pay less in the case that energy generation increasing and consumption decreasing. This can be explained by the fact that when energy generation increases or consumption decreases, there is a surplus generation in the energy system. The ICES and the local community members then benefit from selling surplus energy to the grid and the ICES. However, local community members pay more in the case of energy generation decreasing and consumption increasing, compared to when energy generation increases and consumption decreases. In this case study, the majority of local community members pay less compared to the costs they should pay or their energy bills in the year before.

From the analysis in Section 6.2.1, Section 6.2.2 and this section, it can be concluded that cost reflectiveness and predictability only retain their merits if changes are minor; these merits evaporate in the event of significant sudden changes in generation and consumption. For this reason, the cost allocation results should remain more or less the same in the short-term and only gradually change in the long-term.

#### 6.2.4. Sensitivity analysis

It is also essential to see how cost allocation would perform in terms of the two criteria, cost reflectiveness and predictability, in the event of a change in the number of consumers taking part in the ICES. A sensitivity analysis for the ten cost allocation methods in that scenario has therefore been conducted. Figs. 9 and 10 show the probability density of the distribution of cost reflectiveness and predictability for the ten cost allocation methods with 20, 50, and 80 consumers in the ICES. From the results in this regard, it can be concluded that there is almost no change in the distribution profile of the two criteria. This implies that the number of consumers has little or no influence on the performance of the ten cost allocation methods in terms of cost reflectiveness and predictability. In other words, this sensitivity analysis demonstrates that the performance of a cost allocation method is not dependent on the size of the community.

#### 6.2.5. Cost allocation with different number of prosumers

Another essential aspect to look at is how well the cost allocation methods would handle changes in the roles of local community members. With a higher percentage of prosumers in the ICES, energy consumption changes and energy sharing by those prosumers increases. An effective cost allocation method should retain its merits, cost reflectiveness and predictability, under such changing condition. To gain an insight into how cost reflectiveness and predictability change, the ten cost allocation methods have been assessed with 30%, 60%, and 100% penetration of prosumers in the ICES. In this model, the 100 households are randomly assigned to be prosumers. The installed capacity of DERs follows the same rule that annual generation from DERs equals annual consumption. The resulting cost reflectiveness with different percentages of prosumers for the ten methods is shown in the form of probability densities in Fig. 11 and the relevant statistics are provided in Table 5.

From Fig. 11, it is clear that cost reflectiveness increases in line with the rise in the percentage of prosumers. Cost reflectiveness increases a little or remains more or less the same when the penetration of prosumers rises from 30% to 60%, but there is a significant increase when that figure rises from 60% to 100%. This is easy to explain, since prosumers pay for their own investment in DERs. Methods 1, 5 and 6 have by far the lowest reflectiveness, which can be explained by their special pricing mechanisms. The common costs (annual community energy costs) are allocated evenly in method 1 and based on coincident

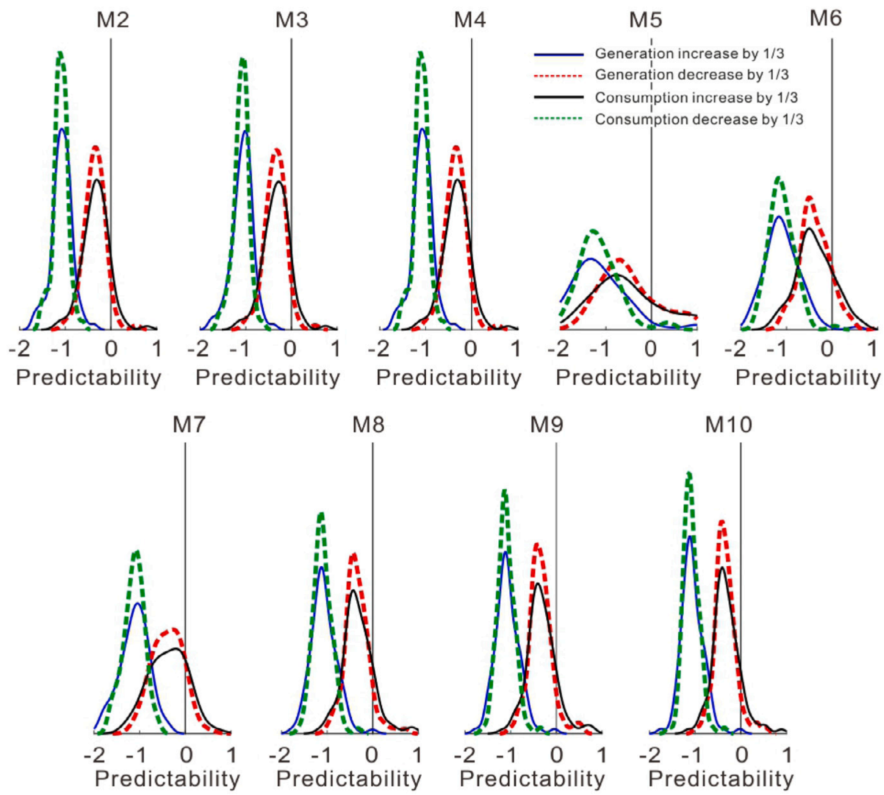


**Fig. 8.** Probability density of the distribution of cost predictability under the ten cost allocation methods for households in abnormal conditions.

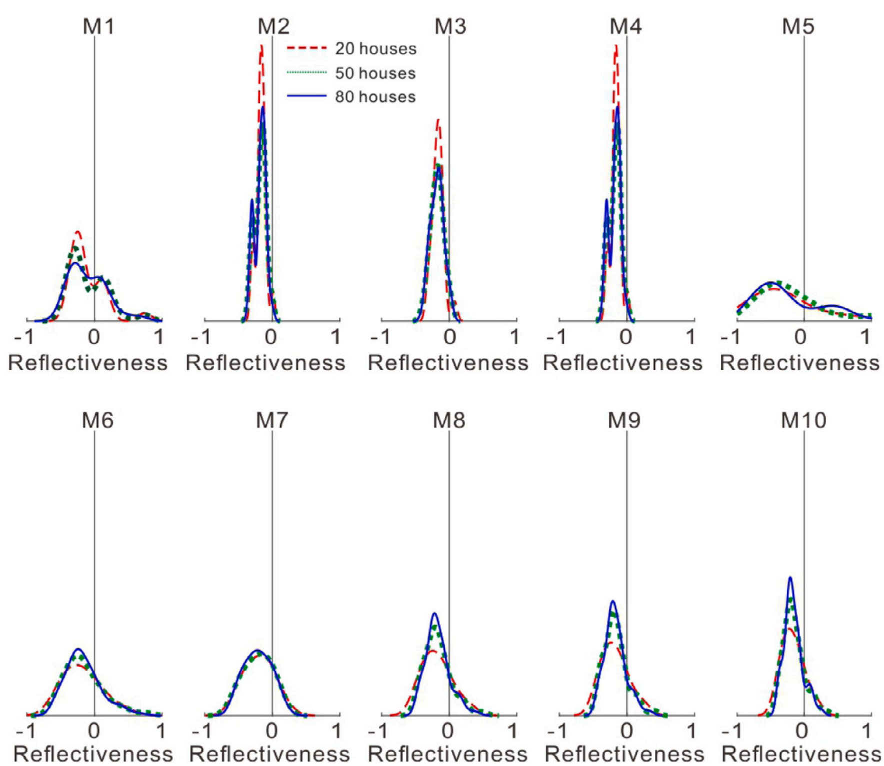


**Fig. 9.** Probability density of the distribution of cost reflectiveness under the ten cost allocation methods with different numbers of consumers.

and non-coincident peak demand in methods 5 and 6, meaning that prosumers may pay for costs they have not actually incurred. In case of methods 2, 3, 4, and 7, the peak of the reflectiveness distribution increases substantially with the increasing penetration of prosumers, an outcome consistent with the statistics shown in Table 5.

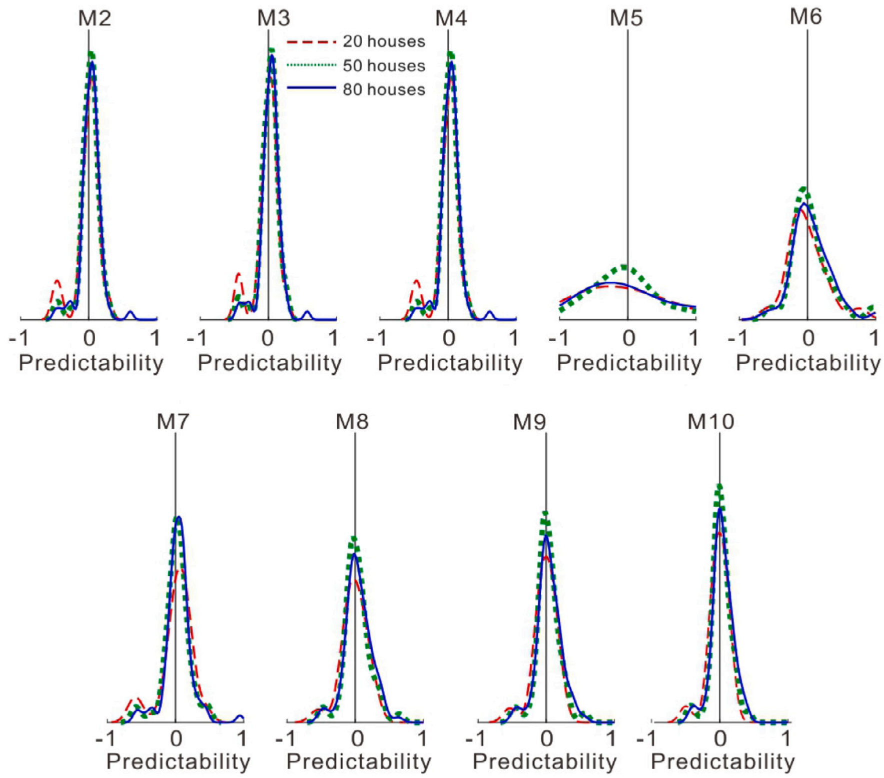


**Fig. 10.** Probability density of the distribution of cost predictability under the ten cost allocation methods with different numbers of consumers.

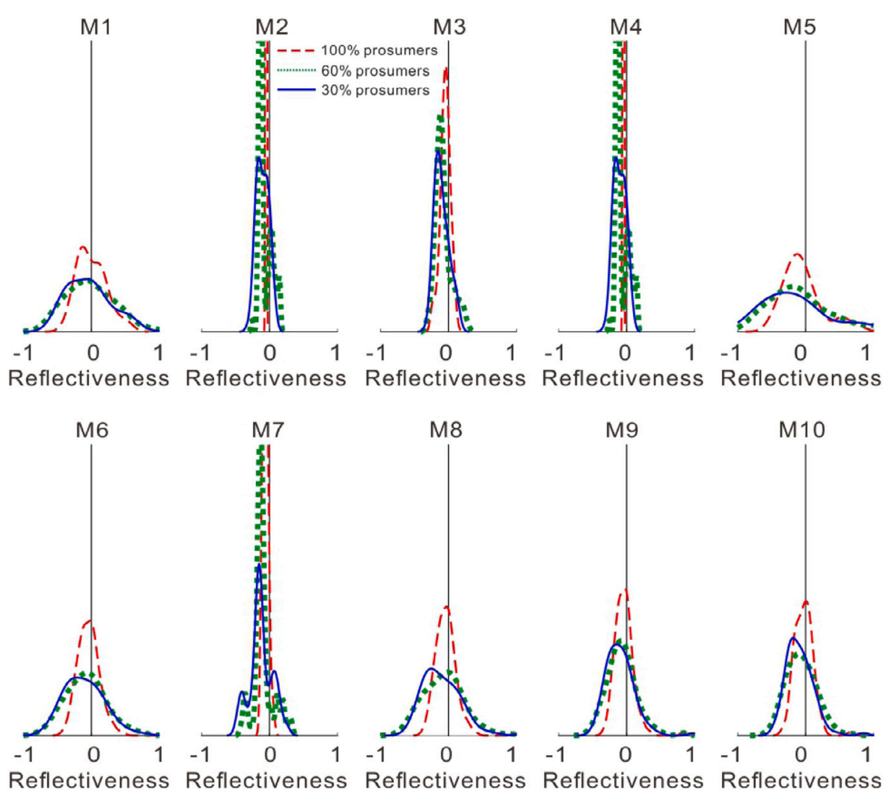


**Fig. 11.** Probability density of the distribution of cost reflectiveness under the ten cost allocation methods with different percentages of prosumers in the ICES.

The same analysis has also been done for cost predictability. The results for the ten cost allocation methods with different percentage of prosumers are shown in Fig. 12, and relevant statistics can be found in Table 6. From the figure, it can be seen that cost predictability when using methods 2, 3, 4, and 7 remains more or less the same as prosumer penetration increases. This can be explained by the fact

**Table 5**
Descriptive statistics of cost reflectiveness under the ten cost allocation methods with different percentages of prosumers.

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 30% prosumers | | | | | | | | | | |
| Median | −0.053 | −0.106 | −0.121 | −0.106 | −0.200 | −0.113 | −0.141 | −0.143 | −0.112 | −0.109 |
| Variance | 0.111 | 0.008 | 0.011 | 0.008 | 0.302 | 0.114 | 0.028 | 0.080 | 0.046 | 0.041 |
| 5th percentile | −0.550 | −0.260 | −0.270 | −0.260 | −0.900 | −0.590 | −0.430 | −0.520 | −0.410 | −0.390 |
| 95th percentile | 0.620 | 0.060 | 0.110 | 0.060 | 1.070 | 0.480 | 0.160 | 0.410 | 0.280 | 0.260 |
| 60% prosumers | | | | | | | | | | |
| Median | −0.037 | −0.122 | −0.108 | −0.122 | −0.146 | −0.089 | −0.123 | −0.072 | −0.077 | −0.085 |
| Variance | 0.115 | 0.008 | 0.015 | 0.008 | 0.206 | 0.102 | 0.020 | 0.084 | 0.048 | 0.045 |
| 5th percentile | −0.600 | −0.170 | −0.250 | −0.170 | −0.780 | −0.580 | −0.350 | −0.560 | −0.420 | −0.420 |
| 95th percentile | 0.620 | 0.120 | 0.180 | 0.120 | 0.850 | 0.500 | 0.210 | 0.460 | 0.320 | 0.330 |
| 100% prosumers | | | | | | | | | | |
| Median | −0.037 | −0.122 | −0.108 | −0.122 | −0.146 | −0.089 | −0.123 | −0.072 | −0.077 | −0.085 |
| Variance | 0.046 | 0.000 | 0.006 | 0.000 | 0.088 | 0.037 | 0.002 | 0.032 | 0.023 | 0.019 |
| 5th percentile | −0.330 | −0.060 | −0.200 | −0.060 | −0.470 | −0.300 | −0.130 | −0.270 | −0.240 | −0.240 |
| 95th percentile | 0.440 | −0.030 | 0.080 | −0.030 | 0.610 | 0.270 | 0.020 | 0.240 | 0.200 | 0.200 |

**Table 6**
Descriptive statistics of cost predictability under the ten cost allocation methods with different percentages of prosumers.

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 30% prosumers | | | | | | | | | | |
| Median | – | 0.031 | 0.034 | 0.031 | 0.077 | 0.020 | 0.032 | 0.018 | 0.019 | 0.022 |
| Variance | – | 0.032 | 0.033 | 0.032 | 10.931 | 0.069 | 0.049 | 0.040 | 0.033 | 0.023 |
| 5th percentile | – | −0.260 | −0.290 | −0.260 | −0.810 | −0.340 | −0.330 | −0.280 | −0.250 | −0.220 |
| 95th percentile | – | 0.220 | 0.230 | 0.220 | 2.000 | 0.460 | 0.300 | 0.350 | 0.350 | 0.300 |
| 60% prosumers | | | | | | | | | | |
| Median | – | 0.035 | 0.037 | 0.035 | 0.076 | 0.036 | 0.043 | 0.038 | 0.041 | 0.037 |
| Variance | – | 0.028 | 0.031 | 0.028 | 0.622 | 0.048 | 0.039 | 0.033 | 0.027 | 0.019 |
| 5th percentile | – | −0.250 | −0.260 | −0.250 | −0.730 | −0.290 | −0.290 | −0.250 | −0.220 | −0.190 |
| 95th percentile | – | 0.240 | 0.270 | 0.240 | 1.650 | 0.400 | 0.300 | 0.330 | 0.310 | 0.250 |
| 100% prosumers | | | | | | | | | | |
| Median | – | 0.041 | 0.040 | 0.041 | 0.070 | 0.048 | 0.044 | 0.047 | 0.045 | 0.041 |
| Variance | – | 0.031 | 0.034 | 0.031 | 0.252 | 0.023 | 0.035 | 0.019 | 0.018 | 0.011 |
| 5th percentile | – | −0.240 | −0.270 | −0.240 | −0.490 | −0.160 | −0.260 | −0.140 | −0.140 | −0.110 |
| 95th percentile | – | 0.270 | 0.300 | 0.270 | 1.200 | 0.290 | 0.300 | 0.270 | 0.260 | 0.210 |

that charging with these four methods is based on a single pricing component, namely, energy. Furthermore, the annual costs to be recovered do not change much since the prior assumption is that the annual costs of community DERs are the same throughout the lifetime of the energy system and the only variable costs are for energy exchange. The costs allocated to local community members will thus not change much, even though their energy consumption increases. For the remaining methods, the peak of the predictability distribution rises with the increase in prosumer penetration. This can be explained by the fact that the prosumers pay for their own individual investments in DERs. Moreover, these methods have either a capacity component only or a combination of energy and capacity components. From these findings we can conclude that the increasing prosumer penetration has a positive effect on cost predictability, which also indicates that the possibility of cost recovery is improved.

### 6.3. Discussion

The cost allocation methods described in this paper all have their own characteristics. They have different charging components (energy, capacity, or the number of users), and they take different factors into account (time and consumption level differences, and so on). And they show different performances with regard to different criteria. It is not easy to satisfy all the requirements at the same time. The case study presented in this paper has assessed the performance of the ten methods in terms of cost reflectiveness and predictability. From the analysis of the results, we can conclude that methods with energy as their single charging component perform better than either those with capacity as their sole component or those allocating costs based on the number of users in terms of cost reflectiveness and predictability. Cost reflectiveness increases with the increasing number of prosumers, while cost predictability remains more or less the same. Methods with energy and capacity-based charging components show comparable performance to the methods with solely energy-based charging component. It is easy to explain that methods with just energy components are a measure of average demand and that the installed capacity of DERs is based on their generation capacity. Peak demand, meanwhile, is dependent on a single moment in the year and differs year on year. Therefore, peak demand-based methods show a lower cost reflectiveness and predictability.

From the consumer perspective, cost reflectiveness is far more important as the costs allocated to them should be in line with the amount of energy they consume. For investors, however, cost predictability is more important, to help ensure that they recover their costs. According to the analysis above, methods with a single energy charging component are the most desirable if both of these metrics are to be satisfied. Moreover, those methods with both energy and capacity charging components are the second-most desirable. The different energy charging component-based methods display similar performances, but each emphasizes different aspects. For this reason, it is not easy to provide a definitive solution regarding the ideal cost allocation method to select based on the quantitative analysis in this paper. The opinions of local community members play an essential role in that process, and they inevitably have different educational backgrounds and, may well hold different points of view regarding the various methods. Some, for instance, may prefer to choose a method with a single charging component over a more complex one with more or less the same

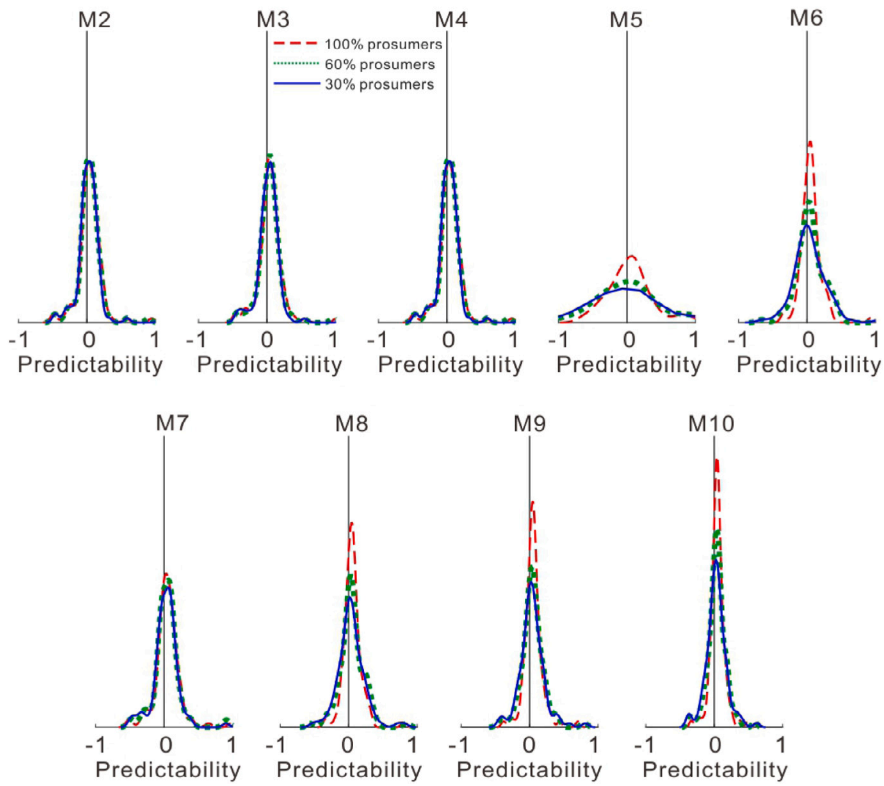


**Fig. 12.** Probability density of the distribution of cost predictability under the ten cost allocation methods with different percentages of prosumers in the ICES.

performance. Moreover, this paper focuses only on the analysis of cost reflectiveness and cost predictability, while other criteria such as cost causality (revealing cost drivers) and time difference will also affect local community members' opinions. In practice, it is therefore critical that those opinions be taken into account and that a method be selected that is socially acceptable to the local community.

According to the abnormal condition analysis, furthermore, the methods addressed here are unable to deal well with sudden changes in energy generation and consumption. Their metrics in terms of cost reflectiveness and predictability are rendered useless in those circumstances. However, the results do still show that the majority of local community members still benefit from joining an ICES, even under such abnormal conditions: they pay less compared to investing in DERs themselves. In normal conditions, meanwhile, the cost allocation methods we present display stable performance in terms of cost reflectiveness and predictability. In this study, the community under consideration is small in scale. According to the sensitivity analysis, however, the methods retain their performance even when the size of the community changes - a desirable characteristic. Furthermore, the ten cost allocation methods can well handle the changes in the roles of local community members from consumers to prosumers in terms of the two criteria. Overall, then, the analyses carried out in this paper help us understand the performance of cost allocation methods.

## 7. Conclusion and future work

### 7.1. Conclusion

Cost allocation for local community energy systems with local DERs, as covered by the current study, is often missing. This study, therefore, proposes a systematic framework and a number of methods applicable in the context of cost allocation in an ICES. Reflectiveness and predictability in cost allocation are favored merits, no matter what the energy system is. The performance in terms of the two criteria for the methods considered here has been assessed based on a case study. The results show that methods with an energy component perform better, they reflect the costs the users should pay. Moreover, their energy bills are stable and predictable when there are only gradual changes in energy generation and consumption. Furthermore, methods with an energy charging component retain their merits in respect of the two criteria in the event of changes in the number of local community members and prosumers. The comprehensive analysis in this paper provides a better understanding of the performance of cost allocation methods. Since local communities are not subjected to statutory regulation, their members need to agree on the method used to allocate costs in the ICES. For this reason, their opinions should be considered carefully before selecting a method that is socially acceptable to them. The study presented in this paper provides multiple choices for cost allocation and can help local communities in selecting one that delivers good performance and also satisfies their other requirements, too.

### 7.2. Future work

In this study, the chosen allocating coefficient - for methods with two or more charging components is load factor. Further research is recommended to reveal the impact of flexible coefficients on the results of cost allocation in ICESs and to see if these can improve cost reflectiveness and predictability when compared to the methods with one single charging component. Moreover, the ICES considered here is grid-connected but remain independent of the grid since community generation is able to satisfy the bulk of demand. The costs of exchanging energy with the grid therefore accounts for only a tiny portion of the total costs - one so small that it can be disregarded. This factor thus has very little influence on our results. In the future, it is worth considering the impacts on the results of cost allocation of a grid-dependent ICES or of a considerable year-on-year increase in energy consumption by the local community members.

### CRediT authorship contribution statement

**Na Li:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Rudi A. Hakvoort:** Conceptualization, Supervision, Writing – review & editing. **Zofia Lukszo:** Supervision, Writing – review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### References

[1] Mendes G, Ioakimidis C, Ferrão P. On the planning and analysis of integrated community energy systems: A review and survey of available tools. Renew Sustain Energy Rev 2011;15(9):4836–54. http://dx.doi.org/10.1016/j.rser.2011.07.067.

[2] Koirala B, Hakvoort R. Integrated community-based energy systems: Aligning technology, incentives, and regulations. In: Innovation and disruption at the grid's edge. Elsevier; 2017, p. 363–87. http://dx.doi.org/10.1016/B978-0-12-811758-3.00018-8.

[3] Koirala BP, Koliou E, Friege J, Hakvoort RA, Herder PM. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. Renew Sustain Energy Rev 2016;56:722–44. http://dx.doi.org/10.1016/j.rser.2015.11.080.

[4] Koirala BP, Chaves Ávila JP, Gómez T, Hakvoort RA, Herder PM. Local alternative for energy supply: Performance assessment of integrated community energy systems. Energies 2016;9(12):981. http://dx.doi.org/10.3390/en9120981.

[5] Li N, Hakvoort RA, Lukszo Z. Cost allocation in integrated community energy systems-A review. Renew Sustain Energy Rev 2021;144:111001. http://dx.doi.org/10.1016/j.rser.2021.111001.

[6] Walker G, Devine-Wright P. Community renewable energy: What should it mean? Energy Policy 2008;36(2):497–500. http://dx.doi.org/10.1016/j.enpol.2007.10.019.

[7] Avelino F, Bosman R, Frantzeskaki N, Akerboom S, Boontje P, Hoffman J, Wittmayer J. The (self-) governance of community energy: Challenges & prospects. Rotterdam, the Netherlands: The Dutch Research Institute for Transitions; 2014.

[8] Xu X, Jin X, Jia H, Yu X, Li K. Hierarchical management for integrated community energy systems. Appl Energy 2015;160:231–43. http://dx.doi.org/10.1016/j.apenergy.2015.08.134.

[9] Zhou Y, Wei Z, Sun G, Cheung KW, Zang H, Chen S. A robust optimization approach for integrated community energy system in energy and ancillary service markets. Energy 2018;148:1–15. http://dx.doi.org/10.1016/j.energy.2018.01.078.

[10] Lin W, Jin X, Mu Y, Jia H, Xu X, Yu X, Zhao B. A two-stage multi-objective scheduling method for integrated community energy system. Appl Energy 2018;216:428–41. http://dx.doi.org/10.1016/j.apenergy.2018.01.007.

[11] Jing X, Hong L, Ke X, Jifeng L, Shiju W, Zan Y, Bo W. Synergistic scheduling in integrated community energy system considering wind power accommodation. Energy Procedia 2018;145:211–6. http://dx.doi.org/10.1016/j.egypro.2018.04.037.

[12] Koirala BP, Hakvoort RA, Ávila JPC, Gómez T. Assessment of integrated community energy systems. In: European energy market (EEM), 2016 13th international conference on the. IEEE; 2016, p. 1–6.

[13] Reneses J, Gómez T, Rivier J, Angarita JL. Electricity tariff design for transition economies: Application to the libyan power system. Energy Econ 2011;33(1):33–43. http://dx.doi.org/10.1016/j.eneco.2010.04.005.

[14] Abdelmotteleb I, Gómez T, Ávila JPC, Reneses J. Designing efficient distribution network charges in the context of active customers. Appl Energy 2018;210:815–26. http://dx.doi.org/10.1016/j.apenergy.2017.08.103.

[15] Abdelmotteleb I. Designing electricity distribution network charges for an efficient integration of distributed energy resources and customer response (Ph.D. thesis), TU Delft University; 2018.

[16] Similä L, Koreneff G, Kekkonen V. Network tariff structures in smart grid environment. VTT, Espoo, Tech. Rep. VTT-R 03173–11 2011. URL: http://sgemfinalreport.fi/files/SGEM%20Network%20tariff%20structures%20in%20SmartGrid%20environment%20-SGEM%20WP51%20FINAL.pdf.

[17] Reneses J, Rodríguez MP, Pérez-Arriaga J. Electricity tariffs. In: Regulation of the power sector. Springer; 2013, p. 397–441.

[18] Picciariello A, Reneses J, Frias P, Söder L. Distributed generation and distribution pricing: Why do we need new tariff design methodologies? Electr Power Syst Res 2015;119:370–6. http://dx.doi.org/10.1016/j.epsr.2014.10.021.

[19] Reneses J, Ortega MPR. Distribution pricing: theoretical principles and practical approaches. IET Gener Transm Distribution 2014;8(10):1645–55. http://dx.doi.org/10.1049/iet-gtd.2013.0817.

[20] Sakhrani V, Parsons JE. Electricity network tariff architectures a comparison of four OECD countries. Center for Energy and Environmental Policy Research (CEEPR) No, 10–008, 2010, http://dx.doi.org/10.2139/ssrn.1711198.

[21] Pérez-Arriaga IJ, Smeers Y. Guidelines on tariff setting. In: Transport pricing of electricity networks. Springer; 2003, p. 175–203, URL: https://doi-org.tudelft.idm.oclc.org/10.1007/978-1-4757-3756-1_7.

[22] Lévêque F. Legal constraints and economic principles. In: Transport pricing of electricity networks. Springer; 2003, p. 3–33, URL: https://doi-org.tudelft.idm.oclc.org/10.1007/978-1-4757-3756-1_1.

[23] Bonbright JC, Danielsen AL, Kamerschen DR. Principles of public utility rates. Columbia University Press New York; 1961.

[24] Nijhuis M, Gibescu M, Cobben J. Analysis of reflectivity & predictability of electricity network tariff structures for household consumers. Energy Policy 2017;109:631–41. http://dx.doi.org/10.1016/j.enpol.2017.07.049.

[25] Koliou E, Bartusch C, Picciariello A, Eklund T, Söder L, Hakvoort RA. Quantifying distribution-system operators' economic incentives to promote residential demand response. Util Policy 2015;35:28–40. http://dx.doi.org/10.1016/j.jup.2015.07.001.

[26] Ortega MPR, Pérez-Arriaga JI, Abbad JR, González JP. Distribution network tariffs: A closed question? Energy Policy 2008;36(5):1712–25. http://dx.doi.org/10.1016/j.enpol.2008.01.025.

[27] CEER. Electricity distribution network tariffs - CEER guidelines of good practice. Technical report, CEER; 2017, URL: https://www.ceer.eu/documents/104400/-/-/1bdc6307-7f9a-c6de-6950-f19873959413.

[28] Kattuman P, Green RJ, Bialek J. A tracing method for pricing inter-area electricity trades. 2004, URL: https://www.repository.cam.ac.uk/bitstream/handle/1810/286/wp0107.pdf?sequence=1&isAllowed=y.

[29] Murali M, Kumari MS, Sydulu M. A comparison of fixed cost based transmission pricing methods. Electr Electron Eng 2011;1(1):33–41, URL: https://www.researchgate.net/profile/M_Kumari/publication/313238033_A_Comparison_of_Fixed_Cost_Based_Transmission_Pricing_Methods/links/59365b4daca272fc556b8627/A-Comparison-of-Fixed-Cost-Based-Transmission-Pricing-Methods.pdf.

[30] Ghazizadeh M, Afsharnia S, et al. A novel approach to allocate transmission embedded cost based on mw-mile method under deregulated environment. In: 2008 IEEE Canada electric power conference. IEEE; 2008, p. 1–6. http://dx.doi.org/10.1109/EPC.2008.4763344.

[31] Lima JM. Allocation of transmission fixed charges: an overview. IEEE Trans Power Syst 1996;11(3):1409–18. http://dx.doi.org/10.1109/59.535682.

[32] Garg N, Palwalia D, Sharma H. Transmission pricing practices: A case study. Iraqi J Electr Electron Eng 2017;13(1):1–9.

[33] Djørup S, Thellufsen JZ, Sorknæs P. The electricity market in a renewable energy system. Energy 2018;162:148–57. http://dx.doi.org/10.1016/j.energy.2018.07.100.

[34] Clò S, Cataldi A, Zoppoli P. The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. Energy Policy 2015;77:79–88. http://dx.doi.org/10.1016/j.enpol.2014.11.038.

[35] Qi F, Zhang L, Wei B, Que G. An application of ramsey pricing in solving the cross-subsidies in Chinese electricity tariffs. In: 2008 third international conference on electric utility deregulation and restructuring and power technologies. IEEE; 2008, p. 442–7. http://dx.doi.org/10.1109/DRPT.2008.4523447.

[36] Shepherd WG. Ramsey pricing: Its uses and limits. Util Policy 1992;2(4):296–8. http://dx.doi.org/10.1016/0957-1787(92)90007-6.

[37] de Sá Ferreira R, Barroso LA, Lino PR, Carvalho MM, Valenzuela P. Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach. IEEE Trans Smart Grid 2013;4(4):2285–95. http://dx.doi.org/10.1109/TSG.2013.2241087.

[38] Yang L, Dong C, Wan CJ, Ng CT. Electricity time-of-use tariff with consumer behavior consideration. Int J Prod Econ 2013;146(2):402–10. http://dx.doi.org/10.1016/j.ijpe.2013.03.006.

[39] Eid C, Guillén JR, Marín PF, Hakvoort R. The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives. Energy Policy 2014;75:244–54. http://dx.doi.org/10.1016/j.enpol.2014.09.011.

[40] Sousa T, Soares T, Pinson P, Moret F, Baroche T, Sorin E. Peer-to-peer and community-based markets: A comprehensive review. Renew Sustain Energy Rev 2019;104:367–78. http://dx.doi.org/10.1016/j.rser.2019.01.036.

[41] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1(4):1–6, URL: https://doi-org.tudelft.idm.oclc.org/10.1038/nenergy.2016.32.
[42] Huang Z, Zhang Y, Lu Y, Wang W, Chen D, Wang C, Khan Z. Cost allocation model for net-zero energy buildings under community-based reward penalty mechanism. Environ Clim Technol 2019;23(3):293–307.
[43] Eid C, Koliou E, Valles M, Reneses J, Hakvoort R. Time-based pricing and electricity demand response: Existing barriers and next steps. Util Policy 2016;40:15–25. http://dx.doi.org/10.1016/j.jup.2016.04.001.
[44] Mulder G, Six D, Claessens B, Broes T, Omar N, Van Mierlo J. The dimensioning of PV-battery systems depending on the incentive and selling price conditions. Appl Energy 2013;111:1126–35. http://dx.doi.org/10.1016/j.apenergy.2013.03.059.
[45] Borenstein S. The economics of fixed cost recovery by utilities. Electr J 2016;29(7):5–12. http://dx.doi.org/10.1016/j.tej.2016.07.013.
[46] Dutta G, Mitra K. A literature review on dynamic pricing of electricity. J Oper Res Soc 2017;68(10):1131–45.
[47] Ajello J. Electric utility cost allocation manual. National Association of Regulatory Utility Commissioners; 1992, URL: https://www.edockets.state.mn.us/EFiling/edockets/searchDocuments.do?method=showPoup&documentId=%7BA00B9EF3-BF34-4AB1-8BE0-A2E1FCC64FF9%7D&documentTitle=2679.
[48] Uddin M, Romlie MF, Abdullah MF, Abd Halim S, Kwang TC, et al. A review on peak load shaving strategies. Renew Sustain Energy Rev 2018;82:3323–32. http://dx.doi.org/10.1016/j.rser.2017.10.056.
[49] Smets AH, Jäger K, Isabella O, Swaaij RA, Zeman M. Solar energy: The physics and engineering of photovoltaic conversion, technologies and systems. UIT Cambridge; 2015.
[50] Zarnikau J, Thal D. The response of large industrial energy consumers to four coincident peak (4CP) transmission charges in the Texas (ERCOT) market. Util Policy 2013;26:1–6. http://dx.doi.org/10.1016/j.jup.2013.04.004.
[51] Harunuzzaman M, Koundinya S. Cost allocation and rate design for unbundled gas services. 2000, URL: https://pubs.naruc.org/pub/D6D39B61-98DF-E0B7-0F49-0A2AA324A77D.
[52] Alt L. Energy utility rate setting. Lulu.com; 2006, URL: https://books.google.nl/books?hl=nl&lr=&id=RW3tycY4TToC&oi=fnd&pg=PA15&dq=Energy+Utility+Rate+Setting&ots=etUOfRZe5C&sig=z5tId69JXu9Y1fxVLUpxrCXRzXg&redir_esc=y#v=onepage&q=Energy%20Utility%20Rate%20Setting&f=false.
[53] Li N, Hakvoort RA, Lukszo Z. Segmented energy tariff design for flattening load demand profile. In: 2020 IEEE PES innovative smart grid technologies Europe. IEEE; 2020, p. 849–53. http://dx.doi.org/10.1109/ISGT-Europe47291.2020.9248774.
[54] Coase RH. The marginal cost controversy. Economica 1946;13(51):169–82.
[55] Cludius J, Hermann H, Matthes FC, Graichen V. The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications. Energy Econ 2014;44:302–13. http://dx.doi.org/10.1016/j.eneco.2014.04.020.
[56] Bharatkumar A. Distribution network use-of-system charges under high penetration of distributed energy resources (Ph.D. thesis), Massachusetts Institute of Technology; 2015.
[57] Williams P, Strbac G. Costing and pricing of electricity distribution services. Power Eng J 2001;15(3):125–36. http://dx.doi.org/10.1049/pe:20010303.
[58] Parmesano H. Rate design is the No. 1 energy efficiency tool. Electr J 2007;20(6):18–25. http://dx.doi.org/10.1016/j.tej.2007.06.002.
[59] Lazar J. Electricity regulation in the US: A guide. 2nd ed. Regulatory Assistance Project; 2016, URL: https://www.raponline.org/wp-content/uploads/2016/07/rap-lazar-electricity-regulation-US-june-2016.pdf.
[60] U.K. Power Networks. SmartMeter energy consumption data in London households. https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households [Accessed 24 November 2020].
[61] Renewable.ninja. Renewable.ninja. Available online: https://www.renewables.ninja/. [Accessed 27 June 2019].
[62] InnoEnergy K. Future renewable energy costs: Solar photovoltaics. 2015, URL: https://c2e2.unepdtu.org/wp-content/uploads/sites/3/2016/02/kic-innoenergy-solar-pv-anticipated-innovations-impact.pdf.
[63] IRENA. Electricity storage and renewables: costs and markets to 2030. 2017, URL: https://www.irena.org/publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets.