A Collaborative Approach to Demand Side Energy Management

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Abstract. Integrating the idea of collaborations into the energy domain appears a promising feat, although, relatively contemporary and uncommon. In this study, we implement a Demand Side Management strategy using the concept of Collaborative Virtual Power Plant Ecosystem as a digital representation of an Energy Community. The community uses a sharing platform to share experience, technical and professional knowledge, facilitating members ambition to change their energy use behaviours. Members of the community are represented as software agents. Behaviours in the adopted model are arranged in a framework of tasks and goals for agents to accomplish. Agents join the ecosystem under deterministic and stochastic conditions. A multi-method modelling approach is used. This study revealed that through collaboration, agents are able to accomplish set tasks faster, thus reducing their chances of frustration and subsequent exit from the ecosystem. This approach helps to influence member´s behaviour and increases membership fluidity, facilitating community stability and sustainability.

Keywords: Collaborative Networks · Virtual power pants · Incentivization · Goal setting · Demand Side Management

1 Introduction

According to the European Commission, buildings are responsible for approximately 40% of the EU's energy consumption and 36% of the CO_2 emissions in Europe [1]. This, therefore, makes buildings the single largest energy consumer in Europe. A claim by [2] disclosed that developed countries could reduce energy demand by up to 20% in the short term and by up to 50% of present levels by mid-century through lifestyle and behavioural changes. These facts therefore reveal the significant role households play towards GHG emissions globally, and also unveil its potential contribution towards mitigation. Some published suggestions in this context include: the deployment of energy-efficient appliances [3], consumer behavioural change [4], and Net Zero Energy Building [5], amongst many. However, amongst the prevailing options, consumer behaviour change is said to offer the lowest cost and fastest switching option for Demand Side Management (DSM) as compared to the others [6].

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In this simulation study, we approach DSM using a collaborative approach. Our primary objective is to influence ecosystem members to delegate their deferrable loads such as washing machines, dishwashers and tumble dryers to the ecosystem manager for collective control. However, we precede this action with some antecedent interventions in the forms of goals and tasks, to help facilitate the delegation process. The essence of the intervention is to induce or inculcate some fundamental energy use behaviours amongst members in the community. This could help to create a sense of energy conservation awareness within the community before finally introducing delegation. Furthermore, we will also consider how collaborations can also enhance the membership fluidity of the ecosystem. Ensuing from the above our study will be guided by the following research problems (R-P) and research questions (RQ).

RP-1. Delegation of deferrable loads are action that solely depend on the willingness of consumers to engage in. It is therefore envisaged that by introducing this action as a direct and standalone activity in a community, the perceived inconvenience and discomfort may instil anxiety in members, and could make the idea unattractive, resulting in less patronage. We therefore hypnotise that by introducing a set of antecedent interventions, it may be possible to alter the behaviours of consumers towards the enhancement of the delegation process. *RQ1. How can collaborations and antecedent interventions enhance the behaviour of consumers towards the delegation of deferrable loads within an energy ecosystem*?

RP-2. A common problem associated with communities are issues of instability caused by low membership fluidity (LMF). A LMF results in a weak, unstable, and unsustainable community. We further hypnotise that a high membership fluidity could promote a stranger, stable, and sustainable community. *RQ2. How can collaboration through the sharing of experience and knowledge (technical and professional) enhance membership fluidity in an energy ecosystem.*

We consider two scenarios. Scenarios 1: A non-fluid community membership with (a) collaborations, and (b) without collaborations. Scenario 2: A fluid community membership with (a) collaborations, and (b) without collaborations. The selection of these scenarios was based on [7, 8]. According to [8], the ability to attract and retain membership enhances the long term survivability of a community. We adopted a hybrid modelling approach which incorporates a combination of System dynamics, Discrete event and Agent-based technology, using the Anylogic platform [9].

2 Related Works and Theoretical Framework

The emergence of works conducted in the area of DSM and goal setting are currently on the rise. Some of these include works such as [10], where personal goal setting as a way of reducing residential electricity were studied. Another dimension of goal setting was presented in a multidisciplinary study conducted in [11], where a combination of interventions including individual and group goals were studied. An experimental study to compare two groups in terms of their energy conservation behaviour, in combination with energy feedback was also conducted in [12]. A systematic literature review of four behavioural interventions towards residential energy conservation was also conducted in [13].

This study presents a multidisciplinary and interdisciplinary approach to DSM using a combination of concepts borrowed from diverse scientific disciplines. Out of these multiple concepts, a couple has been identified as the core tenet in which this work is grounded. These concepts are briefly explained below.

i. **The CVPP-E concept.** This concept derives its source from the merger of principles and concepts from the disciplines of Collaborative Networks (CNs) and Virtual Power Plants (VPP). At the heart of the concept is the idea of collaborations, which is central to the discipline of Collaborative Networks. CNs represents a rich plethora of knowledge-base and sets of principles that facilitate collaborations in diverse forms as seen in [14–16]. A VPP on the other hand is a virtual entity involving multiple stakeholders and comprising decentralized multi-site heterogeneous technologies, formed by aggregating dispatchable and non-dispatchable distributed energy sources [17]. The synergy of these two concepts led to a hybrid concept called the Collaborative Virtual Power Plant Ecosystem (CVPP-E) introduced in [17, 18]. The CVPP-E can be used to represent a renewable energy community such as in [19]. The CVPP-E depicts a business ecosystem and a community of practice where members approach energy generation, consumption, and conservation from a collaborative approach. The governing structure is polycentric and decentralized with a manager who plays a coordinating role and promotes collaborative behaviours.
ii. **Goal-setting theory.** Theory is summarized in [20], It claims that one's conscious goals affect their achievements. Specific goals improve a person's performance towards the achievement of that goal. Furthermore, it postulates that people with specific goals often perform better than those with vague or no goals. When a goal is met or exceeded, satisfaction increases and vice versa. A goal can instil purpose, challenge, and meaning into what one perceives as a difficult task. Goals can motivate people to develop strategies that will enable them to perform better. In a group context, tasks and information sharing may enhance group performance [21].

3 Modelling Framework

In this section, we describe the building blocks, functions, assumptions and parameters used to develop the model. We propose a sharing platform as the sharing interface for the ecosystem. Membership fluidity is based solely on interest in pro-environmental behaviours. Individuals who are willing to voluntarily make some minor adjustments to their energy use behaviours may join. Members may exit the platform when they persistently fail to accomplish any single task and become frustrated as a result.

3.1 Modelling of Households

In the developed model, households are modelled as software agents. These agents are modelled according to scenarios of behaviour change as described in the Transtheoretical model (TT-M) [22]. We assume that agents have passed the pre-contemplation, contemplation and preparation stages of the TT-M and therefore, we focus attention on the action and maintenance stages only (Fig. 1). We also model all households as having the same schematic behaviour. Households in the ecosystem can only share experiences. We occasionally introduce special agents called technical and professional agents. The population of these special agents is always 5% of the total agent population. Special agents provide only technical and professional knowledge to the community. They do not undergo the behaviour change process.

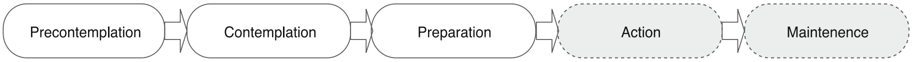

Fig. 1. Sages of change as described by the TT-M model

3.2 Antecedent Interventions and Delegation of Deferable Loads

A goal is represented by a collection of tasks. The number and types of tasks in a particular goal may vary per model, depending on the objectives. In this instance, we have defined three goals. The first two are antecedent intervention goals, modelled to precede a third and the main goal, which is the delegation of deferrable loads. The rationale behind the interventions is to subtly induce a sense of energy conservation and also introduce a wholistic conservation approach in agents. More details as follows:

Goal 1: **Reduce energy waste through prudent energy use practices**.
Task 1: Learn the habit of switching off lights in rooms when not in use.
Task 2: Unlearn the habit of overcharging smart devices.
Task 3: Do household chores at night-time.
Goal 2. **Adapt basic and low-cost energy-efficient technologies**.
Task 1: Use LED/CFL lightbulbs for the household.
Task 2: Use timers for your lighting.
Goal 3. **Delegation of deferrable loads.**
Task 1: Delegate all deferable loads to CVPP-E manager.

An agent can be said to have accomplished a goal when they complete all tasks associated with that particularly goal. All goals are not attempted at the same time. Agents must complete goal 1 before they progress to attempt goal 2 and finally goal 3. On the contrary, all tasks in a particular goal are attempted at the same time.

3.3 Modelling of Tasks

Let us now analyse in more detail the tasks:

i. Task framework and technical description

Figure 2 shows the framework of a task. Each task is represented by one of these frameworks. The framework is composed of state charts. A state chart is a visual construct that enables the modeller to define event and time-driven behaviours. State charts are usually constituted of different kinds of states and their corresponding transitions. A task framework is composed of 9 simple states, 3 composite states and 15 transitions, labelled as T1 to T15. Out of the 15 transitions, 3 (T1, T10, T11) are triggered by messages. Another set of 3 (T2, T12, T14) are also triggered as rates. 4 (T4, T13, T15) are triggered by conditions, and finally 6 (T3, T5, T6, T7, T8, T9) are triggered as timeouts. A task is modelled through a series of four interconnected blocks namely, task completed block, task processing block, frustrated agent block, and feedback block. These blocks and their related algorithms are described below.

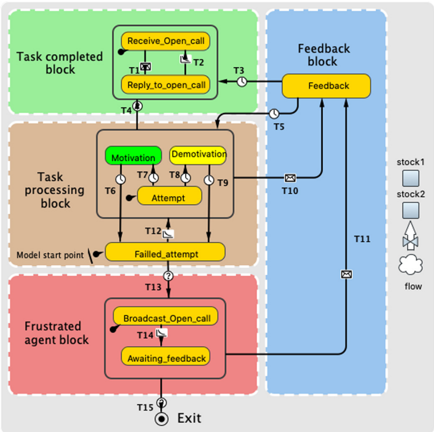

Fig. 2. Framework of a task.

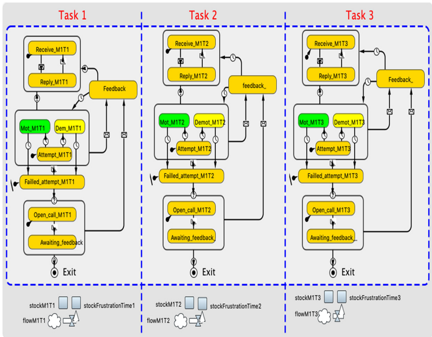

Fig. 3. Model of a goal with three tasks. (E.g. goal 1)

ii. Functions of the various blocks in a task

a. Task processing block (TPB): This is where the agent begins the execution of a task. The sequence of operations starts with T12. T12 is a rate transition and is defined as *the number of attempts per task per day* (N_{aT}). This is used to model the number of times an agent attempts a particular task per day. For instance, the number of times one may attempt to unlearn the habit of turning off the lights after leaving a room, may occur serval times in a day. On the other hand, attempting to unlearn the habit of overcharging smart devices could happen perhaps once, twice or at most three times in a day. These number of attempts could recur for several days, weeks, or even months until the habit is finally unlearned. This suggests that N_{aT} for every task may vary depending on the nature and kind of the task. Nonetheless, we may have to define some tentative boundaries to represent the possible minimum and maximum number of attempts per day. In this model, N_{aT} is modelled using a *uniform discrete distribution* (X, Y) where X is the minimum number of occurrences per day and Y is the maximum number of occurrences per day. For instance, considering goal 1, the following parameters are defined:

Task1 – *(N_{aT1}) = Uniform discrete distribution (0, 10)*; Task 2 −*(N_{aT2}) = Uniform discrete distribution (0, 3);* Task 3 – *(N_{aT3}) = Uniform discrete distribution (0, 1).*

At every instance of T12, the states indicated as "motivation" and "demotivation" are activated. These states are used to model the outcome of each attempted task. The possible outcomes are: (i) Positive experience, resulting in a motivation (through T7), or (ii) Negative experience, resulting in a demotivation (through T8). T7 and T8 are random transitions with equal probability of occurrence. This therefore helps to create equal probability for both motivation and demotivation occurring at every iteration. The model assigns a weight $+K$ for every motivation and a weight $-K$ for every demotivation. These two values are aggregated in parallel, and on continuous basis, until one of them reaches a predefined threshold called the "**Decision constant**" (*Dc*)**.** Since these are stochastic actions, the duration for reaching this threshold could vary from days to weeks or even months for different tasks and for different agents. For instance, considering the same task, one agent could reach the threshold in days, others could achieve it in weeks and for some others, in months. The *Dc* can be varied. Higher values make tasks difficult to achieve and lower values, easy to achieve (Fig. 3).

If the aggregated value for motivations is the first to reach the threshold, the model interprets this event as signifying an agent with sufficiently high motivation to merit the accomplishment of that particular task. On the contrary, if the aggregated value for demotivation is the first to reach the threshold then the model interprets this event as signifying a demotivated agent who has failed to accomplish the said task. The **Decision factor** (*Df*) is the algorithm that is used to monitor these events. The *Df* and the *Dc* work together to decide whether a task has been completed or otherwise.

For example, considering the scenario of unlearning the habit of turning off the lights after leaving a room. Assuming it took the agent three days to overcome this habit. On the first day, the agent entered the room 10 times ($N_{aT} = 10$) and out of the 10 events, the agent remembered to turn off the light on 4 occasion ($M_1 = 4$) but forgot to turn it off on 6 occasions ($D_1 = 6$). On the second day, the agent entered the room on 12 occasions ($N_{aT} = 12$) and remembered to turn off the lights on 8 occasions ($M_2 = 8$) and forgot on 4 occasions ($D_2 = 4$). On the third day, the agent entered the room 8 times ($N_{aT} = 8$) and remembered to turn off the light on 8 occasion ($M_3 = 8$) and forgot none ($D_3 = 0$). Assuming that a weight $K = 1$ is assigned every time, the agent remembers to turn off the lights (motivation) and weight $-K = -1$ is assigned every time the agents forgot to turn off the lights (demotivation). Then the *Df* and the *Dc* will decide based on the following algorithms:

$$Df_{motivation} = [(K * M_1) + (K * M_2) + (K * M_3)] + \ldots\ldots\ldots\ldots(K * M_N)]$$
$$Df_{demotivation} = [(-K * D_1) + (-K * D_2) + (-K * D_3)] + \ldots\ldots\ldots(-K * D_N)]$$

Considering the scenario described above,

$$\begin{aligned} Df_{motivation}\, after\, 3\, days &= (1 * 4) + (1 * 8) + (1 * 8)] \\ &= 4 + 8 + 8 = 20 \end{aligned}$$

$$Df_{demotivation}\, after\, 3\, days = [(-1*6) + (-1*4) + (-1*0)]$$
$$= (-6) + (-4) + (0) = -10$$

Assuming we defined a threshold (Dc) of say: $X_1 = 15$ to represent highly motivated and $X_2 = -15$ to represent highly demotivated, then: When $Df_{motivation} \geq X_1$, the task is said to be completed, and the model transitions to the task completed block. When $Df_{demotivation} \leq X_2$, the task has failed and the model transitions to the "frustrated block. Therefore, considering the scenario above, the condition for $Df_{motivation}$ is true ($20 > 15$), and the condition for $Df_{demotivation}$ is false ($-10 \nless -15$). Hence a transition into the task completed block. Parameters defined for this model are: $K = 1$, $-K = -1$, M and D = Random events, $X_1 = 10$, $X_2 = -10$.

b. ***Task completed block*** (*TC*B): Transition into this block is facilitated by the $DF_{motivation}$ and the *Dc* (X_1) and is activated through T4. A task in this state is considered to be completed. When all other tasks in that particular goal have also transitioned into their respective TCBs it can be inferred that the related agent has completed all tasks for that particular goal, therefore the goal has been achieved.

c. ***Frustrated state block*** *(FSB).* Transition into this block is facilitated by the $DF_{demotivation}$) and the *Dc* (X_2) and is activated through T13. Tasks in this state are time dependent. The time of entry into this block is captured as T_1. Agents are modelled to remain in this state for a limited length of time, denoted as T_2. When T_2 expires whilst the agent is still in this state, the agent will exit the platform. At the instance of entering the FSB, the agent broadcasts an open call.

Open calls are modelled to mimic scenarios of agents sharing their problems with the entire ecosystem. When an open call is broadcasted, all ecosystem members will receive a copy, however, only agents who have completed similar task, and special agents can provide feedbacks. After broadcasting an open call, the agent transition internally into the "awaiting feedback state" through T14. If the agent does not receive a feedback in the form of a message, before T_2 elapses, the task will expire, and the agent will abandon all other goals related to that tasks and exits the platform. On the contrary, when the agent receives a feedback before T_2 elapses, the model transitions into the feedback block through T11, where the agent is afforded another opportunity to either attempt the task again or accomplish the task. This will depend on the kind of feedback that is received. The condition for exiting is modelled as a *uniform discrete distribution between* (T_1, T_2). Where T_1 = time of entry (in days), and T_2 is random between 30 to 60 days from time of entry. Furthermore, open call broadcasts are modelled as a rate (R_{fb}) which is a *uniform discrete distribution* (X, Y) where $X = 0$, $Y =$ 3 per day.

d. ***Feedback block***. The impact of a feedback on the agent can result in one of two actions: (1) If the feedback is helpful to the agent, the task will transition through T3 to the task completed block to complete the task; else (2) the agent will transition through T5 back to the task procession block to repeat the cycle again. T3 or T5 are modelled as stochastic events with equal probability of occurrence. Which means a received feedback has equal probability to facilitating task completion or otherwise.

3.4 Modelling Feedback

Feedbacks is represented by a "variable rate". This rate can be varied. Rates defined for this model are in the range *rate (0, 10) per day*, which means that the rate of feedback could vary from 0 times per day to 10 times per day. This value could be used to indicate the rate at which the agents responds to feedback per day.

In Fig. 4, we illustrate the exchange of open calls and feedbacks to represent the aspects of collaborations in the model. These information items (open call and feedbacks) are modelled as messages which can be sent from one transition to another. Transitions T1a, T1b, T1c and T11, are message receiving transitions and are triggered by the reception of a message(s). On the contrary, transition T2a, T2b, T2c and T14 send out a message(s) anytime they receive a trigger signal. In Fig. 4, these information exchanges are shown using 4 different agents who are at various stages in their respective tasks. These are: experienced agent-1 (EA1), task currently in the frustrated block. Experienced agent-2 (EA2), task currently in task completed block. Experienced agent 3 (EA3), task currently in task completed block, and a technical agent (TA).

a. **Sending open calls.** When T14 of EA1 receives a trigger signal, it gets triggered and, in the process, broadcasts open calls to all agents on the platform. It then transition from *broadcast_ open_call* state into *awaiting_feedback* state.
b. **Receiving open calls.** TA, EA2 and EA3 will each receive a copy of the open call broadcasted by EA1. The open call will be received by transitions T1a, T1b and T1c of TA, EA2 and EA3 respectively. The receipt of the open call message will trigger these transitions from their respective *receive_open_calls* state into their various *reply_to_open_call* states. In this current state, there is a delay which is modelled as a random distribution in hours, i.e. *random () per hour.* This random-delay function is used to prevents all the agents from triggering their respective T2s at the same time. The rationale behind this delay is to prevent all the agents from responding to the open call at the same time. This therefore helps to spread or distribute the feedbacks over the course of the day.

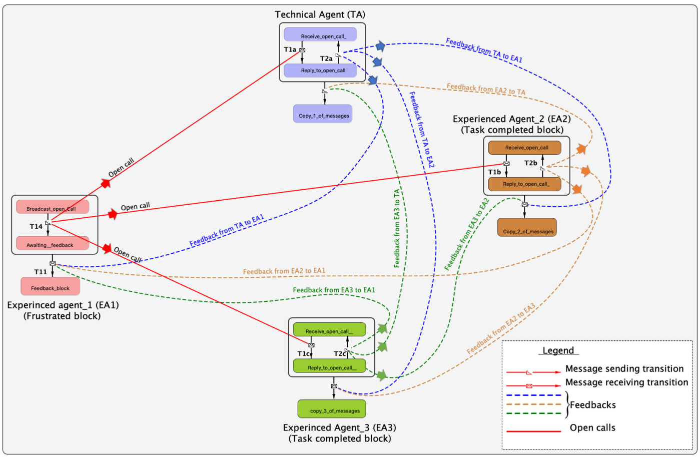

Fig. 4. Illustration of open calls and feedback.

c. **Responding to open calls (feedback).** The delay will elapse at different times for TA, EA2, EA3 and cause transitions T2a, T2b and T2c to be triggered respectively. This causes the various tasks to transition from their respective *reply_to_open_call* state back into the *receive open_call_*state. The triggering of T2a, T2b, and T2c causes three different feedbacks messages to be sent out to the whole community including the specific agent who sent the open call. Although all agents in the community will receive copies of the feedbacks, they are of no relevance to agents who are already in the task completed block, therefore, only agents in the frustrated block can consume such messages. In this scenario, only EA1 can consume these feedbacks. The three feedbacks will be received by T11 of EA1, however, out of the three, only one will be chosen at random to trigger T11, and cause it to transition the task1 out of the frustrated block.

4 Modelling Outcome and Discussion

In the context of this study, a collaborative community is achieved through a network of interconnected agents who share diverse kinds of information through a common sharing platform. It is perceived that the diversity of the shared information is a key element in this kind of collaborations. Using this approach, agents can share their various challenges which made specific task difficult or easy for them to accomplish. Just like real life scenarios, different people will encounter different challenges when attempting to solve the same problem. Therefore, the approach to solving one problem may vary from one person to the other. Consequently, creating a platform where it is possible to share such personal experiences, techniques and skills could help generate a pool of ideas, techniques, skills and experiences that could help others solve the same problem, however, from diverse perspectives. This collaborative idea is what the model under consideration seeks to achieve.

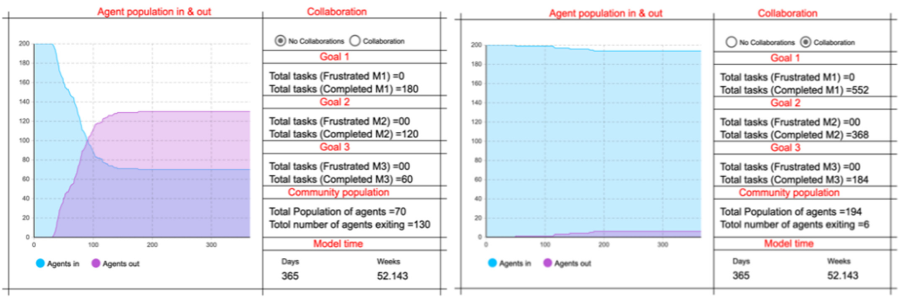

Fig. 5. a. Fixed number of agents with no collaboration b. Fixed number of agents with collaborations

Scenario1. Non-fluid membership with (a) No collaboration, and (b) with collaboration. Figure 5 represents the outcome of the model using a fixed number of agent population consisting of 200 agents in the non-collaboration scenario. It can be seen that 130 agents exited the community due to the absence of feedbacks to help address agent's frustrations. Only 70 out of 200 agents were retained after 365 days representing a scenario of low membership fluidity. In terms of tasks completed, goal 1, recorded 180 completed tasks, goal 2 recorded 120 completed tasks and goal 3, 60 tasks. No task pileups were recorded. On the contrary Fig. 5b is the outcome of the same model, however, with collaboration introduced. It can be seen that 194 out of 200 agents were retained after a period of 356 days. This outcome shows a scenario of high membership fluidity. Only 6 agents exited the community. In terms of tasks, 552 tasks were completed in goal 1, 368 tasks were completed in goal 2, and 184 tasks were completed in goal 3. No task pileups were recorded. By comparing the outcomes of gaol 3 for both scenarios, it can be inferred that the combination of collaborations and antecedent interventions significantly enhanced the delegation of deferrable loads.

Scenario 2. Fluid membership (a) No collaboration, and (b) with collaboration. Figure 6a and 6b shows the outcome of the model with membership fluidity modelled on a weekly basis. The level of fluidity is modelled as a *random function (X, Y) where X* = 0 members per week and *Y* = 5 members per week. Figure 6a shows the instance of the model with no collaboration. The outcome shows that, a total of 222 (152 + 70) agents joined the platform over a period of 365 days, considering there were zero agents at the start of the model. It can also be observed that a total number of 152 agents out of 222 were retained in the community at the end of the model year. Furthermore, 70 agents exited the community. This represent a scenario of low membership fluidity. Figure 6a further revealed that 337 tasks were completed in goal 1, 169 tasks were completed in goal 2 and 78 tasks were completed in goal 3. Furthermore, it can be seen that, at the end of the model run, there was 7 tasks pileups in goal 1, 32 tasks pileups in goal 2 and 53 tasks pileups in goal 3. By comparing Figs. 6a with 6b we notice a significant improvement in the model performance. This is because Fig. 6b represents the scenario with collaborations. In this scenario, we noticed that a total number of 215 (206 + 9) agents joined the community over the model year. Out of this number, the community retained 206 agents and lost only 9 agents. This represent a scenario of high membership fluidity. In terms of tasks management, 511 tasks were completed in goal 1, 294 tasks were completed in goal 2 and, 139 tasks in goal 3.

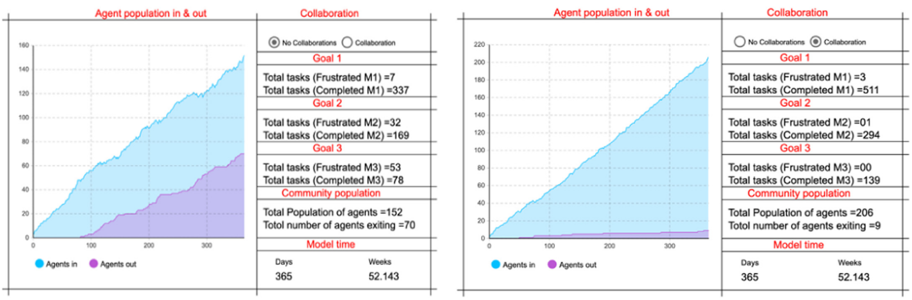

Fig. 6. a. Stochastic addition of agent with no collaboration b. Stochastic addition of agent with collaborations

Task pileups in goal 1, was 3, in goal 2 was 1 and 0 in goal 3. A general conclusion can therefore be drawn that the model performed better under collaborating conditions than otherwise.

One relevant aspect of the ongoing research on CVPP-E, hinges around Delegation of Deferrable Loads (DLs) to the ecosystem manager for collective management. The manager is able to shift the use of these loads to different times of the day to reduce peak demands on the power grid. DLs can also be shifted strategically to utilize renewable energy when generation is high, and curtailed their use when generation is low. These techniques are called “load shifting” and “peak shaving” under DSM.

Although the ultimate goal of the ecosystem is goal 3, which is to influence agents to delegate their deferable loads, we envisage that by introducing this action as a direct and standalone activity, the perceived inconvenience and discomfort to agents could make the idea unattractive, and will result in less patronage. However, we anticipate that through antecedent interventions such as introduced in goal 1 and goal 2, we may be able to take the agent through a journey of small changes preceding the major change. This, we expect, could help to inculcate the necessary discipline and sense of energy conservation, collaborations and community consciousness in the agents before they are due to attempt delegation.

5 Conclusion and Future Work

This study has shown how a combination of collaboration and antecedent interventions could enable some form of behaviour change towards delegation of DLs. It has also been shown that the process could facilitate the achievements of community goals and its subsequent contribution to DSM in general. The study has further shown that when community members are provided with the needed support, in line with community objectives, in a timely manner, using collaborative techniques, they could contribute significantly to the achievement of community gaols. Similarly, efforts at influencing behavioural change could also deliver a promising outcome when implemented within a collaborative environment where members can share relevant and diverse kinds of experiences and knowledge which may not freely be available in a non-collaborating environment. After all, one size does not fit all when it comes to behavioural change approaches. Furthermore, membership fluidity has also been shown to have a significant influence on an ecosystem.

Regarding the ongoing research on CVPP-E and related future works, we intend to model a scenario where the community is constituted of different categories of households. We will consider households with single pensioner, households with multiple pensioners, households with children, households without children and households with single non-pensioner. This categorization and related energy use data is inspired by [23]. In each type of household, we will model different task dynamics to represent the schematic behaviour of each household as they attempt a change in behaviour. For instance, households with children or households with pensioners could be modelled in a way such that they may exhibit different behaviours, which could affect the model outcome significantly. we also intend to advance this study by integrating or coupling each household´s energy consumption so that it is possible to visualize how these behaviours impact on the global community´s energy use.

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