



# Modelling Mutual Influence Towards Sustainable Energy Consumption

Kankam O. Adu-Kankam<sup>1,2</sup> and Luis M. Camarinha-Matos<sup>1</sup>

<sup>1</sup> School of Science and Technology, and UNINOVA - CTS, Nova University of Lisbon, Campus de Caparica, 2829-516 Monte Caparica, Portugal  
kankamadu@gmail.com, cam@uninova.pt

<sup>2</sup> School of Engineering, University of Energy and Natural Resources (UENR), P. O. Box 214, Sunyani, Ghana

**Abstract.** The notions of Collaborative Virtual Power Plant Ecosystem (CVPP-E) and Cognitive Household Digital Twin (CHDT) have been proposed to contribute to the efficient organization and management of households within Renewable Energy Communities (RECs). Both ideas can be represented by digital twins, which complement each other. CHDTs can be modelled as software agents, designed to possess some cognitive capabilities which could enable them to make autonomous decisions, based on the preferences or value system of their owner. Due to their cognitive and decision-making capabilities, these agents could exhibit some behavioural attributes such as engaging in collaborations, mutually influencing one another and the ability to adopt some form of social innovation. These behavioural attributes are expected to promote collaboration which are envisioned to increase the survivability and sustainability of the CVPP-E. This study therefore seeks to demonstrate the capability of CHDTs to mutually influence one another towards a common goal - thus promote sustainable energy consumption. We adopted a multi-method simulation technique that involves the integration of multiple simulation paradigms such as System Dynamics, Agent-Based, and Discrete Event simulation techniques on a single simulation platform. The outcome of the study shows that mutual influence could enhance the sustainable consumption in the ecosystem.

**Keywords:** Mutual influence · Collaborative networks · Sustainable consumption · Digital twins · Renewable energy communities

## 1 Introduction

It was claimed in a recent study that buildings consume nearly 40% of global energy, 25% of global water and 40% of global resources [1]. The study further advanced the argument that one-third of global greenhouse gases are emitted by residential and commercial buildings. Other similar studies such as [2] have also affirmed that energy consumption in households (HHs) is in the rise and this could partially be attributed to the increasing demands for comfort and its consequent requirement for larger HH equipment. This has

also been attributed to higher purchasing power and improvement in the standard of living of occupants [2].

Generally, it is known that the Earth's resources are depleting rapidly. This depletion can partly be ascribed to the global surge in energy demand, of which HHs play a key role. The adverse effect of depleting the earth resources is currently resulting in the problem of climate change. This phenomenon poses severe threats to the survivability and sustainability of planet earth and its entire occupants. To help address this immense concern, several studies have suggested diverse approaches that can help reduce energy consumption at the HH levels. One of such approaches, as described in [3, 4] and [5], involves the notions of Collaborative Virtual Power Plant Ecosystem (CVPP-E) and Cognitive HH Digital Twin (CHDT). These are a pair of concepts that are proposed to complement each other and can be conceptualized as digital twin representation of (a) a Renewable Energy Community, which is hereby represented as the CVPP-E, and (b) the constituent HHs of the community, also represented as CHDTs. According to the authors of [5], CHDTs can be designed and modelled as software agents that can possess some cognitive capabilities which could enable them to make autonomous and rational decisions based on the preferences of their owners. Furthermore, it is claimed that CHDTs could exhibit some behavioural attributes such as engaging in collaborations and mutually influencing one another towards collective decision-making. In this study we attempt to demonstrate "Mutual Influence" capabilities of these CHDTs, and further endeavour to show how such influence can be adopted to alter the decision making of CHDTs. The study is therefore guided by the following research questions:

- RQ-1. In the context that "influencer" CHDTs could convey either positive or negative influence on "influencee" CHDTs in a CVPP-E, how can the aggregation of these influences over time be used to determine the overall behaviour of a CHDT?
- RQ-2. How can the overall behaviour of a CHDT be used in decision-making?
- RQ-3. Considering that CHDTs could be influenced to alter their decisions, how can "mutual influence" be used to alter the decisions of CHDTs towards sustainable energy consumption.

## **2 Relationship with Technological Innovation for Digitalization and Virtualization**

Advances in digitalization and virtualization are helping to gradually bridge the divide between the physical and virtual worlds. The coupling of these two worlds unveils the possibility of mirroring the real world in its equivalent form within the virtual space [6]. These concepts represent facets of a major transformation that is currently ongoing in industry and services, often referred to as industry 4.0. They encompass the adoption and integration of a variety of new information and communication technologies for the development of more efficient, flexible, agile, and sustainable solutions [7]. In the domain of energy, these concepts are helping to facilitate the integration of intelligence in the form of software agents for optimum grid management and operation. In this context, this study proposes the virtualization of Renewable Energy Communities (RECs) and their constituent HHs into a form of Digital Twins (DTs). Furthermore, the study suggests the

digitalization of energy use preferences of the constituent HHs of these RECs, in a form of delegated autonomy, which is assigned to their DT counterparts. It is perceived that these DTs could possess some cognitive or intelligent attributes that could enable them to make rational and autonomous decisions on behalf of their owners. This could help to provide flexible and sustainable energy consumption within these virtualized RECs. In view of the above, the scope of this work aligns well with the ongoing trend in the digital transformation.

### 3 Theoretical Framework and Related Works

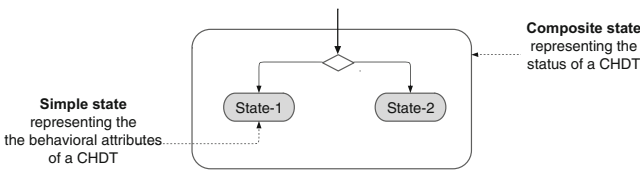
We derived the Collaborative Virtual Power Plant Ecosystem concept by merging principles and concepts from the disciplines of Collaborative Networks (CNs) [8], and Virtual Power Plants (VPP) [9]. The central theme for the concepts of CNs is the idea of collaboration, where multiple entities come together with the primary objective of achieving a common goal. In studies such as [10] and [11], CN concepts are well elaborated. Conversely, VPPs are virtual entities that involve the interaction between multiple stakeholders and are comprised of decentralized multi-site and heterogeneous technologies, formed by aggregating deferrable and non-deferrable distributed energy sources [3]. The mix of these two concepts resulted in the proposed hybrid concept called Collaborative Virtual Power Plant Ecosystem (CVPP-E). This idea was first introduced in [3]. A CVPP-E can be perceived as a Digital Twin (DT) model of a REC, such as described in [12]. Other relevant studies described a CVPP-E as a form of a business ecosystem or a community of practice where members approach energy generation, consumption, and conservation from a sustainability point of view using collaboration as a key technique. The governing structure is claimed to be polycentric and decentralized with a manager who plays a coordinating role and promotes collaborative behaviours. Our current work extends previous developments by focusing on the effects of mutual influence among CHDTs and how such influence can be channelled to promote more sustainable energy consumption.

### 4 Modelling Framework

**Modelling the CVPP-E and CHDTs:** According to [13], a REC is a community that is formed based on open and voluntary participation. It is usually owned, managed, and controlled by shareholders or members who are autonomous and located within the proximity of the projects. Essentially, members of a REC can generate renewable energy for their own consumption, and may store, sell, or share excess with community members. In this context, the study, attempt to replicate the REC concept by aggregating several autonomous software agents into a population of CHDTs. Each CHDT represents a unit of HH within the community. In the model, we categorized the constituent HHs (CHDTs) into 5 different categories. The categorization and related data was sourced from [14]. The considered categories are: (a) HHs with single pensioner (b) HHs with single non-pensioner (c) HHs with multiple pensioners (d) HHs with children (e) HHs with multiple persons with no dependent children.

A key aspect of the CHDTs concept is their cognitive capabilities. In this study, CHDTs are modelled at three abstraction levels. The upper-level is used to model the community status and decision making processes, while the mid-level is used to model the different behavioural attributes of the CHDT. At the low-level is where energy assets such as HH appliances, energy storage devices, as well as the PV systems are modelled. Although it is acknowledged that the physical layer involves the integration of diverse energy assets, it is expected that several technical factors should be taken into consideration as far as the organization and efficient management of these energy assets are concerned. However, the emphasis of the study was focused primarily at the upper and mid layers where decision-making and varied behavioural attributes occur. Therefore, the lower level technical factors are not addressed in this work. This is because this study hinges around two key principles: (a) collaborations which is based on some common goals, and (b) the notion of community. Currently, the literature on energy communities suggests that members usually form a cohesive union around the energy infrastructure, due to the notion of “community membership”, “sense of belonging”, “common identity”, etc. Furthermore, it is claimed that members of these communities are usually expected to conform to community norms, practices, and rules. Therefore, the behavioural traits as well as the decision-making attributes of members is what we deem paramount in this work.

In modelling a CHDT, we first consider its community status, which defines a CHDTs long-term characteristics which enables it to play some specific roles in the community. For instance, being a prosumer, consumer, influencer, or influencee. Thus, the status of a CHDT is modelled using a “composite state” as shown in Fig. 1, and is assumed at the model initialization stage, and is remembered and maintained as an “active state” by the agent throughout the model run. The behavioural attribute at the mid-level includes behaviours such as the ability to convey influence (influencer) or being the recipient of an influence (influencee). These behavioural attributes are also modelled as internal states, using “simple states” which are embedded inside the “composite state” as shown in Fig. 1.



**Fig. 1.** A composite and simple states of a CHDT

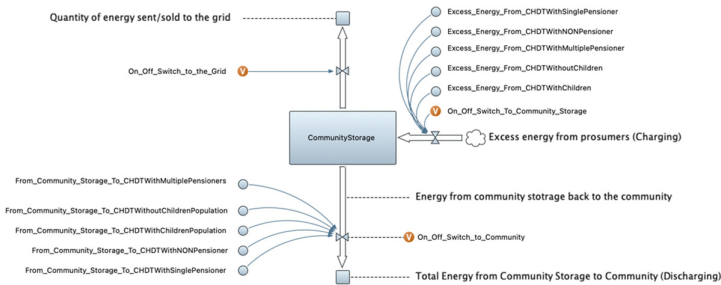
At the low-level, prosumer CHDT are modelled to possess a Photovoltaic (PV) unit for energy generation, a local energy storage system, and nine (9) HH appliances. An Anylogic [17] model of the nine considered appliances as shown in Fig. 2. The Anylogic enables the integration of multiple simulation paradigms such as system dynamics, agent based, and discrete event techniques on a single platform. The considered appliances are: (a) Washing machine, (b) Dishwasher, (c) Tumble/clothes dryer, (d) Audio-visuals, (e) Microwave, (f) Cooker, (g) lighting, (h) Oven, and (i) Refrigerator. The consumption

priority of a prosumer is firstly from the PV system, then the local storage, followed by the community storage, and finally the grid. Prosumers can share excess energy with the community through a common community storage system as shown in Fig. 3. Consumers are also modelled to possess nine HH appliances. Their primary energy source is the grid, however, when community storage is found to be available, they switch sources to utilize the storage until it runs out, then they revert to the grid.

In the model, the consumption of each HH appliance per CHDT is continuously aggregated throughout the period of the model run. The data from these aggregated values form the load profile for each appliance per household. Furthermore, the consumption for all appliances per household are also aggregated to form the load profile for that HH. Finally, the consumption for all the households in the community is also aggregated to form the global load profile of the entire community. The anylogic simulation platform has a built-in graphical analysis tool that enables these data to be plotted. In Sect. 6 of this study, the data collected at the global level is used in the analysis of the global behaviour of CHDTs in the community.



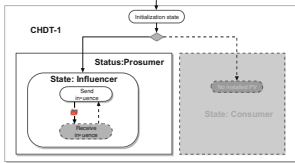
**Fig. 2.** Anylogic model of the nine HH appliances.



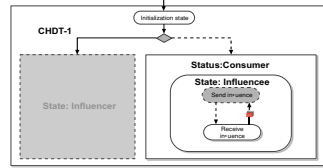
**Fig. 3.** Anylogic model of the community storage

An active state, as mentioned earlier, defines the aspects of the CHDT that are functional. An inactive state, on the contrary, describes attributes that are dormant. As shown in Figs. 4 and 5, active states are depicted using unshaded regions with continuous

boundary lines. Inactive states on the other hand are shown as shaded regions with dotted boundary lines. In Fig. 4 as an example, we elucidate an active CHDT (CHDT-1) whose status as a prosumer is active and a state describing this CHDT as an influencer is also active. Likewise, in Fig. 5, we show an active CHDT (CHDT-2) whose status as a consumer is active and a state describing this CHDT as an “influencee” is also shown active.



**Fig. 4.** A CHDT with active prosumer status, active influencer state and active “send influence” state



**Fig. 5.** A CHDT with active consumer status, active “influencee” state and active “receive influence” state

Additionally, Influencer CHDTs also have an active internal state labelled “send influence” which contains algorithms responsible for the conveyance of influence.

Similarly, influencee CHDTs have an active “receive influence” states which also contain algorithms responsible for the reception of influence. In this described scenario, it is assumed that influencer CHDTs do not receive influence and influencee CHDTs also do not convey influence. Generally, when the status or state of a CHDT is active it executes algorithmic instructions that are associated with that particular status or state, and this enables the CHDT to behave according to the embedded instructions. Having knowledge of all active states (both composite and simple) as well as the accompanying algorithmic instructions, and making basic rational decisions based on this knowledge is what gives the CHDT its cognitive capabilities.

**Modelling Influences and Decision-Making:** In this study we consider two types of endogenous influences. These are positive and negative influences. Endogenous influence refers to influences that are of external origin relative to a CHDT. These influences could originate from the CVPP manager or other influential CHDTs that are within the ecosystem. Each influence possesses the following attributes (a) Polarity (b) Intensity (c) Impact and (d) Frequency of transmission. Polarity signifies whether an influence is positive or negative. The intensity on the other hand describes the magnitude of the influence. For instance, a positive influence may have a positive polarity and a minimum intensity/magnitude of “X” and a maximum intensity/magnitude of “Y”. Likewise, the impact describes the severity (how strong or weak) of the influence on the CHDT. A high-impact influence affects the CHDT for a longer duration while a low-impact influence has a short duration. The frequency of transmission describes how often an influencer CHDT convey influence to the community. CHDTs make decision based on a predefined threshold called the “decision constant” which is represented by “ $\alpha$ ”. This parameter is a positive value and can be reached when the aggregated impact of all influences acting on the CHDT equals this constant. A negative constant could also be adopted and used to determine when a CHDT makes a negative decision such as refusal to participate in collaborations. Additionally, influences are conveyed and received in the form of “pulses”

that are transmitted sporadically from several sources (i.e., from the various influencer CHDTs) to random destination (influencee CHDTs). The pulsating characteristics of the influences are modelled using a probability distribution functions. These functions are expressed as follows: (a) Positive influence: *Uniform distribution* ( $+a, +b$ ), (b) Negative influence: *Uniform distribution* ( $-c, -d$ ), (c) Frequency of transmission:

*Uniform distribution* ( $e, f$ ) times per hours, days, weeks, months, or years. (d) Impact: *Uniform distribution* ( $g, h$ ) hours, days, weeks, months, or years, (g) Decision threshold  $= \alpha$ . Where  $+a, -c, e$ , and  $g$  are the possible lower limits, and  $+b, -d, f$ , and  $h$  are the possible upper limits for each related elements of the influence.

## 5 Demonstration of the Modelling Technique Using Selected Scenarios

**Scenario for Modelling CHDT Population:** In Table 1, we define the population size for each category of HH within the CVPP-E. This population shall be maintained throughout the demonstration.

**Table 1.** CHDT population considered for each category of HHs

Item	Category of CHDT	Population size
1	CHDT with single pensioner	10
2	CHDT with single non-pensioner	10
3	CHDT with multiple pensioners	10
4	CHDT with children	10
5	CHDT with multiple persons with no dependent children	10
<b>Total population size</b>		<b>50</b>

**Scenario for Modelling Installed PV Systems:** For the prosumers population, four different capacities of PV systems are considered. Each prosumer CHDT can inherit any one of them. The PV systems and their respective capacities are: (a) BainSystem = 6.930 kW, (b) BrainSystem = 1.950 kW, (c) Helius = 3.99 kW, and (d) DaSS = 3.22 kW. All PVs are located in the Great Britain [15]. Data from these real-life systems are used to model the PV generation aspects of the model. The aspects of the energy storage is modelled as following: (a) State of charge =  $M$ , (b) the storage capacity =  $N$ , and (c) depth of discharge =  $K$ . Condition for discharging storage is when  $M > = 70\%$  of  $N$ . Condition for charging is when  $M < = 30\%$  of  $N$ .

**Scenario for the Modelling of Influences and Decision-Making:** The defined parameters for this scenario are as follows: (a) *Positive influence: Uniform distribution* ( $0, 2$ ), (b) *Negative influence: Uniform distribution* ( $-2, 0$ ), (c) *Frequency of transmission: Uniform distribution* ( $0, 3$ ) times per week, (d) *Impact: Uniform distribution* ( $0, 5$ ) hours

from the moment of receiving the influence, (e) Decision threshold ( $\alpha$ ) = 50. Community Storage capacity ( $N_C$ ) = 300 Kwh. Local storage capacity ( $N_L$ ) = 20 kwh for Brain-System, 15 kwh for helious, 12 kwh for DaSS, and 10 kwh for BainBridge. Finally, the depth of discharge for all storage was 70% of  $N$ .

**Scenario for Modelling Embedded HH Appliances:** The parameters that were used to model the use-behaviours of all the nine (9) HH appliances are shown in Table 2. The parameters were obtained from [14] and [16]. The data from [14] was sourced from the Household Electricity Survey: A Study of Domestic Electrical Product Usage (Intertek Report R66141) [14]. The report is a comprehensive and extensive one that covers several aspects of household’s energy use. The data was collected from 251 households in England spanning the period May 2010 to July 2011. For each category of HH, the survey captured the HH size i.e., the number of occupants per HH. For instance, Table 2, shows the number of HH per each category, that was used for that survey. For each HH, the number of occupants or household size was different. Therefore, the data that was used to model the appliance’s consumption, which was borrowed from this report captures the different occupants per household.

**Table 2.** Parameters used to model the use-behaviour of the considered appliances

Type of inhabitant	Number of HH
Single pensioner households	34
Single non-pensioner household	35
Multiple pensioner household	29
Household with children	78
Multiple person household with no dependent children	74

**Table 3.** Parameters used to model the use-behaviour of the considered appliances.

Type of Appliance	DoU (hrs)		APR (kW)		FoU/ week		
	min	max	min	max	min	ave	max
Wash. Mach	0.50	3.00	0.500	1.000	0.00	4.00	8.00
Tumble dryer	0.50	3.00	1.000	3.000	4.38	6.00	5.38
Dishwasher	0.50	3.00	1.000	1.500	4.19	6.19	5.19
Audio-visuals	0.50	6.00	0.025	0.148	1.00	11	21.0
Microwave	0.16	1.00	0.600	1.150	1.00	7.00	14.0
Electric Cooker	0.50	3.00	2.000	4.000	1.00	7.00	14.0
Lighting	0.16	8.00	0.015	0.165	1.00	7.00	21.0

(continued)



**Table 3.** (continued)

Type of Appliance	DoU (hrs)		APR (kW)		FoU/ week		
	<i>min</i>	<i>max</i>	<i>min</i>	<i>max</i>	<i>min</i>	<i>ave</i>	<i>max</i>
Refrigeration	24.0	24.0	0.011	0.091	–	–	–
Oven	0.50	2.00	2.000	4.000	1.00	7.00	14.0

Table 3 shows the Duration of Use (DoU), Appliance Power Rating (APR), and Frequency of Use (FoU).

**Scenario for Testing Collective Decision Making:** As shown in Table 4, two different cases, constituting of different population sizes, were considered. In all cases, the influencer CHDTs attempt to influence the “influencee” CHDTs towards the Delegation of Deferrable Loads (DDL), i.e., suspend the use of loads whose utilization can be deferred to a later time without causing much inconvenience to the user. The appliances that were considered for DDL are (a) washing machines, (b) dish washers and (c) tumble dryers. DDL appliances avoid consumption from the grid and wait until local storage or community storage is available. To help test these cases, the Anylogic simulation platform [17] was adopted.

**Table 4.** Two cases with varying population sizes are used to test collective decision making.

Cases	Population (%)					
	Influencer population “A”	Influencee population	Positive Influencer Population	Negative Influencer population	Prosumer population	Consumer population
Case-1a	90% of 50	10% of 50	90% of A	10% of A	20% of 50	80% of 50
Case 1b	90% of 50	10% of 50	10% of A	90% of A	20% of 50	80% of 50
Case-2a	10% of 50	90% of 50	90% of A	10% of A	80% of 50	20% of 50
Case-2b	10% of 50	90% of 50	10% of A	90% of A	80% of 50	20% of 50

## 6 Results and Discussion

**RQ-1 & RQ-2:** In this section, we attempt to answer research questions 1 & 2. After running the simulation model for a period of 728 h (30 days) the following sample behaviours were extracted from some selected CHDTs. In Figs. 6a & 6b we show the characteristics of the modelled influence that was received by two different CHDTs, i.e., CHDT-1 and CHDT-2. The pulses that appear below the x-axis represent negative influences whilst the ones above the x-axis are positive influences. Attributes such as polarity, intensity, impact, and frequency of transmissions can be observed in both Figs.

In Figs. 7a to 7d, we show how the aggregation of influences over time, can be used to determine the overall behaviour of a CHDT. We also demonstrate how the overall behaviour can be used in decision-making. For instance, Figs. 7a, 7b and 7c, show CHDTs 3, 4 & 5 that initially behaved negatively. However, the duration of their negative behaviour lasted differently. It lasted longer with CHDT-4 than CHDTs 3 & 5. Eventually, all three CHDTs changed behaviour from negative to positive. However, CHDT 3 changed behaviour faster than CHDT 4 & 5. This was because CHDT 3 was highly influenced positively than CHDTs 4&5. For this reason, CHDT-3 exceeded the decision threshold “ $\alpha$ ” and therefore was able to decide within the simulated period (30 days) but CHDT 4 and CHDT 5 were unable. Finally in Fig. 7d, CHDT 6 behaved positively right from the beginning of the model execution and it was also able to decide much quicker than CHDTs 3, 4 and 5.

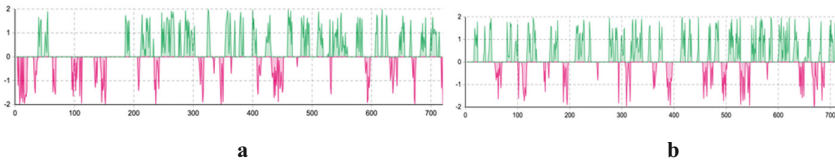


Fig. 6. a. Influences received by CHDT-1. b. Influences received by CHDT-2

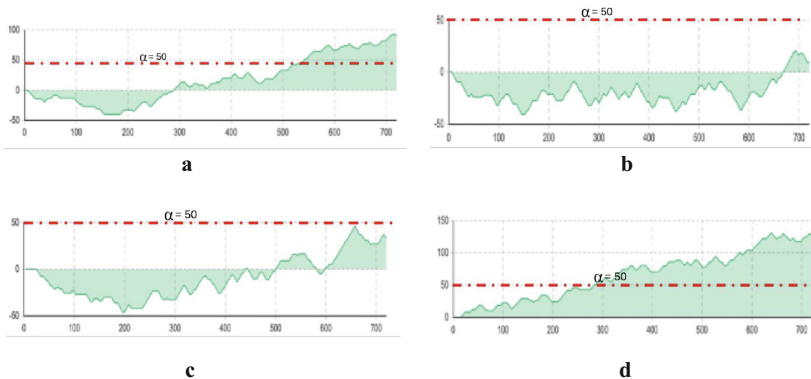


Fig. 7. a. CHDT-3. b. CHDT-4. c. CHDT-5. d. CHDT-6

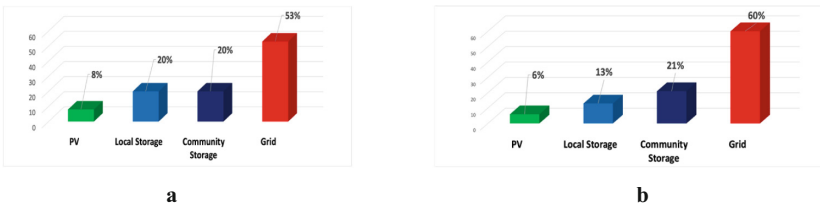
**RQ-3:** Also in this section, we attempt to answer research question 3. By referring to Table 4, we hereby consider cases 1a & 1b. The outcome of the model for these cases are shown in Fig. 8a & 8b. For this case, the population of prosumers, consumers, influencers, and influencees were maintained the same. The difference between the two scenarios is the number of positive and negative influencers. In case 1b, 10% of the influencer population were positive influencers and 90% were negative influencers. For this reason, the majority of the CHDTs were influenced negatively and this resulted in few decisions-making causing high proportion of energy to be consumed from the grid, (about 69%). Furthermore, it is observed that consumption from the community storage

was also low (about 13%). By comparing case 1b to case 1a, where the population of positive influencers was high, thus, 90% and the population of negative influences was low, thus, 10%, it can be seen that the majority of the CHDTs were influenced positively resulting in more decision making, hence a reduction in the consumption from the grid, thus, 51%, and an increase in the consumption from the community storage thus, 24%.



**Fig. 8.** a. Case-1a. 90% positive influencers. b. Case-1b. 10% positive influencers.

Referring to Table 4 and Figs. 9a and 9b, we hereby consider cases 2a and 2b. In case 2a we consider 90% of the influencer population to be positive influencers and 10% to be negative influencers. On the contrary, in case 2b, we consider 10% of the influencer population to be positive influencers and 90% to be negative influencers. It can therefore be observed that in case 2a where the number of positive influencers was high, the use of the grid is relatively low, about 53%, as compared to case 2b where the use of the grid is relatively high, about 60% due to the rather low population of positive influencers (i.e., high population of negative influencers). The use of PV and local storage also appreciated significantly in case 2a as compared to case 2b. The difference in both cases resulted from the population difference between negative and positive influencers.



**Fig. 9.** a. Case-2a. 90% positive influencers. b. Case-2b. 10% positive influencer

There are several techniques that can be used to help spread influence in a social system or network. In particular, the power of online information diffusion is one effective method that has been utilized to positively influence citizens in many ways. For instance, in the response to natural or man-made disasters [18] and the Hotmail phenomenon in the early 1990s [19]. This effect, which is often referred to as the “viral phenomenon” or “viral marketing” has been adopted by companies to encourage sharing between individuals with social connections, because it is known that social recommendations can help increase traffic to websites of businesses, resulting in higher engagement and revenue. In

this study, positive influencers in the ecosystem could utilize the power of viral marketing and social recommendation. When combined with incentives (monetary incentives or social recognition incentives) it is possible to increase the number of influencers and thus help spreading their influence out to other members of the ecosystem.

## 7 Conclusion and Future Work

This study has enabled the furtherance of the notions of CHDTs by demonstrating the decision-making and mutual influence capabilities of these software agents. Firstly, we showed how influence is exchanged between influencer and influence CHDTs. Furthermore, we illustrated how the aggregation of influences over time can help to determine the overall behaviour of a CHDT. Again, the study has shown how CHDTs are able to make influence-induced decisions using the principle of thresholds. This work has further helped to establish the fact that CHDTs could engage in collective actions that could result in the global achievement of some common goals. It has further been shown that a high population of positive influencers can help influence the community positively and a high population of negative influencers could also influence the community negatively, subsequently affecting the sustainability of the ecosystem. In future studies, we shall consider the use of incentives to help increase the number of positive influencers and thus leverage the positive effect. Finally, we draw the conclusion that the notion of CVPP-E and CHDTs are feasible concepts. In terms of possible implementation, IoT, sensors, and smart HH devices could be adopted as interfaces between the various HH appliances and the respective CHDT. For the software aspect, a CHDT could have the form of smart software agents or a HH energy management system which could be used to initiate the exchange of information between energy assets, the community manager, and other CHDTs. A local area network with network devices like routers, edge servers, and IoT gateways on top of the physical layer could also surface for the communication aspects.

**Acknowledgment.** We acknowledge project CESME (Collaborative & Evolvable Smart Manufacturing Ecosystem and the Portuguese FCT program UIDB/00066/2020 for providing partial financial support for this work.

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