Using game theoretic approaches to implement smart grids

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Except where acknowledged in the customary manner, the material presented in this thesis is, to the best of my knowledge, original and has not been submitted in whole or part for a degree in any university.

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Abstract

The smart grid is a user system that will elevate the conventional electrical grid system to one that functions more cooperatively, responsively and economically. One of the most important features of smart grid technology that makes it smart or smarter than the current grid is the integration of bi-directional flow of information along with electricity, which can be used to provide effective and controlled power generation and consumption. In this project, first we investigate how game theory can be used in smart grid communication due to its proven efficiency in wireless and wireline communication. And then to implement algorithms using cooperative game theory to solve the problem of the power loss during power transfer process. We have applied the game theoretic coalition formulation strategy and explain how the micro-grid action as to form coalition group to minimize the power loss when power is transmitted from a micro-grid to another micro-grid or the macro station. To maximize the profit of coalition, a micro-grid will find partners which are able to maximize the payoff function value. In this project we focused in particular on using cooperative game theory to solve the problem of power loss.

Contents

List of Figures

List of Tables

When theory and experiment agree, that is the time to be especially suspicious.

Niels Bohr

1 Introduction

The smart grid is envisioned to be a large-scale cyber physical system that can improve the efficiency, reliability and robustness of power and energy grids by integrating technologies. Thus, the smart grid is a power network that contains intelligent nodes that can operate, communicate, interact in order to efficiently deliver power and electricity to their customer. The future of energy could be a network of renewable micro-grids.

Recently the consumption of electricity has increased with the growth of technology, however the demand of electricity is not balanced during a day. Therefore , new type of intelligent power grid called smart grid is becoming popular because it can help to organise effectively the demand of electricity and reduce the power loss and wasted power.

There are a number of problems in supplying power at a national level. One arises when the national grid supplied by eg coal and nuclear power plants is supplemented by renewable energy generated at a local level (eg solar panels). Here there is a load balancing problem where the power generated from various sources must be shared equally across the grid. Another problem is due to energy loss. Energy can be lost when the electricity travels great http://reneweconomy.com.au/2015/australias-energy-future-could-be-network-of-renewable-micro-grids-84534

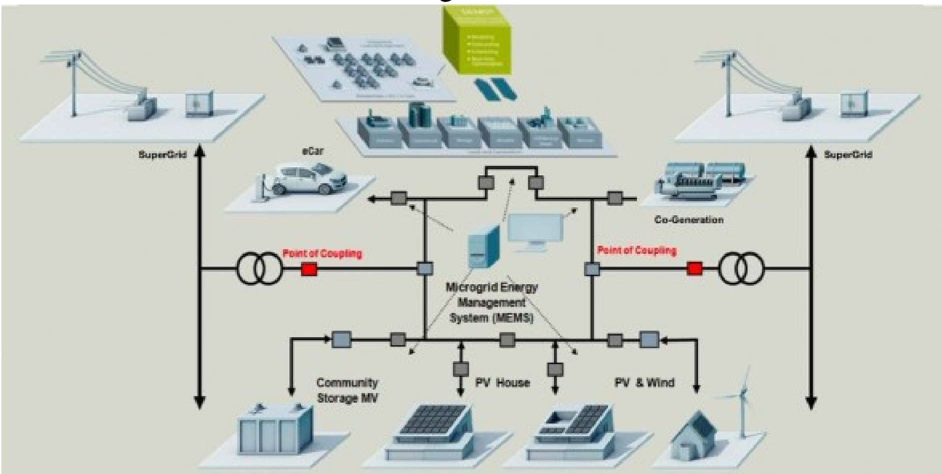

Figure 1.1: Future of energy grids

distances. This is primarily due to the quality of the cables. In this project we will focus on techniques to reduce this kind of power loss by using game theory techniques to formulate the coalition group of micro-grids. Recent work has shown that there can be some efficiency savings when the architecture of the grid is considered as a market where electricity can be bought and sold [1]. When considered as a market it has been proposed to use game theoretical results to find the optimal way to arrange power distribution. We outline the relevant game theory in section 2.3.1. In the next section we summarize how the grid can be viewed as a market for electricity, and describe the research challenges that we address in this thesis.

1.1 Detail about the grid in general

In this section, we describe the smart grid architecture in general [2]. There are 2 main components of smart grid which are distribution system and communication layer.

As they can considered to be separated, We then can consider the general model of distribution system as following. In a power grid organised as a market we assume that there is a centralised macro station supplying power over a wide geographical area. This macro station supplies power to local micro grids which in turn distribute power to houses and businesses. Micro-grids have been introduced recently as a way to reduce power loss , which can supply electricity to end users linked to corresponding micro grids. Micro grids can exchange power with others and also transfer power with Macro station, which play roles as substation of the smart grid Macro-station is the main substation of smart grid, micro-grids are deployed near

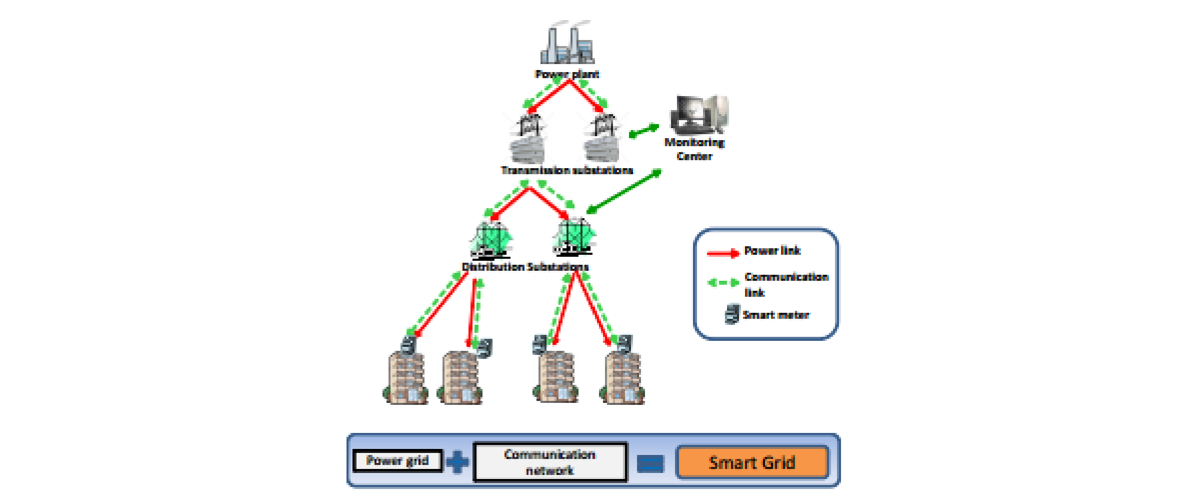

Figure 1.2: Smart grid communication networ

the users to avoid power loss.Users are residential customers, schools , companies which use electricity. The end users can install a smart meter. As shown in above figure, the users are supplied electricity by the macro station or number of micro grids , because the power loss between the macro station and a micro grid is more than between micro grids thus forming coalition is the way to reduce power loss. Every micro-grid is connected with macro-station via medium voltage line through a voltage transformer while it is connected with other micro-grids with low voltage line. Therefore, if micro-grids transfer power with macro-station then loss will occur at transformer device. The efficiency of power transformers is quite high and may reach 99 percentages thus power loss occurring in the transformer can be ignored. For cables its the contrary, when power is transfer via lines, temperature can be raised and heat bleeds away as lost energy.

1.2 The challenges today

The assumption is that the distance between the macro station and the micro grids is large whereas the distance between some micro stations can be relatively smaller. This suggests that there is an opportunity for micro-stations that are geographically close can trade power thereby reducing overall power loss because the power can be transferred directly between micro grids. This can be more efficient than eg wasting energy when there is a surplus rather than redirecting it to a nearby micro grid. The micro grids can cooperate by forming coalitions where the total power requirements of the coalition can be balanced between members trading between each other.

There are several challenges for organizing an effective cooperation. We address the following:

1. What is the best way to form coalitions to optimize power loss?
2. Once the coalition has been formed, how can the power be balanced across the coalition?.
3. How are the communications arranged so that the load balancing can be implemented?.

1.3 Research method

There are a number of proposals in the literature for using game theory to form coalitions in the context of power grids. We first reviewed these methods. Next we chose an algorithm proposed by Chakraborty et al. [3] and studied its advantages and disadvantages as follows.

1. We first implemented the algorithm proposed by [3].
2. We tested the algorithm to reproduce their results.
3. We analysed shortcomings of the algorithm, and in particular evaluated its effectiveness for reducing power loss.

The contribution of this thesis is to reevaluate the techniques used to justify the algorithm proposed by [3] In doing so we discovered some problems with their proposed approach, together with some discrepancies in their experimental results.

We report our findings and recommendations in Section 4.

2

Game theory used in designing a Smart Grid

2.1 Review of game theory

Game theory is a key tool in the design of future smart grid, which is a formal analytical as well as conceptual framework with a set of mathematical tools that can help to study the complex interactions among independent rational players [4]. For many years, game theory has been applied to wide range of disciplines from economics to politics. In this thesis, we aim to apply cooperative game theory to solve the problem of power loss of micro grid distribution network and also provide algorithm which can be deployed using game theory approach. A game consists of a set of players, each of whom may select a strategy having the an objective of maximizing payoff.

For example, one could easily set up a game similar to the one above using companies as the players. This game could include product release scenarios. If Company 1 wanted to release a product, what might Company 2 do in response? Will Company 2 release a similar competing product? By using game theory we can set up the payoff function as the profit each company can get with a set of predefined strategies.

In many forms of game, there is also a quantitative component describing the amount if winnings a player will receive. In abstract terms, a player can choose a strategy to play a game. Depending on his strategy he will entire win or lose, and usually his objective is to choose a strategy to maximize his payoff or to minimize his losses.

Types of game theory. Game theory is a mathematical framework that can be divided into two main branches: noncooperative game theory and cooperative game theory.

2.2 Non-cooperative game theory

In the smart grids, the applications of non-cooperative games are numerous. On the one hand, non-cooperative games can be used to perform demand side management[4].On the other hand, market and dynamic pricing are a crucial part of the smart grid which non-cooperative games can be used to optimize pricing strategies. Game theory, where there are many players , there is a choice between cooperating with other players or not [4]. Non-cooperative game theory,(NCGT) models the actions of agents, maximizing their utility in a defined procedure, relying on a detailed description of the moves and information available to each agent. Non cooperative game theory can be grouped into two categories: static games and dynamic games. Static games are games in which the notions of time or information do not affect the action of choices of the players. In contrast, dynamic games are games which the players have some information about each other choices, can act more than once, and time has a central role in the decision marking. When the game is dynamic, one needs to also define additional components such as information sets, time or histories which are usually reflected in the utility function. The objective of non-cooperative game theory is to provide algorithms and techniques suitable for solving optimization problems, when the players are making their choice without any communication. Nash equilibrium is one of the crucial concepts for game theory. A Nash equilibrium recommends a strategy to each player that the player cannot improve upon unilaterally, that is, given that the other players follow the recommendation. Since the other players are also rational, it is reasonable for each player to expect his opponents to follow the recommendation as well. A Nash equilibrium of a static non-cooperative game is a vector of actions $(s_1, ..., s_n)$ for each player i, hold that $u_i(s_i, s_{-i}) >= u_i(s_i', s_{-i})$[1] The Nash equilibrium serves as a building block for many types of non-cooperative games. non-cooperative games can be used in the distributed control of micro-grids. The work in [5] shows that the use of non-cooperative games can model the interactions between sources and load in a small-scale power system. Game theory can also constitute a foundation for enabling distributed control of loads and sources in small scale system by developing objective optimization. Another application of non-cooperative game is to use in price load balancing [6].

2.3 Cooperative games

In non-cooperative games, the players are unable to communicate with one other. However, cooperative game theory models how agents complete and cooperate as coalitions in unstructured interactions to create and capture value[7]. Cooperative games allow to investigate how agent can provide an incentive for independent decision makers to act together as one entity so as to improve their payoff in the game. For example, in politics, parties can merge or split into a coalition group as to improve their chances in obtaining a share of power. Cooperative game theory is divided two parts: Nash bargaining and coalitional game. In the first part, a number of players need to agree the terms under which they cooperate while in the second part the formation of cooperative groups is introduced. Cooperative game theory in both situations provides that the players to decided on whom to cooperate with and under which terms given several cooperation incentives and fairness rules.

2.3.1 Game theory applied to the smart grid

Game theoretic approaches present a promising tool for the analysis of the smart grid. The applications of non-cooperative games are numerous. Non-cooperative games can be used to perform demand side management and real time monitoring to control micro-grids.Others application of non-cooperative game theory for smart grid is for autonomous consumer load balancing. In the traditional power market, electricity consumers often pay a fixed retail price for electricity usage. Agarwal and others [6] formulate non-cooperative games among the consumers with real-time pricing schemes to derive autonomous load balancing solutions. The problem of maximizing the payoff at each consumer by designing the distributed load balancing strategy under real-time pricing schemes set by the retailer. The first is the average cost based pricing scheme and the second is the increasing block pricing scheme. Cooperative game theory can be applied to enable a limited form of communication between the micro-grids. The integration of power , communication and networking technologies in future smart grids opens up the door to several application in which smart grid nodes can cooperate to improve the robustness and efficiency of the grid. In this thesis, we provide coalition game theory on the deployment of micro-grids and we provide the communication protocol over the coalition form algorithm. There are 3 parts in game theory - the set of players N, the strategy of players and the function v that assigns for every coalition showing total benefits achieved by this coalition group. Players are the micro grids and their objective to supply users with sufficient power whilst minimizing power loss. It has been observed that if the micro grids form coalition so that they can transfer power directly between members of coalition rather than going through the macro grids,then the is some benefit in terms of reducing power loss

Introduction to micro-grid distribution network A power grid can be divided into two main phases: electric power transmission and electric power distribution. Electric power transmission deals with the transmission of the energy generated at the power plants or macro grid. Electric power distribution is for delivering electricity in which the distribution network carries the electricity received at a substation and delivers it to the consumers.The concept of a micro-grid is defined as a networked group of distributed energy sources such as solar panels or wind turbines located at the distribution network side and which can provide energy to a small area. Thus controlling the operation of the micro-grids and integrating them in the smart grid introduces several technical challenges that need to be solved.

Coalition game theory to solve the power loss of micro-grid distribution The novel cooperative strategies for micro-grid distribution network was proposed by Walid Saad and others [8] but the algorithm to form the coalition was not explained clearly.

In figure 4.2 we illustrate the architecture of an electrical grid. Let MG be the set of micro grids and $P_{i,j}$ be the power loss incurred by i sending power to j and we denote 0 for Macro station. Let $S \subseteq MG$ be a coalition of the micro grids which contain power seller and S_s and power buyer S_b, and $S = S_b \bigcup S_s$. In one coalition, it consists of buying and selling power of micro grid so in order to calculate the payoff functions of all coalition we calculate the payoff function of each coalition . In one coalition, the power loss between seller and buyer is

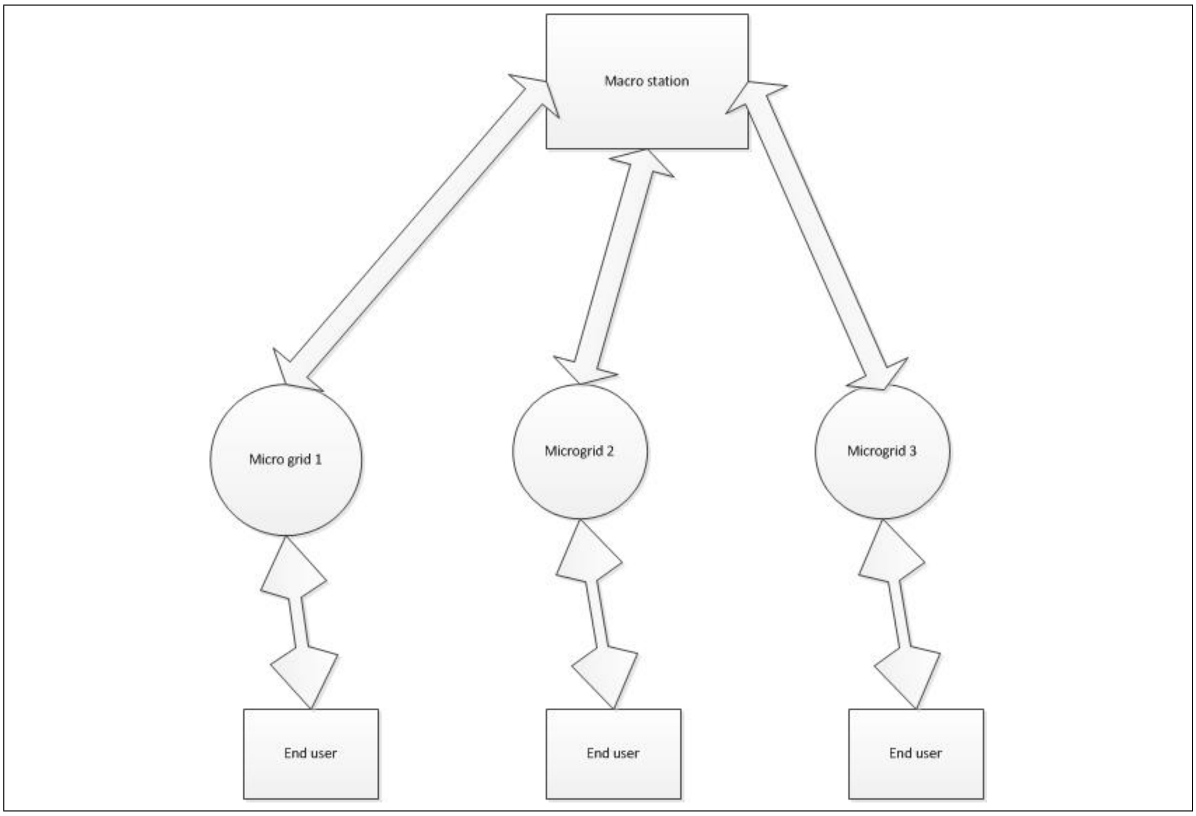

Figure 2.1: Architecture of an electrical grid

expressed as follows :

$$P_{ij} = R_{ij}Q_{ij}^2/U_{ij}^2$$

where R_{ij} is the resistance of the distribution lines between micro grid i and micro grid j, Q_{ij} is that power micro grid i wants sell , and U_{ij} is the transfer voltage between micro grid i and micro grid j. Due to power loss between micro grid, then micro grid j buy an extra power $U_{ij}^2/2R_{ij}$ from micro grid i. The total payoff function of one coalition group can calculated by following formula.

$$u(S) = -(\omega_1 \sum_{i\in S_s, j\in S_b} P_{ij} + \omega_2 \sum_{i\in Ss} P_{i0} + \omega_2 \sum_{j\in Sb} P_{j0}) \tag{2.1}$$

where ω_1 and ω_2 are the price of a unit price. As shown in the equation above, in one coalition S, total payoff function consists 3 parts - power loss between the micro grids and the power loss by the micro-grid selling power to the macro station, and the power loss caused by the micro grid buying power from micro station. The resistance between micro-grids or micro-grid with macro station depends on the quality of wire and the length of wire, thus the resistance between micro-grids is much smaller than between micro-grid and macro-station. The value function for the micro grid coalition game and we need to find the maximum of this function. While this work described the coalition formation problem but the algorithm to form coalition still not clearly developed. In this project, we review the work in paper [3] and implement algorithm to form coalition group of micro-grids and research how it can help to reduce the power loss. Then we compared the results by experiments and provided the data structures for proposed algorithm.

3

Algorithm to form coalition group

Problem In game theory, each micro grid acts as player that can make different choices about which coalitions to join and which micro-grid or macro station to buy power from. And the problem is that how to get the best decision for each player or micro grid. One way to fulfill the power demand is to buy power directly from macro station but in this arrangement there is a lot of power loss. Better is to find a cooperative strategy whereby micro-grids form coalition which allows them to trade power without going through the macro station. For example, let us look at the formation with total of 9 micro-grids. The coalitions are formed based on their location, power demand or surplus to achieve the goal of minimizing the power loss. In coalition 1, micro-grid will generate surplus power of 250 kWh while micro-grid 1 has power demand of 70 kWh. After the power need of micro-grid 1 is satisfied, the surplus power of 180 kWh will be sold to macro-station. In the coalition 2, micro-grid 2 can supply about 80 kWh and the total demand is 80 kWh. Thus, total demand can be satisfied in the coalition.

The problem now is to find the best way to form coalitions so that all micro-grids fulfill their

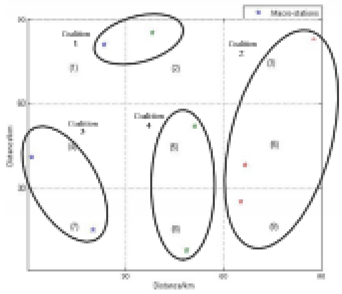

Figure 3.1: Micro-grid coalition form example

power demands, whilst as a whole there is as little power loss as possible. In a coalition, one micro grid could be in surplus that allows the surplus to be sold direct to another micro-grids in the same coalition. Let denote for micro-grid i, the total supply is S_i and the demand is D_i, the coalition C. We can calculate utilities of micro-grids and for coalitions. Utility function for micro-grids:

$$U_i = \frac{1}{1 + |S_i - D_i|} \tag{3.1}$$

Utility function for coalitions. The aggregated energy status of a coalition - E_C is defined by following:

$$E_C = |\sum_{i \in C} \left(D_i - S_i \right) \tag{3.2}$$

The utility function for a coalition can calculated by following :

$$U_C = \frac{1}{1 + E_C} \tag{3.3}$$

In proposed game, the characteristic function of coalition C is defined by:

$$\vartheta\,(C) = \sum_{i \in C} U_i - U_C \tag{3.4}$$

We then try to show the convexity of the game. The meaning of that convexity is to show no micro-grid can increase its payoff by switching coalitions unless one of the other microgrids decreases the payoff and thus decrease the payoff of the coalition where they belong. The characteristic function can rewrite as follow:

$$\vartheta(C) = \sum_{i \in C} U_i - U_C = \sum_{i \in C} [\frac{1}{1 + |E_i|}] - \frac{1}{1 + |\sum_{i \in C} E_i|} \tag{3.5}$$

Then we can reformulate as to find maximum of following function:

$$V(C) = \sum_{i \in C} |E_i| - |\sum_{i \in C} E_i| \tag{3.6}$$

S and T are the two subsets of N. We can rewrite as follow:

$$V(S)+V(T) = (\sum_{i\in S})|E_i|-|\sum_{i\in S} E_i|)+(\sum_{i\in T}|E_i|-|\sum_{i\in T} E_i|) = (\sum_{i\in S}|E_i|+(\sum_{i\in T}|E_i|)-(|\sum_{i\in S} E_i|+|\sum_{i\in T} E_i|)$$

$$\leq (\sum_{i\in S\cup T}|E_i| + (\sum_{i\in S\cap T}|E_i|) - (|\sum_{i\in S\cup T} E_i| + |\sum_{i\in S\cap T} E_i|)$$

$$\leq (\sum_{i\in S\cup T})|E_i| - |\sum_{i\in S\cup T} E_i|) + (\sum_{i\in S\cap T}|E_i| - |\sum_{i\in S\cap T} E_i|)$$

$$\leq V(S\cup T) + V(S\cap T)$$

$$\Rightarrow V(S\cup T) \geq V(S) + V(T) - V(S\cap T)$$

(3.7)

Therefore, V is convex. A micro-grid can get highest payoff when energy exchange is maximized. The Optimal Coalition is state that every micro-grid is stay with the current coalition that mean no micro-grid can increase its utility by joining to other coalitions.

We redo the algorithm with more clearly data structure and test with different number of micro-grids and thresholds. While in the paper [3], they mentioned about the power loss but did not take into account the power loss without clear explanation. The power loss ignored in the their paper is between micro-grids itself because of short distance but the power loss reduction is that instead of buying energy from macro-station which has long distance to micro-grids and the users , the micro-grid can buy and sell between each other in one coalition to avoid long distance transfer power loss.

3.1 Cost to the consumers

Traditionally, a micro-grid operates in the grid connected mode where the demand is fulfilled by buying energy between that microgrid and macrostation. However , micro-grid prefers to sell or purchase energy from another micro-grid between formed coalition than to buy from macro station because power loss caused by the energy transmission and transformers . Microgrids inside the coaltion can transfer necessary energy to minimize losses. Let denote, ω_1 is the selling/purchasing price between micro-grid, ω_2 is the purchasing price from macrostation. For example $\omega_1 = 0.1, \omega_2 = 0.2$ A micro-grid always try to buy from other micro-grids to get benefit as $0.2 - 0.1 = 0.1$ and a micro-grid will make profit if sell to macrostation $0.2 - 0.1 = 0.1$. Without coalitions, the cost to the consumer is $\omega_1 * S$. The consequence of power loss to the consumer is that they need to buy more power to satisfy the demands. Thus the power loss is proportional to the amount saved.

When there is no power loss at all, S matches D and so the cost is $\omega_1 * D$ so $\omega_1 * |S - D|$ is the extra that the consumer pays. Therefore, if micro-grids form the coaltion the power losses will be significantly reduce and the cost to the customer is reduced too.

3.2 Algorithms to form coalition

Hierarchical priority based Coalition (HR Coalition) We describe how to model the formation of coalitions and how to distribute energy one the coalitions had been formed. We model a micro-grid as a point on a map; each micro-grid has an Energy Status which means the power demand or surplus.A coalition is a set of of micro-grids. Each coalition has an energy status which is given by sum of power surplus over power demand of all micro-grids inside the coalition.

The first phase of the algorithm is to group the mirogrids in such a way as to minimise the energy loss. We follow approach [3] for this, given that we want to maximise the convex function V.This is done by grouping together micro-grid and then transfer energy between them.

HR Coalition form optimal micro-grid coalitions and analyze the characteristics through the eyes of coalitional game theory. HR coalition formation scheme pairs up two high priority coalitions(highest aggregated load and highest aggregated supplier), if they are located within certain distance from each other.[3]. We develop the following data structures to implement the algorithms.

```
// Data structures
class micro-grid {
        Coordinate(X,Y); // position of micro-grid
        double EnergyStatus; // can be surplus or need
}
class coalitionGroup {
        double energyStatus;
        function addmicro-grid();
        function removemicro-grid();
        function calculateEnergyStatus();
        // method to calculate the energy status a coalition
        function getCenterOfcoalition();
        // calculate the centroid of  a coalition
}
```

```
class smartGrid{
        macroStation(X,Y); // position of macrostation
        connectivityMatrix[][]; // connectivity matrix
        double resistanceValue; // resistance value of wire
}
```

The first algorithm to form the coalition, a micro-grid lg tries to find the nearest pg which located in the distance threshold d from lg and the connectivity between lg and pg exist.

Data: Input: Information of microgrids - Location, energy status G, connection matrix, where conn(i,j) = 1 if there is a physical connection between i and j. Based on location we can estimate the distance between i and j. Distance threshold - d

Result: Output: Set of coalitions.

forall <set $C_i = i$>;

Find the centroids of C_{is};

change = True;;

while *change* **do**

    Set CPG = Group of C_{is} who can provide energy;

    Set CLG = Group of C_{is} who need energy;

    Sort CPG in descending order of energy supply amount;

    Set CLG in descending order of energy demand amount;

    for C_l *in CLG* **do**

        Find the coalition in CPG whose central is located within the distance threshold d;

        $C_l = C_l \cup C_p$;;

        Remove C_p from CPG;

        update energy status of C_l;

        update centroid of C_l;

        change = False;

    end

end

Algorithm 1: Algorithm 1 Hierarchical priority based coalition formation

Algorithm 2 is used to manage the proper distribution of energy among the microgrids after coalition groups formed.

Data: Input : micro-grid Coalition result from algorithm 1, connection matrix conn(i,j), distance threshold d

Result: Output: Energy transfer matrix between i and j.

Set PG = Group of energy provider in coalition C;

Set LG = Group of energy need in coalition C;

Sort LG in descending order of energy demand;

for *each* $lg \cup LG$ *do* **do**

  while *lg.energy > 0* **do**

    pg = find the nearest available micro-grid in PG from lg;

    pg is not found then ET(0,lg) = lg.energy;

    t = min(pg.energy,|lg.energy|);

    lg.energy = lg.energy - t;

    pg.energy = pg.energy - t;

    ET(pg,lg) = t;

    available(pg,lg) = False;

  end

end

Algorithm 2: Energy management within a coalition

4

Experimental results

Our aim in this section is to reproduce the experiments in paper [3] and to re-evaluate the results.

In [3] the result was that there was up to 70-80 percents reduction in power loss using the algorithms explained above.

In summary, we were unable to reproduce their results, but we did find that there could be some relationship between the parameters used in the simulation and the degree of power loss. This suggests that the claimed reduction in power loss is not generally observed, but only in scenarios where the parameters are close to those used in the simulation experiment reported in [3].

We randomly put numbers(10 to 100) of micro-grids within of 5 square km, the distance threshold is 2.5, 5 and 10 km and the power requirement is randomly generated. The distance between micro-grids are randomly generated based on the location of micro-grids. The power losses are both from transformer high/low voltage and from distance between micro-grids and macro-station, the power loss occurs in the transformer device are now about 5 percents, thus the most loss when power is travel via line. The more coalitions are formed can make the power loss reduce by shortening transmission distance.

4.1 Power loss reduction

Power loss is loss to transfer energy E over the geographical distance between node i and node j, between micro-grids of a coalition and between micro-grids and macro station.

$$loss(i,j) = I^2 R = \frac{P(E)^2}{\Psi} \times \alpha(i,j)$$

where $P(E)$ is the power required to transfer energy, Ψ is carrying voltage of transmission line, α is the resistance of the wire , $d(i,j)$ is geographical line distance between i and j.

We first explored how the power loss was affected by the formation of coalitions as show in the figure 4.1.

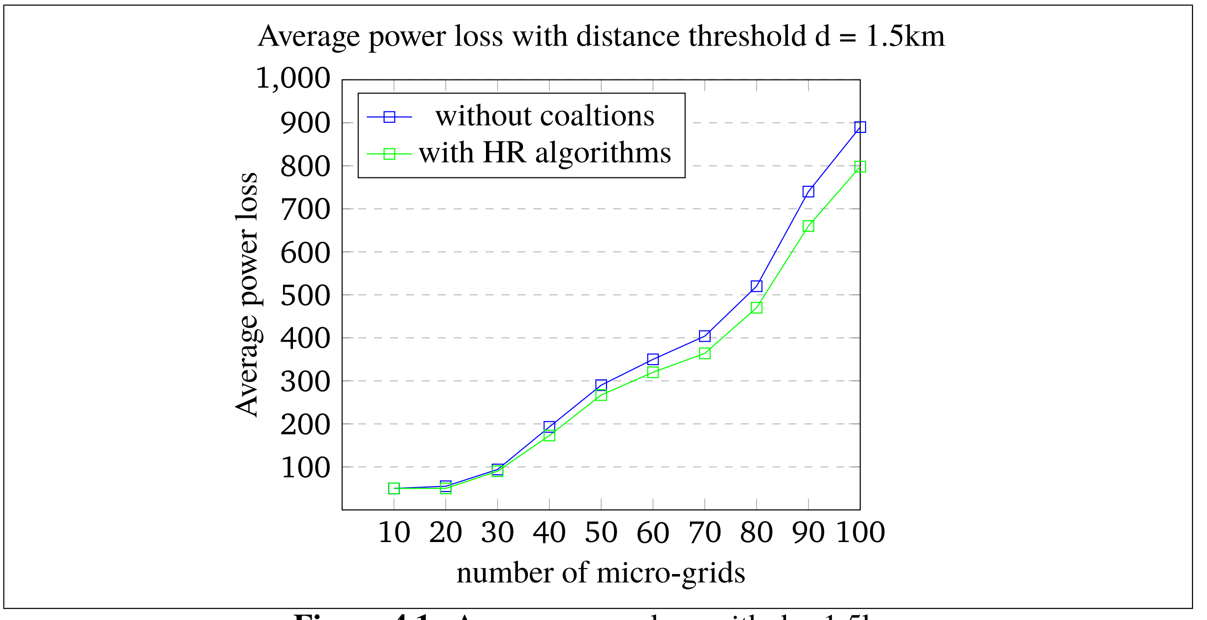

Figure 4.1: Average power loss with d = 1.5km

As the number of micro-grids grow, HR coalition algorithm increases power loss reduction. The average percentage of reduction is about 7 percents.

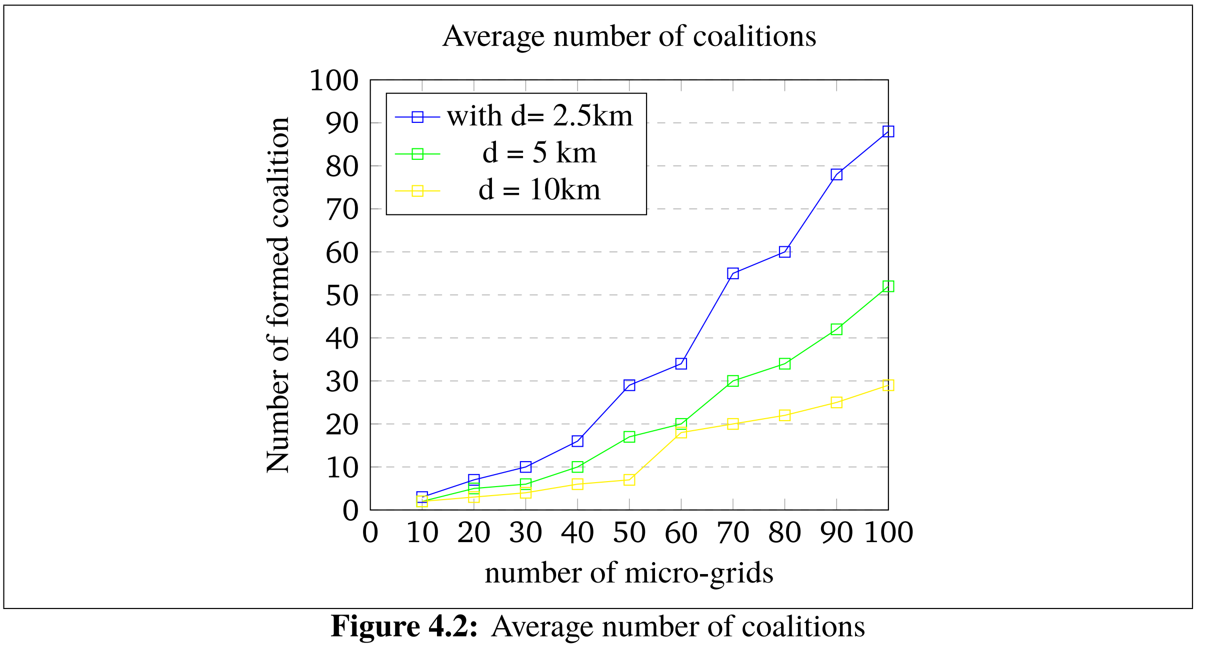

Figure 4.2: Average number of coalitions

As we can see from 4.2 , more coalitions are formed when the number of micro-grids is increased.

As the 4.1 shows , when the distance threshold is increased, more micro-grids join a coalition which means that there are fewer coalitions in total.

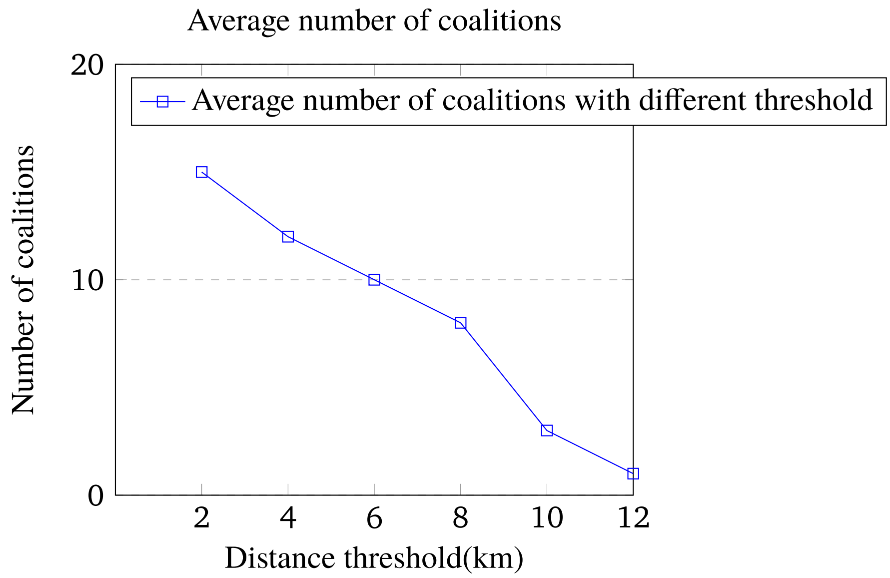

Figure 4.3: Average number of coalitions with different thresholds

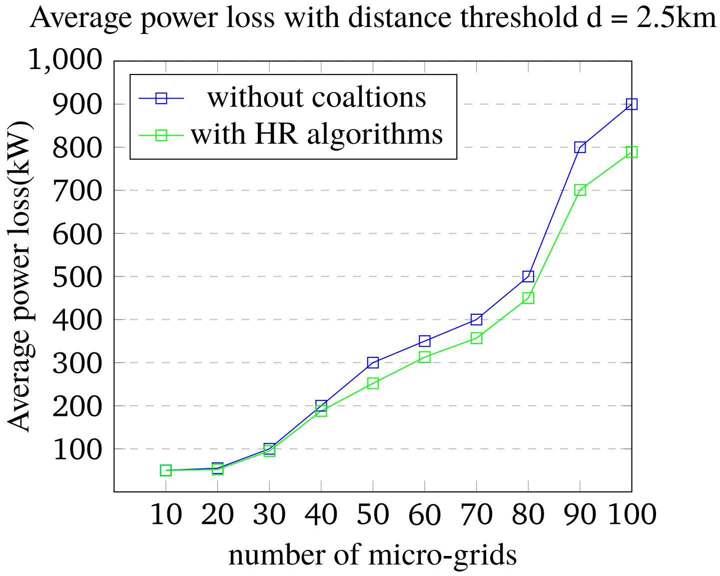

Figure 4.4: Average power loss with d = 2.5km

As show in 4.4, the average percents of power loss reduction is about 10 percents if we use HR algorithm to form the coalition, also the reduction will see clearly if there are many more micro-grids in the distance threshold of 2.5km. We then change the parameter distance threshold with d = 5km and d = 10 km to verify relation between distance thresholds and number of formed coalitions as in figures 4.5, 4.6

Figure 4.5 shows that when we increase the distance threshold d = 5 and 10 km, the number of formed coalitions reduced and this trend makes the reduction of power loss is reduced.

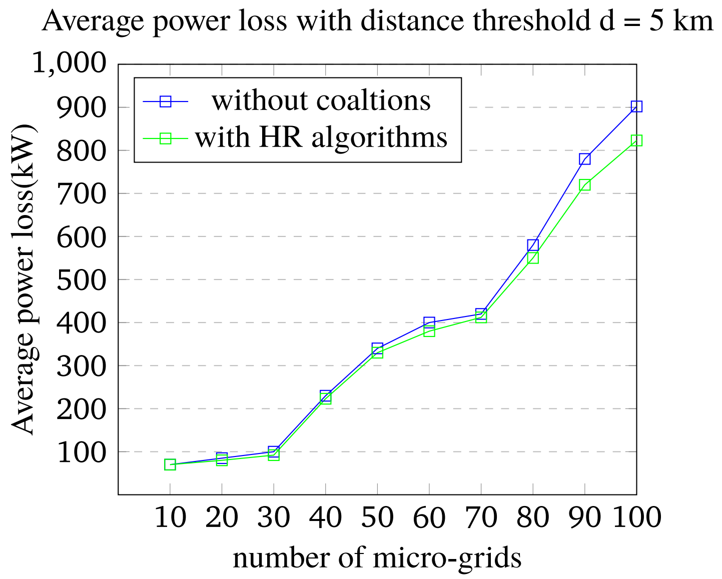

Figure 4.5: Average number of coalitions with d = 5km

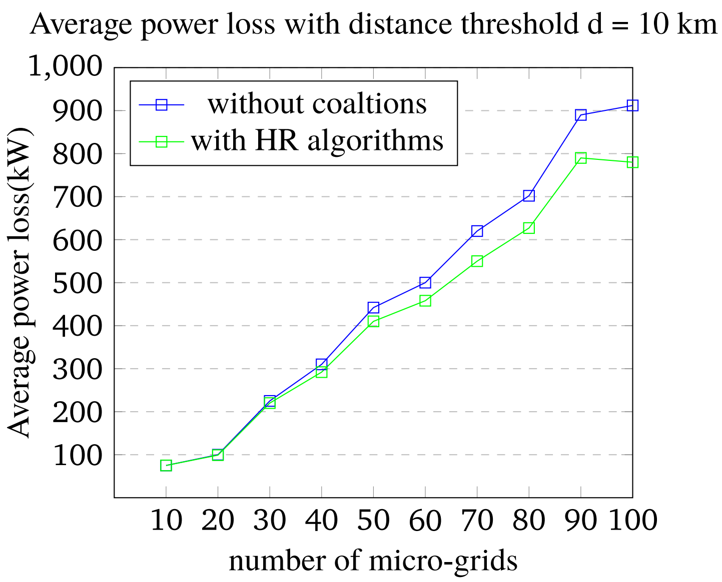

Figure 4.6: Average number of coalitions with d = 10

Table 4.1 show that the power loss occur when micro-grids buy from macro-station is more than 2 times between power loss between micro-grids in one coalition.

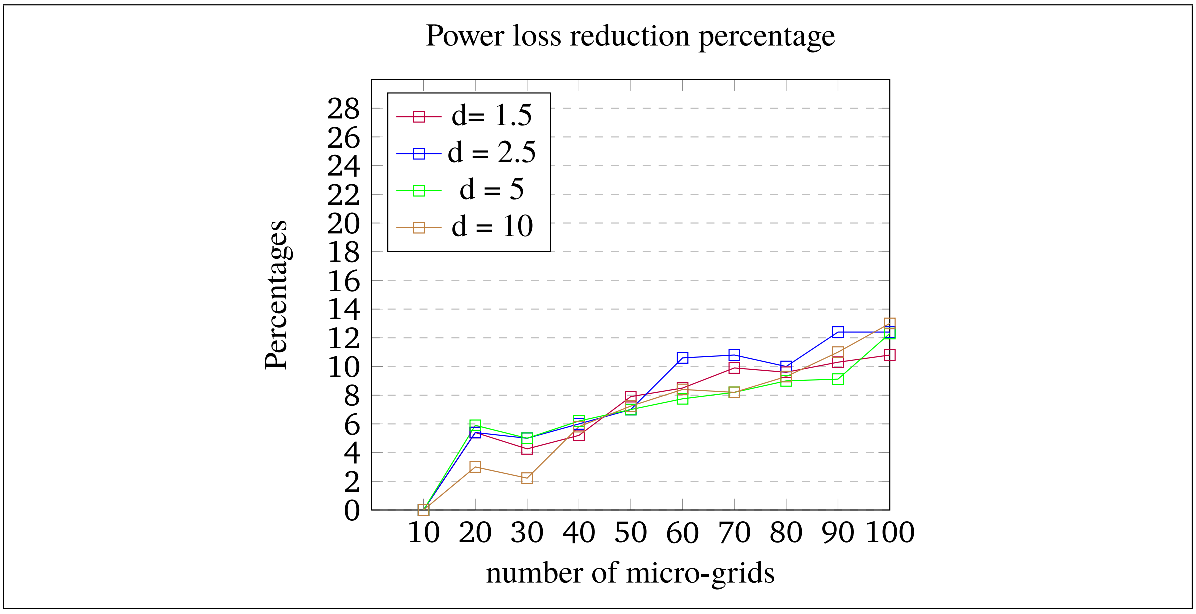

Figure 4.7: Power loss reduction percentage

Table 4.1: Average power loss with d = 2.5

Number of micro-grids	Number of coalition	Between coaltions(kW)	From micro-grids to macrostation(kW)
10	3	10	20
20	7	12	25
30	10	9	21
40	16	12	23
50	29	13	26
60	34	8	16
70	55	10	22
80	60	11	22
90	78	12	25

Above figures show the number of average number of coalitions, we can see the more micro-grids the more coalitions are formed.As we can see from graph, when the number of micro-grids more than 50 then the power loss is significantly reduced with coalitions (about 10 percents).

These figures shows the average power loss reduced with HR coalition scheme for different thresholds and number of micro-grids. As the micro-grids increased, the power loss reduction is also increased.

Figure shows when the distance threshold is increased, the number of coalitions formed tend to be reduced and this trend lead to power loss reduction declined. From figure 8, we can see the power loss reduction depends on the number of coalition micro-grids are formed and the number of micro-grids in the areas. The more micro-grids and more coalition groups are formed the more power loss reduction.

4.2 Relation between grid size and threshold

Another factor affect to power loss reduction is the grid size(the distance between micro-grids). When we change the grid size in experiments to recheck the relation between power loss and grid size with different threshold d = 1.5km and d = 2.5 km.

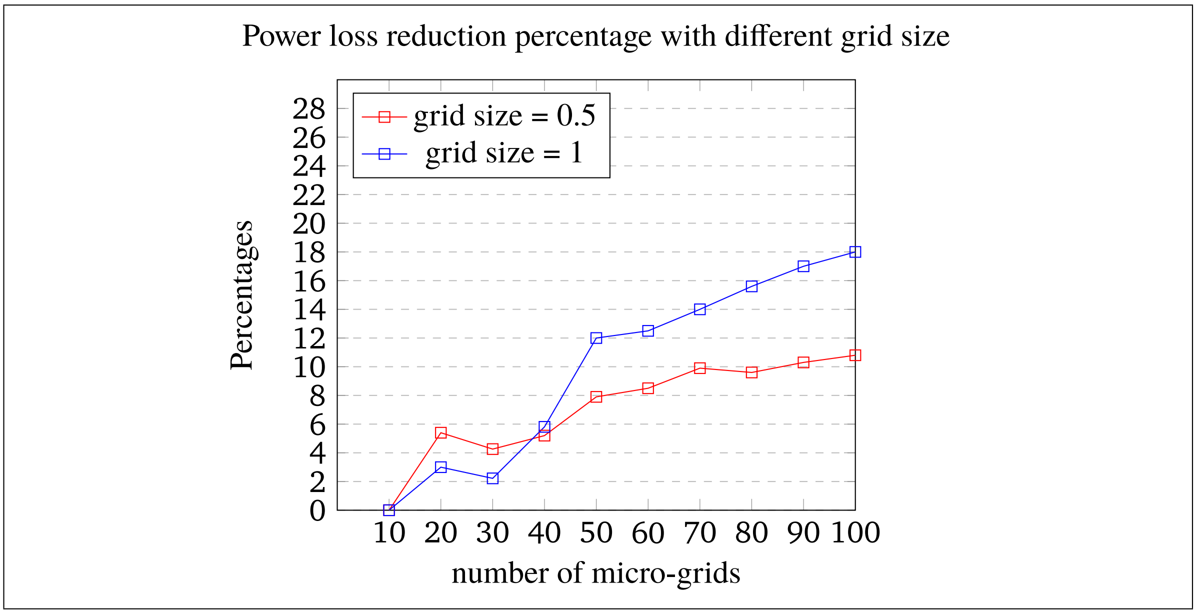

Figure 4.8: Power loss reduction percentage with d = 1.5

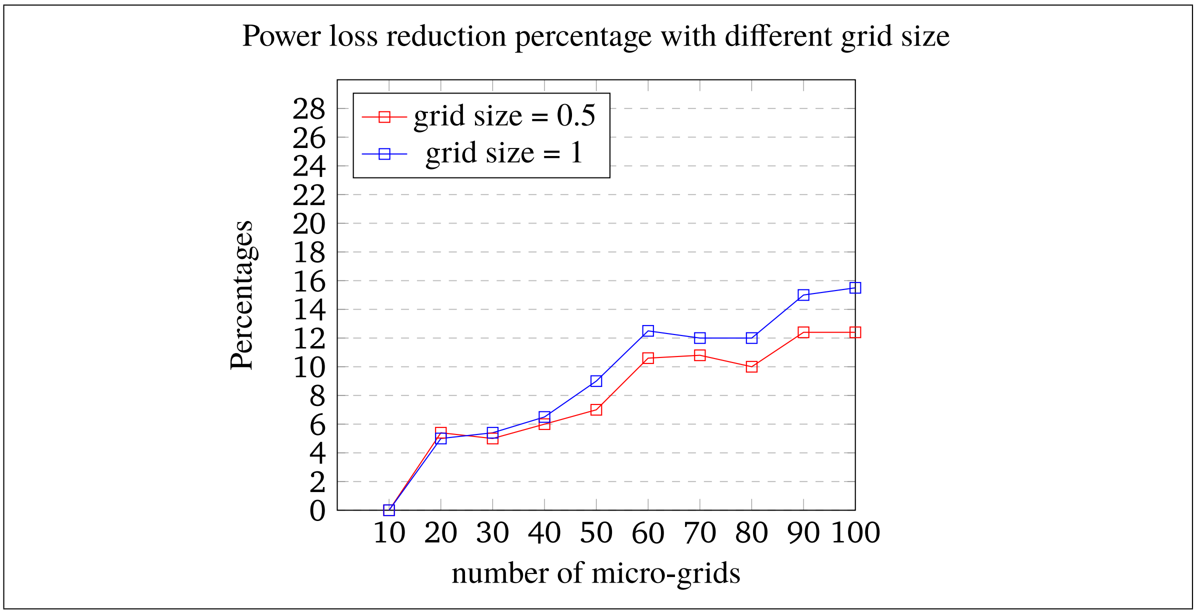

Figure 4.9: Power loss reduction percentage with d = 2.5 km

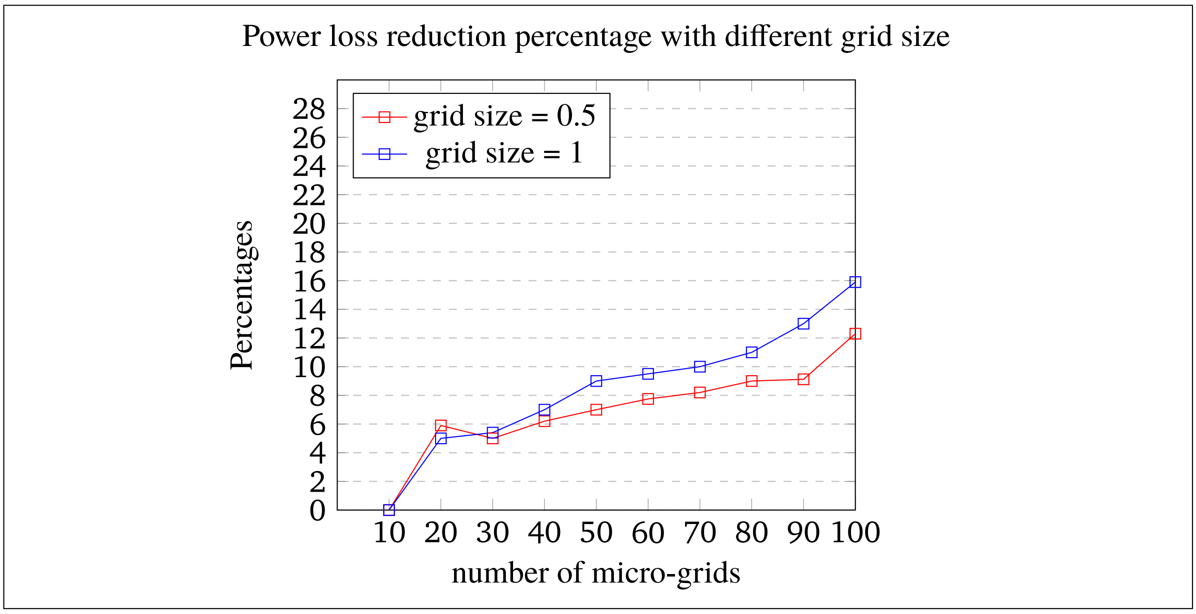

Figure 4.10: Power loss reduction percentage with d = 5 km

We then compare the power loss reduction percentages with different distance thresholds as shown in figure 4.10. When the number of micro-grid is more than 90 then the distance threshold will not effect to the percentages of power loss reduction when we used HR algorithms.

Figure 4.8, 4.9 and 4.10 show that when the grid size is longer, there is a radical improvement in the power saved. So we can conclude that the distance between micro-grid is important factor when coalition groups are formed and power loss are significantly reduced with longer distance.

4.3 Summarizing section

While the proposed algorithms are clear but the experiments were not clear described in the paper [3], there are problems with their results part as follow:

1. The power loss reduction in the paper significant higher than in this thesis. We were unable to reproduce the results in the paper. The power loss after coalition forming also depends on the distance threshold and grid size between micro-grids.

2. When the grid size is changed, the power loss reduction is effected. When the distance threshold is small and the grid size is close to threshold the power loss is significantly increased.

If cats looked like frogs we'd realize what nasty, cruel little bastards they are. Style. That's what people remember.

Terry Pratchett

5 Conclusion

Cooperative game theory among smart grid is the new way of implementation. Researchers have already applied cooperative game algorithms. However, mentioned algorithms have not verified for implementing Coalition group to reduce power loss and pricing. In this thesis, we implemented HR coalition form algorithm and verified HR algorithm with power loss.

We also verified the results by changing the distance thresholds and the grid size. Coalition formation is not only effective way to reduce energy burden from macro-stations,but also help to reduce the power loss while transferring energy via long distance. However, for the small number of micro-grids in the distribution system, the percentages of power loss reduction is not significant in compare with the power loss reduction in the bigger distribution systems. We also found shortcomings of algorithm as they did not provide the problem of inter-connection between micro-grid in one coalition.

The algorithms studied in [] can be used as a basic to develop more advance cooperative forming. There are also future opportunities for extending the work in [3] as following:

1. We can continue develop the payoff function not only for power loss, but also the prices

during energy trade and communication protocols between micro-grids.

2. We can propose a practical implementation that can be used to enable cooperative energy exchange effectively using game theory.

3. We can implement at different algorithms to implement load balancing in smart grids during pick and off-pick time.

A

An Appendix

A.1 Appendix A: Coalition group class

```
package smartgrid_demo;

import java.awt.Point;
import java.awt.Polygon;
import java.util.HashSet;
import java.util.Set;

public class coaltionGroup {
        /**
         *
         */
        private final smartGrid coalitionGroup;
```

```
public coaltionGroup(smartGrid smartGrid) {
        coalitionGroup = smartGrid;

}

Set<microGrid> mgs = new HashSet<microGrid>();

public double distanceMicrogrid(Point X, Point Y) {
        double dis = Math.sqrt((X.x - Y.x) * (X.x - Y.x) + (X.y
                        * (X.y - Y.y));
        return dis;

}

double energyStatus;

public double getEnergyStatus() {
        return energyStatus;
}

public void addMicroGrid(microGrid mg) {
        this.mgs.add(mg);
}

public void removeMicroGrid(microGrid mg) {
        this.mgs.remove(mg);
}

public Point getCentroid() {
        Polygon polygon = new Polygon();
        mgs.forEach(mg -> {
```

```
                polygon.addPoint(mg.coordinate.x, mg.coordinate.
        });
        return this.polygonCenterOfMass(polygon);

};

public double PolygonArea(Point[] polygon, int N) {

        int i, j;
        double area = 0;

        for (i = 0; i < N; i++) {
                j = (i + 1) % N;
                area += polygon[i].x * polygon[j].y;
                area -= polygon[i].y * polygon[j].x;
        }

        area /= 2.0;
        return (Math.abs(area));
}

public Point polygonCenterOfMass(Polygon pg) {

        if (pg == null)
                return null;

        int N = pg.npoints;
        Point[] polygon = new Point[N];

        for (int q = 0; q < N; q++)
                polygon[q] = new Point(pg.xpoints[q], pg.ypoints
```

```
        double cx = 0, cy = 0;
        double A = PolygonArea(polygon, N);
        int i, j;

        double factor = 0;
        for (i = 0; i < N; i++) {
            j = (i + 1) % N;
            factor = (polygon[i].x * polygon[j].y - polygon[
                            * polygon[i].y);
            cx += (polygon[i].x + polygon[j].x) * factor;
            cy += (polygon[i].y + polygon[j].y) * factor;
        }
        factor = 1.0 / (6.0 * A);
        cx *= factor;
        cy *= factor;
        return new Point((int) Math.abs(Math.round(cx)),
                    (int) Math.abs(Math.round(cy)));
    }

    public void calculateEnergyStatus() {
        this.energyStatus = 0;
        this.mgs.forEach(p -> {
            this.energyStatus += p.getEnergyStatus();
        });
    }
}
```

A.2 Appendix B: Micro-grid class

```
package smartgrid_demo;

import java.awt.Point;
```

```java
public class microGrid {
        /**
         *
         */
        private final smartGrid microGrid;

        public microGrid(smartGrid smartGrid, Point Cor, double ener) {
                microGrid = smartGrid;
                coordinate = Cor;
                energyStatus = ener;
        }

        Point coordinate;
        double energyStatus;

        public Point getCoordinate() {
                return coordinate;
        }

        public void setCoordinate(Point coordinate) {
                this.coordinate = coordinate;
        }

        public double getEnergyStatus() {
                return energyStatus;
        }

        public void setEnergyStatus(double energyStatus) {
                this.energyStatus = energyStatus;
        }
```

}

A.3 Appendix C: smartGrid class

```
package smartgrid_demo;

import java.awt.List;
import java.util.ArrayList;
import java.util.Collection;
import java.util.Comparator;
import java.util.HashMap;
import java.util.HashSet;
import java.util.Map;
import java.util.Map.Entry;
import java.util.Random;
import java.util.TreeMap;
import java.util.TreeSet;
import java.util.concurrent.ThreadLocalRandom;
import java.util.function.ToDoubleFunction;
import java.awt.Point;

import javax.swing.text.html.HTMLDocument.Iterator;

class ValueComparator implements Comparator {

    Map map;

    public ValueComparator(Map map) {
        this.map = map;
    }

    public int compare(Object keyA, Object keyB) {
```

```
            Comparable valueA = (Comparable) map.get(keyA);
            Comparable valueB = (Comparable) map.get(keyB);
            return valueB.compareTo(valueA);
        }

}

class smartGrid {

        public static Map sortByValue(Map unsortedMap) {
            Map sortedMap = new TreeMap(new ValueComparator(unsortedM
            sortedMap.putAll(unsortedMap);
            return sortedMap;
        }

        public static void main(String[] args) {
            int[][] conn = new int[10][10];

            Random rand = new Random();
            for (int i = 1; i < 10; i++) {
                for (int j = 1; j < 10; j++) {
                    conn[i][j] = rand.nextInt(2);
                }
            }
            double min = 2; // min max of distance
            double max = 10;

            double[][] dist = new double[10][10];
            microGrid[] mg = new microGrid[10];

            // double[] energy = new double[10]; // energy of microg
            for (int i = 1; i < 10; i++) {
```

```
        double energy = ThreadLocalRandom.current().next

        // say
        // if
        // negative
        // then
        // need
        // energy
        double x = ThreadLocalRandom.current().nextDoubl
        double y = ThreadLocalRandom.current().nextDoubl
        Point p = new Point();
        p.setLocation(x, y);
        mg[i].setCoordinate(p);
}

for (int i = 1; i < 10; i++) {
        for (int j = 1; j < 10; j++) {
                if (i != j)
                        dist[i][j] = ThreadLocalRandom.c
                                        max); // random
                // distance
        }
}
double d = 2.5; // distance thresold

HashSet<coaltionGroup> C = null;
for (int i = 1; i < 10; i++) {
        coaltionGroup initCoaltion = new coaltionGroup(n
        initCoaltion.addMicroGrid(mg[i]);
//      C.add(initCoaltion);
}
```

```
HashSet<coaltionGroup> CPG = null;
HashSet<coaltionGroup> CLG = null;

/*
 * HashMap<Integer, Double> CPG = new HashMap<Integer, D
 * provide // energy HashMap<Integer, Double> CLG = new
 * Double>(); // require // energy
 */
boolean change = true;
while (change) {

        CPG.clear();
        CLG.clear();
        C.forEach(element -> {
                if (element.getEnergyStatus() > 0)
                        CPG.add(element);
                else
                        CLG.add(element);
        });
        TreeSet<coaltionGroup> OPG = new TreeSet<coaltion
        OPG.addAll(CPG); // how to sort with energy need
        TreeSet<coaltionGroup> OLG = new TreeSet<coaltion
        OLG.addAll(CLG);
        change = false;
        for (coaltionGroup elem : OLG) {
                boolean found = true;
                coaltionGroup Cp = null;
                while (found) {
                        coaltionGroup elem2 = OLG.iterat
                        if (elem.distanceMicrogrid(elem.
                                        elem2.getCentroi
```

```
                                        found = false;
                                        Cp = elem2;
                                        break;
                                    }
                                    ;
                                }
                                ;
                                change = true;
                                for (microGrid microG : Cp.mgs) {
                                    elem.addMicroGrid(microG);
                                }
                                OPG.remove(Cp);
                            }
                        }
                        // show results here

                        ;

                    }

}
```

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