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Dynamic Coalition Formation in Energy Micro-grids

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Abstract. In recent years the notion of electrical energy micro-grids, in which communities share their locally-generated power, has gained increasing interest. Typically the energy generated comes from renewable resources, which means that its availability is variable-sometimes there may be energy surpluses and at other times energy deficits. This energy variability can be ameliorated by trading energy with a connected main electricity utility grid. But since main electricity grids are subject to faults or other outages, it can be advantageous for energy micro-grids to form coalitions and share their energy among themselves. In this work we present our model for the dynamic formation of such micro-grid coalitions. Our agent-based model, which is scalable and affords autonomy among the micro-grids participating in the coalition (agents can join and depart from coalitions at any time), features methods to reduce overall discomfort, so that even when all participating micro-grids in a coalition experience deficits; they can share energy so that overall discomfort is minimized. We demonstrate the efficacy of our model by showing empirical studies conducted with real energy production and consumption data.

Keywords: Renewable Energy, Multi-agent Systems, Coalition Formation, Micro-grids.

1 Introduction

A micro-grid (MG) is a local energy system that provides for the generation, storage, and consumption of electrical power within a community [8]. The function of a micro-grid is to utilize the distributed local renewable energy resources (such as wind and sun) and to satisfy power needs locally, thus minimizing the reliance on nearby utility grids. As a result, the power losses during transmission are reduced. Typically, a MG is connected to the nearby utility grid, so it can sell during surplus generation (generation is more than demand) or buy during deficient generation (generation is less than demand) power from an energy utility company. However, renewable energy sources are intermittent in nature and vary from hour to hour, and even from minute to minute, depending upon local conditions [8]. This means that at any time, a MG may have an excess or shortage of power generation. Different energy management strategies are used to mitigate the impact of supply variations, such as storage devices (batteries, fly wheels, capacitors, etc.), forecasting techniques, demand load management, and backup generators. One of the approaches to address this issue is the interconnection of nearby micro-grids which, by trading among the communities , can reduce the impact of irregularity with respect to renewable energy sources [8]. An agent-based architecture for local energy distribution among micro-grids has been presented in Yasir *et al.* [22], where each micro-grid represents a community which has its own power generation based on renewable energy sources and also has its own electric energy demand which varies hourly. Every community has a coordinator agent which, when it has a power surplus or deficit, is responsible for power trading with other interconnected communities or to the utility grid. We use that architecture as a basis on top of which we build our energy trading model.

Due to the centralized nature of existing electric generation and distribution systems, any technical fault or natural disaster can cause a wide-area blackout. Such power outages from the utility grid will also affect communities having MGs (hereafter interchangeably referred to simply as "communities"). Ordinarily MGs are not able to fulfill all their power needs by themselves all the time. So when a MG does not meet its demand, then the community will suffer hardship from having to cope with an insufficient energy supply. For brevity, we will refer to this hardship as "discomfort", and we note that the discomfort level (as discussed further below) is a nonlinear function of the energy deficit. So if the energy deficit is doubled, then the discomfort level is more than doubled. In order to address this problem, we believe that a useful approach is the formation of coalitions among the communities. A coalition here is considered to be a group of MGs that can distribute their electric power among each other. By operating in coalitions, communities can reduce their overall discomfort level, even when there is no additional external supply of energy.

In multi-agent systems, a coalition can be defined as a group of agents who decide to cooperate in order to achieve joint goals [14]. According to [19], coalition formation includes three activities: coalition structure generation, solving the optimization problem of each coalition, and dividing the obtained value among the agents. In this paper, our work is focused on the first activity of the coalition formation. We introduce a cooperation mechanism for dynamic coalition formation to reduce the overall discomfort level of the communities present in the system over time. The goal of our mechanism is not to find the optimal solution, but to find a satisfactory coalition match for the community in a non-deterministic environment (where community demand and generation vary hourly without advance knowledge) by relying on recent power and generation data.

The major contributions of this paper are twofold: 1) We have developed an algorithm for dynamic coalition formation to reduce discomfort at two levels: individual community level and at the system level (i.e. aggregation of communities). 2) We have investigated different power sharing mechanisms within the coalition and their impact on the discomfort level of the community and the system.

The rest of the paper is organized as follows. Related work on coalition formation in smart grids is discussed in Section 2. In Section 3 we present the problem scheme addressed in this work. Section 4 presents our approach to addressing that problem. Experiments and discussion are covered in Section 5. Section 6 presents conclusions and future work.

2 Related Work

Coalition formation in smart grids has been widely studied in the multi-agent system community (see for example [18] [16] [11] [6]), and much of this work has centered around two objectives: 1) reducing power losses and loads over the utility grids by forming local coalitions among MGs and customers. 2) optimizing monetary outcomes by trading power locally among MG participants.

Work in the first of these two areas has been conducted by studying coalitions among MGs, between MGs and consumers, or between MGs and the utility grid [17][3][6][13]. For example Chakraborty et al. [3] seek to reduce transmission losses by encouraging power-trading among MGs based on locality. Wei et al. [6] employ a game-theoretic coalition formation strategy to minimize power losses. However, although these approaches seek to reduce transmission losses, they do not address the coalition-formation process itself, as there are no mechanisms for how distantly located MGs can form efficient coalitions. Also these studies assume that the main utility grid is always available, so they have not considered circumstances when the coalitions may be cut off from such grids.

Other MG coalition studies have focused on optimizing monetary outcomes (the 2nd objective presented above) [4][5][13]. Some work has examined coalitions of plug-in hydroelectric vehicles (PHEV), which can form coalitions in order to have sufficient aggregate power to qualify for power trading markets [4][5]. In such approaches there is a broker that represents the coalition, and the individual PHEVs have little autonomy. Mondal et al. [13] describe a model for MGs competing with each other to attract consumer customers. In their work there is no cooperation between the MGs, and hence no coalitions are formed.

In contrast, the goal of our coalition formation mechanism is to form coalitions among the MGs in such a way that the members of a coalition complement their weather and demand patterns. As a result, the coalition becomes more resilient even during calamitous conditions and tries to reduce the aggregate discomfort of the members. In our model, each community also has the autonomy to join or leave the coalition by considering its demands, generation, and discomfort.

3 Problem Model

The scenario presented in our work concerns situations where communities having MGs must rely on their production to meet their demand. In cases of their own energy surpluses or deficits, they cannot get energy supplements from or sell excesses back to the grid, which is now cut off from them. When a community encounters an energy deficit, it will suffer "discomfort" because of the power shortage. We know from previous studies [1] [2] [20] that people or communities are willing to pay more than 100% of the original electric tariff if the power outage lasted for more than 24 hours. So we have assumed that there is a continuous polynomial function that can represent the discomfort of the community. So when a deficit increases, the discomfort level increases non-linearly. Supposing that dmd_i is the demand of the community at a given time i, where i is any hour of the day. gen_i is the generation of the community at given time i, def_i is the deficit of the community at time i, then we can calculate it as:

$$def_i = Max[\frac{dmd_i - gen_i}{dmd_i}, 0] * maxRange \tag{1}$$

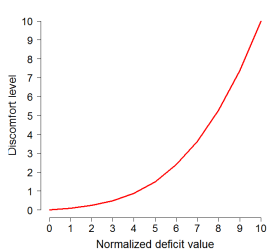
For simplicity we normalize the value of def_i between 0 and 10, where 0 means no deficit (i.e. generation is more than or equal to the demand) and 10 means extreme deficit (i.e. no generation is produced locally). In Equation 1, maxRange represents the maximum range of normalization i.e. 10.

The function for calculating the discomfort level is presented in Equation 2. The value of discomfort is assumed to lie between 0 and 10 (where 0 means no discomfort and 10 means extreme discomfort). This function takes def_i as an input and gives the discomfort level for time i. Mathematically this function can be expressed as:

$$f(def_i) = a * def_i + b * (def_i)^2 + c * (def_i)^3 \tag{2}$$

where a = 0.1, b = -0.01 and c = 0.01. A plot of this function is given in Figure 1.

Fig. 1: Discomfort because of deficit



For example, at a particular hour of the day, say at 10 am, a community generates the electric power of 200 kWh, and its demand for that hour is 350 kWh. So, by using Equation 1, we calculate the normalized deficit value to be 4.28. By inserting this value into Equation 2, the value of discomfort for this hour becomes 1.02. The specific values used in this function are not important and have been chosen for illustration. We do believe, however, that the non-linear shape of this function is generally representative of how discomfort is related to power consumption deficits.

Communities are assumed to be dispersed across a varied geography such that some communities may sometimes have surplus power generation(have more available power than their consumer demand levels require) due to good wind or sun, while at the same time others may face deficits and thereby suffer discomfort. The idea of coalition formation among the communities is to help communities that suffer from extreme discomfort by receiving support from those who have a much smaller level of discomfort. A community in a coalition that offers assistance at one time would expect to receive reciprocal assistance when it encounters energy deficit at a later point in time. To illustrate why this would be beneficial, let us consider a simplified example of just two communities, C1 and C2. Suppose that during a certain hour of the day C1 has enough energy generation that exactly matches its demand (and hence has a discomfort level of 0), while C2 has no energy generation at all (and so has a discomfort level of 10). During another hour of the same day, both communities C1 and C2 each have a power deficit level of 5 and so have discomfort levels of 1.5. This means that during the first hour period the aggregate discomfort of C1 and C2 is 10, and during the second hour period the aggregate discomfort level of the two is 3 (computed using Equation 2, also shown in Figure 1). So over the two hour period, the aggregate discomfort level is 13.0.

If C1 and C2 were to form a coalition for mutual assistance, then during the first hour C1 might offer 10% of its power to C2. This would result in a discomfort level of 0.1 for C1 and a discomfort level of 7.48 for C2. During the other mentioned hour of the day, C2 would reciprocate by giving 10% of its power back to C1, meaning that C2's power deficit will be 6 and C1's deficit will be 4. Their corresponding discomfort values for this period would then be 2.4 for C2 and 0.88 for C1, making their aggregate discomfort level is 7.48 + 0.1 + 2.4 + 0.88 = 10.86. So even though C2 would give up some power when it is in a deficit, it benefits from being in the coalition. Note that the new comfort level is smaller than the discomfort level of 13 when no coalition is formed.

So operating within a coalition is likely to have beneficial results for all parties. The most effective coalitions will be those for which the excesses and deficits of community members complement each other. The worst periods for some coalition members match up with better periods for others, who may even have energy excesses during those periods.

Of course, energy generation conditions may change over time, and so the most effective coalition combinations over a geographic area may thereby change, too. It would be best if we would allow MG communities to have the autonomy of moving to a new coalition if it so desires. So in the following we present our examination of communities that operate in four different configurations: 1) Standalone - there are no coalitions and no energy sharing. 2) Fixed coalitions - there is a single, unchanging coalition arrangement. 3) Dynamic coalitions - communities have the option of joining a different coalition at the beginning of every day. 4) Centralized system - all communities are members of one single coalition.

For all coalition configurations (thus not the standalone configuration), a community may share its power with others when it has relatively low discomfort. Similarly, a community can receive power from the coalition if it has a relatively high discomfort level. The details of energy sharing within coalitions are described in the next section. The dynamic coalition arrangement allows communities to change coalitions, and this coalition formation mechanism is described in the next section. The centralized system considers a single large coalition that is managed centrally. This system affords optimal energy swapping, but offers less autonomy and has the vulnerability of a single point of failure and high transmission losses. Since MGs are located at dispersed geographical locations, there will always be transmission losses associated with energy transfer. These transmission losses are determined by the following formula:

$$P_i^{Loss} = (Q_i^2 * R/U^2) + \theta * Q_i \tag{3}$$

where: P_i^{Loss} is the transmission power loss during one hour (i) in watts (W) from one community to another, Q_i is the total amount of power transmitted during hour i in kWh, R is the resistance of the distribution line between two MGs, U is the optimal voltage of the line, and θ is the fraction of power lost in the transformer during step up and step down process. The power lost during transmission is taken into account by the receiving MG.

4 System Model

In this section, we present the dynamic coalition formation mechanism. As with any coalition formation, the goal is to reduce the overall discomfort level of communities present in the coalition. The value of a coalition $(v(c_j))$ is represented by:

$$v(c_j) = \sum_{i=1}^{s} discomfort\_of\_community_i \tag{4}$$

where j is the coalition number, s is the number of communities present in the coalition j. The goal of coalition formation is to minimize the value of $v(c_j)$.

At the start of every day, two processes run in a coalition. In the first process, communities in the coalition calculate the amount they can give and take to/from the coalition for the next 24 hours by using their predicted demand and forecasted generation categorized into the best and worst hours. We assume that the forecasted wind pattern for the next 24 hours is up to 93% accurate [9]. Typically a community has twelve best and worst hours in a day. However, sometimes the best and worst hours may not be equal in number. Best hours are the hours in which a community has no discomfort or less discomfort. During those hours, the community can help other members of the coalition by sharing some proportion of its generation. Worst hours are the hours in which a community has less generation or no generation and it suffers from extreme discomfort. In other words, the community suffers more discomfort and seeks some power from the other members of the coalition to get some relief from its discomfort. Hence as a result, its overall discomfort of the day will be reduced.

In the second process, a community is selected to be the coordinator agent for the coalition. In this work, the coordinator agent is selected by lexicographic order. The responsibility of the coordinator agent is to broadcast an invitation message to other communities outside its coalition, identify the potential members of the coalition for joining the coalition, and manage the power-sharing distribution within the coalition.

There are two main phases of our coalition mechanism. The operational phase deals with the power distribution within the coalition, and the recruitment phase deals with recruiting other communities to join the coalition. First we discuss the operational phase. At the beginning of every hour, the coordinator agent calculates the total amount of electric power from coalition members who commit to give to the coalition and distributes the amount proportionally among the members of the coalition who are expecting the power from the coalition for the particular hour. We assume that communities do not cheat and reveal correct information about their give and take commitment.

A community can make a commitment about the amount of power to be given or taken from the coalition by using two approaches: dynamic offer and fixed offer. In a dynamic offer a community curtails a calculated at-the-time percentage of its generation from its 12 best hours and gives to its coalition. In return, the community expects the same amount back from the coalition during its 12 worst hours. However, in fixed offer, a community has a certain fixed value (in percentage) to curtail its generation from its best hours and then expect the same amount to return back during its worst hours.

Algorithm 1: Algorithms for fixed and dynamic offer of a community

```
input  : Generation & demand of next 24 hours
output: Give & take amount for exisitng coalition
Calculate best and worst hours slot
Total_discomfort_in_best_hours = ∑ discomfort_in_best_hour_discomfort
Total_discomfort_in_worst_hours = ∑ discomfort_in_worst_hour_discomfort
Total_actual_discomfort = Total_discomfort_in best_hours +
                          Total_discomfort_in_worst_hours
Algorithm for fixed offer
    set certain value of α // value in percentage of generation
    curtailment
    Total_new_discomfort = Compatibility Check(Best & worst hours, α)
    if Total_new_discomfort < Total_actual_discomfort then
        Make Offer(α) // amount to be given and taken from the
        coalition
    else
        No offer
    end
Algorithm for dynamic offer
    set i = 1% // cutail of generation in percentage
    while i ≤ 100 do
        Total_new_discomfort = Compatibility Check(Best & worst hours,i)
        if Total_new_discomfort < Total_actual_discomfort then
            Store order-pair (i, Total_new_discomfort) into discomfort-track-list
        else
            break
        end
        increment in i by 1
    end
    if discomfort-track-list then
        Sort discomfort-track-list in ascending order w.r.t Total_new_discomfort
        Pick the first order pair from discomfort-track-list & set the value of α
        Make Offer(α) // amount to be given and taken from the
        coalition
    else
        No offer
    end
```

Algorithm 1 gives the pseudo-code of the fixed and dynamic offer of a community to a coalition. At the beginning of each day, all communities in the system calculate their best and worst hours of the next 24 hours by using predicted demand and forecasted wind and sun information (line 1 of Algorithm 1). After identifying the best and the worst hours of the next 24 hours, a community aggregates the discomfort of the best and worst hours (line 4). For a fixed offer, the community selects the fixed arbitrary value of percentage for curtailing its generation from best hours (line 6 of Algorithm 1). If the selected value helps in reducing the aggregate discomfort of the day, then the community makes the offer otherwise the community does not participate in the coalition(lines 7-12 of Algorithm 1). However, for a dynamic offer (lines 13 to 30 of Algorithm 1), the community looks at all the possibilities of curtailing its generation (from 1% to 100%) from the best hours and observes its potential impact on the worst hours (lines 14 to 23 of Algorithm 1). After assessing all the possibilities, the community picks the best possible proportion (in percentage) for curtailing its generation among all the possibilities (line 26) and then calculates the amount of electricity to be given and taken to/from the coalition for the next 24 hours (line 27 of Algorithm 1).

We now discuss, the recruitment phase. From a recruitment perspective, we assume that the coalition is always looking for new communities to join the coalition in order to reduce a coalition's discomfort level. The coordinator agent collects the best and worst hours information from all the members of the coalition and categorizes the hours of the day into best hours and worst hours of the coalition. For recruiting the new community in the coalition, the coalition follows the following steps: at the start of every day, the coordinator agent of each coalition calculates the average discomfort of each hour of the next day by collecting best and worst hours information from the members of the coalition. The twelve hours with the lowest discomfort are ranked as the "best hours", while the remaining twelve hours are marked as the "worst hours". The "best hours" imply hours of the day during which the coalition can commit to sharing some of its power with newcomer communities. The "worst hours" signify hours when the coalition seeks to gain power assistance from a potential newcomer community. After calculating best and worst hour information, the coordinator agent broadcasts the invitation message to join its coalition along with the information of its average discomfort for the worst and best hours. A new community must remain with the coalition it joins for at least one day. In addition to what each coalition coordinator agent does, all communities also calculate their own discomfort level at the end of each day (see Algorithm 2). If the existing discomfort level of the community is less than its rolling average discomfort, then the community is not interested in leaving its present coalition and will reject all invitation messages (line 10 of Algorithm 2). Otherwise, the community analyzes which coalition's invitation suits it best. The community identifies the matched and non-matched hours. Matched hours are those hours in which the invitation-receiving community's best and worst hours match the inviting coalition's worst and best hours. While the remaining hours of the invitation-receiving community are declared as non-matched hours (line 2 of Algorithm 2). An invitation-receiving community can only make offers to the inviting coalition if the matched hours are present (line 3 of Algorithm 2).

The offer mentions how much electric power it can expect from coalition during the community's worst hours and how much power a community can give to the coalition during the coalition's worst hours. The offer could be either a dynamic offer or a fixed offer. The community then makes offer for matched (by using Algorithm 1) and non-matched hours (by using Algorithm 3). For non-matched hours offer, a community calculates its average discomfort level over the next 24 hours (line 1 of Algorithm 3). If the community employs a dynamic offer mechanism, then the community offers a certain percentage of its generation (line 5 of Algorithm 3) to the coalition if the non-matched hour's discomfort is lower than the average discomfort of the next 24 hours. For example, if average discomfort of the day is 5 and the discomfort of the non-matched hour 4 is 3, then the value of ψ is 20% ((5-3)/10). However, if the non-matched hour's discomfort is higher than the average discomfort of the next day, then community expects certain percentage of its deficit from the coalition (line 7 of Algorithm 3). In contrast to dynamic offers, for a fixed offer of non-matched hours, a community always uses fixed proportions for making offers for give and take to/from the coalition. The offer made in non-matched hours either by using the dynamic or fixed offer mechanism is always less than the offer made in matched hours. Once a coalition receives an offer from a community, it calculates how much the coalition's average discomfort level would be decreased by inducting this community. This calculation is done by adding and subtracting the power (the amount offered by the prospective newcomer community) from the next day's data of the coalition and recalculating what the discomfort level would be. As part of this calculation, the coalition also takes into consideration the location of the prospective new member by calculating the expected transmission losses associated with this community during power trading. These losses result in deficits that affect the coalition's discomfort level. The coalition then ranks the offers in descending order in terms of how much they would reduce its discomfort level, and then it selects the top community from the list and sends its willingness to recruit the community. After receiving the willingness signal from the coalition, the prospective community also performs the same calculations done by the coalition and selects the best coalition that helps in reducing its own discomfort level. The community then sends a joining message to that coalition, while sending a refusal message to any other coalition.

Once the community joins the coalition, the community and coalition must fulfill their commitments. We assume that there is no cheating in fulfilling these commitments. However, sometimes the community or the coalition is unable to comply with their commitments because they were not able to generate the required power due to the intermittent nature of renewable sources such as wind and sun.

5 Simulation Results

In our experiments, we investigated two questions: 1) What would be the impact on discomfort level of a community present in a coalition as compared to a

Algorithm 2: A community's analysis of invitation

if *current's day discomfort value* $\geq$ *rolling average discomfort* + β *value* **then**
  `// where` β `is the threshold value`;
  find matched and non-matched hours between community and invited coalition;
  if *matched hours are found* **then**
    if *community's best hours = coalition's worst hour & Vice versa* **then**
      `// matched hours`;
      Make offer ;
      Send offer to coalition;
    else
      Make offer for non-matched hours `// Algorithm 3`
  else
    Reject coalition's invitation
else
  Reject coalition's invitation

Algorithm 3: Algorithm for making offers during non-matched hours by a community

Calculate the average discomfort of the day;
if *offer mechanism is dynamic* **then**
  foreach *non-matched hours* **do**
    if *average discomfort of the day* $\geq$ *discomfort of non-matched hour* **then**
      ψ = (average discomfort of the day) - (discomfort of non-matched hour);
      `//` ψ `is the proportion of generation a community is willing to give to coalition for the hour`
    else
      η = (discomfort of the non-matched hour) - (average discomfort of the day);
      `//` η `is the proportion of its deficit a community is expecting to take from coalition`
else
  `// offer mechanism is fixed`;
  α is the certain fixed value (in percentage);
  if *average discomfort of the day* $\geq$ *discomfort of non-matched hour* **then**
    community can give α of its generation to coalition
  else
    community expects α of its deficit from the coalition

community in no coalition? 2) What is the impact of different power-sharing mechanisms on the discomfort level (of a community and the system) in dynamic coalition formation.

5.1 Experimental Setup

Our experiments involved forty communities (C1 to C40). Each community has an average hourly consumption of 1150 kWh and a wind turbine or array of solar photovoltaic (PV) of 2000 kW generation capacity. However, the power generation values for an individual community will vary, due to the dispersed geography involving different wind speeds and solar radiations.

It could be possible that a community having renewable energy generation (either wind or solar PV) always or most of the time has surplus. Similarly, it is possible that a community has no surplus or most of the time it faces deficit of generation. For our model, we have chosen a general configuration such that most of the communities are in deficit most of the time. However, our mechanism is also applicable to situations where communities have a surplus most of the time. In our system, 13 communities have arrays of solar PV and the rest of them have wind turbines. The power generated by a wind turbine is calculated by using the formula [12]:

$$P = 1/2\rho AV^3C_p \tag{5}$$

where P is the power in watts (W), ρ is the air density in kilograms per cubic meter (kg/m^3), A is the swept rotor area in square meters (m^2), V is the wind speed in meters per second (m/s), and C_p is the power co-efficient.

We obtained the wind speed (V) data of forty different New Zealand areas from the National Institute of Water and Atmospheric (NIWA) database [21]. We also obtained hourly power consumption data of forty different places from the Property Services office of the University of Otago [15]. The assumptions made while running our experiments are as follows. All communities are situated at sea level, so the air density value of is 1.23 kg/m^3. The blade length of the wind turbines is 45 meters (m). The cut-in and cut-out wind speeds of the turbines are 3 and 25 meters per second (m/s), respectively. Theoretically the maximum value of Cp is 59%, which is known as the Betz limit [12]. However, in practice the value of Cp is in between 25%-45% [12], depending upon the height and size of the turbine. The value of the power co-efficient (Cp) is 0.4 (i.e. 40%). Similarly, the power generated by a solar PV is calculated by using the formula [7]:

$$E = A * r * H * PR \tag{6}$$

where E is the power in kilowatt-hour (KWh), A is the total solar panel area (m^2), r is the yield of solar panel (%). The value of r for PV module of 4kWp is 15%, H is the solar radiation in kilo-Watt per meter square (kW/m^2), PR is performance ratio, which ranges between 0.5 and 0.9, with a default value of 0.75. We obtained the solar radiation (H) data of 13 different New Zealand areas from the National Renewable Energy Laboratory [10].

The simulation runs for 4 years (i.e. 48 months). At the start of the simulation, there are four coalitions present in the environment. Communities are initially assigned to each coalition on the basis of proximity, i.e. communities located in the same region of the grid belong to one coalition (see Figure 2). In Figure 2, house symbols represent a community. The arrow points to the centroid of the coalition. The communities within a coalition can transfer power among each other by using nearest point in the transmission line. The transmission lines are the black horizontal and vertical lines intersecting at the center of the figure. Transmission loss is calculated by using Equation 3. The initial value of R (resistance in Equation 3) in our experimental setup is 0.2 ohms per km. The value of θ is 0.02. The value of U is 33 kV. We setup the distribution network within a square region of 500 km x 500 km.

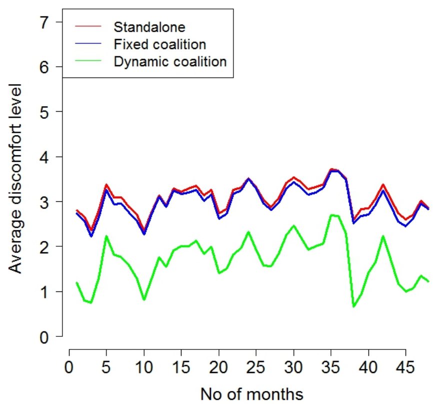


Fig. 3: C1: Standalone vs. Coalition

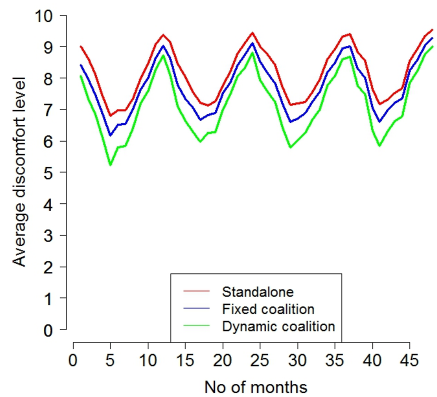
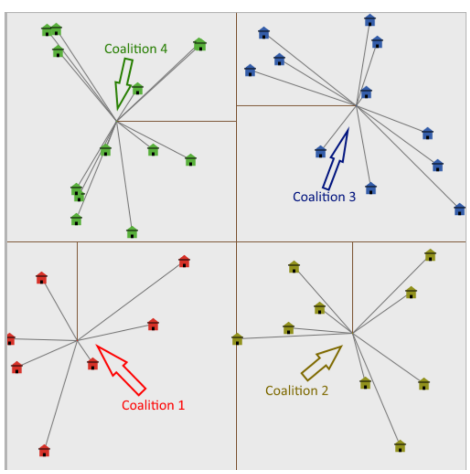


Fig. 4: C2: Standalone vs. Coalition

5.2 Results

Fig. 2: Proximity based coalition

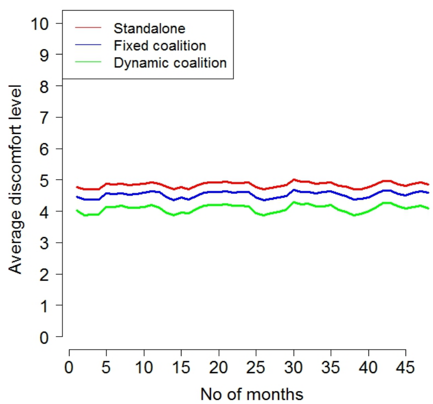


All communities in the environment used our dynamic coalition formation mechanism. As stated above, we examined two areas: a) the effect of coalition sharing and b) the effect of dynamic versus fixed offer.

Coalition vs no coalition

In order to measure the effects of our dynamic coalition mechanism, we conducted comparative experiments by using three other approaches: standalone, fixed coalition, and the centralized system (discussed in Section 3). We show the effectiveness of our coalition mechanism at two levels: at the individual community level and at the system level (the aggregate result of all communities). Due to space constraints, we are not able to show the results of all the communities present in the environment. So at the community level, we have chosen two representative communities (C1 and C2). The total power generation for C1 during the simulated four years period was more than its demand, while the overall generation of C2 was less than its demand during that period.

Fig. 5: System level: Standalone vs. Coalition



Figures 3 and 4 show the discomfort level of community C1 and C2 over the simulated time period of four years respectively. The results show that the community employing the standalone (no coalition) approach suffers much more discomfort, as no other community is able to help the standalone community. The community staying in a fixed coalition does better compared to the community in standalone mode, because, it gets help from other members of the coalition when it has severe discomfort levels. However, when the community employs our dynamic coalition approach, it experiences lower discomfort levels compared to using the alternative approaches. This is because, communities present in a coalition that complement each other for one day may not complement on the next day, as the wind or solar pattern changes from minute to minute and the prediction of wind pattern for more than 24 hours is not very accurate [9]. So our approach lets the communities leave their original coalition (created on the basis of proximity) and join the coalition that has a contrasting wind pattern or solar radiation. Similarly, Figure 4 illustrates the discomfort level of community C2 for the simulated time period of four years. Again, when the community operates under the dynamic coalition formation suffers less discomfort compared to the community configurations using the fixed coalition and the standalone approach. Figure 5 shows the average discomfort of all 40 communities (i.e. the system level result) in three configurations. It highlights that the dynamic coalition is the best in reducing the discomfort of all the communities. The results (Figure 3-5) clearly show that the dynamic coalition formation mechanism not only helps in reducing the discomfort in the individual community, but it is also helpful in reducing discomfort at the societal level. By employing our dynamic coalition formation approach, communities find the coalitions that complement the best and worst hours of each other. As a result, there is an overall reduction in the discomfort at the system level.

Dynamic coalition: Fixed vs dynamic offers

In Section 4, we described two methods (fixed and dynamic) of making offering in the dynamic coalition formation mechanism. We compared these two methods with the centralized system at the community and at the system level. In

Fig. 6: Comparison of C1's discomfort in different approaches

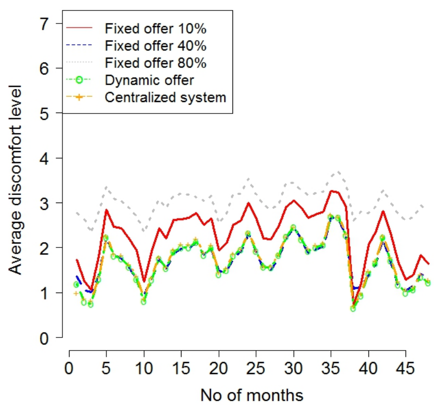
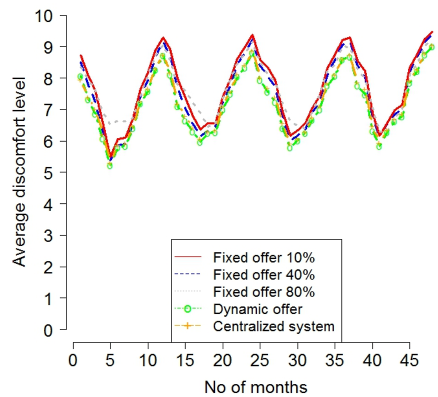


Fig. 7: Comparison of C2's discomfort in different approaches



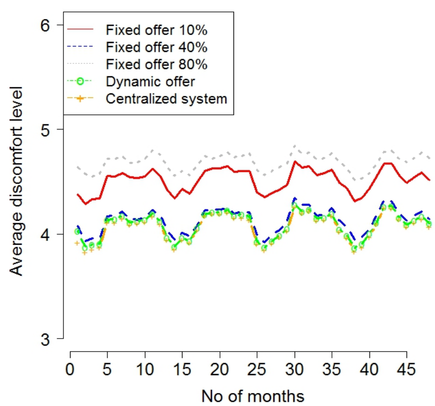
the fixed offer mechanism, we ran the experiments by varying the value of α (Algorithm 1) i.e. 10%, 40% , and 80%.

Figure 6 depicts the result when C1 employed the two approaches for dynamic coalition formation. The result shows that the fixed offer approach does not give the optimal reduction in discomfort unless the community knows the best value of α. However, in dynamic offers, C1 does not need to know the value of α which gives the least possible discomfort. In our experiments, after trial and error we found that the optimal value of α in fixed offers is 40%. Any increase or decrease in the optimal value of α (i.e. 10% or 80%) results in the increase of discomfort level. 40% is the optimal value of α for the configuration we had in our experiments. However, this is likely to change based on the underlying data (e.g. sun and wind), whereas dynamic offers always finds the best possible value to offer, which results in reducing its discomfort without any trial and error method on any data set. We also found that the dynamic coalition formation by using dynamic offers is also significantly closer to the centralized system which is considered to be the optimally arranged power sharing mechanism. However, because of the centralized system's single-point-of-failure nature, it is not resilient. Similarly, Figure 7 shows the result of C2, where a similar trend of result was observed. The dynamic offer mechanism gives the highest reduction in discomfort and is closer to the centralized system approach.

At the system level, it was also evident that the dynamic coalition with dynamic offers performs better than others. We ran our dynamic coalition formation mechanism using fixed and dynamic offers on low-loss transmission systems. Results are shown in Figure 8. We found the dynamic coalition formation mechanism using dynamic offer performs better and closer to the centralized system. Hence by employing our dynamic coalition formation using dynamic offer, not only was the discomfort reduced significantly, but it also overcomes the issue of single-point-of-failure present in the centralized system. We also conducted the same set of experiments on high transmission loss systems and found the same trends also exist.

6 Conclusion & Future work

Fig. 8: System's discomfort level in low losses configuration



In this paper, we have presented our dynamic coalition-formation mechanism for micro-grids when they operate in a situation where there is no available support from a main utility grid. The goal of the coalition formation is to reduce the discomfort of communities because of deficit power generation.

Experiments show that our mechanism of dynamic coalition formation using dynamic offers is effective in reducing discomfort level (i.e. discomfort) of a communities. We have also shown that, compared to the standalone, fixed coalition, and dynamic coalition formation using fixed offer approaches, the dynamic coalition with dynamic offers outperforms and reduces the discomfort level at community and at the system level by considerable amounts. We believe the mechanism presented in this paper can be used by remote (rural) communities to reduce their discomfort by improving the availability of power required through local power sharing, while avoiding the reliance of the main utility grid.

For future work, we intend to introduce a split and merge algorithm for the coalition, so that coalitions could merge with other coalitions in order to more optimally reduce transmission losses.

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