Self-Organising Energy Demand Allocation through Canons of Distributive Justice in a microgrid

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Abstract

The energy sector is being driven into a new era where considerable portions of electrical demand will be met through distributed energy resources (DERs). Microgrids have been suggested as a tool for integrating and managing DERs. In this context, we formulate the energy demand allocation problem in order to provide service to a given load. We then propose a dynamic method for agreeing and setting the rules to perform the allocation. The methodology is based on self-organisation and the concept of distributive justice which integrates different principles of fairness represented as *legitimate claims*. Legitimate claims are implemented as voting functions and are used to determine how the DER requests are satisfied. The method is tested by considering different configurations of DERs, mainly of the renewable type, and comparing them with other allocation methods. Results show that this self-organising allocation method provides a better balance amongst all the representations of justice, but also it is more robust for the external authorities that manipulate the allocation process.

Keywords: Electric power, multi-agent, resource allocation, distributed generator, smart grid, self-organisation

1. Introduction

In power systems with distributed energy resources (DERs), energy demand allocation consists of determining the energy production of each DER; or, in other words, which portion of the energy demand should cover each DER. In this regard, the energy demand allocation becomes a problem where different agents (DERs) compete to appropriate a particular quantity of a common pool resource (energy demand). Traditionally the allocation is performed according to the price or to rules set by a central authority, i.e. the system operator. However, the microgrids need alternative methodologies for locally managing the microgrid and allocating the energy generation. This paper proposes a methodology based on self-organisation to set the rules to perform the energy demand allocation. Therefore, the proposed method avoids the need of a central authority dictating the allocation of energy production. At the same time, as a method it is not only based on the price of the energy because it uses other indicators to perform the allocation. Accordingly, this method seeks to agree the rules of the allocation which, at the same time, are based on different principles of justice.

Without a centralised authority, it may seem ineffective to manage situations where a resource has to be allocated amongst a group of agents willing to appropriate a particular amount. The reason is because agents may tend to appropriate as much as they can, draining the resource and damaging the community or even destroying it. However, Ostrom has observed that, without a centralised intervention, some communities have formed institutions that defined a set of rules regulating the resource allocation in order, in time, to preserve either the institution or the resource.

On the other hand, Rescher (1966) introduces distributive justice by representing canons in which participants can provide *legitimate claims* regarding a resource which are implemented as voting functions. Based on

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these previous research, Pitt et al. (2012) propose an approach of distributive justice that allocates a common pool resource amongst self-organised agents in regard to a linear public good game. This paper proposes grounding the methodology in power systems and their particularities. To this end, we have adapted the method proposed by Pitt et al. (2012) to energy demand allocation and power systems requirements in a microgrid (Piagi & Lasseter, 2006), where a set of DERs makes joint decisions regarding the energy demand allocation problem. Such an approach allows heterogeneous DERs to enjoy fair outcomes, including situations in which external interference could arise, such as when green energy quotas of generation are imposed.

This paper is organised as follows: first, we provide some necessary background on self-governing institutions and distributive justice. Second, we present some related work to the energy demand allocation problem. Third, we present the methodology proposed in this paper based on canons of distributive justice. Fourthly, we present the experimentation we have conducted while analysing and discussing the performance of the method proposed. Finally we finished the paper by stating the conclusions and proposing some future research work.

2. Background

Institutions define a set of rules that determine several aspects of a system: who can perform what actions and under what circumstances; what are the consequences of performing such actions; and how are agents sanctioned when not complying with the rules. Ostrom (1990) observes that efficient management of the resources need not to resort to centralised approaches, but could instead be performed by the members of the institution themselves (i.e. self-governance). From her fieldwork and subsequent analysis, she has derived a set of principles necessary for an institution to endure (i.e. not ending up in a depletion of its resources). These principles are concerned with issues such as: who belongs to the institution; congruence between allocation rules and local conditions; participation of those affected by the operational rules in the selection and modification of those rules; graduated sanctions for violating rules; and layered or encapsulated systems.

On the other hand, the allocation of resources was studied by Rescher (1966) who introduces the concept of distributive justice in which people are treated according to different concepts (or canons) of justice: equity (treatment as equals); needs (treatment according their needs); productivity (treatment according to their actual productive contribution); effort (treatment according to their efforts and sacrifices); social utility (treatment according to a valuation of their social-useful services); supply and demand (treatment according to supply and demand) and ability (treatment according to their ability, merit or achievements). Rescher argues that each canon alone is inadequate as a sole dispensary of distributive justice. Instead, he holds that distributive justice is found in the *canon of claims*, which consists of treating people according to their legitimate claims, so leaving open questions of what the legitimate claims are, how they are accommodated in case of plurality and how they are reconciled in case of conflict.

3. Related Work

New challenges posed by the increased distributed generation distributed generation of electric power have been tackled taking advantage of the possibilities of coalitions of distributed generators, loads and storage systems in form of Virtual Power Plants (VPPs), microgrids, etc. Roughly speaking, microgrids are a collection of interconnected generators and (or not) loads islanded or semi-islanded (i.e. connected through only one link) from the main grid. On the other hand, Virtual Power Plants (VPPs) are collections of coordinated generators that behave as a single generator to have access to electricity markets or provide services that small generators cannot reach (more information about microgrids and VPPs can be found in (Bakari & Kling, 2010, Piagi & Lasseter, 2006)). Thus, microgrids and VPPs (Bakari & Kling, 2010) need methods to control DERs locally and allocate the energy generation. These methods can reproduce or copy the mechanisms used in the power grid where a system operator coordinates and monitors a set of auctions. Kok et al. (2005) argue that these control and management mechanisms should be based on market-economic mechanisms. Following this hypothesis, Ausubel & Cramton (2010) and Mashhour & Moghaddas-Tafreshi (2011) propose auction-based systems to allocate the energy generation in VPPs which aim to participate in energy markets. However, due to environmental concerns, it is necessary to perform the allocation of the energy generation not solely based on the economic cost of producing energy. According to this, Ramchurn et al. (2011) propose an alternative pricing model based on carbon emissions.

However, Ostrom (1990) demonstrates that a community can perform an allocation of a resource without following centralised market-based rules, but through self-organisation and enduring through time. Accordingly, and conversely to Kok et al. (2005), this paper proposes the use of self-organisation to set the rules; these are based on different canons of distributive justice, after allocating energy generation. Niese et al. (2012) and Wedde et al. (2008) also propose the use of self-organisation for determining the matching between load and generation. However, they propose a distributed negotiation between consumers and producers. Therefore, the allocation is ultimately based on the bids of the involved agents. Conversely, this paper proposes to perform the allocation according to distributive justice, and as a consequence, prioritising the fairness and satisfaction of DERs. In this regard, Kohler & Steghofer (2014) studies fairness mechanisms for self-organised systems and highlights the advantages of including fairness in resource allocation problems.

Moreover, there is in depth research now available on developing new methods for managing groups of DERs, but considering that they are owned by the same agent. Some examples are Wang et al. (2014), Peik-Herfeh et al. (2013) and Bu et al. (2011) who propose different scheduling methods for optimising the costs of producing energy. However this hypothesis may not match the reality, being that many DERs or storage systems are expected to be placed in residential buildings and will be owned by the landlords (Dibangoye et al., 2015). To this end, Dibangoye et al. (2015) is also focused on optimising the generation schedules of a set of DERs, but considering that they are managed by independent agents. As a consequence, the problem is modelled as a distributed scheduling problem, where agents share some private information and collaborate in order to find the optimal generation schedule of a whole set of DERs. Conversely to Dibangoye et al. (2015), this paper does not propose a methodology to find the optimal schedule, but a methodology to allow DERs to agree the rules to perform the allocation of energy generation. Furthermore, Dibangoye et al. (2015) only considers controllable generators such as Fuel Cells (FC) and not renewable and stochastic DERs. Therefore, the only source of uncertainty comes from possible breakdowns of the generators or the network. However, the method proposed in this paper considers different kind of generators, and also, renewable DERs.

4. Problem formulation

Microgrids are constituted by a collection of different DERs which are usually independent and have their own interests. Each DER wants to produce a particular amount of energy to increase its benefits and satisfaction. The mission of a microgrid is to manage DERs or provide tools for coordination and/or cooperation in order they can cover a load, so that there is balance between energy production (fulfilling DERs' requirements and/or constraints) and consumption (load). Thus, this scenario presents a resource allocation problem where an infinitesimal divisible good (load) has to be allocated among a set of agents (DERs), $\{1, \ldots, N_{DER}\}$, in such a way that the constraints of DERs are satisfied.

DER constraints are determined by design (minimum and maximum DER generation bounds) and by their present running state and context (minimum and maximum available production). First, design constraints mean that the DER will not be able to produce in any situation involving an energy amount out of the design limits, p_i^{min} and p_i^{max}. And second, when a DER is actually producing $p_i(t)$, the generation bounds for $t+1$, $p_i^{min}(t+1)$ and $p_i^{max}(t+1)$, depend on the technical specifications of the DER as well as the weather forecast (i.e. wind or solar radiation), as follows:

$$p_i^{min}(t+1) = \max\left\{p_i^{min}, p_i(t) - s_i^d\right\} \tag{1}$$
$$p_i^{max}(t+1) = \min\left\{p_i^{max}, p_i^{forecast}(t+1), p_i(t) + s_i^u\right\}$$

where $p_i^{forecast}(t+1)$ is the expected production conditioned to the weather forecast; and s_i^u and s_i^d are the up and down ramp limits respectively, as determined by the technical specifications of the DER. To summarise, constraints regarding the production $p_i(t)$ of a DER can then be expressed as follows:

$$p_i^{min} \leq p_i^{min}(t) \leq p_i(t) \leq p_i^{max}(t) \leq p_i^{max}, \forall i \tag{2}$$

Consistently, we can define the total minimum and maximum energy production limits of the microgrid at time t as follows:

$$P^{min}(t) = \sum_{i=1}^{N_{DER}} p_i^{min}(t) \tag{3}$$
$$P^{max}(t) = \sum_{i=1}^{N_{DER}} p_i^{max}(t)$$

According to their strategic goals, each DER is interested in producing a given amount of energy $d_i(t)$, subject to the constraints shown in Equation 2. Whenever $d_i(t) \leq p_i(t)$ or $d_i(t) \geq p_i(t)$ that would depend on the DERs' business, but $d_i(t)$ can never surpass DERs' energy bounds.

Consistently then, the total energy production demanded (henceforth total demand) inside the microgrid is defined as follows:

$$D(t) = \sum_{i=1}^{N_{DER}} d_i(t) \quad (4)$$

subject to $P^{min}(t) \leq D(t) \leq P^{max}(t)$.

The inputs of the problem are both the load $L(t)$ and the DERs' demand $d_i(t) \forall i$, which vary along time. Load and total demand do not necessarily match, while the microgrid should decide what is the amount of energy $a_i(t)$ each DER should produce, subject to DER constraints. Thus, the energy demand allocation problem consists of determining the amount of energy each DER should produce $a_i(t)$.

5. Methodology

The allocation methodology proposed consists of a self-organised approach based on distributive justice (Pitt et al., 2012). Self-organised means that DERs agree the rules for performing the allocation. This allocation is then computed by any of the agents assuming the microgrid coordinator role; they can also take turns on that role. Distributive justice means that the allocation is performed according to a set of canons (principles, criteria; see Section 2).

To this end, in order to agree the allocation of the load at a given time t (hour), we propose the following procedure:

1. The microgrid coordinator has information about the load $L(t)$
2. Each DER_i sends a demand message to the microgrid coordinator for covering $d_i(t)$ of this load, as well as the generation limits $p_i^{min}(t)$ and $p_i^{max}(t)$.
3. The microgrid computes the total demand $D(t)$. There may be different situations:
   (a) $L(t) \leq P^{min}(t)$. If the equality fits, all DERs produce at their minimum capacity, $a_i(t) = p_i^{min}$. Otherwise, there is a surplus of energy and mechanisms, such as the disconnection of DERs or energy export to the main grid which should be activated to balance the energy generation and the load.
   (b) $\boldsymbol{P^{min}(t) < L(t) < P^{max}(t)}$: DERs get individual allocations within their feasible production range. The microgrid coordinator calculates the energy production of each DER according to a ranking based on a set of weights. Weights are set up among all of the DERs according to an achieved consensus for the relevance of a set of canons.
   (c) $L(t) \geq P^{max}(t)$: all DERs produce at their maximum capacity, $a_i(t) = p_i^{max}$, but, if the equality is not fulfilled, the load cannot be covered with DERs' production. Thus, other mechanisms should be activated to meet the load, i.e. disconnecting loads or importing energy from the main grid.
4. The microgrid coordinator sends the computed allocation $a_i(t)$ to each DER
5. Each DER delivers an energy amount $r_i(t) \sim a_i(t)$. The ideal situation is $r_i(t) = a_i(t)$ but uncertainty on generation cannot guarantee that the equality is fulfilled.
6. Each DER receives a payment $\tau_i(t)$ according to the delivered energy $r_i(t)$

The key step of the protocol is 3(b) where the agents, according to the distributive justice fundamentals, should agree on how the load is shared. For carrying out the allocation, the legitimate claims of Rescher's canons are implemented as voting functions f_* and the importance of each function is determined by its corresponding weight w_*. Basically, the determination of how the load is shared is an allocation process which is repeated over time. The initial value of the weights is set to $w_* = \frac{1}{m}$ (where m is the number of functions) and the process follows the next protocol:

1. **Sorting**. Each function f_* sorts all the DERs, while the microgrid coordinator takes all partial orders and computes a new ranking of DERs, taking into account the weight w_* assigned to each function.
2. **Allocation**. The microgrid coordinator computes the allocation $a_i(t)$ of each DER_i according to the resulting ranking
3. **Voting**. Each DER_i votes about the relevance of each function f_*, and the microgrid computes a ranking of functions based on a consensus method that updates the weight w_* for each function to be used in the next allocation round.

In the remainder of the section we explain the implementations of the claims and the different steps of this protocol.

Before continuing, it is worth noting, that the application of this methodology assumes that no monitoring costs are incurred and that there is no cheating in the reporting of $p_i^{min}(t)$ and $p_i^{max}(t)$.

5.1. Legitimate claims

Canons are used to determine rank lists, reflecting DERs' relative merits in the microgrid. Canons are based on statistical data during the time-range T_i in which the DER has been an active member of the microgrid. T_i varies over time ($T_i(t)$), and serves as a counter of the time-steps that each DER has been active in the microgrid. However, for the sake of clarity we denote it T_i.

A total of six canons have been used, among the seven available in the methodology proposed in Pitt et al. (2012): equality, need, productivity, effort, social utility, and supply and demand. The last canon, ability, has not been used because it is not appropriate in the microgrid management context. They have been instantiated to the energy problem we are facing.

Canon of equality: we have used three ways to represent this canon: by their average allocations (f_{1a}); by the number of rounds they have received allocation (f_{1b}); and by the average payment received (f_{1c}).

$$
\begin{aligned}
f_{1a}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} a_i(k)}{T_i} \\
f_{1b}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} (a_i(k) > 0)}{T_i} \\
f_{1c}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} \tau_i(k)}{T_i}
\end{aligned}
\tag{5}
$$

where τ_i is the payment received. Note that f_{1a} and f_{1b} represent equality according to the workload and f_{1c} represents equality according to the awards for producing energy.

Note that f_{1a} and f_{1b} are very close but are used to avoid two different situations: (i) a situation where a DER receives only a very big allocation for a long period, and (ii) a situation where a DER continuously receives very small allocations. This latter situation can be faced through f_{1c}, but leaving f_{1b} in do not represent a drawback to the methodology, but another way to rate DERs. In addition to this, f_{1b} and f_{1c} are usually preferred than f_{1a} according to the experimentation we have performed (see Section 6.5).

Canon of needs: this second canon, f_2, ranks the agents in increasing order of their satisfaction $\sigma_i(t)$ (therefore $f_2(DER_i, t) = \sigma_i(t)$). Note that satisfaction is not a verifiable attribute, so it has to be based on an estimation of it, as with Equation (6). The DERs then increase or decrease their satisfaction depending on whether the allocation received is (or is not) close to their demand. To represent the closeness concept to the demand, we define the interval $I_i = \left[\underline{d}_i(t), \overline{d}_i(t)\right]$ as the interval which determines whether the DER i increases (or does not increase) its satisfaction and whether the allocation received is inside (or not inside) such interval. Thus, we model satisfaction as follows:

$$
\sigma_i(t+1) = \begin{cases} \sigma_i(t) + \alpha \cdot (1 - \sigma_i(t)) & a_i(t) \in I_i \\ \sigma_i - \beta \cdot \sigma_i(t) & a_i(t) \notin I_i \end{cases} \tag{6}
$$

where α and β are coefficients in [0, 1] which determine the rate of reinforcement of satisfaction and dissatisfaction respectively. If $d_i(t) = 0$ then $\sigma_i(t+1) = \sigma_i(t)$. α and β are the same for all $DERs$ but a different value could eventually be defined by each DER_i, representing their tolerance.

Canon of productivity: this canon f_3 ranks the agents in decreasing order of their average production success rate as the relationship with the allocated load $a_i(t)$ and the delivered energy $r_i(t)$, represented as follows:

$$
f_3(DER_i, T_i) = \frac{\sum_{k=1}^{T_i} \frac{r_i(k)}{a_i(k)}}{T_i}
$$

Therefore, f_3 measures the DER reliability. When $f_3(DER_i, T_i) = 1$, the corresponding DER has been always providing the allocated energy.

Canon of effort: this canon f_4 ranks the agents in decreasing order according to the time spent as an active member of the microgrid i.e. T_i. This is thus the time that the DER has been a member of the microgrid, excepting the time when the DER has stopped due to maintenance or repair.

Canon of social utility: there are two representations of social utility: first f_{5a} ranks the agents in decreasing order according to the amount of time spent in a distinguished role i.e. any microgrid using the allocation method of this paper would need a coordinator that computes the allocation at each time-step. It also involves agents that, among other roles, monitor every DER (or agent) ensuring that they follow the rules, even agents with the role of sanctioning those who are not following the rules. Some DERs will then be required to perform these extra roles (or distinguished) besides being energy generators. Including a function that considers the effort of performing these roles is a way to award DERs performing them. Second, f_{5b} ranks the agent in increasing order according to their CO_2 emissions.

Canon of supply and demand: The sixth canon f_6 aims to benefit DERs that can produce energy when it is needed while others cannot. For example, if a microgrid with only PV generators cannot produce energy at night, then any other type of DER capable of covering the energy demand at night (i.e. batteries) would be promoted by this canon. But if there is not any energy demand at night, batteries would not be promoted by this canon because, is such situation is useless at providing energy at night. Thus, this canon ranks agents in decreasing order according to

$$f_6(DER_i, T_i) = \frac{1}{T_i} \sum_{k=1}^{T_i} \left(\varpi_i(k) \cdot L(k) \sum_{j=1, j \neq i}^{N_{DER}} \left(1 - \varpi_j(k)\right) \right)$$

where $\varpi_i(k) = \frac{p_i^{max}(k)}{p_i^{max}}$ indicates the relative generation capacity of DER i at time k.

Summing up, we have a total of $m = 9$ criteria derived from the six canons. Note also that some functions (f_{1a}, f_{1b}, f_{1c} and f_3) present an indeterminacy when a DER appears in the microgrid for the first time ($T_i = 0$). These indeterminacies have been solved by setting the results to zero. This fact benefits new DERs according to the functions of the canon of equity, but penalises them according to the canon of productivity. However, this situation has not been seriously considered since it is not expected to be be relevant consistently to new DERs in the context of a microgrid.

5.2. Sorting

Each function f_* makes a sorted list of all DERs. A consensus should then be agreed on a single ranked list of the DERs to proceed to the allocation accordingly. To that end, Pitt et al. (2012) proposes a Borda count protocol Emerson (2007), considered a consensus-based voting method. Then, for each partial rank list provided by each function f_*, Borda points $p_{i,*}^{DER}$ are assigned to each DER_i, so rank k scores $N_{DER} - k + 1$ points.

The points from each DER regarding f_* are multiplied by the corresponding weight w_* and summed for all the functions to give a total Borda score to each DER. This finally enables a sorted list of DERs then used to allocate the load. We can therefore say that canons *agree* a ranked list of the DERs.

5.3. Allocation

Once agents are sorted according to the canons, the allocation method proceeds to determine the amount of energy each DER has to generate according to DER's demand and system constraints.

It is worth pointing out first that, the allocation required meets the minimum and maximum DERs' generation limits ($P^{min}(t) < L(t) < P^{max}(t)$, see Step 3b). However, the allocation depends on whether there is scarcity of load or not in regard to the available demand, that is:

1. $L(t) < D(t)$: there is scarcity of load and some DERs have to produce below their demanded amount d_i, but not below its reported limit $p_i^{min}(t)$.
2. $L(t) = D(t)$: all DERs produce the demanded amount $d_i(t)$.
3. $L(t) > D(t)$: there is a surplus of load and some DERs have to produce over their demanded amount d_i, but not over its reported limit $p_i^{max}(t)$.

Then, for case 1 and 3, the microgrid adjusts the allocation that each DER receives according to the list sorted by the canons. Note that since there are opposite cases (scarcity of load versus excess of load), the methodologies to follow are also opposite. On the one hand, when there is scarcity the most meritorious DER is the first to receive allocation. On the other hand, when there is an excess of load, the least meritorious DER is the first to receive an allocation greater than its demand.

Scarcity of load: each agent receives an allocation equivalent to $p_i^{min}(t)$. Then each agent (from the first to the last of the list) receives another allocation according to its $d_i(t)$ and the canons. Therefore,

$$a_i(t) = p_i^{min}(t) + \min\left\{LR(t), d_i(t) - p_i^{min}(t)\right\} \quad (7)$$

where $LR(t)$ is the (yet) non-allocated load. When an allocation $a_i(t)$ is assigned, its value is subtracted from $LR(t)$.

Excess of load: each agent receives an allocation equivalent to $d_i(t)$. Then each agent (from the last to the first of the list) receives another allocation equivalent to

$$a_i(t) = d_i(t) + \min\left\{LR(t), p_i^{max}(t) - d_i(t)\right\} \quad (8)$$

Note that $p_i^{min}(t)$ and $p_i^{max}(t)$ are reported continuously by DERs and also express their maximum and minimum desired amount of energy to produce energy. Therefore, no DER will be commanded to produce energy outside its limits or desires. Note that DERs could adjust $p_i^{min}(t) = d_i(t) = p_i^{max}(t)$ in order to obtain the best allocation. However, as we have previously stated, cheating behaviour like this one is not considered in this paper but might be penalised through an extra function of the canon of social utility that considers the span between $p_i^{min}(t)$ and $p_i^{max}(t)$.

Besides, all of the allocation procedure can be constrained by external authorities as, for example, by imposing some quotas of green energy. When this is the case, the allocation method first fulfils operational constraints; secondly it allocates energy demand to green DERs following the rank list until the green quota is completed or there is no more energy demand. Finally, if there is still energy demand to allocate, it is shared amongst all DERs according to the list. In doing so, we expect the community to be more robust to withstand external interferences.

5.4. Voting

To enable the participation of the DERs in the allocation method, each DER i votes each function f_*, giving it Borda points $p^c_{i,*}$ according to the rank index f_* that has been given to DER i at time t. Therefore the canon that has given the best rank to i receives the best Borda punctuation m (being m the number of functions) from DER_i. In case of a draw, each canon receives a punctuation equal to the sum of points reserved for the positions they occupy divided by the number of canons in the draw. For example, suppose we have four functions which ranked DER_i second, third, third and fourth. Then DER_i's vote would give 4 points to the first function, 2.5 points to the second and third functions (they share the punctuations of $3+2$), and 1 point to the fourth function.

Once DERs have voted canons, all Borda points of each function are summed and the resulting scores are used to update the weight w_* of each function f_* as follows:

$$w_*(t) = w_*(t) + w_*(t)\,\frac{Borda(f_*, microgrid) - AvgBorda}{TotalBorda} \quad (9)$$

where $Borda(f_*, microgrid)$ is the total Borda points that function f_* receives from DERs ($\sum_{i=1}^{N_{DER}} p^c_{i,*}$); $AvgBorda$ and $TotalBorda$ are the average and the total Borda points of all functions in the current round t ($\frac{1}{m}\sum_{\forall f_*} Borda(f_*, microgrid)$ and $\sum_{\forall f_*} Borda(f_*, microgrid)$ correspondingly).

It is worth pointing out that those canons that perform better than the average, increase their weight in the next round. Thus, DERs affected by the allocation method *agree* the weight of each canon representation and therefore its relative importance in the allocation process.

6. Experimentation

In this section, we present the experimentation that we have conducted and the results we have obtained, comparing our method with other two allocation methods. Results are measured in relation to the DERs' benefits (payments received τ_i minus costs) and agents' satisfaction (measured according to Equation (5.1)). The fairness of the last two measures (benefit and satisfaction) is analysed using the Gini index (note that the lower the better) as we are pursuing a distributive justice approach. Special attention is given to the results obtained regarding reliability and carbon emissions. Claims' weights are also used as a measure of the adaptability of the approach to the microgrid composition and context (including external interferences). We end this section with a discussion of the results obtained regarding its effect in microgrid.

6.1. Testbed

We have conducted experiments over Presage2 (Macbeth et al., 2012) modelling agents as DERs of different types (FC, PV, wind turbines or batteries) and sizes. The DERs were interconnected in a 14-bus grid with the global electricity load of Figure 1 which was periodically repeated over time. The load was distributed among all the buses. We also considered time-dependent electricity prices. Simulations consisted of 1000 rounds, representing each round a time-step of one hour.

DERs are modelled as greedy agents desiring to produce the amount of energy that maximises their benefits. We have considered four kinds of generators, FC, PV plants, wind turbines and batteries since the trend in microgrids is to incorporate green generators and batteries, while at the same time complementing them with the presence of more controllable generators such as FC. The features of the considered DERs are:

- Fuel cells: they can produce energy whenever they want, considering their up and down ramp limits (2MW/h). Their production cost is 37\$/MWh and their start up and shut down costs are 20\$ and 25\$ respectively. They only demand to produce energy if the payment they will receive compensates its cost. They produce 390 kg/MWh of CO_2.
- PV plants: they only can produce energy depending on the solar radiation (we have considered the average meteorological data in Catalunya[1]). Their production cost is zero, so they require the production of as much energy as they can considering the weather forecast. They have an average prediction relative error of 25% (Pelland et al., 2013).

[1] Data from Servei Meteorològic Català (Catalan Meteorological Service).

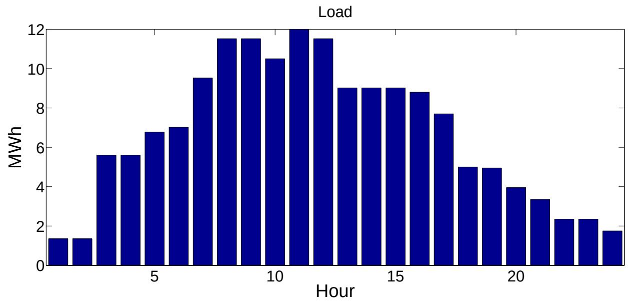

Figure 1: Time-dependent load

- Wind turbines: they can produce energy depending on the wind speed[1]. Their production cost is zero, so, as PV plants, they require the production of as much energy as they estimate they can according to the weather forecast. Their average prediction error is 0.85m/s (Soder, 2004). They are thus the more inaccurate DERs.

- Batteries: they do not produce energy, but they can buy energy and sell it later, complementing those DERs that cannot produce energy whenever they want. They thus buy energy when it is very cheap and demand to sell it when it is more expensive. They cannot exceed their storage capacity and their charge/discharge ramp limits (1.5MW/h). They have an associated CO_2 emissions factor of 240 kg/MWh which corresponds to the average Spanish electricity emissions factor.

We define two test scenarios over two microgrid configurations with scarcity of electric load:

- Case 1: all DERs has the same capacity C = 10.0MW. There are two FC, two PV plants, two wind turbines and two batteries.

- Case 2: there are four PV plants and four batteries with C = 2.0MW, two wind turbines with C = 2.0MW and one FC with C = 20MW.

Therefore, we will compare results on a partially homogeneous microgrid (DERs with the same size) against a heterogeneous microgrid (composed of different DERs of different sizes).

To test the performance of our approach, we distinguish the following configurations in regard to the methods used:

SO-canons: the method explained in this paper, self-organisation with legitimate claims. It is labelled as SO in the figures.

NONSO-equity: a non self-organised approach where the equity claim f_{1b} is the only one used. This situation is equivalent to other fair mechanisms in the literature based on a single measure (fairness) (Pla et al., 2015). This method is labelled as f1b in the figures.

NONSO-reliability: a non self-organised approach with the productivity claim f_3 alone. This scenario means to favour reliable DERs in regard to the others, so minimising problems of imbalance in the grid. This method is labelled as f3 in the figures.

Finally, to test the challenges regarding external interferences, we consider three forms of green quotas (percentage of green energy that has priority in the allocation process): Q of 0%, 50% and 75%. These percentages state that the corresponding percentage of the load has to be covered by green energy if possible.

6.2. Results of DERs' profit

We considered DERs' profit as the difference between the income they receive for producing energy (the energy produced multiplied by the corresponding price) and the energy generation cost (not including amortisation and maintenance costs).

At the end of the simulations (see Figure 2), we see that, as was expected, the increase of Q conveys an increase in the overall profit of green DERs (especially PV plants which are the most promoted by the most voted canons) in exchange of a reduction of the benefits of the rest of the DERs. Comparing allocation methods, NONSO-equity provides the highest equity in terms of profit for case 1 (see Figures 2 and 3). However, if there is a much bigger FC than the others, SO-canons obtains better values of equity because DERs foster canons of equity and need.

When analysing in depth the results with the Gini index, for case 1, SO-canons obtains worse results because, despite allocating similar amounts to FCs and

PV plants, FCs obtain lower benefits due to its lower profit margin. To obtain better equity values, we should have added a canon of equity considering profit margins; however, this is an internal information for each DER and it is not likely to be verifiable. Therefore we decided not to use such information. On the other hand, NONSO-reliability is highly unfair (see Figure 3) because it tries to allocate all demand to FC and when $Q > 0$ it allocates the demand imposed by the green quota to PV plants and the rest to the FCs, omitting wind turbines and batteries (batteries are useless when producers can guarantee energy whenever it is needed as FCs do).

6.3. Results on DERs satisfaction

Regarding satisfaction (estimated according to Equation (6)), the NONSO-equity and SO-canons results are comparable and, as in terms of wealth, it depends on the configuration of the microgrid. Thus SO-canons obtains similar results to NONSO-equity in terms of equity when it takes account of other claims such as productivity or social utility. On the other hand, Figures 4 and 5 illustrate the unequal allocation provided by NONSO-reliability, reaching satisfaction levels lower than 0.2 for DERs other than FC. These low wealth and satisfaction values convey the risk of depopulating the microgrid (unsatisfied DERs might leave the microgrid) and reducing the diversity of energy resources with their associated problems, such as oligopolies, contamination, etc.

6.4. Reliability and carbon emissions

We considered that a reliable allocation is one that minimises the percentage of uncovered energy demand due to the lack of DER production fulfilment.

Despite SO-canons and NONSO-equity reporting good results in terms of equity, NONSO-reliability obtains the best results in terms of reliability. Figure 6 shows the part of the allocated load that is finally uncovered by the corresponding DER. It shows that NONSO-reliability obtains the lowest uncovered amounts because it allocates all the load it can to FCs, but with its corresponding drawbacks like CO_2 emissions (see Figure 7). However, this uncovered demand does not correspond to an imbalance in the power grid between load and generation, it corresponds to typical imbalances due to beforehand (i.e. day-ahead) estimations of the load and generations schedules. Obviously, a reduction of the prediction error of stochastic DERs will convey an improvement in the credibility values of the results, as well as, an increase of the storage capacity in the microgrid.

Given these results we can say that the proposed energy demand allocation method provides distributive justice dealing with the plurality of legitimate claims according to Pitt et al. (2012). Furthermore, the method presented has been proven to be robust against external authorities (green quotas). Nevertheless, an allocation method designed to optimise a particular canon or minimise a particular interference will usually obtain better results regarding the optimised target than a plurality approach, but it will err in rigidity when tackling other situations. Besides, with SO-canons, DERs have more power to decide how the allocations are performed, which they cannot do with the other mechanisms.

6.5. Results on weight claims

Figure 8 shows the evolution of the claims' weights for cases 1 and 2 and for different values of Q. As a consequence, which are determined the preferred canons or which canons will have a major impact on the allocation.

Figure 8 shows that f_6 (canon of supply & demand), which promotes DERs that can produce energy when others cannot, is usually the most preferred weight. Considering a scenario with different types of DERs, this result is not surprising. Furthermore, for case 1 we see that f_3 has a very significant weight, and it increases when $Q > 0$. In this sense, when an external interference appears, weights evolve to minimise its effect. Thus, if energy from green DERs, which are at the same time DERs with the lowest productivity success rate, is prioritised, then weights prioritise DERs with a high productivity success rate. Note that for case 1 $Q = 50\%$ they also increase the weight of f_{1c} (equity in payments) but it is also a way to prioritise FC and batteries since they have a lower wealth (see Figure 2) because they receive smaller allocations.

When there are differences between DERs' capacities (there are larger DERs than others), the weights of claims of equity and needs are increased (see differences between case 1 and 2 with $Q = 0\%$). However, f_3 and f_6 are still important claims. Thus, there is a balance between claims that promote equity, diversity and productivity. Nevertheless, when Q is increased for case 2, DERs respond reducing equity claims because green DERs are more satisfied (all green DERs get most of the allocation they demand), so they reduce their votes for claims of equity and need. But f_6 becomes predominantly what benefits the large FC, but at the same time prioritises PV plants over wind turbines (which are usually allocated most of their demand). In this sense, they

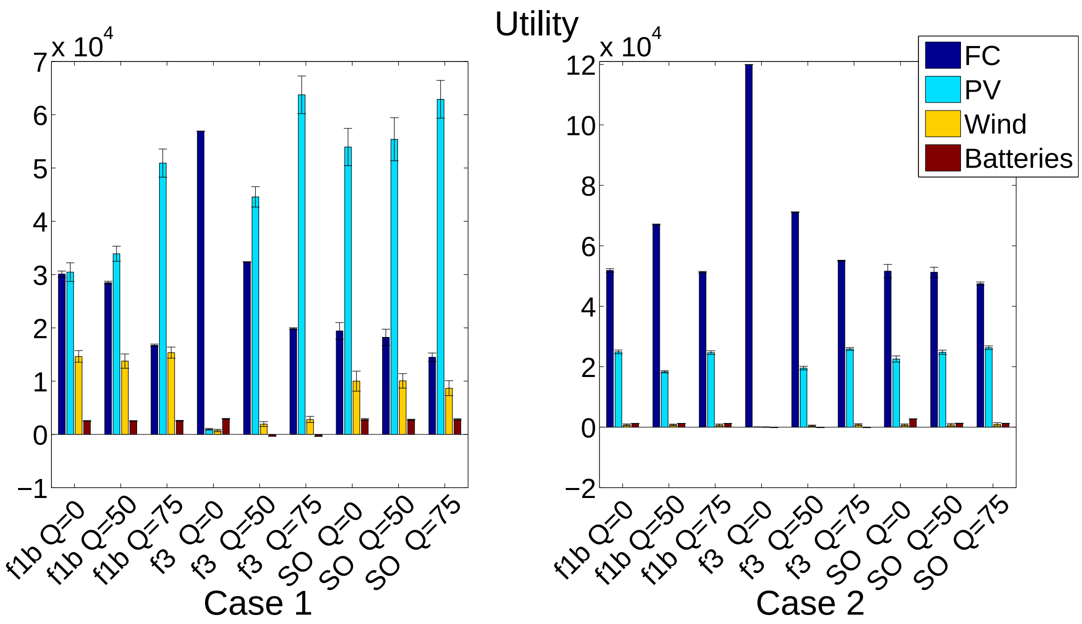

Figure 2: Average and standard deviation of the benefits of each type of DER for cases 1 and 2.

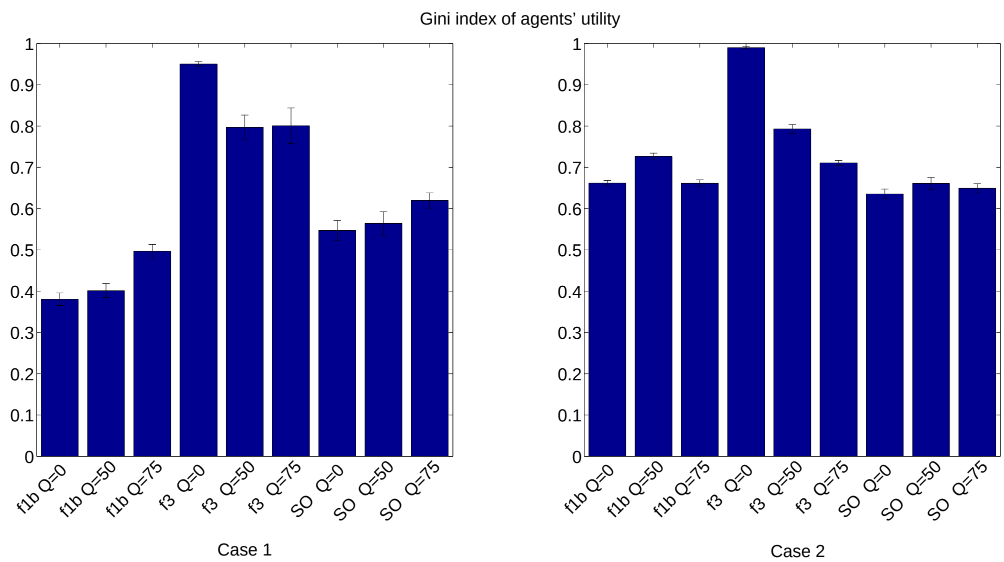

Figure 3: Gini index of the accumulated benefits by the DERs.

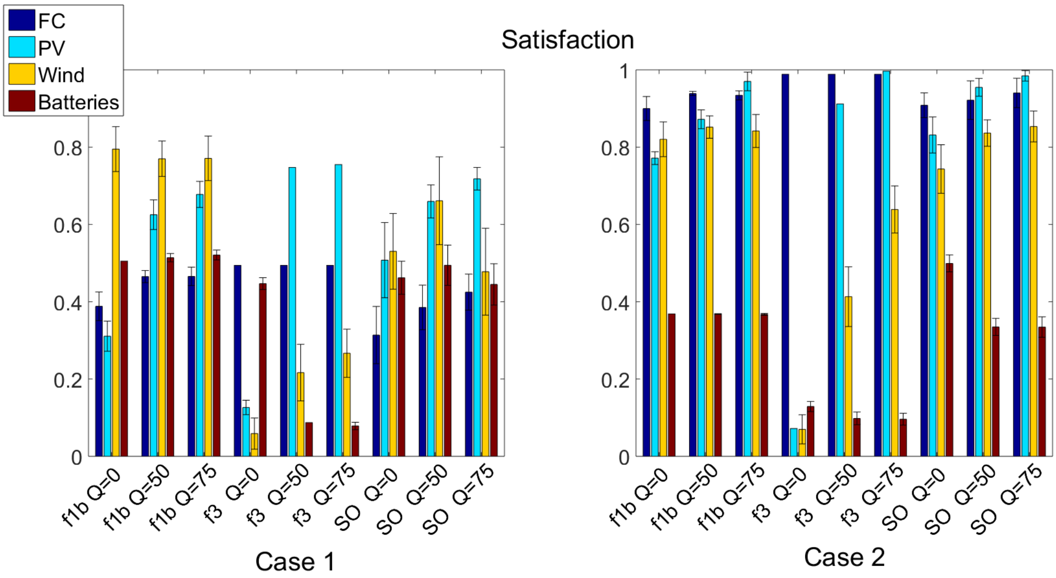

Figure 4: Average and standard deviation of the satisfaction of each type of DER for cases 1 and 2.

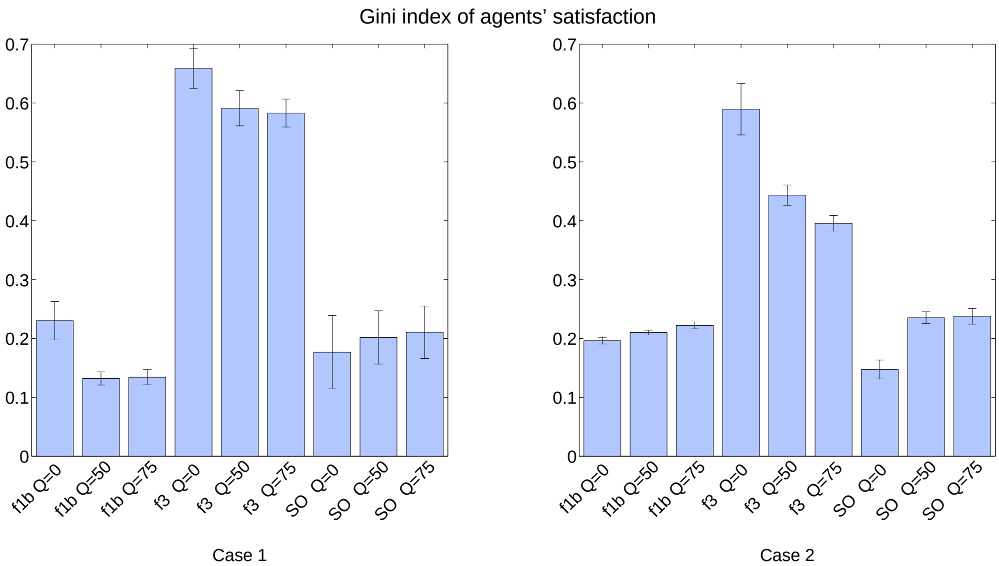

Figure 5: Gini index of the final satisfaction of the DERs.

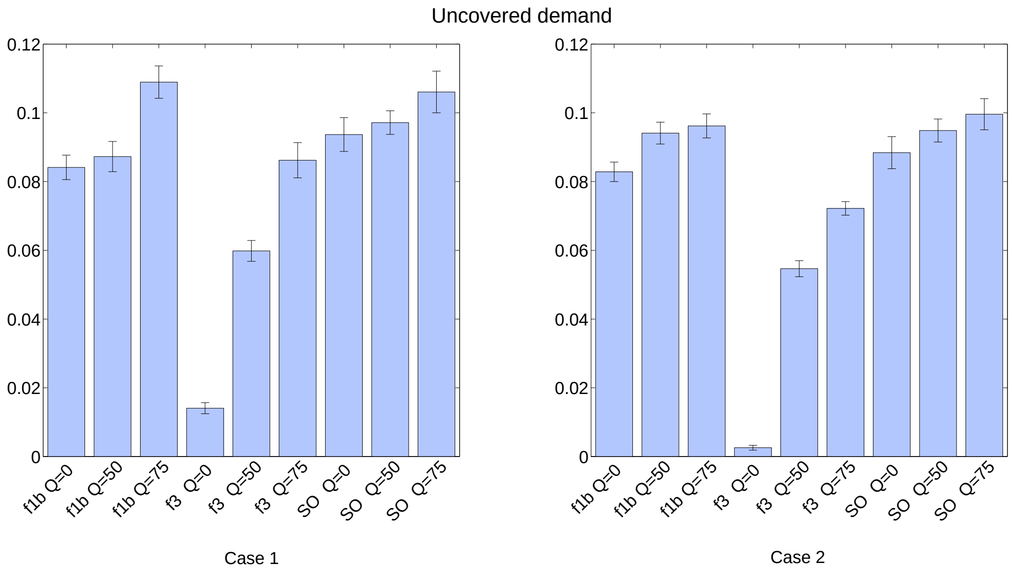

Figure 6: Part of the allocated load that, in the end, cannot be covered by the corresponding DER it was allocated.

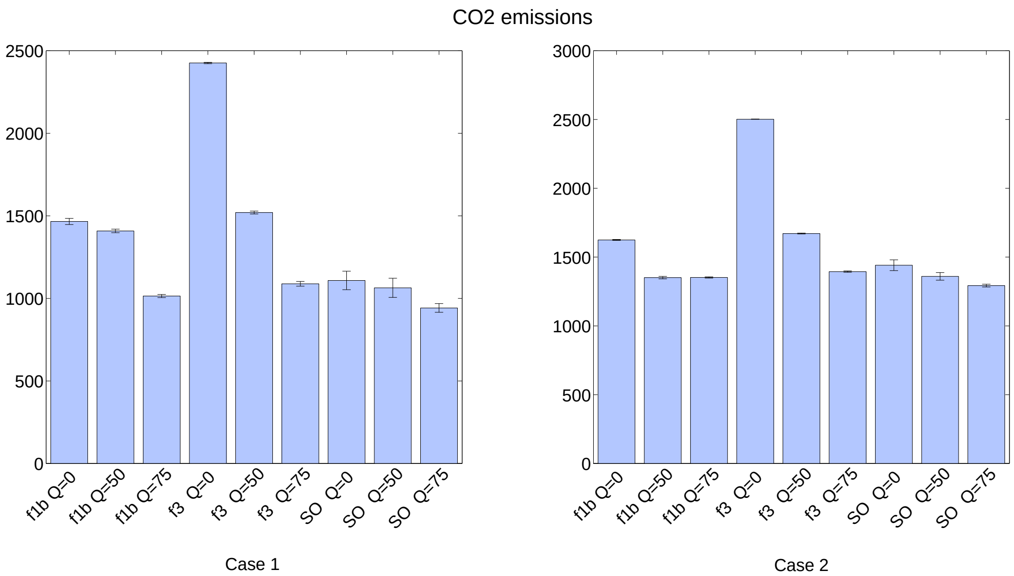

Figure 7: CO_2 emissions

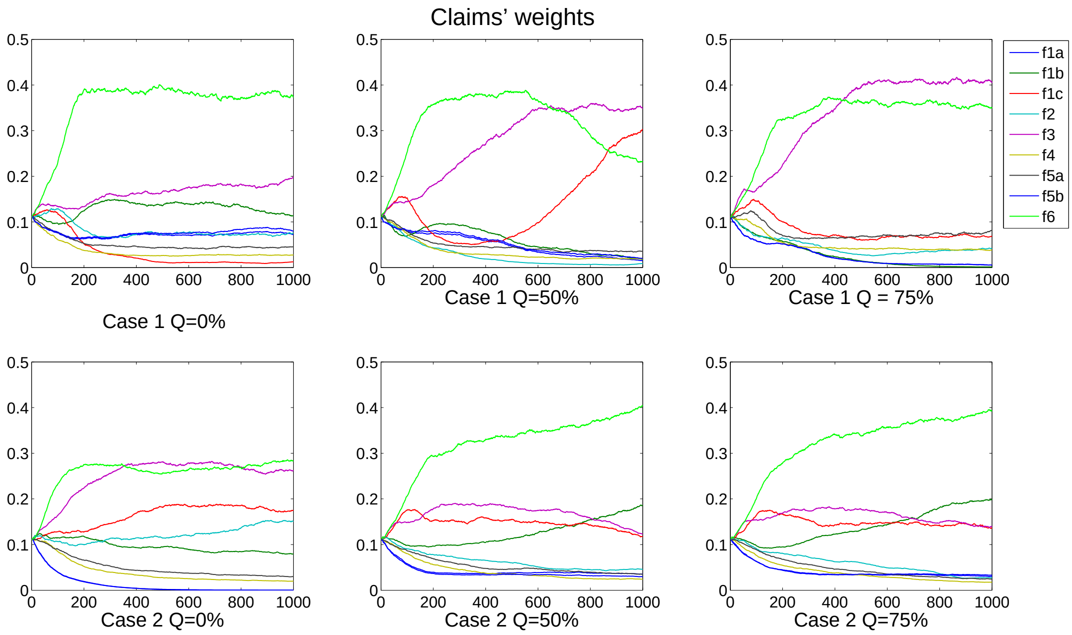

Figure 8: Claims' weights for cases 1 and 2 and with green quotas of 0%, 50% and 75%.

again find a balance between all claims that benefits all them (or at least the majority).

6.6. Discussion: potential of the method in microgrids

Power grids such as microgrids are being required more and more to rely continuously on renewable generators to reduce CO_2 emissions. However, renewable generators, such as PV plants or wind turbines, depend on meteorological events that are hardly predictable to produce energy. As a consequence, there is a trade-off between promoting green energy and keeping or increasing the reliability of the system. The proposed method presents the best results in terms of CO_2 (see Figure 7) since it promotes renewable generators (especially when there are no external interferences involved in promoting them). However, the promotion of green DERs is paid by a lower performance reliability (see Figure 6). This is due to the fact that green DERs have inaccurate predictions of their generation capacity. Thus, we propose a methodology for a day-ahead allocation. However, weather forecasting techniques, from which the capacity prediction depends on, are being improved every day and they are capable to perform very accurate short-term weather forecasts. Thus, our methodology may also be appropriate for shorter-term allocations such as an hour-ahead.

On the other hand, it is crucial to consider that any used allocation method promotes cheap energy generation DERs in order to contribute to the reduction of the energy price. The presented allocation method does not directly consider energy generation costs, but these are indirectly managed: a low level of CO_2 emissions implies the use of green DERs which have in turn a low energy generation cost. In addition to this, the canon of equity (f_{1c}) penalises expensive energy generation DERs which are interested in producing energy when its price is high (i.e. batteries buy cheap energy to sell it when it becomes more expensive). Despite of that, these kind of DERs such as batteries or FCs are needed because they are capable to supply energy when others cannot, improving reliability. Then, the aggregation of all the canons can model the transition from expensive carbon-based energy to cheap renewable energy.

Price, CO_2 emissions and reliability are tightly coupled and the smart grid pursues all of them by diversifying the energy generation. The presented methodology, tries to incentive the participation of the maximum number of agents by keeping adequate satisfaction values for all the members of the microgrid (or most of them) as Figures 4 and 5 show.

Another interesting outcome of the presented methodology is that it is capable of self-adapting to new situations such as the incorporation of new DERs to the microgrid or the presence of external commands that modify the allocations, as the results with $Q = 0$, $Q = 50\%$ and $Q = 75\%$ show. That enables us to think that the methodology could be capable of dealing with a new DER that appears in the micro-grid threatening the rest of DERs. Whenever the new DER alone can cover the demand, weights change in order to mitigate the effect of the new DER, as shown in Figure 8 for case 2.

Comparing the presented method with other existing works such as Bu et al. (2011) or Wang et al. (2014), which aim to optimise one or a few targets (i.e. minimise costs while ensuring a particular degree of reliability), we will obtain similar conclusions that when the presented method is compared with NONSO-reliability, which aims to minimise only the percentage of uncovered demand (maximise reliability). As the results show in Figure 6, previous works will obtain better results regarding reliability than our methodology, but in exchange of worsen results on other terms, i.e. CO_2 emissions (see Figure 7), fairness (see Figures 5 and 3), satisfaction (see Figure 4), etc.

The presented allocation method considers a situation where all DERs production limits can be met (situation 3(b) of Section 5). Then it first aims to meet these constraints and then allocate the remaining energy generation according to the canons (see Equations (7) and (8)). Thus, any DER will not be commanded to produce more or less energy than the limits it reported (minimum/maximum desired production). However, if all DERs production limits cannot be met (situations 3(a) and 3(c) of Section 5), which is beyond the scope of this paper, another methodology or protocol (i.e. exchanging energy with the main grid) should be applied to extend the presented methodology.

7. Conclusions

This paper presents a self-organising energy demand allocation method based on distributive justice represented as legitimate claims. It also takes into account grid constraints such as the balance between generation and consumption, and energy producers' constraints such as their generation bounds. In this sense, we provide an implementation of the legitimate claims grounded to an energy demand allocation scenario.

Regarding the results obtained from the simulations we can conclude that the proposed allocation method provides a balance between the canons of distributed justice, while this balance is determined by the agents which, at the same time, are able to adjust the allocation method to be more robust against external interferences. Nevertheless, allocation methods that minimise a particular interference or optimise results regarding a particular canon, will obviously obtain better results in terms of the optimised target, although they may err of rigidity when dealing with other situations. The capacity to adapt to new situations may then be a wiser option, especially in the long run.

The work remains open to further research since the presented approach is initially an experimental work. There are some idealisations, like network constraints, that have to be considered. However, these idealisations can be tackled in other stages of the energy demand allocation process (i.e. hour-ahead allocation), as well as the need for further increasing the reliability or performing an allocation for a given reliability rate. Other interesting lines of research may involve how to integrate dispensable loads or how to manage, by self-organisation, the disconnection of generators when there is deep a valley of demand. Furthermore, the allocation method does not present computational problems when it scales because it is not solved as a combinatorial problem. However, it would be interesting to study the scalability of the presented method from the communication and message passing point of view.

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