

Received 8 December 2023, accepted 27 December 2023, date of publication 8 January 2024, date of current version 24 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3351376

## RESEARCH ARTICLE

# Trust & Fair Resource Allocation in Community Energy Systems

SANJUKTA BHATTACHARYA<sup>1</sup>, ANASTASIOS OULIS ROUSIS<sup>2</sup>, (Member, IEEE),  
AND AIKATERINI BOURAZERI<sup>3</sup>

<sup>1</sup>Department of Electrical Engineering, Indian Institute of Technology Jodhpur, Jodhpur 342011, India

<sup>2</sup>Smart Power Networks Ltd. (SMPnet), W14 9BN London, U.K.

<sup>3</sup>School of Computer Science and Electronic Engineering, University of Essex, CO4 3SQ Colchester, U.K.

Corresponding author: Aikaterini Bourazeri (a.bourazeri@essex.ac.uk)

**ABSTRACT** The energy sector faces numerous challenges, including rising electricity costs and inconsistent services due to network overload, often requiring the involvement of a central network operator to address these issues. However, a user-centric approach that prioritizes demand-side management, exemplified by decentralized Community Energy Systems (dCES), presents a promising solution to energy distribution and supply network challenges. dCES can be conceptualized as a small-scale, dynamic distribution network seamlessly integrated into the broader framework of the Smart Grid. In this paradigm, prosumers play an active role, as they must contribute to and draw from a shared energy resource pool, with the overarching goal of avoiding depletion. Specifically, various individuals with different energy consumption patterns and preferences work together to solve collective action problems, i.e., blackouts. Motivated firstly by fair resource allocation, and secondly by the idea that *trust* is a crucial factor for successful collective action among diverse individuals, we developed a suitable Multi-Agent System (MAS) for dCES to prevent resource depletion. Our experimental results show that introducing *trust* into dCES can lead to successful collective action, resulting in stable energy networks.

**INDEX TERMS** Collective action, decentralized community energy systems, multi-agent systems, resource allocation, trust.

## NOMENCLATURE

### PARAMETERS

$\eta$	Round-cycle efficiency of storage device(s) during charging/discharging.
$ES^{max}$	Maximum state of charge.
$ES^{min}$	Maximum depth of discharge.
$P_{PV, rated}$	Rated capacity of solar photovoltaic.
$P_{WT, rated}$	Rated capacity of wind turbine.
$S^{max}$	Maximum storage power.
$S^{min}$	Minimum storage power.

### VARIABLES

$ES(t)$	Energy content in storage at the end of the current allocation cycle.
$P_{ls}(t)$	Involuntary loss of active load at allocation cycle $t$ .

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Mottola<sup>1</sup>.

$P_l(t)$	Active load at allocation cycle $t$ .
$P_{PV}(t)$	Active power generation of solar photovoltaic at allocation cycle $t$ .
$P_{WT}(t)$	Active power generation of wind turbine at allocation cycle $t$ .
$S^{c/d}(t)$	Storage charging/discharging at allocation cycle $t$ .

## I. INTRODUCTION

The Digital Society can be regarded as a socio-technical system [21], and is engineered for solving collective action problems, such as distribution of physical resources (e.g., energy, water, etc.). In collective action problems, individuals should work together for a common good or to resolve a common problem, even if their individual goals may be in conflict with the common goal, and each other's goals [2]. In many large-scale, ubiquitous computing systems for the Digital Society, a pervasive challenge lies: it may be difficult

for an individual to recognize that they are involved in a collective action situation or, that any small individual action can contribute to resolving a problem [16]. The lack of coordination and synchronization of individual actions may lead to diminishing the available common resources [4].

In this context, the motivation for our research is propelled by the critical need to address this conspicuous gap. To illustrate, consider a community energy system designed for local energy generation and distribution, where community members need to collaborate on energy allocation, and avoid incipient problems, such as unstable energy networks, that originate from depletion of the fixed amounts of energy that are available [22]. Community energy systems encompass both the social dimensions of human behavior, attitudes, beliefs, values, norms, collaborations, and competencies, as well as the technical aspects involving technology and organisational structures. The pivotal point revolves around the incorporation of users, with an emphasis on communities and groups rather than individual users, as their objective collectively resolves an urgent collective action problem [5].

Collective action problems for resource allocation and distribution can be resolved using Multi-Agent Systems (MAS) that can convert a centralized control system into a distributed and decentralized system [17]. MAS represent a promising platform extensively employed in decentralized Community Energy Systems (dCES), particularly in the context of resource allocation. For instance, Binyanmin and Ben Slama [3] introduced a MAS framework that harnesses a combination of negotiation protocols, decision-making mechanisms, and communication protocols to enhance the efficiency of energy resource allocation and scheduling within a decentralized smart grid.

However, in dCES where individuals need to collaborate on how to distribute and allocate the available energy resources, *trust* is considered an essential requirement for achieving successful collective action e.g., ‘fair’ allocation of resources maintains the balance of the energy community and avoids energy problems [24]. *Trust* is introduced in the proposed MAS as a reliability measure an individual has on the community, so that the dCES would cater to its energy consumption needs if all agents abide by the rules of the community.

Hence, the core focus of this paper is to investigate the dynamics of a collective action scenario within a dCES using MAS, while incorporating *trust* as a central element to facilitate more effective collaboration among individuals. Our motivation for employing MAS in a dCES setting stems from the hypothesis that introducing a social aspect into the round-robin allocation algorithm will incentivise individuals to better coordinate and synchronize their actions and behaviors, thereby mitigating energy-related problems like blackouts. This research aims to bridge the existing gap by examining the role of *trust* and social elements within the framework of dCES, thereby contributing to more efficient and harmonized energy resource management in the Digital

Society. Specifically, these are the research questions that are being examined:

- 1) Do individuals have a collective choice in dCES?
- 2) Are individuals aware of the effects that their actions have on the community and/or on themselves?
- 3) How are individuals motivated to show favourable behavior for the common good?

## A. MAIN CONTRIBUTIONS

The main contributions of this paper lie in:

- addressing the challenges within the Digital Society, specifically focusing on collective action problems in socio-technical systems,
- proposing the use of MAS to resolve collective action problems in dCES,
- identifying *trust* as a crucial element in dCES, influencing successful collective action and fair resource allocation,
- incorporating *trust* as a reliability measure, ensuring that different individuals adhere to community rules for balanced energy distribution.

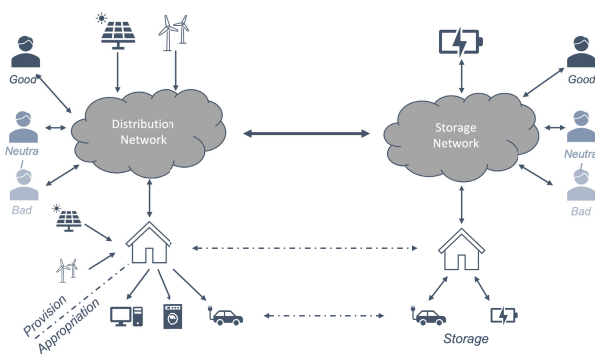
Accordingly, this paper is structured as follows. Section II presents the problem of resource allocation in energy communities, and how we can solve that by developing an appropriate MAS and integrating *trust* in that. Section III presents Elinor Ostrom’s design principles for self-governing and self-organising communities, and how these principles have been encapsulated in the proposed dCES. Section IV introduces *trust* as a social capital, which is an essential element for energy communities to achieve a successful collective action (i.e., stable energy network), and in Section V the experimental results actually show that when *trust* is being introduced in a dCES, a successful collective action can be achieved. Section VI summarises and concludes with the argument that these results have important implications for energy communities, as well as that *trust* can positively impact the individual members (i.e., encourage them to change their energy consumption patterns) to significantly reduce the total number of energy instabilities in the community; a significant outcome considering that the energy transition should be perceived not only at a technical level but also at social in order to become a reality and reverse the climate change impacts.

## II. THE PROBLEM OF RESOURCE ALLOCATION

Energy systems, transmission and distribution networks, face various challenges arising from the proliferation of renewable energy resources and the underlying energy transition – including stability and power quality issues that potentially lead to decreased network resilience and security of supply down to the end users, i.e., consumers and prosumers. These problematic situations are usually solved by transmission or distribution network operators however, management of energy distribution and supply networks could also be addressed by a user-centric, decentralized

approach, eliminating the requirement of maintaining an aggregating body altogether [6].

Decentralized Community Energy Systems (dCES) for local energy generation and distribution are a type of 'islanded' micro grid, where individuals need to collaborate on how to 'appropriately' distribute and allocate the available community energy resources. Specifically, dCES include different individuals, geographically co-located which have to provision to, and appropriate from, a Common-Pool Resource (CPR) [5]. In each dCES, there are two concurrent and co-dependent provision and appropriation systems, one for energy generation and one for storage. Actions in one system affect the other, and instead of each individual generating, storing and using its own energy, and thus suffering the consequences of over- or under-production, supply and demand are cross correlated with the common-pool which provides energy to all individuals in the dCES [4]. Given that dCES are 'islanded' from the grid, they need to be completely self-sufficient in terms of energy generation, distribution and consumption (such systems are increasingly common in rural communities and the developing world). However, if demand exceeds generation plus storage, there will be a blackout. In such scenario, it becomes essential for individuals to cooperate and coordinate their efforts to ensure a fair distribution of resources and avoid energy problems (Figure 1).



**FIGURE 1.** Decentralized community energy systems (dCES) for local energy generation and distribution.

In the context of dCES, where the focus is primarily on demand-side management, individuals are considered controllable grid resources. Consequently, it falls within their purview to dictate the allocation of available resources. Decentralized approaches are essential for the scheduling and allocation of resources in dCES, as the uncertainty associated with renewable energy resources have made the resource allocation problem even more challenging, and there is an urgent need for safe and stable operation of the energy systems. A promising approach to achieve a 'fair' resource allocation and avoid energy problems is through Multi-Agent Systems (MAS) that refer to computerised systems encompassing a collection of intelligent agents which actively interact within their environment and try

to achieve an overall objective [17], [23]. The agents are capable of perceiving their environment and have the ability to take critical decisions in order to improve or achieve their objective; they are also autonomous, meaning that the commands do not come from a user, but they are in form of individual goals to be achieved or satisfied [9], [11]. They are only partially dependent on their environment for the provision of resources, whereas they are independent of it in terms of managing those resources; agents are both open systems as they need external elements to survive and closed systems as they strictly regulate exchanges with the external environment. A MAS approach involving managing resources through a central optimisation problem is proposed in [1]. The algorithm fulfils certain important components such as resource management, maintaining overall common decisions and following a trust driven consumption change.

Similar examples of MAS approaches can be observed in diverse problem domains; [26] introduces a novel MAS architecture for controlling multiple micro-grids. The MAS in this context comprises management, micro-grid control, and local agents. This hierarchical and distributed MAS provides a dependable and adaptable control system for micro-grids. One limitation, however, is the absence of problem-solving mechanisms and resource consumption management. An alternative approach investigates the incorporation of combined heat and power, renewable energy sources, and battery storage into electric vehicle (EV) systems for grid-to-vehicle (G2V) and vehicle-to-grid (V2G) operations [8]. This approach emphasises the use of MAS to enhance the optimisation of micro-grid operations, aiming to reduce costs and carbon emissions. However, it also highlights a deficiency in decision-making and societal interaction. In essence, while a centralised optimisation based on MAS effectively tackles intricate allocation issues, it neglects fundamental principles of resource allocation as highlighted in Table 1.

Reference [15] highlights the need for an intelligent control mechanism that can adapt to the dynamic and uncertain nature of the grid. In this work, the agents interact with each other through communication protocols and decision-making mechanisms to optimise the operation of the smart grid. Following this approach, the efficiency, reliability, and flexibility can be improved and there is potential for reducing energy costs and carbon emissions. Reference [14] focuses on leveraging Demand Response management techniques including storage and renewable energy integration, to a flat load-profile. This work emphasises the increasing importance of MAS in handling uncertain renewable generation and load, offering critical insights into data science, advanced metering, and blockchain technologies for efficient micro-grid Demand Response management implementation and reduced electricity costs. Reference [25] discusses the potential for peer-to-peer energy trading and the importance of data exchange platforms for efficient coordination, presenting opportunities for MAS-based resource allocation systems, while [19] developed a decentralized trading application

TABLE 1. A comparative summary of this study and other papers.

Ref	Decentralized Energy Allocation	Energy Consumption Management			Decision-Making			Intelligent Control Mechanism			Social Interaction & Norms			Problem Solving Mechanism
		Demand Response	Consumption Reduction Requests	Effective Resource Management	Common Decisions	Decision Mechanisms	Making	Intelligent Mechanism	Control	Multi-Agent Systems	Social Behavior	Social Capital	Trust Driven Consumption Change	
Brisbois, M.C. (2020) [6]	✓	No	No	✓	No	✓		No	No		No	No	✓	No
Kanakadhurga, D. and Prabakaran, N. (2022) [14]	No	✓	No	✓	No	No		✓	No		No	No	No	No
Villar, J., Bessa, R. and Matos, M. (2018) [25]	No	✓	✓	✓	No	No		✓	No		No	No	No	No
Du, P., Lu, N. and Zhong, H. (2019) [10]	No	✓	✓	No	✓	No		✓	No		No	No	No	No
Binyamin, S.S. and Ben Slama, S. (2022) [3]	No	✓	No	✓	No	✓		✓	✓		✓	No	No	No
Mahela, O.P., Khosravy, M., Gupta, N., Khan, B., Alhelou, H.H., Mahla, R., Patel, N. and Siano, P. (2020) [15]	No	✓	No	✓	No	✓		✓	✓		✓	No	No	No
Brooks, N.A., Powers, S.T. and Borg, J.M. (2022) [7]	✓	No	✓	✓	No	No		✓	✓		✓	✓	No	No
Bourazeri, A. and Pitt, J. (2018) [5]	✓	No	✓	✓	✓	No		No	No		✓	✓	✓	No
Daramola, A.S., Ahmadi, S.E., Marzband, M. and Ikpehai, A. (2023) [8]	No	No	No	✓	No	No		No	No		No	No	No	✓
Ghazimirsaeid, S.S., Jonban, M.S., Mudiyansele, M.W., Marzband, M., Martinez, J.L.R. and Abusorrah, A. (2023) [12]	No	✓	No	✓	No	✓		✓	✓		No	No	No	No
Anders, G., Steghöfer, J.P., Siefert, F. and Reif, W. (2013) [1]	No	No	No	✓	No	✓		No	✓		No	No	✓	✓
Zhang, S., May, D., Atrazhev, P., Gul, M. and Musilek, P. (2020) [26]	No	No	No	No	No	✓		✓	No		No	No	No	No
Nair, A.S., Hossen, T., Campion, M., Selvaraj, D.F., Goveas, N., Kaabouch, N. and Ranganathan, P. (2018) [17]	✓	No	No	No	No	✓		✓	✓		No	No	No	No
Our study	✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓

aimed at streamlining the trading process of generated solar energy, minimizing complexities for both prosumers and utility providers, resulting in a 17.1672% reduction in the total cost of consumption.

A complete overview of response management in smart grids is provided in [10], and highlights the role of MAS-based optimisation in enhancing grid efficiency and reliability. A MAS-based energy management system (EMS) for residential green buildings integrated with distributed energy resources (DERs) is explained in [12]. The MAS effectively orchestrates DERs, load consumption, and demand response (DR) initiatives, optimising energy efficiency and profit within a local grid. The suggested model efficiently oversees resources, promotes participation in demand response programs, and curtails costs and emissions through decentralized communication methods. This essentially underscores the advantages and prerequisites of a decentralized collaborative approach. Integrating a problem-solving mechanism into DR allocation algorithms

can present challenges, particularly when considering factors like social interaction and norms (i.e., social behavior, social capital, and trust-driven changes in consumption). Often, the pursuit of effective management is compromised in favour of efficient accountability and reliability in decentralized approaches.

Brooks et al. [7] proposed a multi-agent system approach to reduce peak electricity consumption by promoting social behavior among consumers. The authors argue that traditional methods such as demand-response programs or pricing incentives are not effective in achieving long-term energy conservation goals because they do not address the social dynamics of energy consumption. Therefore, they introduced social capital to incentivise agents to act flexibly by accepting exchanges that do not immediately benefit them.

In this paper, a distributed approach in dCES using MAS is being explored. Here, each individual in dCES is assumed to be an agent which receives energy from the CPR but cannot communicate with its neighbours, only with the

distributed system. The proposed MAS is considered as being competitive, given that the agents do not have the same individual goals or interests. Agents despite having different behaviors in the community, i.e., good, neutral and bad agents, they all want to achieve the overall objective of the community; maintain the balance of the community and avoid energy problems. Even though agents do not receive any incentive from the community to declare their energy patterns, lying about this information will not be beneficial to them, as they will not receive the amount of energy they need. Therefore, no protocol has been defined to give agents incentives in order to declare their energy patterns or behaviors. The authors used the concept of the round-robin allocation system among agents to obtain the optimum solution for dCES and ensure fairness. The authors validated the approach with repeated simulation-based experimentation on 1000 agents, and found that *trust* as a social factor, can significantly contribute to the stability of the dCES. As highlighted in Table 1, our approach meets all the pertinent criteria for a fair resource allocation approach in a Digital Society.

### III. SELF-GOVERNING & SELF-ORGANISING DCES

Elinor Ostrom [18] proposed eight different socio-economic principles for self-governing institutions that help sustaining common but limited resources. These principles, which are necessary and sufficient conditions for creating enduring self-organising institutions, define who is a member of an institution, how the resources are managed and distributed, and who is affected by the rules of this institution. In particular, the principles on clearly defined boundaries define who is a member of an institution and how the available resources are managed. The principles on collective-choice arrangements specify that anyone who is affected by the rules of the institution should participate in their selection, and the principles about interference by external authorities state that the institution cannot be overruled by an external body.

In the proposed dCES, different self-interested and autonomous individuals should self-organise to share a common, yet limited resource, in a way to avoid its depletion without having long-term interests for the resource. Ostrom's principles are essential elements for the proposed energy community as individuals should be aware of the effects that their actions have on the community and its sustainability (please see Table 2). The first three principles define the proposed dCES; clearly defined boundaries, well-adapting rules, and participation in a collective situation. A good sets of rules for the energy community have been created to ensure its sustainability. The next two principles specify the members of the proposed dCES and their behavior. A rewarding scheme has been included to give an advantage to 'flexible' individuals. Conflict-resolution mechanisms are also included in the energy community to maintain its endurance and sustainability. The final two principles ensure that no external governmental authority can challenge the

members of the dCES, while energy communities can be organised in multiple levels.

In this paper, the definition of *trust* given by [13] is being followed, where "*A trusts B*" if two conditions held: firstly, that *A believes* there is a rule; and secondly, that *A expects the behavior of B* to comply with this rule [5]. We argue *trust* to be a social lubricant that can enhance collaboration and cooperation among all members of dCES through a combination of beliefs and expectations for the common good. Analogous to Ostrom's social capital, *trust* can help communities to build strong relationships that can resolve collective action problems as it stimulates robust social interactions avoiding disputes or conflicts in an effective manner. Without trust, community members cannot form a synchronised and accumulated body which works together for a collective goal. Our hypothesis is that by integrating *trust* in dCES, individuals' behaviors and actions will change towards a successful collective action. We therefore try to address the following questions with respect to each of Ostrom's principles while designing the proposed dCES:

Principles 1-3 define the characteristics of the CPR in dCES.

- Does the dCES have clearly defined boundaries?
- Are the provision rules adaptable?
- Do individuals have a collective choice?

Principles 4-6 focus on the individuals and their behaviors.

- Are individuals aware of their actions and their effects in the dCES?
- Is there a penalty scheme for offenders?
- What are the criteria for rewarding individuals? Are they fair?

All resource-allocation conflicts are sorted by an external party which is a randomly allocated individual for each conflict, who passes an informed judgement based on the past energy transactions and the behaviors of all individuals to ensure a fair judgement. The motivation for the randomly allocated individual is to ensure a fair judgement based on energy efficiency and sustainability of the community. The proposed dCES includes different individuals – some might consume a specific amount of energy, others might consume specific amounts of energy at certain fixed times of the day, while others might be highly flexible in terms of the time they consume energy but might need a certain amount of energy. Moreover, some individuals could be highly flexible in regards to their consumption patterns. These behaviors are captured by broadly categorising individuals in the proposed dCES.

The proposed dCES mainly includes three types of individuals; 'good', 'neutral' and 'bad' individuals indicating their behavioral aspects towards energy consumption as part of an energy community. 'Good' individuals are highly flexible both in terms of their energy consumption schedule as well as the amount of energy they consume. 'Bad' individuals, or individuals with the type 'bad' demand energy tokens in an incongruous way. They do not follow an energy

TABLE 2. Ostrom’s principles visualised in dCES.

P	Ostrom’s principles	Visualization in dCES
P1	Clearly defined boundaries	Outside individuals cannot participate or have access to dCES.
P2	Congruence between rules and local conditions	No restrictions by central authorities on how to allocate the resources; this is done by the individuals on the basis of trust.
P3	Collective-choice arrangements	Common choices and decisions about the allocation of resources.
P4	Monitoring	Individuals can control their energy consumption in real-time.
P5	Graduated sanctions	A rewarding scheme for ‘flexible’ individuals.
P6	Conflict-resolution mechanisms	An external party resolves the conflicts based on past energy transactions and individuals’ behaviors to ensure fairness.
P7	Minimal recognition of rights to organise	No intervention ensures that dCES cannot be controlled by external agents.
P8	Nested Institutions	Nested institutions organised in different layers for provision and appropriation of resources.

schedule, nor do they limit their energy requirements to the bottleneck constraint attached. ‘Neutral’ individuals are flexible with their schedule but are inflexible regarding their total energy consumption. These different individuals with different energy consumption patterns and needs are simulated to interact and collaborate together trying to avoid depleting the CPR.

#### IV. RESOURCE ALLOCATION & TRUST IN DCES

The proposed dCES distributes and reallocates the resources using a round-robin allocation system. Resource allocation networks use the physical grid as the channel to transfer energy units to individuals. The allocation network outlines the system of allocation between individuals, following directive principles defined on the basis of Ostrom’s principles, and the algorithm utilised is based on the AC optimal flow algorithm presented in [20] which is a typical algorithm for solving operational problems for all types of networks, including radial and meshed across low, medium and high voltage levels; note that the network serving the community under consideration is an ‘islanded’ AC micro-grid. The network under consideration includes a wind turbine, a solar photovoltaic panel and a battery storage unit along with load units. A short summary of the mathematical model utilised is presented hereafter (for more details refer to [20]). Equation (1) represents the active power balance equation.

$$S^{c/d}(t) + P_{WT}(t) + P_{PV}(t) + P_{ls}(t) = P_l(t) \quad (1)$$

Inequalities (2) and (3) represent the active power generation of the wind turbine and solar photovoltaic respectively, which follow the natural resource i.e. a deterministic input to the model, up to the installed capacity of each energy resource. Inequality (4) denote the limits for the charging and discharging power of the energy storage devices.

Additionally, inequality (5) corresponds to the maximum depth of discharge and state of charge rating for an energy storage device, and equation (6) ensures that energy stored in a storage device shall be conserved from one time step to the next one.

$$0 \leq P_{WT}(t) \leq P_{WT, rated} \quad \forall t \in T \quad (2)$$

$$0 \leq P_{PV}(t) \leq P_{PV, rated} \quad \forall t \in T \quad (3)$$

$$0 \leq S^{c/d}(t) \leq S^{max}, \quad \forall t \in T \quad (4)$$

$$ES^{min} \leq ES(t) \leq ES^{max}, \quad \forall t \in T \quad (5)$$

$$ES(t) = ES(t - 1) + \eta \cdot S^{c/d}(t) \cdot \Delta t, \quad \forall t \in T - \{1\} \quad (6)$$

A power outage within the community is defined as a situation where the energy allocation system cannot fulfil the energy demands of all individuals in the community. To address this, a designated *threshold* value is introduced as the minimum resource consumption level for individuals during a blackout. Algorithm 1 is used to distribute the energy units in the community, between different types of individuals. The different types of individuals {good, bad, neutral} in the dCES are assigned randomly. They are free to change their consumption patterns in subsequent allocation cycles. Algorithm 1 also introduces parameters  $\alpha_1, \alpha_2, \beta_1, \beta_2$  for the ‘bad’ and ‘neutral’ individuals. To enhance the validity of the experiment, the system generates modelled consumption demands within a range of values extracted from the dataset<sup>1,2</sup>. The demand curves are evenly categorised into ranges that distinguish individuals as ‘good’, ‘neutral’, and ‘bad’ based on their total energy consumption profiles. These parameters improve the generalisation of the results.

The allocation system places a high priority on meeting the needs of ‘bad’ individuals, making it a strict requirement for the optimisation algorithm. This approach benefits the community as it ensures that the demands of ‘bad’ individuals are addressed at the start of each energy distribution cycle. This prioritisation allows for flexibility among ‘good’ individuals and semi-flexibility among ‘neutral’ individuals, enabling them to adjust their energy usage in response to community demands. This proactive approach helps prevent potential blackouts and brownouts.

After allocating the desired resource portion to the ‘bad’ individuals, the algorithm moves on to the ‘neutral’ individuals. The semi-flexible nature of the ‘neutral’ individuals aids the community in maintaining a balance in the consumption distribution by partly reiterating its consumption schedule. However the *neutral* individuals are given a higher priority than the ‘good’ or flexible individuals since they are not flexible regarding their total consumption. A simple method to reduce the number of power outages is to monitor the amounts of resources demanded and limit

<sup>1</sup> [https://data.nationalgrideso.com/carbon-intensity1/historic-generation-mix/r/historic\\_gb\\_generation\\_mix#](https://data.nationalgrideso.com/carbon-intensity1/historic-generation-mix/r/historic_gb_generation_mix#)

<sup>2</sup> [www.renewables.ninja/](http://www.renewables.ninja/)

**Algorithm 1** Resource Allocation Without Trust Factor

---

```

Input: Threshold, tkn,  $\alpha_1$ ,  $\alpha_2$ ,  $\beta_1$ ,  $\beta_2$ , {type}
Output: {[e]}
if Individual type  $\rightarrow$  Bad then
  for All individuals in type ‘bad’ do
     $tkn_i = F(\alpha_1, \beta_1)$ 
     $e_i \rightarrow tkn_i$ 
  end for
end if
if Individual type  $\rightarrow$  Neutral then
  for All individuals in type ‘neutral’ do
     $tkn_i = F(\alpha_2, \beta_2)$ 
     $e_i \rightarrow tkn_i$ 
  end for
end if
if Individual type  $\rightarrow$  Good then
  for All individuals in type ‘good’ do
     $e_i \rightarrow \frac{Threshold - Sum(e)}{num_g}$ 
  end for
end if
return {type}, {e}

```

---

allocation accordingly. To correctly capture the value of interactions between individuals and the community, and among individuals themselves, *trust* is used as a social capital.

The resources left after allocating resources to the ‘bad’ and ‘neutral’ individuals are consumed by the ‘good’ individuals. The flexible nature of the ‘good’ individuals allows them to provide extra stability to the community and helps reducing power outages the most. Despite developing this allocation rule in alignment with Ostrom’s principles, instances of power outages in the community may still occur. A *trust* factor is awarded to all individuals as an indicator of their cooperative behavior, which is determined by their level of adaptability in energy consumption throughout the allocation cycles. *Trust* is introduced to promote the socio-cultural factors holding a community together. For the proposed energy distribution system, *trust* of the agents on the dCES is regarded as the degree of cooperation by an individual to avoid power outages. The *trust* factor is a direct reflection of the level of *trust* an individual enjoys within both the community and among their peers. The *trust* factor can be improved if an individual makes appropriate changes to their consumption patterns to reduce the number of power outages in the community. According to Ostrom’s third principle, the *trust* factor associated with each community and each individual is a common decision. The community may take certain choices and decisions based on the net energy consumption pattern of the whole community. A circulation of the *trust* factor, gives rise to a societal hierarchy favouring the individuals who are the most trusted in and by the

**Algorithm 2** Resource Allocation With Trust Factor

---

```

Input: Threshold, tkn,  $\alpha_1$ ,  $\alpha_2$ ,  $\beta_1$ ,  $\beta_2$ , {type}
Output: {[e]}
if Individual type  $\rightarrow$  Bad then
  for All individuals in type ‘bad’ do
     $tkn_i = F(\alpha_1, \beta_1)$ 
     $e_i \rightarrow tkn_i$ 
     $\Delta_i = \overline{H}(e_i - Threshold)$ 
    type = type *  $\Delta_i * \overline{S}(type, \{bad, neutral, good\})$ 
  end for
end if
if Individual type  $\rightarrow$  Neutral then
  for All individuals in type ‘neutral’ do
     $tkn_i = F(\alpha_2, \beta_2)$ 
     $e_i \rightarrow tkn_i$ 
     $\Delta_i = \overline{H}(e_i - Threshold)$ 
    type = type *  $\Delta_i * \overline{S}(type, \{bad, neutral, good\})$ 
  end for
end if
if Individual type  $\rightarrow$  Good then
  for All individuals in type ‘good’ do
     $e_i \rightarrow \frac{Threshold - Sum(e)}{num_g}$ 
  end for
end if
return {type}, {e}

```

---

community.

$$trustfactor(t) = \begin{cases} 1 + trust\ factor(t - 1) & \text{cooperation} \\ 0 + trust\ factor(t - 1) & \text{no cooperation} \end{cases} \quad (7)$$

The *trust* factor is initially set to 0 for all individuals regardless of their type. As the system begins to distribute resources among the individuals in each subsequent cycle, the *trust* factor is being updated (equation (7)). This change in the *trust* factor favours the group of individuals who cooperate in order to reduce the power outages in the community. With the motivation to lead the community towards stability, individuals are given the option to change their types or patterns of consumption at the beginning of the next cycle. Individuals can change their types various times, if they are not satisfied with their current consumption patterns or not able to fulfil their individual goals. Since the collective motivation of the system is to reduce significantly the number of power outages in the community, individuals should become more cooperative and work towards the common goal. The *trust* factor awarded to each individual acts as an indication of the system’s reliability on them. The choices regarding the individuals’ consumption patterns depict their cooperation and involvement in the stability of the community.

Algorithm 2 (i.e., the energy allocation algorithm including the *trust* factor) follows a similar outline to Algorithm 1 (i.e., without the *trust* factor); all variables are initialised

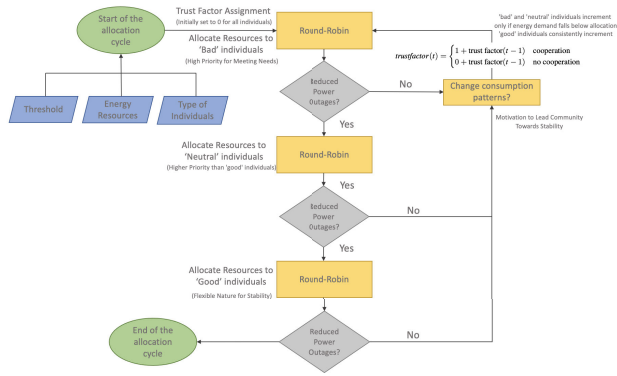


FIGURE 2. High-level view of the energy allocation algorithm.

at the very beginning of each allocation cycle based on Ostrom’s principles. After each allocation cycle, individuals receive an increment in their *trust* factor score, reflecting their level of cooperation with the community. Notably, ‘bad’ and ‘neutral’ individuals do not receive an increment unless their energy demand falls below the predicted energy token allocation. In contrast, ‘good’ individuals consistently receive an increment, as their demand for energy tokens remains consistently null in every allocation cycle (please see Figure 2 which provides a high-level overview of the energy allocation algorithm). It is important to note that for ‘bad’ and ‘neutral’ individuals, transitioning to a different category may not immediately align with their energy consumption interests. However, such a shift could contribute to a more stable community with reduced risk of power outages, benefiting all types of individuals and the community as a whole. The anticipated outcome is that the proposed energy allocation algorithm, integrated with the *trust* factor mechanism, could evolve into a versatile energy allocation algorithm suitable for supporting various energy networks. Regardless of the diverse energy consumption patterns and preferences among consumers and prosumers, the algorithm’s ultimate goal is to facilitate successful collective action, ensuring the efficient functioning of these networks.

**A. FUNCTIONS USED IN ALGORITHMS 1 AND 2**

*F*(\*): Generates a random value ranging between the parameter inputs to the function

$$F(\alpha, \beta) = \gamma$$

where  $\alpha < \gamma < \beta$

*Sum*(\*): The sum of all the values in the parameter array  
*H*(\*): Function that calculates the change in trust factor, essentially a piece-wise step function.

$$\bar{H}(\alpha) = \begin{cases} 1 & \alpha > 0 \\ 0 & \alpha < 0 \end{cases}$$

*S*(\*): The choice among the different types of individuals.

TABLE 3. Experimental parameters.

<i>Threshold</i>	The threshold limit of the system to handle the allocation of resources.
<i>tkn</i>	The consumption of energy tokens by a single individual.
$\alpha_1, \alpha_2$	The upper and lower limits of <i>tkns</i> for the ‘bad’ individuals.
$\beta_1, \beta_2$	The upper and lower limits of <i>tkns</i> for the ‘neutral’ individuals.
{ <i>type</i> }	Type of individual <i>i</i> in the system.
<i>e<sub>i</sub></i>	Consumption of resources by each individual <i>i</i> in the system.
$\Delta_i$	The change in trust factor over the different cycles for each individual <i>i</i> in the system.

**V. SIMULATION RESULTS**

In this section, the experimental results along with the relevant discussion and analysis are being presented. The motivation behind this comparison is to showcase the benefits of the *trust* factor and its applicability in a dCES. The experimental results involve a comparison between distributions with and without the *trust* factor, while keeping all other experimental parameters consistent (please refer to Table 3). It is worth noting that the total number of individuals and tokens allocated for distribution remains the same in both scenarios (equation (8)).

$$n_g + n_b + n_n = n_g^* + n_b^* + n_n^* \tag{8}$$

where *n<sub>i</sub>* and *n<sub>i</sub><sup>\*</sup>* are the number of *i* type of individuals before and after the different allocation cycles.

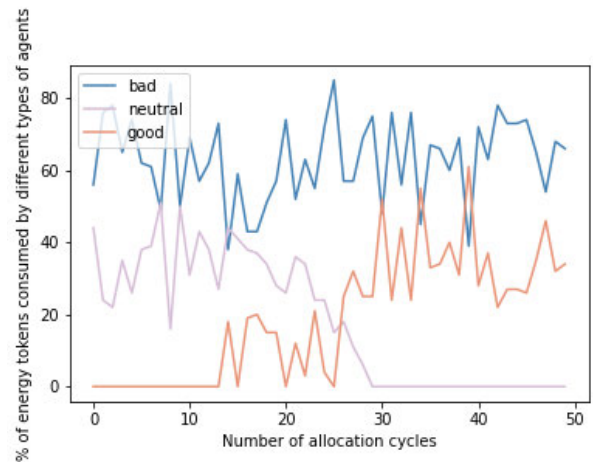


FIGURE 3. Energy consumption without *trust* factor.

Figures 3 and 4 compare the allocations with and without the use of *trust* factor respectively. Overall, the graphs show the energy consumption profiles among the different types of individuals. Figure 3 shows the consumption of different individuals across different allocation cycles. The ‘bad’ individuals maintain a high demand profile throughout



this allocation cycle. At the beginning of the allocation, it is observed that ‘good’ individuals exhibit the lowest resource consumption, while ‘neutral’ individuals, on the other hand, have a notably high token consumption. After some of the allocation cycles, the energy consumption by the ‘good’ and the ‘neutral’ individuals fluctuates. The graph shows a drastic decrease in the energy consumption by the ‘neutral’ individuals and at the same time, a drastic increase in the energy consumption by the ‘good’ individuals. This is because both ‘bad’ and ‘neutral’ individual consume resource units without considering the impact on society. Therefore, net consumptions are normalised to present a comparable consumption profile to Figure 4.

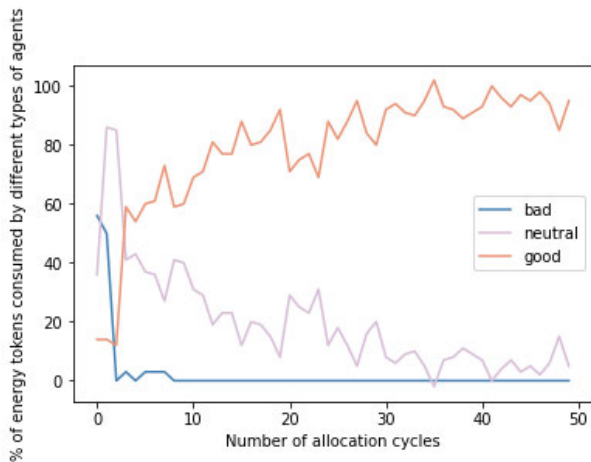


FIGURE 4. Energy consumption with *trust* factor.

Figure 4 presents the energy consumption, with the introduction of the *trust* factor. The *trust* factor gives an indication to the individuals to alter their consumption patterns (P4 from the Ostrom’s principles) and obtain a better *trust* factor in the next allocation cycle. A trust factor is considered to be ‘better’ if it shows a positive increment after an allocation cycle has been completed. The ‘good’ individuals do not need to change their consumption patterns, since these individuals always see a positive increment in their *trust* factor. The ‘neutral’ individuals observe a zero increment when their energy consumption demands are outside the range of allotted values. These situations tend to arise predominantly in the final few allocation cycles, primarily because, in those instances, the energy demand of the ‘neutral’ individuals might remain unmet if a higher energy token allocation is not made. It is worth noting that ‘bad’ individuals receive a negative increment in their *trust* factor when their consumption demands exceed the recommended limits established by the community.

The societal hierarchy based on the consumption patterns of the different types of individuals is already established in terms of how trustworthy certain groups of individuals are to the community. The ‘bad’ and ‘neutral’ individuals are given a chance to change their type by monitoring the changes

in their *trust* factor. The ‘bad’ individuals are therefore very likely to change their type after the first few cycles of allocations, and the ‘neutral’ individuals subsequently after that. In the experiments, an equal probability is used for the ‘bad’ individuals to change their types either to ‘good’ or ‘neutral’. An increase in the number of the ‘good’ and ‘neutral’ individuals in the system balances the spikes of consumption demands from the ‘bad’ individuals. Therefore in Figure 4, the consumption of ‘bad’ individuals and essentially the number of ‘bad’ individuals decrease drastically. At the same time, the consumption profile of ‘good’ and ‘neutral’ individuals is increasing. Eventually, a lot of ‘neutral’ individuals alter their consumption patterns to shift towards a ‘good’ individual.

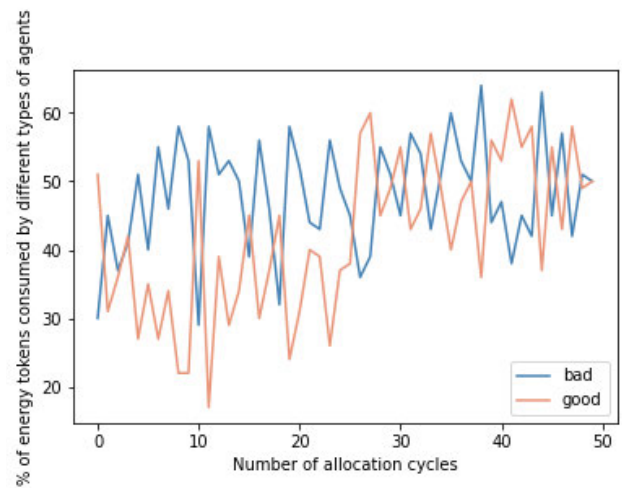


FIGURE 5. Energy consumption without neutral individuals.

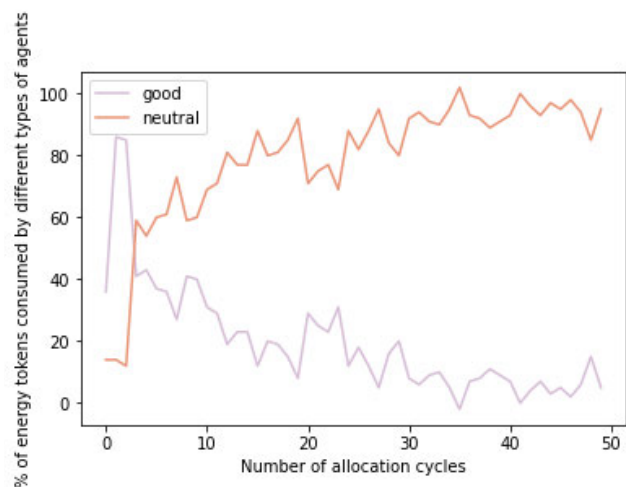


FIGURE 6. Energy consumption without bad individuals.

To better understand the role of the different types of individuals in the community, simulations with only two types of individuals are being run, and note the changes

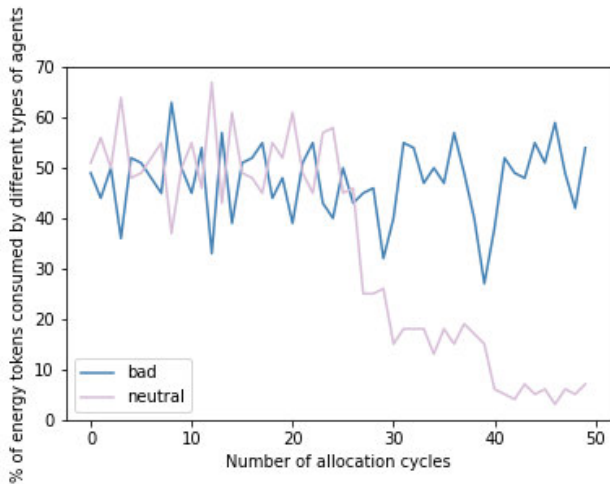


FIGURE 7. Energy consumption without good individuals.

observed due to the absence of the third type of individuals. In order to produce comparable results, the experimental parameters are always kept the same. The effect of the number of individuals of each type is a debatable parameter since increasing the number of individuals of each type, equivalent to the total number of individuals earlier in the system, expands the size of the system to a larger space which might affect the distributions subsequently. The experiment is described as the same system in the absence of a particular type of individuals. Figures 5, 7, and 6 display the absence of ‘neutral’, ‘good’ and ‘bad’ individuals respectively. Hence, in Figure 5, the tokens allocated to the ‘good’ individuals at the beginning of the allocation cycles are comparatively higher in comparison to the instances when the ‘neutral’ individuals are also present in the allocation cycles. The ‘neutral’ individuals do not modify the distribution of the remaining individual groups, and therefore can be seen as having low impact on the energy distribution patterns of the community.

In figure 6 the ‘good’ individuals are very flexible with both their energy demands and schedule, whereas the ‘neutral’ individuals are flexible with their schedule. The absence of ‘bad’ individuals leads the system to prioritise meeting the needs of the ‘neutral’ individuals, who are also relatively flexible and therefore leading to a better performance overall. In figure 7, the ‘bad’ individuals as usual demand a random amount of tokens, while the ‘neutral’ individuals are given the remaining energy tokens until their consumption demands are met. Therefore, we observe the allocations for the ‘neutral’ individuals to get reduced significantly after a few allocations.

The changes in the number of different types of individuals are presented, while the allocation cycles in the presence of the *trust* factor proceed. As the allocations begin, the individuals change their consumption patterns to obtain a “better *trust* factor”. The *trust* factor is the reason why the number

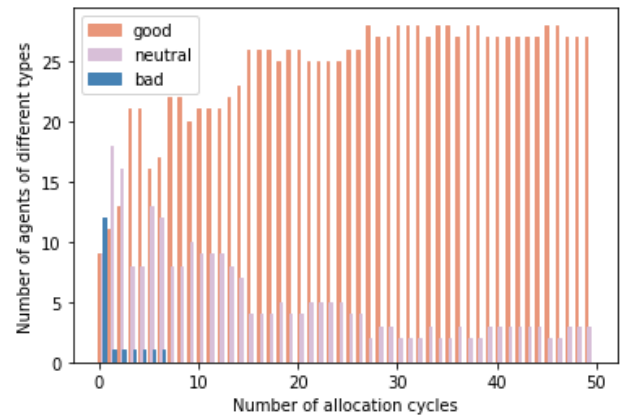


FIGURE 8. Different types of individuals in the community.

of different types of individuals change strenuously during the first few allocation cycles. We can see that the number of ‘good’ individuals increases constantly as the number of allocations progresses. ‘Neutral’ individuals are also on a constant increase, while the number of ‘bad’ individuals reduces. Ultimately, the number of ‘good’ individuals is the highest, followed by the ‘neutral’ individuals and then the ‘bad’ individuals.

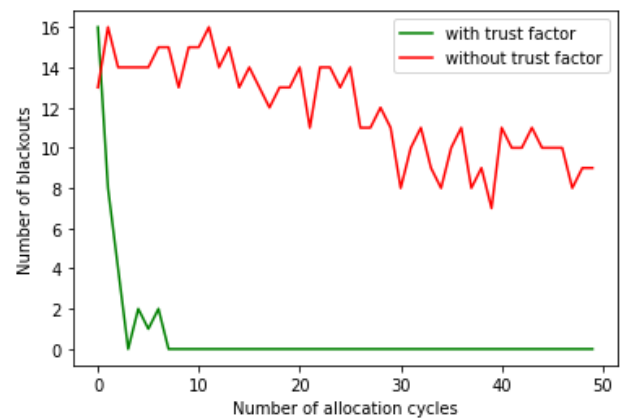


FIGURE 9. Number of blackouts in each allocation cycle.

To further support our findings, further experiments are being run to show the reduction in the number of blackouts. Blackouts are defined as the incidents where the energy demand exceeds the available energy for the community. We compare the effect of the *trust* factor by looking at the number of blackouts. Figure 9 shows the number of blackouts when the community starts using a *trust* factor to regulate the energy token distribution versus when it doesn’t. The number of blackouts decreases significantly with the introduction of the *trust* factor, especially in the later cycles when the effect of the *trust* factor is prevalent.

In Figure 10 we observe how the *trust* factor changes over different allocation cycles in the community when it does not govern the allocation in the system. The *trust* on ‘good’

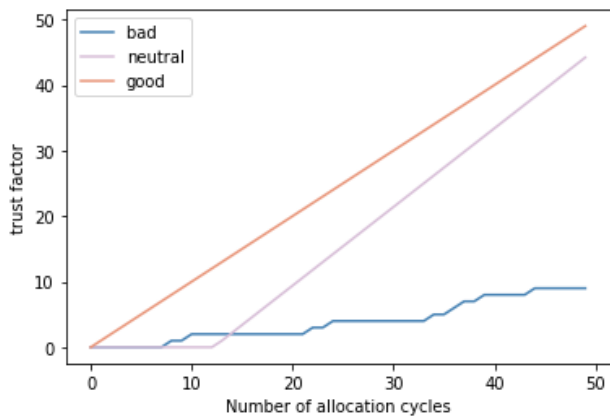


FIGURE 10. Individuals change their types based on *trust* factor.

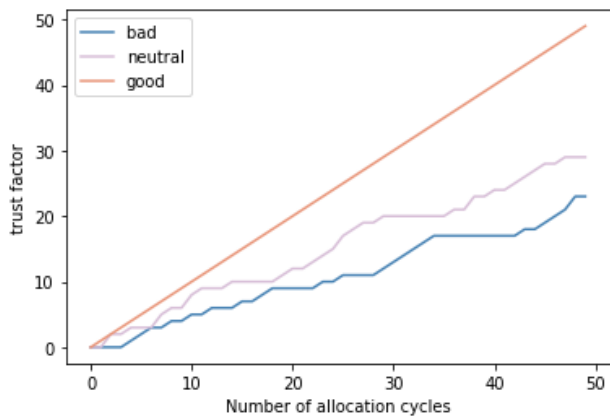


FIGURE 11. Individuals change their types based on *trust* factor.

individuals is the most prevalent followed by the ‘neutral’ and the ‘bad’ individuals. Figure 11 shows the changes in the *trust* factor over different allocation cycles in the community when the distribution is governed on the basis of collaboration. It can be observed that the *trust* factors of both the ‘neutral’ and ‘bad’ individuals become very similar to the ‘good’ individuals, demonstrating that the community has grown in terms of cooperative energy allocation and has significantly reduced the number of blackouts. The results show that the ‘neutral’ individuals are excellent ‘maintainers’, however they are not capable of solely helping the community to avoid blackouts. The ‘neutral’ individuals are not significant supporters nor significant opposers of the collective goal of the community, and by completely removing them from the community brings no significant change to the distribution. The possibility of a blackout occurring after a round of allocation cycles is determined by the energy demands and overall consumption. Individuals are therefore aware of the consequences of their choices (i.e., energy consumption patterns) given the number of blackouts occurring in the community. It is therefore safe to state that the individuals are aware of the effects that their actions have on the community.

Individuals can change their type before each allocation cycle starts. They usually change their type if the *trust* factor remains constant over multiple allocation cycles. Since the *trust* factor is a measurement of how much the community trusts an individual, if the *trust* factor remains constant over multiple allocation cycles, this indicates that the current consumption patterns of the individual are not the best for the common goal. We observe the effect of the changes in the consumption patterns to obtain a more stable network in the later allocation cycles during the day.

## VI. CONCLUSION

The aim of this paper was to identify and implement a resource allocation approach using MAS in a dCES, adhering to Ostrom’s principles. A form of social capital, represented by *trust*, was introduced to impart stability to the society by influencing the energy consumption patterns of the individuals within the system. This social capital plays a crucial role in sustaining the social dynamics of energy consumption in the system. The main contributions of this paper are:

- the development of an energy allocation system founded on Ostrom’s principles, specifically addressing self-governed communities and Common-Pool Resources (CPR),
- introduction of *trust* as an important social capital within a dCES. This paper investigated the impact of *trust* on the frequency or occurrence of blackouts in the community,
- (preliminary) foundation of a framework that integrates ‘fair’ resource allocation in dCES, incorporating a *trust* factor to foster stability within energy communities. This framework lays the groundwork for further exploration and application in the field.

Introducing a *trust* factor in an energy community, it can positively impact its individual members (i.e., encourage them to change their energy consumption patterns) to significantly reduce the total number of blackouts in the community. The methodology employed in this paper involves a direct comparison of consumption profiles and blackout frequencies both before and after the introduction of *trust*, along with ablation studies. The methodology extends to analysing the change in population distribution and the influence of the *trust* factor, contributing to understanding the proposed algorithm’s impact on enhancing system stability. The key parameters used in this analysis include demand and consumption profiles, as well as the distribution of individual types. To mitigate data-related dependencies in experimental results, randomly sampled data points were employed in these experiments.

Both Algorithm 1 and Algorithm 2 propose resource allocation in dCES; however, the latter incorporates a *trust* factor. According to our findings, this incorporation significantly reduces the number of blackouts experienced by the community. As blackouts in the community are followed by a

temporary shutdown, individuals are aware of these incidents, which are understood result of their energy consumption during the last allocation. In dCES, all individuals share both a collective and individual motivation to reduce or eliminate the occurrence of blackouts entirely. Consequently, each individual adopts an energy consumption pattern that aligns with their individual and collective goals most effectively. Our experiments reveal the following insights:

- ‘neutral’ individuals have a minimal impact on the stability or instability of the system compared to ‘good’ and ‘bad’ individuals, who contribute to stability and instability, respectively,
- in a stable state, the majority consists of ‘good’ individuals, followed by ‘neutral’ and then ‘bad’ individuals,
- the presence of *trust* factor leads to a reduction in the number of blackouts after the initial allocations,
- *trust* factor serves as a measure of community collaboration and, consequently, satisfaction. Figures 10 and 11 illustrate that the overall levels of community collaboration and satisfaction are higher when *trust* is used as a social capital in resource allocation.

Based on our findings, we can conclude that incorporating *trust* as a social factor has an overall positive impact on the community. Recent literature has used social factors for resource allocation in various contexts, such as centralised allocation mechanisms [1] and enhancing customer satisfaction to encourage social behavior within a community [7]. In [1], the *trust* factor is employed to approximate consumption profiles for allocation, and the mean scheduling time to stability aligns with the number of cycles in our simulation to reach a stable state in the presence of a *trust* factor. When compared with [7], a similar comparison underscores the role of social capital, indicating that overall community satisfaction attains optimality only when the number of social individuals surpasses that of selfish individuals. This further validates our experimental results involving a social capital and solidifies the introduction of *trust* as a social capital in dCES. In future work, we plan to enhance our proposed dCES by incorporating diverse economic inputs and various renewable resources. This expansion aims to create a more comprehensive representation, taking into account the interplay of social, economic, and environmental factors within the context of an energy community.

## REFERENCES

- [1] G. Anders, J.-P. Steghöfer, F. Siefert, and W. Reif, “A trust- and cooperation-based solution of a dynamic resource allocation problem,” in *Proc. IEEE 7th Int. Conf. Self-Adapt. Self-Organizing Syst.*, Sep. 2013, pp. 1–10.
- [2] I. Benson, “The logic of collective action revisited,” in *Proc. 26th Int. Conf. Circuits, Syst., Commun. Comput. (CSCC)*, 2022, pp. 268–279.
- [3] S. S. Binyamin and S. Ben Slama, “Multi-agent systems for resource allocation and scheduling in a smart grid,” *Sensors*, vol. 22, no. 21, p. 8099, Oct. 2022.
- [4] A. Bourazeri, “Collective awareness in self-organising socio-technical systems,” Imperial College London, London, U.K., Tech. Rep., 2015, doi: 10.25560/30771.
- [5] A. Bourazeri and J. Pitt, “Collective attention and active consumer participation in community energy systems,” *Int. J. Hum.-Comput. Stud.*, vol. 119, pp. 1–11, Nov. 2018.
- [6] M. C. Brisbois, “Decentralised energy, decentralised accountability? Lessons on how to govern decentralised electricity transitions from multi-level natural resource governance,” *Global Transitions*, vol. 2, pp. 16–25, Jan. 2020.
- [7] N. A. Brooks, S. T. Powers, and J. M. Borg, “Promoting social behaviour in reducing peak electricity consumption using multi-agent systems,” 2022, *arXiv:2211.10198*.
- [8] A. S. Daramola, S. E. Ahmadi, M. Marzband, and A. Ikpehai, “A cost-effective and ecological stochastic optimization for integration of distributed energy resources in energy networks considering vehicle-to-grid and combined heat and power technologies,” *J. Energy Storage*, vol. 57, Jan. 2023, Art. no. 106203.
- [9] A. Dorri, S. S. Kanhere, and R. Jurdak, “Multi-agent systems: A survey,” *IEEE Access*, vol. 6, pp. 28573–28593, 2018.
- [10] P. Du, N. Lu, and H. Zhong, *Demand Response in Smart Grids*, vol. 262. Cham, Switzerland: Springer, 2019.
- [11] M. Fisher, V. Mascardi, K. Y. Rozier, B.-H. Schlingloff, M. Winikoff, and N. Yorke-Smith, “Towards a framework for certification of reliable autonomous systems,” *Auto. Agents Multi-Agent Syst.*, vol. 35, no. 1, pp. 1–65, Apr. 2021.
- [12] S. S. Ghazimirsaeid, M. S. Jonban, M. W. Mudiyansele, M. Marzband, J. L. R. Martinez, and A. Abusorrah, “Multi-agent-based energy management of multiple grid-connected green buildings,” *J. Building Eng.*, vol. 74, Sep. 2023, Art. no. 106866.
- [13] A. J. Jones, “On the concept of trust,” *Decis. Support Syst.*, vol. 33, no. 3, pp. 225–232, 2002.
- [14] D. Kanakadhurga and N. Prabakaran, “Demand side management in microgrid: A critical review of key issues and recent trends,” *Renew. Sustain. Energy Rev.*, vol. 156, Mar. 2022, Art. no. 111915.
- [15] O. P. Mahela, M. Khosravay, N. Gupta, B. Khan, H. H. Alhelou, R. Mahla, N. Patel, and P. Siano, “Comprehensive overview of multi-agent systems for controlling smart grids,” *CSEE J. Power Energy Syst.*, vol. 8, no. 1, pp. 115–131, Jan. 2022.
- [16] J. Muringani and J. Noll, “Societal security and trust in digital societies: A socio-technical perspective,” in *Proc. 14th CMI Int. Conf.-Crit. ICT Infrastruct. Platforms (CMI)*, Nov. 2021, pp. 1–7.
- [17] A. S. Nair, T. Hossen, M. Campion, D. F. Selvaraj, N. Goveas, N. Kaabouch, and P. Ranganathan, “Multi-agent systems for resource allocation and scheduling in a smart grid,” *Technol. Econ. Smart Grids Sustain. Energy*, vol. 3, no. 1, pp. 1–15, 2018.
- [18] E. Ostrom, *Governing the Commons: The Evolution of Institutions for Collective Action*. Cambridge, U.K.: Cambridge Univ. Press, 1990.
- [19] U. Pati and K. D. Mistry, “Design and implementation of an enhanced demand-side management solution for distribution end prosumers,” in *Proc. IEEE IAS Global Conf. Renew. Energy Hydrogen Technol.*, Mar. 2023, pp. 1–7.
- [20] A. O. Rousis, I. Konstantelos, and G. Strbac, “A planning model for a hybrid AC–DC microgrid using a novel GA/AC OPF algorithm,” *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 227–237, Jan. 2020.
- [21] J.-P. Steghofer, A. Diaconescu, S. Marsh, and J. Pitt, “The next generation of socio-technical systems: Realizing the potential, protecting the value [introduction],” *IEEE Technol. Soc. Mag.*, vol. 36, no. 3, pp. 46–47, Sep. 2017.
- [22] D. Strickland, M. A. Varnosfederani, J. Scott, P. Quintela, A. Duran, R. Bravery, A. Corliss, K. Ashworth, and S. Blois-Brooke, “A review of community electrical energy systems,” in *Proc. IEEE Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2016, pp. 49–54.
- [23] K. Tazi, F. M. Abbou, and F. Abdi, “Multi-agent system for microgrids: Design, optimization and performance,” *Artif. Intell. Rev.*, vol. 53, no. 2, pp. 1233–1292, Feb. 2020.
- [24] A. Vasalou, A. Hopfensitz, and J. V. Pitt, “In praise of forgiveness: Ways for repairing trust breakdowns in one-off online interactions,” *Int. J. Hum.-Comput. Stud.*, vol. 66, no. 6, pp. 466–480, Jun. 2008.
- [25] J. Villar, R. Bessa, and M. Matos, “Flexibility products and markets: Literature review,” *Electr. Power Syst. Res.*, vol. 154, pp. 329–340, Jan. 2018.
- [26] G. Zheng and N. Li, “Multi-agent based control system for multi-microgrids,” in *Proc. Int. Conf. Comput. Intell. Softw. Eng.*, Dec. 2010, pp. 1–4.



**SANJUKTA BHATTACHARYA** received the bachelor's degree in electrical engineering from the Indian Institute of Technology Jodhpur. She is currently pursuing the M.Sc. degree from the University of Edinburgh, with a strong passion for leveraging technology to tackle real-world challenges. She is an Engineer. She is actively working on the quantification of real-world problems, also addressing the domains of energy efficiency and sustainability. Her research interests include human-computer interaction (HCI), smart cities, multi-agent systems (MAS), and algorithmic game theory. She was awarded the Mitacs Globalink Scholarship with the University of Regina to work on game-theoretic rough set-based problems.



**ANASTASIOS OULIS ROUSIS** (Member, IEEE) received the dual master's and Ph.D. degrees from Imperial College London. He is a highly accomplished engineer-turned-entrepreneur who serves as the CEO and the Co-Founder of Smart Power Networks Ltd. (SMPnet), an emerging software company in the energy sector. His work at SMPnet is focused on breaking down the barriers to a sustainable energy transition, promoting digitalization, and decarbonization in the process. With his vast experience working alongside C-level executives and thought leaders in the energy sector, he brings a unique perspective to the industry. He also serves as an advisor to the Greek government in his capacity as a member of the Greek Sectoral Council for Environment, Energy, and Sustainability Mobility, which falls under the Ministry of Development and Investments. He has authored or coauthored more than 30 publications, book chapters, and patents.



**AIKATERINI BOURAZERI** received the B.Sc. degree in computer science from Piraeus University, Greece, the M.Sc. degree in internet and wireless computing from the University of York, U.K., and the Ph.D. degree in electrical and electronic engineering from Imperial College London. She is currently a Lecturer in computer science and AI with the School of Computer Science and Electronic Engineering (CSEE), University of Essex. She is an expert in designing, implementing, and evaluating technologies that address everyday problems with a direct impact on people's lives, such as energy efficiency and sustainability, people's empowerment and inclusivity in societies, and independent living at home for people with disabilities or chronic conditions. Her research interests include human-computer interaction (HCI), game design and development, interface design, information visualization, health informatics, smart cities, multi-agent systems (MAS), and the Internet of Things (IoT).

...