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Agent-based community coordination of local energy distribution

Muhammad Yasir · Martin K. Purvis · Maryam Purvis · Bastin Tony Roy Savarimuthu

Abstract The diminishing availability of fossil fuels will necessitate a shift toward renewable energy resources to supply vital electrical energy needs in the future. Two abundant renewable energy sources, solar and wind, are increasingly cost-competitive and also offer the potential of decentralized, and hence more robust, sourcing. However, the intermittent nature of solar and wind power can present difficulties in connection with integrating them into the main electric power grid. In this paper, we present an agent-based architecture for coordinating locally connected micro-grids, thereby supporting more cost-effective integration into the main power grid. These interconnected micro-grids, with renewable energy sources and energy storage devices, employ agents so that each micro-grid can choose to save or resell its stored energy in an open market in order to optimize its utility and costs. We show via simulation experiments how the micro-grid agent society operates and adapts under varying conditions of renewable energy availability and energy demand patterns. Such a system provides not only financial advantages but also local autonomy and a more robust energy distribution. In addition, these interconnected agents can also facilitate the reduction of carbon emission. In this connection, we compare five different micro-grid energy trading strategies. Thus, the experimental design and evaluation are motivated by a policy modeling perspective whereby the utility of an energy policy to a community (i.e., the strategy) is computed based on two attributes, the financial gain and the reduction in carbon emissions. Further, by means of "what-if" analysis, different energy policies that can potentially be employed by a community are compared against one another. Also, the implications of these policies for a community are discussed.

Keywords Micro-grids · Renewable energy · Agents

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M. Yasir (✉) · M. K. Purvis · M. Purvis · B. T. R. Savarimuthu
Department of Information Science, University of Otago, Dunedin, New Zealand
e-mail: muhammad.yasir@otago.ac.nz

M. K. Purvis
e-mail: martin.purvis@otago.ac.nz

M. Purvis
e-mail: maryam.purvis@otago.ac.nz

B. T. R. Savarimuthu
e-mail: tony.savarimuthu@otago.ac.nz

1 Introduction

Low-cost and seemingly ample nonrenewable energy sources from fossil fuels were used to fuel the twentieth-century economies. But, there was a growing awareness that available fossil fuel resources were running out and that their heavy usage had serious negative consequences on human health and the environment (Asif and Muneer 2007). With increasing population and living standards worldwide, demand for energy is increasing relentlessly. According to one study, the population of the world will reach to 9.1 billion by 2050 (Asif and Muneer 2007), and this entails at least a corresponding increase in energy consumption. Thus, at an annual growth rate of 2.3 %, the world energy, was generating 19.1 terawatts (TW) as of 2008, is expected to grow 84 % by 2,035, to 35.2 TW (Conti and Holtberg 2011). Yet, available energy resources to satisfy this demand are declining. So nowadays, it is finally recognized that there must be a massive turn to renewable energy in order to have a sustainable future for the global environment.

As a consequence of this realization, renewable energy is the fastest-growing source for the production of energy (Conti and Holtberg 2011). Currently, almost 19 % of world electrical energy is derived from renewable energy sources, and this share is expected to reach 23 % by 2,035 (Conti and Holtberg 2011). In fact, several studies have analyzed the technical, environmental, and economical feasibility of generating all global energy requirements from renewable sources (wind, water, and solar) and using electricity as the primary energy distribution medium (Fthenakis et al. 2009; Jacobson 2009). This paper describes our investigations into multi-agent-based coordination mechanisms that can be used to support and enhance these developments.

Although renewable energy sources offer promise, they present operational challenges, because they are often intermittent in the nature of their generation. Though hydroelectric power generation is relatively stable, solar and wind power generation at a single location can vary hour–hour, even minute–minute, depending upon local conditions. Due to this variability, sometimes a single generation plant produces nothing, and sometimes, it produces more power than needed. Energy management approaches to mitigate these problems include the use of local storage devices (batteries) and energy distribution by means of energy grids and micro-grids (Delucchi and Jacobson 2011). So in order to move to a world largely driven by renewable energy sources, there is a need for developing improved methods of coordinating and distributing these variable energy sources over such grids in an efficient and reliable manner.

We characterize a local micro-grid as a local energy system that can generate and store its own renewable energy and can also be connected to a main electrical energy supply grid. When connected to the main energy grid, it can either buy or sell energy to an energy utility company. The micro-grid can also operate independently of the main grid ("island mode"), such as during general utility power outages.

In our work, micro-grids may also have local connections to neighboring micro-grids. Thus, they can trade energy among themselves, as well as trade energy with the utilities on the main power grid. In terms of energy generation, we assume that the micro-grids produce energy purely from renewable sources (e.g., solar, wind) and that the main power grid supplies energy that is at least partially derived from nonrenewable energy sources. By means of local coordination and power sharing, the micro-grids may be able to counteract the ill effects of energy intermittency associated with wind and solar power generation.

In this paper, we employ a multi-agent-system architecture to manage the key functional subcomponents of a micro-grid: energy consumption, energy generation, energy storage, and coordination with external agents. We assume that our agents generally have two separate overall goals:

- Maximize profits in connection with the local micro-grid energy production.
- Minimize the generation of environmentally damaging (i.e., global warming inducing) gases, by minimizing the micro-grid's consumption of energy from the main power grid.

Since these micro-grid agents have some autonomy, they can employ different strategies in terms of how they trade and share energy among the other neighboring agents in pursuit of these goals. By means of multi-agent-based simulation, we empirically compare five different general strategies that may be employed by micro-agent communities in terms of how successfully they are in achieving their goals. We also investigate the impact of local storage battery capacities on both local micro-grid profits and the degree to which they protect the community from the vicissitudes of main-grid power outages.

In the following section of the paper, we review some related work in this area. In Sect. 3, we discuss our multi-agent micro-grid system architecture. Section 4 covers our empirical comparison of different micro-grid community strategies, and Sect. 5 concludes the paper by discussing some future prospects.

2 Related work

Recently, there has been increasing interest in the application of multi-agent systems to the management and control of distributed energy resources on micro-grids. For example, Diemas and Hatziargyriou (2005) proposed a multi-agent system for operational control of micro-grids. Their proposed multi-agent system specifically focused on controlling the optimal use of local distributed resources and the feeding of local loads within a micro-grid. Similarly, Logenthiran et al. (2008) proposed a multi-agent system for efficient control of distributed energy resources inside a micro-grid. Cossentino et al. (2011) also proposed a multi-agent system for the management of micro-grids. The primary responsibility of their proposed system is to provide an electronic market to the consumers and generators within a micro-grid. In case of any mismatches between supply and demand, their agent-based system will disconnect the loads or feeders depending upon the priority.

Ishowo-oloko et al. (2012) presented a model for a dynamic storage-pricing mechanism that uses storage information from the renewable energy providers to generate daily, real-time electricity prices that are communicated to the customers. In the same way, Vinyals et al. (Vinyals et al. 2012) have introduced a concept of virtual energy consumers. In their model, individual consumers formed a coalition via their social network connections in order to buy electricity as an aggregate, which could be of value in connection with demand-side peak shaving. Alam et al. (2013) introduced an agent-based model for energy exchanges among communities. In their proposed model, agents use a game-theory approach to form a coalition to exchange power. The paper demonstrates that the coalition results in a reduction in battery usage and also a reduction in energy losses.

With respect to the above-mentioned proposed systems, the first two (Diemas and Hatziargyriou 2005; Logenthiran et al. 2008) consider only the intelligent and autonomous controlling of a micro-grid. The third system (Cossentino et al. 2011) uses a trading mechanism among the internal agents of the micro-grid to balance supply and demand inside the micro-grid's boundaries. The two models (Ishowo-oloko et al. 2012; Vinyals et al. 2012) consider the role of individual consumers of a society in setting the price of power and reducing the demand peak of a smart grid. However, there has not been much attention given to the consideration of robust energy distribution across locally connected communities. Even though the model of Alam et al. (2013) considers energy exchanges between members of a coalition (i.e., a community of individual households), it does not consider the profitability of the individual households (in monetary terms) and also the amount of carbon emission mitigated through coalition formation.

In contrast, our research is focused on a community-driven approach for robust energy generation and distribution. We consider a local community as one micro-grid which has local generators and dedicated storage devices that not only increase the reliability of the micro-grid but also give financial advantages to the local community.

Typically, when a micro-grid has a surplus or deficit of power, it engages in trading with the local feeder or main utility grid. Normally, any shortfall that occurs takes place during the peak usage hours. During such peak usage hours, the main utility grids charge higher prices for electricity. At the same time, due to such high demand for electricity, congestion on the transmission and distribution network is often observed. Instead of selling or buying power to or from the utility grid, however, it is preferable for nearby micro-grids to make their own local market where they can do their own trading first instead of going to the main utility grid directly. In this way, they can enjoy not only better tariffs but also benefit from reduced stress placed on the main transmission and distribution lines.

3 Agent-based community micro-grid architecture

Our agent-based architecture for energy coordination among interconnected micro-grids is presented in Fig. 1. The goal is to provide locally based mechanisms to enhance overall local generated power usage and also to provide reliability in cases of main-grid power failures. Each community micro-grid (e.g., C1) has four fundamental functional components, each of which is managed by an associated agent:

- *Generator agent* This agent manages the community's renewable energy generators that may exist in different locations within the local area. It reports on available energy at any given time.
- *Battery agent* It is responsible for regulating the battery chargers and reporting on battery energy availability.
- *Consumer agent* This agent represents the aggregate energy consumption load of the community. During main-grid power outages, it may cut back on consumption.
- *Coordinator agent* This agent represents the entire community to the external environment and interacts with other micro-grid coordinator agents and the power utility. As shown in Fig. 1, it interacts with the other three agents and represents its community's energy generation, consumption, and storage capacity to the outside world.

Of course in a future deployed system, each of these agents could be in charge of or coordinate numerous subordinate agents (such as consumers) that operate at a more detailed level. But, our focus here is on the general coordination architecture and how it might operate at this higher level. That forms the focus of the next section.

4 Effects of battery storage on coordination

In connection with the battery storage capacity, we investigated two issues:

1. What is the impact of battery storage size in terms of local energy production "profits" (each micro-grid can be assumed to be a local power company that is trying to make a profit by its operations)?
2. To what extent does the battery availability shield the local community from main-grid power outages and maintain the reliability of the local micro-grid?

To investigate these questions, we set up three micro-grid communities: C1, C2, and C3. Each community had a different energy load at a given time. Every community had two generators of identical generation capacity. Each has a different size of batteries installed.

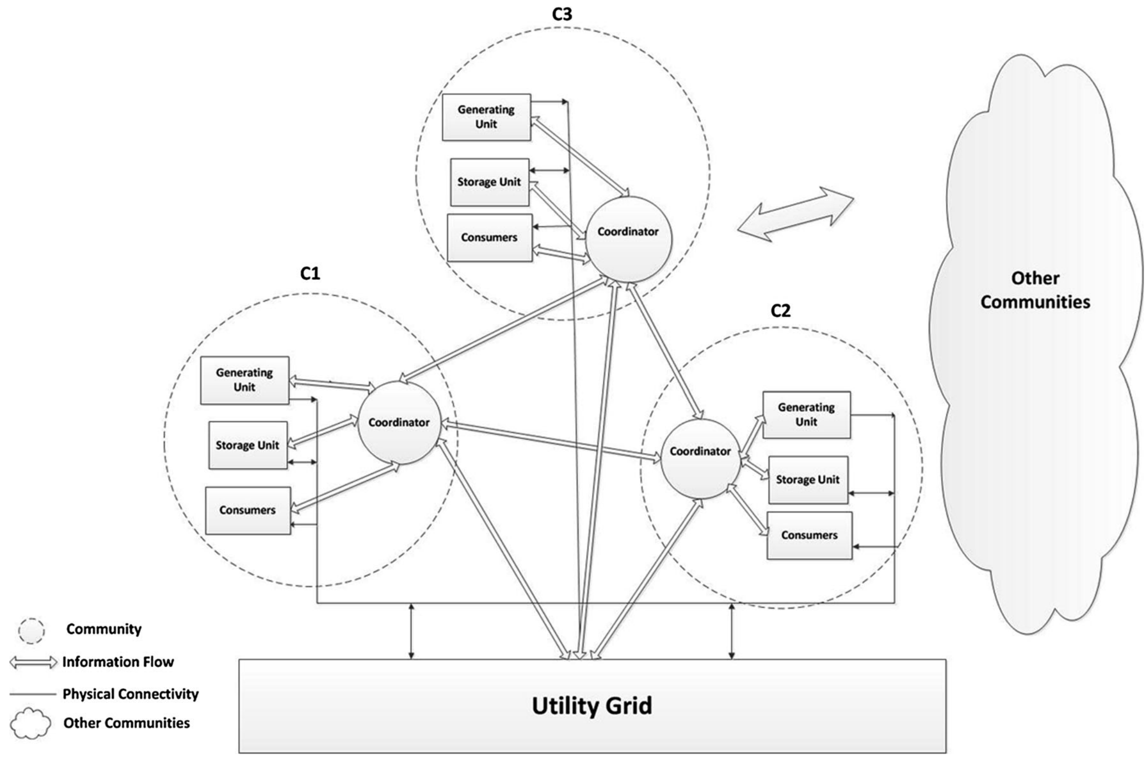

Fig. 1 Agent-based community micro-grid architecture

- C1 has an average hourly consumption of 150 kWh and has two wind turbines of generation capacity of 200 kW each and an overall storage capability of 200 kWh.
- C2 hourly consumption is 850 kWh and also has two turbines of 1,000 kW generation capability each, with a storage capacity of 1,000 kWh.
- C3 has an average hourly consumption of 300 kWh, a generation capability of 450 kW by two generators, and can store power in its batteries up to 200 kWh.

On the basis of electric tariff information obtained from a local micro-grid project manager in New Zealand (Willis 2012), we set some prices for power generation and local sales. The electric tariff is shown in Table 1. According to the data obtained from the project manager, the utility grid will purchase power from micro-grids at a price of $0.15 (all prices are in New Zealand currency) per kWh and will sell to the micro-grid at a price of $0.28 per kWh. The micro-grid power generation cost is $0.07 per kWh. Surplus generation is first stored in batteries, and any power left over is sold first to other neighboring micro-grids if they need it at $0.18 per kWh. Otherwise, the surplus power is sold to the main utility grid at the rate of $0.15 per kWh. In case of a shortage of supply, a coordinator agent first uses its batteries. If the batteries are empty, then electricity is purchased from the other micro-grids for $0.18 per KWh; otherwise, the power is purchased from utility grid at $0.28 per kWh.

Table 1 Electric tariff offered by the utility grid and micro-grids in per kWh

	Micro-grid	
	Sell	Buy
Utility	$0.28	$0.15
Micro-grid	$0.18	$0.18

To investigate the first of the above-listed questions of this section (the one concerning the effect of battery size), we ran our simulation three times on two different micro-grid configurations using randomized wind patterns appropriate for the condition near the city of Dunedin, New Zealand, for 25,000 simulated hours (simulation rounds). In the first configuration, the micro-grid is only connected to the utility grid (i.e., not to neighboring micro-grids), and any trading of electricity can only be done with utility grid.

For the second configuration, micro-grids were connected with neighboring micro-grids. In the event of surplus or shortage of power under this configuration, the coordinator agent of a particular community first checks with coordinator agents of the other micro-grid communities. After their demand is attended to, any surplus will be sold to the utility or to the community that needs it.

In order to examine the effect of battery size, given the current relatively high cost of battery storages, we looked at

Table 2 Impact of battery sizes

Battery (kWh)	Battery surplus (utility connected) (%)	Battery surplus (with networked multi-agent mode) (%)
160	41.1	25.6
80	44.6	36.7
40	47.4	43.5

smaller-sized batteries in three different experiments to compare the suitability of batteries in the main-grid-connected mode (with no connection between local micro-grids) and the networked multi-agent mode (with connections between local micro-grids). The sizes of the batteries were 160, 80, and 40 kWh. The results of the simulation are presented in Table 2. The battery excess in the table quantifies the proportion of the time when there was generation that was in excess battery's storage capabilities, i.e., there was surplus energy for that percentage of time that could not be stored in the battery because the battery was full.

Results indicate that power in the networked multi-agent mode was more effectively distributed and that is why it got less battery surplus when compared to those that were not so connected. The battery surplus for the large 160-kWh battery in the community-interconnected mode was lower (25.6 %) than in the main-grid-only mode (41.1 %). However, the costs of batteries are currently quite high (for lithium-ion batteries, it is US $1,000 per kWh), and it would take longer for communities to pay off the cost of investment.

To investigate the second of the above-listed questions (the one concerning the degree to which batteries can be used to share power during main-grid power outages), we again ran our simulation on three different configurations for 25,000 simulated hours to get the average price paid by community per hour. The three configurations were as follows:

- Config 1 (utility grid connected). Communities are directly connected to utility grid, and there is no power storage facility available.
- Config 2 (utility grid connected with battery backup). It is the same as Config 1, but with storage capability.
- Config 3 (interconnected micro-grids and utility grid connected plus battery backup). Communities are connected to both utility grid and each other and have storage capabilities.

The experimental arrangement features three communities (C1, C2, and C3) of different sizes and wind patterns.

Table 3 shows that the average price paid by the community per kWh using Config 3 was less than the other two configurations. It should be noted that in interconnected community mode (Config 3), a community enjoys better tariffs (lower tariffs) by trading its surplus energy (from

Table 3 Average price paid per hour by the local community

Configuration	Community C1	Community C2	Community C3
Config 1	$28.53	$138.62	$41.36
Config 2	$26.68	$134.46	$40.09
Config 3	$5.67	$133.54	$38.73

Table 4 Average price paid per hour per kWh by community having MAS with different average wind patterns

Community pattern	Random wind pattern	Low wind pattern	High wind
C1	$0.16	$0.18	$0.15
C2	$0.15	$0.17	$0.14
C3	$0.19	$0.21	$0.18

generation and batteries) with its neighboring micro-grids, as opposed to trading with the utility grid.

We also tested the interconnected community configuration by considering varying wind patterns. For a high wind pattern, community generators experience 20 days of wind at high average speeds followed by 10 days of wind at low average speeds, whereas for the low wind pattern, it is vice versa (10 days of high-speed wind and 20 days of low-speed wind). For the random wind pattern, generators get 10-day segments that are randomly set to be either high or low wind speeds. (Thus, it is possible that a generator could experience 20 or 30 consecutive days of a high or low level of wind.) Table 4 shows the relative effect that the different wind patterns have on the average price paid per hour per kWh by the community.

In the experiments discussed so far, power trading always involved a fixed price. Also, whenever a community coordinator agent determined that it has an energy excess or deficit, it would first inquire with other local communities, and if they are unable to trade, it trades with the utility. This is a fixed pattern.

In the next section, we consider a more dynamic situation in which communities (as represented by their coordinator agents) may have different strategies. Some communities may be environmentally conscious and more interested in minimizing environmentally harmful emissions, while other communities may be more concerned about maximizing profits. Others may be primarily concerned about stable power availability. Accordingly, the micro-grid coordinator agent would adopt different strategies in connection with buying and selling.

5 Community trading strategies

This section describes a set of five strategies that individual communities can employ when they trade electricity with other communities and the utility grid. It also presents the experimental results comparing these strategies with respect to two important variables: (1) the profit obtained and (2) the amount of carbon emission produced as a result of the strategy. Also, comparisons of two strategies with and without power outages are also presented.

5.1 Description of the strategies

In this section, we provide a description of the five strategies that could be employed by the communities.

5.1.1 Fixed strategy (FS)

In this strategy, a micro-grid has an agreement with the utility grid that all of its surplus will be bought by the grid, and the extra power required will be provided by the utility grid based on a special agreed-upon tariff rate. Making this type of agreement with the utility grid is advantageous, because the community is immune to external fluctuations that may result in high tariff rates during peak hours (or seasons). The tariffs for each of the strategies are given in Table 4.

5.1.2 Shared strategy (SS)

In the shared strategy, local communities share excess power among each other for a preagreed (fixed) price (all the communities share the same buy and sell price). Any surplus energy after sharing is sold to the utility grid.

5.1.3 Profit-based green power strategy (PGPS)

The goal of a community that employs this strategy is to maximize its use of renewable energy. The community does so in order to minimize carbon emissions. So this community, when in need of power, is willing to buy at any price (i.e., a high price) for green power, if green power is available in the market. However, when this community has surplus green power, then it offers power in the market at a price set to maximize its financial return (i.e., it does not sell green power for a low price, since it buys it for a high premium).

5.1.4 Altruism-based green power strategy (AGPS)

This strategy is similar to the PGPS green strategy. The only difference between the two is that instead of maximizing its profit when selling the surplus green power, this strategy offers its power in the market at a fixed rate (which is slightly above its generation cost). The objective of the community employing this strategy is not only to use green power but also to promote green power usage in other communities by offering it for a lower price. Since this strategy forgoes profit it could have made (by taking into account "greater good" of the society), this strategy is called Altruism-based green power strategy.

5.1.5 Greedy strategy (GS)

A community employing this strategy always wants to buy power at a low price and always aims to sell power at a high price. The objective of this strategy is to optimize its financial outcomes.

5.2 Market mechanism for clearing prices

There is a need for a market mechanism to facilitate a fair trade of electricity in the communities. The first two strategies described in the previous subsection are based on fixed prices that do not need a market mechanism. However, the last three strategies need a marketplace, where buyers and sellers can trade power. This market must have some market price clearing mechanisms to match the bids with the offers. We employ a double auction algorithm (Nicolaisen et al. 2001) to facilitate market clearing in our work. In this algorithm, the buyer of the highest bid will be matched with the seller with the lowest bid. The unit price for their contract (i.e., the clearing price) is set as the mean of the two (bid and offer) prices. For example, let us assume there are three sellers and three buyers in the market. Let S1, S2, and S3 be the sellers, and B1, B2, and B3 be the buyers. Sellers and buyers submit their offers and bids along with the quantity. Let us suppose that the following are the offers and bids submitted in the market (where the dollar values listed indicate the price paid for 1 mWh):

- S1: 10 mWh @ \$3; S2: 10 mWh @ \$2; S3: 10 mWh @ \$4.
- B1: 10 mWh @ \$9; B2: 10 mWh @ \$8; B3: 10 mWh @ \$10.

The market clearing mechanism first sorts the buyers and sellers by their price offers in descending and ascending order, respectively. Then, the buyer with the highest bid price (B3) is matched with the lowest ask price (S2) at a price of \$6 for 10 mWh. Similarly, the next pairs will be matched in the same fashion.

5.3 Operation of the strategies

The operations of the five strategies described above are schematically listed here in pseudocode.

5.3.1 *Pseudocode for fixed strategy (FS)*

```
/* Step 1: Coordinator agent collects information */
Gather generation information from generator agent
Gather demand information from demand agent
/* Step 2: Coordinator agent acts */
IF Generation > Demand
 THEN
   Authorize consumption according to local demand
   Sell excess amount to the utility grid
 ELSE
   Consume local generation
   Buy deficit demand from the utility grid
```

5.3.2 *Pseudocode for shared strategy (SS)*

```
/* Step 1: Coordinator agent collects information */
Gather generation information from generator agent
Gather demand information from demand agent
/* Step 2: Coordinator agent acts */
IF Generation > Demand
 THEN
   Authorize consumption according to local demand
   Offer excess amount to the nearby micro-grids
 ELSE
   Consume local generation
   Buy deficit demand from neighboring micro-grids
/* Step 3: */
IF Surplus power still available
 THEN
   Sell leftover surplus to the utility gird
/* Step 4: */
IF Demand Deficit Still exists
 THEN
   Buy deficit demand from the utility grid
```

5.3.3 *Pseudocode for PGPS, AGPAS, and greedy (GS) strategies*

```
/* Step 1: Coordinator agent collects  information */
Gather generation information from generator agent
Gather demand information from demand agent
/* Step 2: Coordinator agent acts */
IF Generation > Demand
 THEN
   Authorize consumption according to local demand
   Set ask price for leftover energy based on market history
 ELSE
   Consume local generation
   Set ask price for leftover energy based on market history
/* Step 3: */
Participate in The market
/* Step 4: */
IF A match is found through the market
 THEN
   Update revenue
 ELSE
   Trade with Utility Grid
/* Step 5: */
Update History Of interactions (prices)for future use
```

In the fixed strategy (FS, Sect. 5.3.1), the coordinator collects information from its generator and consumer agents in order to update its knowledge of production and demand for that particular hour. In order to achieve a balance between demand and supply, the coordinator agent then sells or buys power from the utility grid.

The pseudocode for the shared strategy is given in Sect. 5.3.2. The shared strategy uses the same rate for buying and selling power to nearby communities. If even after trading with local communities there is surplus or deficit power, then it goes to the utility grid.

Section 5.3.3 presents the pseudocode for the community employing PGPS, AGPAS, or GS strategies. For each such strategy, instead of taking directly from the utility grid, the coordinator agent consults its bidding and offering price history. Then, it sets a new bid or asking price (offer) depending upon its strategy and enters into a market. If its bid or offer is successful, its community revenue will be updated, and the bid or asking price is recorded as successful for future use. If the bid or offer is not successful, then the coordinator agent goes to the utility grid for selling or buying energy and updates its history (as an unsuccessful record).

Each of the different types of strategies has specific tariffs associated with it. Table 5 shows the different electricity tariffs ($/kWh) for different strategies. Note that the trading prices with the utility are fixed[1] (sell to the utility at $0.18/kWh and buy at $0.25/kWh). We again ran our comparative simulation study for 25,000 h by changing our experimental setup. This time for comparative purpose, all communities have the same average consumption and generation capability, i.e., 850 and 2,000 kW, respectively. Also, we assume that there are no power storage facilities available for the communities. Since the communities are at different locations, the generation amount for a given period can vary across communities. Whenever there was a power excess or deficit, a coordinator agent had to coordinate with other micro-grids' coordinator agents or the main utility grid in order to sell or buy power, depending upon its adopted strategy. During this set of simulation runs, there were no power outages associated with the main utility grid. Thus, there was always power from some source available. For a specific simulation run, all three interconnected communities were following the same strategy.

We computed the values of two variables of interest during the simulation: net profit/loss[2] and carbon

[1] Although real utility prices for purchasing and selling energy would be expected to vary over time, we have kept them fixed here in order to simplify the discussion of the model operation. It is a straightforward adjustment to our model to incorporate varying utility price settings.

[2] Net profit/loss = ((cash in − generation cost) − cash-out).

Table 5 Electric tariffs offered in different strategies

Strategy	Sell to utility	Buy from the utility	Sell local generation to local community	Sell to other micro-grids	Buy from other micro-grids
FS	\$0.18	\$0.25	\$0.10	NA	NA
SS	\$0.18	\$0.25	\$0.10	\$0.12	\$0.12
PGPS	\$0.18	\$0.25	\$0.10	Market determined (\$0.10–\$0.25)	Market determined (\$0.10–\$0.25)
AGPS	\$0.18	\$0.25	\$0.10	\$0.10	Market determined (\$0.10–\$0.25)
GS	\$0.18	\$0.25	\$0.10	Market determined (\$0.10–\$0.25)	Market determined (\$0.10–\$0.25)

emission.[3] If a community is self-sufficient in terms of power, that means the community can produce more than its demand and the net profit/loss would be positive. However, if the community does not meet its demand from its own generation, then the net profit/loss will be negative (since it has to pay to buy electricity from another provider).

For comparison purposes, we also considered a baseline scenario of a community arrangement that had no local power generation unit, no battery storage, and it only took power directly from the main utility grid. Since we are interested in considering the effect of power usage on carbon emissions, we still calculated the effective amount of carbon emissions produced in connection with all the energy obtained from the main utility grid. For this purpose, we used an electricity emission factor of 0.137[4] (kg CO_2-equivalent per kWh) for New Zealand (Ministry for the Environment (New Zealand) 2010). For this baseline scenario, the total carbon emission for the three communities is 7,697,723 kg for 25,000 h.

5.3.4 *Discussion of results on net profit/loss*

Table 6 shows the results of these simulation runs. In financial terms, FS has the highest loss because it always sells and buys from the utility grid at fixed rates that are usually higher than the trading prices of market-based trading. Similarly, GS also has higher financial loss (but a slightly lower loss than FS), because the GS strategy does not bind its sellers and buyers to trade first into the market. Sellers and buyers can leave the market and trade with the utility grid depending upon the price offered in the market. Although AGPS sells at the lowest price, its net profit/loss is lower than GS. In order to explain why this is the case, let us consider an example where all three communities adopt the greedy strategy. Let us suppose that for a particular hour there is a seller who offers 2 kW of electricity and two buyers who want 1 kW of power. Let us also assume that the seller gets a higher price from the utility grid, so it sells the power to the utility. Since there is no other seller available in the market, the other two communities also move to the utility grid (i.e., they buy from the utility grid). The overall net profit/loss for that hour would be then \$−0.28[5] (generation cost is \$0.07/kWh). However, for AGPS (which offered the lowest rate in the market), the total net profit/loss for the above-mentioned assumption would be \$0.

Table 6 Total profit and percentage of green power used

Strategy	Total net profit/loss	CO_2 emission (kg)
FS	\$−3,107,564	3,290,353
SS	\$−2,328,337	2,122,673
PGPS	\$−2,512,465	2,122,673
AGPS	\$−2,512,465	2,122,673
GS	\$−2,645,670	2,383,375

The shared strategy financially is the best among all the strategies because selling and buying is done at the same fixed price. The selling price of AGPS is also fixed (\$0.10); however, the buyers whose bids were not successful in the past increase their bids for the next hour, which would be substantially higher than \$0.10. For the SS strategy, the selling and buying prices (for transactions that happen within the three communities (i.e., not the grid)) are \$0.12. So, the net profit/loss in this case will be zero, while for AGPS strategy there will be net loss. Hence, SS does financially better than AGPS.

5.3.5 *Discussion of results on carbon emissions*

The shared (SS), profit-based green power (PGPS), and altruistic-based green power (AGPS) strategies were evidently more environmentally friendly, because of the lesser amount of carbon emitted associated with these strategies.

It can be observed that the fixed strategy (FS) always buys power from the utility grid when there is an energy

[3] Carbon emission stores the amount of carbon dioxide emitted during electricity production, transmission, and distribution.

[4] Value is calculated by the mentioned authority in 2010. This value is derived by considering the proportion of natural gas (15.9 %), liquid fuels (0.142 %), and coal (10 %) as nonrenewable energy source in New Zealand's grid.

[5] Net profit/loss = ((2 * (0.18) − 2 * (0.07)) − 2 * (0.25)).

deficiency, which thereby results in the greatest amount of carbon emissions. This is followed by the greedy strategy (GS), which always looks for a cheap rate and does not concern itself with the energy source. The Altruism-based green power strategy (AGPS) turned out to be one of the most environmentally friendly approaches, with the lowest carbon emissions. However, in terms of profitability, it is lower than PGPS because of its altruistic pattern of selling excess green power at a cheap price. The CO_2 emissions for SS, PGPS, and GS are the same, because they all are sharing excess energy with local communities before selling to the utility.

In order to observe the impact of batteries on net profit/loss and on carbon emission, we also conducted experiments that introduced batteries for storing surplus power. In these scenarios, communities charge their batteries first if surplus power is available and consume power from their batteries in case of a power deficit, before going to the market or to the utility grid. In our experimental setup, we have set the same large battery size, i.e., 20,000 kWh, for all communities. There are also some battery constraints we considered in our simulation. The constraints are:

- At any time, the maximum charge rate is equal to the maximum generation capability of the wind turbine.
- The maximum rate of discharge is equal to the maximum charging rate of the battery.
- The efficiency[6] of the battery is 85 %.
- The depth of the battery discharge[7] is 80 %.
- The self-discharge[8] of the battery is about 1 % per month.

We again ran our simulation for 25,000 h with the same experimental setup as discussed above (in the same section) with the addition of a battery for each community. Table 7 shows the results of uniform strategies (i.e., all the three communities have the same strategies) with power storage facilities. We found that the net profit/loss and the carbon emission of all strategies decreased (when compared to the results shown in Table 5), because instead of taking deficit power (i.e., additional power required) from the utility grid, communities first used the power stored in their batteries and then obtained power from the utility grid if needed.

5.4 Mixed strategies

In Sect. 5.3, we discussed the results of simulations when all communities have the same strategy at a given time. In this section, we consider scenarios where communities have different strategies from each other at a given time. We only considered the strategies that involve the market mechanism for trading power among themselves. This way, we have ten different combinations of strategies that are as follows[9]:

1. C1, C2, and C3 have PGPS (PsPsPs).
2. C1, C2, and C3 have AGPS (AsAsAs).
3. C1, C2, and C3 have GS (GsGsGs).
4. C1 has PGPS, C2 has AGPS, and C3 has GS (PsAsGs).
5. C1 and C2 have PGPS and C3 has AGPS (PsPsAs).
6. C1 and C2 have PGPS and C3 has GS (PsPsGs).
7. C1 and C2 have AGPS and C3 has PGPS (AsAsPs).
8. C1 and C2 have AGPS and C3 has GS (AsAsGs).
9. C1 and C2 have GS and C3 has PGPS (GsGsPs).
10. C1 and C2 have GS and C3 has AGPS (GsGsAs).

We ran the simulation 25,000 h for each combination of strategies by keeping the same experimental setup as discussed in Sect. 5.3.

Figure 2 shows the total net profit/loss for all the three communities when different combinations of strategies are used. The results are presented according to the descending order of net profit/loss. It can be observed that when all communities employ the greedy strategy, the total loss for all the communities is the worst. We observed that GS has a higher electric tariff than the others, while AGPS and PGPS strategies have lower net loss than the greedy strategy. Hence, any combination with at least one greedy community does worse than combinations of AGPS and PGPS strategies.

Table 8 shows the range of net profit/loss (maximum and minimum losses) for a community by adopting a strategy irrespective of what other strategies have been chosen by the nearby communities. For example, if a community chooses the greedy strategy, there are six different configurations that are possible (see the first six combinations of strategies in Fig. 2). Maximum and

Table 7 Total profit and percentage of green power used with batteries

Strategy	Total net profit/loss	CO_2 emission (kg)
FS	\$−1,579,388	1,888,636
SS	\$−1,464,906	1,712,992
PGPS	\$−1,489,644	1,712,992
AGPS	\$−1,489,644	1,712,992
GS	\$−1,499,848	1,732,963

[6] Loss of power when the battery is charging.

[7] Maximum power that can be drained out from the battery.

[8] Loss of stored energy if no discharging takes place.

[9] Note that the first three are uniform strategies (all three communities have the same strategy). The rest are the mixed strategies (i.e., at least one community has a strategy that is different to its neighbors).

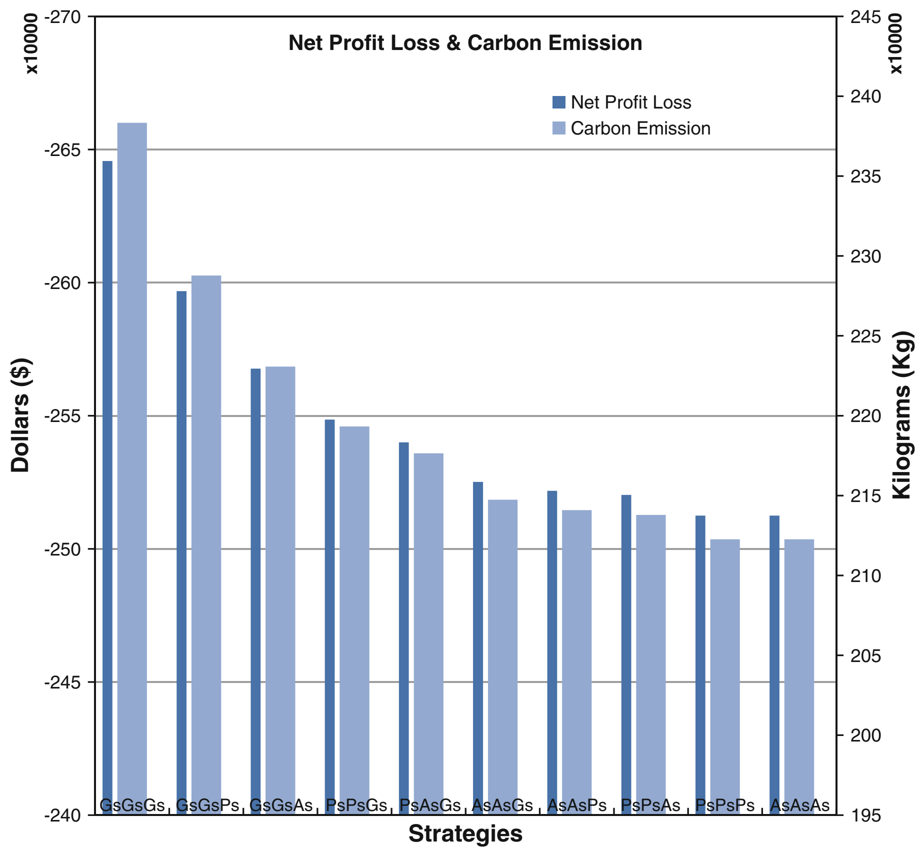

Fig. 2 Total net profit/loss and carbon emission in mixed strategy

Table 8 Range of net profit/loss for each strategy

Strategy	Net profit/loss	
	Minimum	Maximum
PGPS	\$−958,664	\$−607,372
AGPS	\$−1,234,225	\$−791,149
GS	\$−933,356	\$−604,953

Table 9 Range of carbon emission for each strategy

Strategy	Carbon emission	
	Minimum (kg)	Maximum (kg)
PGPS	620,912	743,743
AGPS	626,867	721,298
GS	782,320	881,428

minimum losses for an individual community for choosing the greedy strategy are \$−933,356 and \$−604,953, respectively. This information can be used by the power management committee of a community to decide on which strategy to adopt.

Figure 2 also shows the carbon emission produced by each combination during 25,000 h. The same trend is observed for net profit/loss. When all the three communities have the same PGPS and AGPS strategies, these configurations have the lowest carbon emission. The carbon emission increases as communities start adopting heterogeneous strategies. The combinations with no community using the GS have relatively low carbon emissions when compared to the combinations that have one GS involved. Carbon emission increases further as two GSs are introduced in combination and is the worst when all communities have the greedy strategy. Table 9 shows the minimum and maximum emission of carbon for each strategy.

This information in conjunction with the information available in Table 8 can be helpful in deciding about the adoption of a good strategy for the community. For example, a community that wants to optimize both variables (profitability and carbon emission) will choose PGPS, because the maximum carbon emission produced by this strategy is somewhere between AGPS and GS and also the minimum loss is also between AGPS and GS.

5.4.1 Discussion

From a policy modeling perspective, there are three main applications of the model described above. First, a community that is a part of a network of communities can use the simulation model to investigate the net profit/loss and carbon emissions if it were to employ a particular strategy. For example, if a community were to choose the greedy strategy, then it can know that the worst net profit/loss for all the communities would be \$ (−2,645,670) and the best would be \$ (−2,525,112). However, if AGPS is used, the communities would likely be better off (net loss between \$−2,512,465 and \$−2,567,670).

Second, an agent that is responsible for managing a particular community can also weigh the benefits of playing a particular strategy for itself (instead of considering the overall benefit for all the communities involved as discussed in the previous paragraph), which is indicated in the results presented in Tables 6 and 7. We call this the "individual-community" consideration.

Third, the designer who is in charge of proposing policies for communities (say three communities) can propose policies by considering both the individual-community and all-community results. By considering at both levels, the designer will be able to come up with a configuration that will enable the overall carbon emissions to be reduced and also reduce the amount of net loss in the communities.

5.5 Effect of main-grid power outages

We also conducted experimental simulations of power usage in the context of occasional power outages on the part of the main utility grid. When such power outages occur, the micro-grid communities operate in "island mode" and can still supply some energy to their local communities. In this case, we compared differences between the fixed (FS) and shared (SS) strategies.

We considered two types of power outage in a given day:

- a single hour of power outage after every 6 h,
- 6 h of power outage after every 6 h.

We assume that communities would attempt to conserve power consumption during power outages so that when a power outage occurred, communities that have a deficit in their own local power generation reduce their power consumption by 50 %.

However, communities with a surplus in power would also decrease their power demand (by 20 % in this case) so that they could earn more profit by selling power to other communities. We observed that during a power outage, the rate of power traded among communities also doubled. Comparative results for the fixed and shared strategies are shown in Tables 10 and 11.

The earlier results indicated that when there is no power outage from the main utility grid, then the fixed strategy yields the better profit. However, there is a significant difference in the amount of carbon emissions produced due to each strategy. Similarly, when power outages occur, both strategies experience power shortages. However, the amount of surplus power lost (because it cannot be sold back to the main utility grid) in connection with the shared (SS) strategy is lower than the lost power in the fixed (FS) strategy. This is because surplus power among communities having a coalition strategy can be traded among themselves, and then only afterward any leftover energy can be offered to the main utility grid if it is available.

There is a similar advantage of the shared strategy in connection with energy deficits in the case of main-grid power outages. The shared strategy communities first coordinate among themselves, and if there are still deficits, then they transact with the main utility grid. For this reason, the unsatisfied demand (i.e., the demand amount that cannot be satisfied because of the unavailability of the main utility grid) of the shared strategy remains low compared to the fixed strategy.

Thus, the shared strategy, afforded by multi-agent-system coordination among the functional units of the interconnected communities, clearly outperforms the fixed strategy. It not only produces a lower level of carbon emissions, but it also results in a lower level of unsatisfied demand. When there is a power outage, communities already decrease their power demands by 50 %, but there is still a large amount of unsatisfied demand remaining with the fixed strategy.

We also conducted the same experiment in connection with the market-based mixed strategies. The results showed that even in power outages, the combinations of strategies that promote trading of green power (i.e., PGPS and AGPS) are better than GS in terms of net profit/loss and carbon emission (similar to the result reported in Sect. 5.4).

In order to improve the reliability, or fault tolerance (power outage) of micro-grids, neighboring micro-grids are best advised to exchange their excess power resources, and agent-based technology can be used to automate this coordination. At the present state of technology, battery storage capacities are relatively limited as a mean to provide significant support during power outages. However, new storage technology may be developed in the future that will provide valuable relief in this area. When such developments do appear and are cost-effective, they will further add to the coordination option of agent-based energy exchange among interconnected micro-grid communities.

6 Conclusion

The agent-based architecture that we have presented here offers a high-level scheme for automated coordination and

Table 10 Results with power and no power outage

Strategy	Net profit/loss (in thousands of dollars)			Surplus lost (mWh)			Unfulfilled demand (mWh)		
	A	B	C	A	B	C	A	B	C
Fixed	$−3,107	$−2,543	$−1,085	0	4,223	12,015	0	1,243	4,366
Shared	$−2,328	$−1,927	$−808	0	3,154	8,553	0	587	2,228

A no power outage, *B* 1-h power outage, *C* 6-h power outage

Table 11 Carbon emission in power and no power outage

Strategy	Carbon emission (kg)		
	A	B	C
Fixed	3,290,353	2,796,168	1,653,003
Shared	2,122,673	1,820,135	1,066,975

distribution of energy resources among interconnected micro-grid communities. Such coordination can be conducted with and without battery storage available. This kind of coordination is significant, because such communities can experience varying energy generation conditions (such as varying hourly wind and sunshine patterns) even over relatively small areas and over short time periods. By having agent managers and coordinators that take into account these local conditions and then carry out exchanges on an hourly basis in accordance with community-approved strategies, the interconnected communities can arrive at more satisfactory energy usage and environmental emissions scenarios.

In this connection, we have conducted experimental simulations of these types of coordination using our agent-based architecture and employing realistic wind data and current energy pricing data. Based on these measurements, we found, for example, that an Altruistic-based green power coordination strategy, which offers power to neighboring communities at a low rate, can have beneficial environmental outcomes. And these outcomes may well be worth the profits that are sacrificed in this process. We also conducted "what-if" analyses of different energy policies that can potentially be employed by a community and compared the effects of using one strategy against another in terms of net profit/loss and the amount of carbon emissions produced.

We believe that it is through simulations of the kind presented here that such trade-offs between different variables (e.g., net profit/loss and carbon emission) can be evaluated in order to arrive at an agreed-upon energy usage policy for each local community, both from the viewpoint of individual communities (e.g., an individual community modeling the possible behaviors of others) and from the viewpoint of the designer who tries to come up with an optimal policy to be used by the communities involved.

We also presented simulation results when micro-grids operate in "island mode" due to power outages from the main utility grid. Under those circumstances, coordination of limited locally generated power can be of enormous value to communities in desperate need of power.

Agent-based system coordination and collaboration is inherently scalable. So in the future we intend to extend our analysis by conducting more elaborate tests with our agent-based modeling approach. We will then be examining

- Large-scale, interconnected micro-grid communities (i.e., more than three).
- More variation in energy storage capabilities (e.g., fuel cells, hydrogen storage, elevated water storage, etc.).
- More dynamic change to coordination strategies (e.g., coordinator agents could switch among strategies according to local conditions and the behavior of interconnected coordinator agents).

But even with the results presented in this paper, we believe we have demonstrated the efficacy of distributed agent-based system for the real-time modeling and management of intermittent and variable power generation sources.

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