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A progress report submitted for continuation towards a PhD

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Cooperative Energy Barter in Microgrids

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ABSTRACT

FACULTY OF ENGINEERING AND APPLIED SCIENCE
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With the advent of proposals for new energy generation and distribution systems such as microgeneration, microgrids and smart grids, comes the possibility of the exchange of energy between smart houses. Energy exchange has already been found effective for the efficient use of energy on large scale such as between electric companies. In this work, we show how energy exchange can also be beneficial on a smaller scale. We develop a proof-of-concept model of two houses each with some microgeneration units and an energy storage device. We compute the optimal energy allocation in each house when energy exchange in not an option. We then show how these houses can use axiomatic bargaining in general and the Nash bargaining solution in particular, to exchange energy. We compare the utility of houses when the exchange is an option and when it is not and conclude that energy exchange can result in better utilities for the houses. We then list our planned future work in order to make such exchange feasible between houses.

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Nomenclature

AP	Set of available power at each time period.
ap_t	A member of AP.
B	Maximum storage capacity of a battery.
BF	Set of battery flows at each time period.
bf_t	A member of BF.
Cr_r^-	Maximum discharging rate of a battery.
Cr_r^+	Maximum charging rate of a battery.
L	Set of loads at each time period.
l_t	A member of L.
$Link$	Set of power transfers over transmission line.
$link_t$	Member of Link.
P	Set of preferences at each time period.
p_t	A member of P.
PG	Set of power generation at each time period.
pg_t	A member of PG.
Q	Set of battery charge state at each time period.
q_t	A member of Q.
T	Set of time periods, $\|T\| = 24$.
t	A member of T.
t_c	Maximum transmission capacity.
u	overall utility, i.e. $\sum_t u_t$.
u_t	utility at time period t.
W	Set of waste energy at each time period.
w_t	A member of W.

Chapter 1

Introduction

One of the main challenges of 21st century is to meet the ever-increasing global demand for energy. It has been estimated that this demand will be more than 50% higher in 2030 than today (IEA, 2008). Meeting this demand with fossil fuels poses two main problems. Firstly, fossil fuels are finite and despite the controversy over the amount left in the earth, there is no escape from the fact that we will run out one day. Secondly, the burning of fossil fuel is a major contributor of CO_2 emission, one of the greenhouse gases, which accelerates climate change. It has been estimated that energy-related greenhouse gas emissions will be around 30% higher in 2035 than today (Stern, 2008).

The continued reliance on fossil fuel also creates additional issues. The future energy demand estimates presented above are based on today's scenario and given the growing dependence of our society on power-hungry machines in our daily life, these estimates may be well below the real demand, worsening the crisis. Also, the escalating energy needs of emerging economies such as China and India and their wish to maintain their astonishing rate of economic growth, are likely to create tougher and more bitter competition for energy. Increasingly disputes over territories such as waters around the Falkland Islands, Barents Sea, Arctic seabed and Middle East are incited by the likely presence of energy resources in these areas. Furthermore, accidents that occur during the extraction and processing of fossil fuels are costly to humans and the environment (a recent example is the accident in Gulf of Mexico).

The hazards and issues with fossil fuels have long been identified and the need to consume fossil fuels more wisely and to seek cleaner and sustainable energy resources, have long been advocated. The suggested proposals are quite diverse in nature and examples include microgeneration, microgrids, smart houses and smart grids. Each proposal focuses a particular area to improve efficient energy use. For example, microgeneration proposes the generation of energy on a very small scale to avoid energy loss at the point of generation and transmission. For instance, in coal-fired power stations, energy is lost to the air through the cooling towers in the form of hot air. Energy loss in such power stations can be somewhere between 1/3 to 2/3, followed by further energy loss in the transfer of electricity to consumers through power lines. On the other hand, micro-CHP (combined heat and power) units in homes generate electricity and the waste heat is used for space-heating. Given that in the UK, almost 50% of the primary energy consumption is used to provide heating and hot water in buildings (Abu-Sharkh et al., 2006) this can be a significant step to use energy more efficiently.

More generally, microgeneration is defined as the small-scale production of heat and/or electricity from a low carbon source.[1] It includes energy generation from small wind turbines, photovoltaic solar systems, geo-thermal, micro-CHP, micro hydro, fuel cells and biomass burners. Microgeneration is considered to be a key technology to address energy and emission issues and countries across the globe are encouraging the use of microgeneration technologies in homes. For example, the UK Government launched a scheme in 2006 to incentivise households to use microgeneration, particularly the renewable energy generation such as wind turbines (BERR, 2008a). This has resulted in approximately 100,000 microgeneration installations across the UK (BERR, 2008b, p. 2).

Another proposal aimed at energy efficiency is the future vision of a smart house. A smart house consists of programmable electronic controls and sensors that can regulate heating, cooling, lighting., ventilation and other equipments to conserve energy or to reduce carbon emission (Stauffer, 1991; Christian et al., 2010; Davidsson and Boman, 2000). This energy and appliance controlling system is usually referred to as a house energy controller. It monitors the use of energy in the house and it may control energy demand via dynamic scheduling of energy-consuming tasks. This process is known as load-deferral. Though not strictly a part of their definition, smart houses are envisioned to be equipped with microgeneration and energy storage devices (e.g. an electric battery). Microgeneration units can generate low-carbon energy for smart houses and the energy storage devices can help use energy more efficiently.

The houses equipped with microgeneration units can be connected together to form a microgrid (Markvart, 2006). A microgrid is a small-scale power supply network that is designed to provide power for a small community (Abu-Sharkh et al., 2006). Microgrids can respond to local demands more efficiently and can operate independently of the traditional power grid which makes them more reliable in case of grid failure.

On a larger scale, the idea of a smart grid has been proposed. Initially suggested by Schweppe (Schweppe et al., 1980), smart grids are basically an advanced form of electricity grids where information and communication technologies are incorporated to ensure information flow between suppliers and consumers (DECC, 2009). The purpose of enabling communication between the suppliers and consumers is to avoid peak times, times when demands are higher. The relation between demand and the cost of energy

[1] Energy Act 2004 - Section 82,UK available online at http://www.opsi.gov.uk/acts/acts2004

generation or the volume of carbon emissions can be linear up to a certain threshold and afterwards it increases rapidly in a non-linear fashion as more expensive means of energy generation (such as diesel generators) kick in. Avoiding peaks in demands reduces the use of such expensive and carbon-intensive sources and thus results in savings of both money and carbon emissions.

Though, the aspiration of the smart grid idea is to replace the traditional electricity grid, it is equally applicable on a smaller scale such as a microgrid of smart houses discussed above. Smart grid technologies that facilitate connectivity and real-time information flow can enable such a network to make informed decisions about the energy supply and demand and use energy more efficiently. In this sense, smart houses are the energy suppliers as well as the consumers.

This microgrid of smart houses opens up the possibility of energy exchange between houses. These houses may have diverse demands patterns depicting the preferences and lifestyle of the household. Also, they may have different microgeneration technologies and therefore, may have diversity in energy generation too. Apart from controlling demands and supply to use energy more efficiently, energy exchange between these houses can also be useful . For example, a house with solar panels may provide extra energy to a neighbour house with wind turbine. This house can return this energy later in the evening to the first house which may have to rely on expensive means of generation in the evening.

Energy exchange has already shown to result in the efficient use of energy on a larger scale. For example, it has been shown that energy exchange in utility companies can lead to better energy management and savings (Ruusunen et al., 1991). Also, there are practical examples of energy exchange between countries (e.g. Finland and Sweden) and between cities of a country (e.g. New Dehli and Madhya Pradesh).[2] We argue that the energy exchange between houses can also lead to the same results of better energy management, less energy loss and reduction in carbon emissions. Though, the concept of energy exchange between houses has yet to receive the attention it deserves, it has started to gain increasing attention. An example is the vision of *symmetric energy exchange* between connected sustainable homes[3]. We, therefore, aim to explore this area and to investigate whether energy exchange can result in efficient energy use and if so, what methods are available to ensure that this energy exchange results in efficient and fair use of energy.

In the following section, we show an example to further motivate energy exchange between houses.

[2]Times of India, October 10, 2006

[3]See Connected Sustainable Home project, Massachusetts Institute of Technology - http://mobile.mit.edu/fbk

1.1 Scenario

In a neighbourhood of a small town, a small number of smart houses are connected to form a microgrid. One of these smart houses has solar panels installed on the roof. On a typical day, the energy controller device of this house gets energy from solar panels during the day time and uses it immediately, or stores it for later, based on the demands and preferences of the household. On a very sunny day when the solar panels can generate more power than the total demand and storage capacity in the house, the controller device decides to lend some power to a neighbouring house. It starts negotiating an energy exchange with a neighbouring house which has a wind turbine and currently has difficulty meeting its demand. The energy controller device offers its neighbour a constant power of 5 kW from 12:30 PM till 3:30 PM (a total of 15 kWh of energy) on the condition that it will return the 25 kWh after four days when the weather forecast is for a windy but cloudy day. However, the energy controller of this house considers that the demand is not fair and make a counter offer of a 20 kWh at a constant rate of 4 kW for 5 hours on that day. The first energy controller knows that on that day its energy generation can not meet its demand (since it is a cloudy day) and it will have to run a micro-CHP unit to meet with demand on that day which will result in a raise in the gas bill as well as in the carbon footprint of the household who are environment-conscious. Thus, it considers the counter offer to be reasonable and accepts it. Since the houses are already linked, the energy controller device has no problem in providing power to the other house and receiving it back as per the agreement.

This general scenario shows how an energy exchange can lead to efficient energy use. In the following section, we give very specific examples to show the merits of energy exchange.

1.2 Benefits of Energy Exchange

The following section lists the motivation of energy exchange. With each motivation, we give an example where this exchange can result in efficient energy use and reduced carbon emissions.

1. **Efficient Use of Energy**
   Imagine a windy evening when the wind turbines are generating their maximum output power, producing more energy than can be used by each individual house equipped with a wind turbine. Such is not the case for the houses with solar panels and they may have to use some other more costly or carbon intensive microgeneration units (e.g. micro-CHP which burns natural gas) to generate energy. In such scenario, the houses with wind turbines may lend some energy to the houses

with solar panels. These solar-panel houses may return this energy during daytime when the wind is not blowing. In such cases, these houses can exchange energy to minimize wastage and make more efficient use of their resources.

2. **Avoiding Energy Storage Loss**
   Following the above example, when a house has more generation capacity than the demand and opts to store energy, then some of this energy is lost. This loss is known as the storage loss and results due to the fact that no energy storage device is 100% efficient. Now imagine that this house lends this energy to another house which needs to use it right away. This house uses the energy and returns the same amount of energy later. Thus, energy is not stored and therefore the storage loss is avoided. Energy loss in storage depends on many factors including the duration it was stored for, the type and operational age of the storage device and it can be significant in some cases. For example, in lead-acid batteries it could be up to 24% (Stevens and Corey, 1996). Therefore, energy sharing can help reduce energy storage losses and may also mean that smaller capacity storage devices can be used.

3. **Coping with intermittent energy**
   Given that renewable energy resources are intermittent as they are dependent on the weather, one technical solution is to use a reserve generator to ensure a constant supply or in other words, to stabilize the output. In the case of a smart house, this reserve generator could be a micro-CHP. However, we argue that energy exchange can help cope with this intermittency as the power from renewable energy can be augmented by borrowing some power from a neighbour to stabilize the output. Imagine a group of houses coordinating their micro-CHPs so that only one micro-CHP at a time is used as a backup energy generator to stabilize power in houses. Thus, the houses can take turns to run their micro-CHP but only one house will need to keep a micro-CHP running at a time. Therefore, the use of micro-CHP can be reduced and the intermittency problem can be overcome more effectively.

4. **Coping with sudden demand**
   Occasionally, there can be sudden peaks in energy demands which can not be met by the individual homes own installed microgeneration units. For example, a household may have invited some guests for a party. In such cases, other houses may pour additional energy into the network to cope with sudden demand. The house with additional energy demand may use this energy and return it later. In such cases, energy exchange provides an opportunity to cover unusual demands. Also, a house averts the need to install more microgeneration units to meet with occasional demands. [4]

[4] In contrast, the grid must have installed capacity for peak demands even though this might only be used very occasionally.

5. **Extra storage space**
   Building on above example, houses in an energy network have access to a wider range of microgeneration units and storage devices. For occasional needs, they can borrow some power without the need to install new equipment. The same holds for storage when they have additional power. For example, some consecutive strong windy days may produce more energy than the storage device in houses with wind turbines can store. Thus, the house may utilize someone's storage facility to store this energy. The amount of energy stored is the result of cooperation between two houses and thus it can be divided between these houses according to some criteria or contract established before this cooperation took place.

6. **Reducing carbon emissions**
   Electricity and heating in residential buildings makes up 10% of global carbon emissions (Baumert et al., 2005, p. 5). Apart from the renewable (or zero carbon) energy resource, there is a strong positive correlation between energy generation or consumption and carbon emissions. Thus, using energy efficiently and reducing energy losses can help us reduce carbon emissions. We have already argued that energy exchange can be useful in using energy efficiently and to avoid storage losses. Thus, with energy exchange we may need to generate less energy. Generating less energy means less carbon emission and therefore, energy exchange can be helpful in carbon reduction.

1.3 Research Challenges of Energy Exchange in Houses

We have stated many merits of energy exchange is houses. However, for this idea to be materialize, we need to consider a number of challenges. The house energy controller in above examples are selfish in the sense that their main objective is to meet their own demands efficiently. There is no central authority or body which can enforce an energy controller to take part in an exchange if that exchange does not offer any benefit to it. Thus, an energy exchange between them must be beneficial for all. Such problems where participants are selfish and interested in their own benefit are more difficult to solve than the problems where participants are benevolent and willing to help others even if it is at the expense of their own benefit.

Benefiting all participants in an exchange is a general requirement. Indeed, the benefit to each individual should be equal or fair in some regard; for the exchange to be an acceptable agreement. For instance, if an energy controller has 10 kWh more energy than its storage device can cope with and wants a neighbouring energy controller to store this energy for it in order to save this energy, then any non-zero split of this energy, summing to 10 kWh, is beneficial for both controllers. Each controller will favour the split where it gets the larger share. In such situations, they may settle down for a fair split. However, there is no agreed definition of what a fair share is and the notion of fairness is fiercely debated among philosophers and researchers (Fehr and Schmidt, 1999). The challenge is to find a way to ensure an equal and acceptable benefit to all participants.

A single energy exchange can have multiple characteristics. For example, the amount of energy transferred and returned, time of transfer and return, power maintained during transfer and during return, duration of transfer and return etc. This kind of discussion over multiple issues is harder to solve than a single issue discussion. Also, a single energy exchange agreement (e.g. exchange over a day) can have multiple energy exchange each having multiple characteristics. Thus, the participants need to consider multiple issues for an energy exchange which is more complicated than the discussion over single issue. Furthermore, these discussions have a deadline. For example, if an energy controller knows that it can generate an extra 10 kWh between 9 AM and 11 AM then it must conclude its discussion with another house before 9 AM (assuming this controller can not store this extra energy). Therefore, for this case the deadline is 9 AM and if it cannot reach an agreement before this deadline then the opportunity to generate energy will be lost.

Another challenge is the fact that in this kind of discussion a participant does not know everything about the other participants. They may not know the generation and storage capacity, energy usage pattern or preference of each other which makes it harder to asses whether an offer would be accepted or what counter-offer will be made. One solution is to ask each participants to declare all the relevant information for other participants to make it easier to reach an agreement favourable to all. However, since the participants are selfish, there is always a possibility of them misreporting this information in order to manipulate the agreement in their favour.

A further aspect of the energy exchange between houses is the fact that the renewable energy resources are weather dependent and therefore their output has some uncertainty associated for a given time period. During the discussion, the participants have to consider this possibility that they may not be able to provide energy at an agreed period. In this case, they may have to run some other microgeneration units to make for this shortfall. However, it could be costly for them and they should consider this possibility before agreeing an exchange.

Finally, an important challenge is the distinction between energy exchange and energy trading. In energy trading, the participants can buy and sell energy to each other and can pay in terms of currency (real or virtual). However, in energy exchanges, as the word implies, energy is *exchanged* rather than bought or sold. We are predominately interested in the energy exchange as it can be useful in situation when the payment is not much important or when it is not feasible. For example, if two buildings of the same organization, such as a university, exchange energy with each other then payments may not be required. Also, in developing countries or in remote areas, payment mechanisms can be difficult to implement due to the absence of banking systems.

1.4 Research requirements

Given the research challenges we discussed above, we infer the following the research requirements that any good solution to energy exchange problem must possess.

1. **Beneficial to all**
   A solution must be beneficial to all participants. This is required to ensure that selfish participants are interested to take part in an exchange.

2. **Fair**
   The benefit each participant receives should equate in some manner. In other words, it should be fair and justifiable according to some agreed criteria. Where it is not possible to give equal benefit to each participant, for example due to limited storage capacity of the receiver or some transmission constraint, then the requirement the first requirement of benefiting all must prevail.

3. **Scalable**
   The solution must be scalable from a minimum of two houses to small microgrid.

4. **Decentralized**
   Since each energy controller can only control its own installations and is interested to maximize its own benefit, there is no central authority or control in action that can ensure an optimal and fair solution. Also, the participants may not be willing to reveal all their information to other participants. These aspects makes it difficult to compute a centralized solution and therefore the solution must be applicable in decentralized settings.

5. **Robust**
   Since the participants are selfish, they can provide misleading information in order to get more benefits. A solution must withstand this effect.

6. **Adaptable**
   The output power from renewable energy resources is uncertain and any solution for energy exchange must take this fact into consideration and should be able to cope up in such scenario.

7. **Pareto efficient**
   This property refers to the situation where no participant can do better without making someone worse off. For example, if there is some energy left which is of no importance to any participant but one, then it must be allocated to that

participant, otherwise this solution will not be a Pareto-efficient solution. This ensures that no energy is wasted during energy exchange.

8. **Timely**
   As we discussed earlier, energy generation is associate with time and therefore energy exchange must take place within a specific time period. A solution to such problem must be take this effect into account and also must be to compute an agreement before the deadline.

9. **No payment mechanisms**
   Since, we are interested in energy exchange solutions where payment mechanisms are not required, the solution should not consider payments between participants.

These key requirements and the description of the energy exchange problem such as decentralized control, adaptability and Pareto-efficiency are common to many domains. In the following paragraph, we introduce and discuss such candidate disciplines from which we will withdraw results:

Multiagent Systems
Firstly, we can see that there are certain similarities between the requirements of this problem and a computer science discipline that studies multiagent systems. An *agent* or software agent is a computer program that acts on behalf of a user. Unlike a typical software program, an agent is not invoked or executed for a specific task rather they *activate* themselves. Agents pursuing a goal or some desired outcome may learn or incorporate knowledge to exhibit intelligence. Such agents are called *intelligent agents* and a group of such agents interacting with each other or with the surrounding environment is called a *multiagent system.*

Multiagent systems (MAS) appear to be a good discipline to seek a solution for our problem. For example, a MAS is a group of agents which interact with each other in a decentralised and distributed manner. Furthermore, these agents can be selfish and are thus interested only in their own utility. This is exactly the case in the energy sharing problem where houses controller device are interested in their own benefit. Furthermore, there is no central authority and the houses are connected in a peer-to-peer fashion, a natural choice for decentralized and distributed solution. MAS are robust as there is no single point of failure and in general an individual agent's failure does not undermine the whole system function. MAS are scalable as a single MAS may contain hundreds or even thousands of agents. All these characteristics make the multiagent systems a strong candidate to model our problem.

Game Theory
Though, the entities of our problem can effectively be modeled as agents, the dynamics of their interactions are more complex. The agents interact to pursue their own goals. They have their own requirements, resources and actions which they employ for their

own benefit. Such selfish agents have their own agenda and they plan accordingly to *play* against other agents to pursue their goals. However, the outcome of such interaction depends on the actions of other agents too. The dynamics of of these strategic interactions have been studied in a great detail in the field of *game theory*.

Game theory is a branch of applied mathematics which has been used in many disciplines, especially in economics. It attempts to mathematically capture the behaviour of players in a strategic situation (i.e. where outcomes depend on the actions of all players). Therefore, game theory provides an ideal platform to systematically study these interactions in multiagent systems. Game theory provides solution concepts to predict the outcome of such games and to analyze the properties of such outcomes.

Game theory can be divided into two branches, cooperative and non-cooperative game theory. A cooperative game is one in which players are able to make enforceable contracts. The emphasis in this field is to investigate the outcomes of such games along with their properties and the methods to reach desired outcomes. In non-cooperative game theory, agents are usually competing against each other and the emphasis in this field is to study the strategies and states this competition leads to. In particular, the resulting equilibrium states have been studied in a great detail in non-cooperative game theory.

Based on the players interaction, games can be divided into static or dynamic games. In static games, players move simultaneously while in dynamic games (also called sequential games) players take turns.

Perhaps what makes game theory the most valuable tool is its ability to predict game outcomes even when there is a uncertainty involved around the actions or stages of a game. This is a core requirement of our solution where outcome are associated with uncertainty in the power generation. These outcomes are predicted by different solution concepts such as the Nash equilibrium.

Solution concepts offer a good way to predict how the game will be player and the outcome of the game. For example, Nash equilibrium is a solution concept which states that a game is in an equilibrium state if none of the player wants to change its strategy given the strategy of other players. Nash equilibrium provides a good way of analyzing static games. An equivalent solution concept for dynamic games is the subgame perfect Nash equilibrium. A strategy profile, set of strategies for each player, is said to be in the subgame perfect Nash equilibrium if it represent a Nash equilibrium in every subgame of the original game.

Given the rich methods to model, predict and analyze the complex interaction and outcome of players, game theory can be a very useful domain to look for solutions.

Bargaining Theory

To come up with an energy exchange plan, agents need to negotiate with each other to reach an agreement which describes the amount and time of energy exchange. As described in Section 1.4, we require this agreement to be Pareto-optimal and fair. The study of such problems is found in bargaining theory. Bargaining is a type of negotiation where players bargain over some resource (energy in our case) to reach an agreeable outcome.

Bargaining theory can be divided into two types, axiomatic bargaining and strategic bargaining. Axiomatic bargaining associates the outcomes with certain axioms such as Pareto-optimality and invariance to utility scales. In such bargaining, the emphasis is to reach outcomes associated with axioms but not the process that is used to reach these outcomes (Rubinstein, 1982). On the other hand, strategic bargaining emphasizes the bargaining process and strategies used in bargaining. The uniqueness and existence of an outcome is guaranteed, subjected to some requirements such as the finite number of players, complete information. Rubinstein's bargaining model is an example of strategic bargaining while the Nash bargaining solution is an example of axiomatic bargaining.

These two types of bargaining provide two extremely useful insights to our problem. Firstly, using axiomatic bargaining, we can explore possible outcomes of our energy exchange problem which satisfy certain axioms. For example, we can use the axiomatic approach to reach outcomes which can satisfy our requirements such as fairness and Pareto-optimality as listed in Section 1.4. Secondly, we can investigate strategies and protocols that can be used in bargaining for energy. For example, we can explore strategies which can reduce or eliminate the effect of false reporting, or which can guarantee a solution before the deadline. The former is called robustness and later is called timeliness, two of our requirements as listed in Section 1.4.

Although the above approaches seem very promising, there are challenges in using them for our problem. For example, axiomatic bargaining assumes that players are truthful in revealing their information which may not be the case in our settings. Also, axiomatic bargaining involves the role of a central mediator who computes the bargaining outcome given the preferences and disagreement values of the players (see Section 2.3.2). This central component can be difficult to implement where participants are part of a decentralized systems such as peer-to-peer networks. On the other hand, in strategic bargaining where players make counter-offers to reach an agreement, it can be complex to compute the counter-offer in some cases where more than one issue is under consideration, as in the problem of energy exchange (see Section 2.3). Therefore, although bargaining provides a good starting point to explore bargaining for energy exchange, there is no off-the-shelf bargaining solution for it at present.

Peer-to-Peer Energy Networks

As we mentioned earlier, the houses are connected to each other to form an energy network. In a traditional energy network (such as the grid or the natural gas distribution systems) the houses are linked to a cable which connects them to a distribution point (e.g. a step-down transformer) and energy flows in one direction, from the distribution point to homes. On the contrary, in our model, the houses are connected directly to the neighbouring houses via a physical link and the energy flows in both direction during energy exchange. The exchange is not required to be between fixed participants. i.e. a house is allowed to exchange energy with any other house on the network. Also, there is no central authority.

Such attributes of our model can be modeled using a peer-to-peer (P2P) architecture. A P2P system is a distributed network architecture where participants share or exchange their resources with others. These attributes the P2P architecture a natural choice to connect houses in an energy network. Also, a participant in a P2P network can share resources with any other participant of its choice and form an ad-hoc network, i.e. a temporarily network. After the exchange, the participants are free to form another network with any other participants of their choice. This is relevant to our model where a energy controller can negotiate for an energy exchange with other energy controllers of its choice and, if negotiation succeed, establish a link for exchange. The idea of a P2P energy network is not novel. Amoretti (2009) describes exchange of energy in terms of hydrogen distribution in a peer-to-peer network while Beitollahi and Deconinck (2007) review different peer-to-peer topologies that can be used in a decentralized network of distributed generation. However, their ideas are preliminary at this stage and do not address many aspects of energy exchange in the P2P networks. For example, Amoretti (2009) assumes that there is a *virtual network* already in place where hydrogen can be bought and sold by houses. This can be thought of a market place where a peer can search for another peer to buy or sell hydrogen. These peers can then establish a direct connection. This assumption of simplifying the process to look for a peer, induces a central component in the network, and thus, this approach may not be applicable in pure P2P networks. On the other hand, Beitollahi and Deconinck (2007) discusses the advantages of different network overlays, i.e. description of how peers are connected, in a network of distributed generation. However, they do not discuss how peers would interact or engage in negotiation to agree an energy exchange.

It is surprising to see that, though the vision of P2P energy network is shared by many projects [5], there is no comprehensive research which empirically studies a P2P energy network. More specifically, we are not aware of any study focused on the P2P energy networks of houses.

Utility Scale Energy Exchange

Energy exchange is a common practice in utility companies, particularly in electric companies. Usually, this exchange is facilitated by means of a fixed-surcharge, side-payments or barter (see Section 2.4). Since we are interested in exchange without payments, or barter as referred to as in electric companies (Ruusunen, 1994b), we find Ehtamo and Rusuunen's work (Ehtamo et al., 1989b, 1987; Ruusunen et al., 1991) related to our

[5] See Markvart (2005) also, http://www.re-public.gr/en/?p=1946 and http://p2pfoundation.net/

problem of energy exchange between houses. Ehtamo and Rusunnen's idea is to use energy barter to improve overall system utility. They assume group of utility companies each owning a generator. The cost of energy generation for a company varies over the course of a day and it is different for each company. This disparity allows energy exchange to be beneficial to all. Rusunnen and Ehtamo use axiomatic bargaining to ensure fairness in such exchanges. Their settings are different from our problem in two respects. Firstly, their model is focused on utility-level exchange and therefore the energy storage, load deferral and uncertainty in renewable energy generation is not considered. Secondly, they assume that all participants reveal their true cost and utility function and these can be audited to veracity whereas this is not the case in our problem.

1.5 Research Objective

Thus, against this background, our main research objective is to develop a solution for a fair and optimal energy exchange between houses. More specifically, our objective is:

- To develop an interaction-mechanism to enable fair and optimal energy exchange between houses via decentralized negotiation. This solution must withstand misreporting from selfish agents and be able to incorporate uncertainty in the energy generation. In addition, the solution must be applicable to a small microgrid.

1.6 Research Contributions

As a first step towards addressing our research objective, we have developed a preliminary model of two neighbouring houses. These houses have energy controllers which are represented as intelligent agents. These agents have some means of renewable energy generations (one has a solar panel while other has a wind turbine) and batteries to store it. Both agents have non-identical load, power, and preferences profiles and are connected to each other by an electric cable which has a finite load capacity.

At this stage, we assume a mediator between the houses. We assume that both agents truthfully reports their generation, load, preference, utility function and battery information to the mediator which then decides an energy exchange via the Nash bargaining solution. This solutions offers agents more utility than if they work individually. We would like to use this model as a benchmark to see how well agents can perform when they bargain via strategic bargaining.

A detailed and technical discussion of this model can be found in chapter 3 of this report.

1.7 Structure of the report

The remainder of the report is organized as follows:

- In chapter 2, we discuss related literature and research carried out in this domain. We look at the research discussing advantages of smart grid, micro-generation, micro-grid and smart houses. We also discussed negotiation and bargaining techniques that have been employed to solve similar problems.

- In Chapter 3, we discuss technical details of our model along with the experiments carried out. We discuss the bargaining solution in general and Nash bargaining solution in particular and why it is appropriate in our problem. We also discuss the challenges in our optimization objective.

- In Chapter 4, we summarize our findings and outline our future research direction.

Chapter 2

Literature Review

In this chapter we review the existing literature related to our area of research. We begin with the technologies that enable energy generation and storage in a house. Agent-based energy management systems and bargaining solutions are discussed next. We then discuss the present energy exchange solutions. Finally, we discuss literature focused on P2P energy systems.

2.1 Enabling Technologies

In this section, we discuss two technologies that are very important for our vision of energy exchange between houses to be feasible. Firstly, we discuss microgeneration in houses and secondly the energy storage in houses.

2.1.1 Microgeneration

As we stated in Section 1.1, microgeneration is defined as the small-scale production of heat and/or electricity from a low carbon source. Generally, it refers to on-site generation of energy by renewable energy resources or combined heat and power (CHP) units (Abu-Sharkh et al., 2006). The literature points to many obvious advantages of microgeneration. The distributed nature of renewable energy sources such as wind, sunlight and waves makes microgeneration a natural choice. Besides this, microgeneration offers a number of advantages over centralized or large-scale generation. For example, the heat that is generated as a by-product during electricity generation can be used for the purpose of space-heating. Microgeneration also eliminates the need to transfer energy and thus avoids the transmission losses. Microgeneration equipment such as wind turbines, solar panels and CHP units are extremely reliable and need little maintenance. The energy produced is greener and the demand can be met efficiently. Though microgeneration can be integrated with existing grid or the future smart grid, it is possible to run it in standalone mode (i.e. the off-grid mode). This increases the reliability in case of grid failure.

Microgeneration has been estimated to be capable of providing 30-40% of UK electricity needs by 2050 (Energy Saving Trust. et al., 2005). The UK government launched a microgeneration strategy in 2006 to make microgeneraton a realistic alternative [1]. There has been good signs of progress, with the number of microgeneration units installed, reported to be more than 100,000 (BERR, 2008b).

The maximum power that can be generated by a microgeneration unit in a house depends on several factors such as the type of the equipment, fuel type and size. For example, in case of wind turbines the maximum power produced depends on the design, blade lengths, height from the ground and turbine efficiency. Thus, domestic wind turbines range from 400W to 5kW [2] (Bahaj et al., 2007). In case of micro-CHP, units with maximum power of 15 kW are categorized as domestic micro-CHP units (Dentice et al., 2003) and for solar panels, an average output is 8 kW (MacKay, 2007, p. 40).

To give a perspective for comparison, an average UK person needs 18 kWh energy per day for electrical appliances (MacKay, 2007, p. 204).

2.1.2 Energy Storage Devices

In Section 1.2 we mentioned that the energy use can be optimized by using an energy storage device. Energy can be stored in many forms but we focus on technologies that can be utilized on a domestic scale. In general, energy storage devices at homes are reported to be electric batteries and thermal storage (see DTI (2004)).

Generally, an energy storage device is assessed in two terms, storage capacity and power. Storage capacity refers to the total amount of energy that can be stored in the device while power is the charging and discharging rate of the energy from/to the device. Storage capacity can be measured in kilo-watt-hour (kWh) which is the amount of energy stored when a 1 kW power is applied to a battery for 1 hour. The charging/discharging rate or power of a battery is the rate of flow of energy. We measure it in kW.

The storage capacity and the discharging rate depends on a number of factors. For example, in a flow-cell battery, it may depend on the underlying chemical reaction, the nature of chemical reaction, the amount of chemicals or even the size and design of a battery. Therefore, it differs from device to device. Electrical storage devices for homes may have capacities between 5kWh to 10kWh with 1-3kW power(DTI, 2004, p. 9). If electric vehicles are used for this storage, it could be up to 50 kWh with 20-50kW power (DTI, 2004, p. 9). Modern vehicles such as the Tesla Roadster from Tesla Motors, the

[1] $http://www.decc.gov.uk/en/content/cms/uk_supply/renewable/microgen/microgen.aspx$

[2] Some domestic wind turbines are listed here at renewableUK - http://www.bwea.com/small/cases.html, and Greenphase - http://www.greenphase.co.uk/wind.html

E6 from BYD and the Zhong Tai from Zotya are examples of vehicles with a battery pack of 50 kWh. The storage capacity of these are comparable to the average demand of 40 kWh per day per person for transportation (MacKay, 2007, p. 204). However, given the interest in electric vehicles and the number of on-going projects, the storage capacity is bound to increase while cost to go down. In fact, it has been estimated to go down to 65% from 2009 to 2020 (BCG, 2010).

2.2 Agent-Based Energy Resource Management

Multiagent systems have been studied and applied in a variety of domains ranging from information systems to the semantic web (Wooldridge and Jennings, 1995; Wooldridge et al., 1996; Weiss, 1999; Jennings et al., 1998). Its application in the control and management of energy resources has received considerable interest since 1990. This trend is evident from a number of publication and projects in that period where the focus is to apply the multiagent paradigm to distributed systems (see Georgakarakou and Economides (2006)).

In the next sections, we discuss how multiagent knowledge has been applied to energy domain. We observe that the central aim is to conserve energy either by having a single intelligent agent to control energy consumption or by agent coordination and resource allocation in multiagent systems. We also observe that the literature on agent coordination is focused on energy conservation or energy markets.

2.2.1 Single Agent Systems for Energy Resource Management

Inspired by the control theory, agents have been used to control multiple energy resources in a building. In such cases, a single agent in responsible for controling power appliances and environment in a building, (for a survey Georgakarakou and Economides (2006)). Early literature on agents in energy resource management can be divided into two categories. Firstly, the literature where the focus is on automation of appliances for example, control of lights and environment in a building. Secondly, where the focus is on optimization via automation. Here, the same automation techniques are used to switch on and off devices to optimize some criteria, usually to save energy. Such buildings are referred to as *intelligent buildings* or IBs (Abras et al., 2010).

The more recent literature on energy management using single agents mostly addresses smart houses. A Smart house is modeled as an agent controling energy appliances. In this context, the smart house is a trimmed down version of intelligent buildings. The objectives are the same, to control appliance intelligently to optimize some goals, for example, cutting back the energy bills or reducing carbon footprints. The term smart house can be traced back to 1984 when the National Association for Home Builders in USA formed the *Smart Houses* group to push for the necessary technology to wire houses for home automation (Aldrich, 2003).

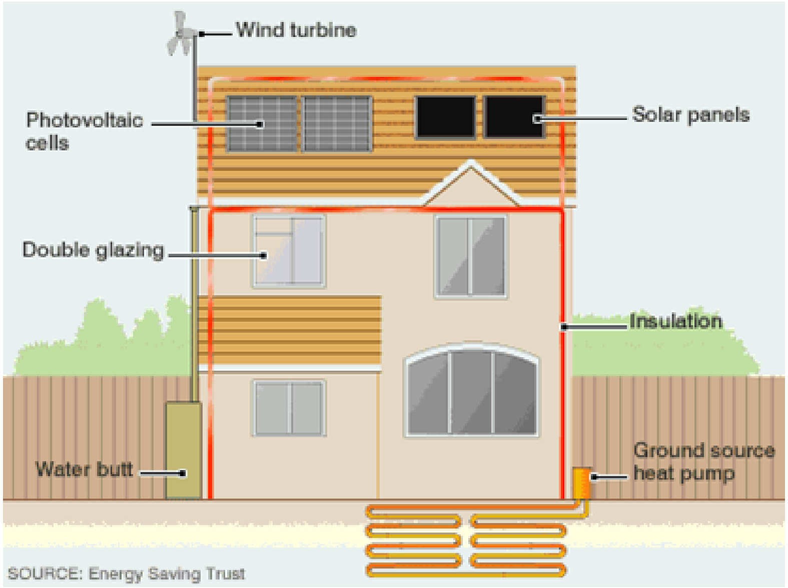


FIGURE 2.1: A smart house. Source - *Energy Saving Trust*

A single agent can make use of energy more efficiently using any or a combination of the following techniques:

1. **Automation of appliances**
   Energy use is automated so that it is used only when it is needed. For example, controlling lights or space-heating based on the presence of persons in a room. This solution needs the least intelligence but can be very effective where human intervention is not reliable, e.g. a public building (see Sharples et al. (1999)).

2. **Storage-based solutions**
   The main idea is to store energy when it is cheaper or not needed and then use it later. In this way, agents can avoid buying energy when its expensive or reduce carbon emissions by using energy when it is clean (Vytelingum et al., 2010).

3. **Load-deferral solutions**
   Here the loads are deferred or delayed to carry out when the energy is cheaper or cleaner. This differs from storage-based solutions where loads may be non-deferrable. (see Vytelingum et al. (2010)).

The efficient use of the energy resources is, at its core, an optimization problem. The general approach is to identify the objective function (which is mostly to minimize the cost but can be any other criteria such as carbon emission) and the relevant constraints. Then this problem is transformed into an optimization problem and solved with a suitable optimization technique. The optimization techniques in such problems range from linear programming to multi-objective convex optimization.

In cases where energy generation or demand is flexible or uncertain, machine learning techniques can be applied to find an appropriate solution (Hagras et al., 2003; Sharples et al., 1999). These ML techniques help to establish beliefs about the environment and make informed decision and consequently more efficient energy use.

Apart from houses and buildings, the single agent systems has also been used to control micro-grids and distributed resources (Chatzivasiliadis et al., 2008; Dimeas and N., 2004). The main idea remains similar to that behind the intelligent building, i.e. to optimize energy use given some loads and energy generation resources.

2.2.2 Multiagent Systems for Energy Resource Management

A multiagent system is a natural extension of a single agent system. A significant amount of literature has applied the multiagent paradigm to the energy management problem. While the focus of a single agent system is the efficient use of energy via control of energy resources by a single agent, the focus in multiagent systems is the efficient use of energy via agent interactions. Coordination, negotiation and coalition are examples of such interactions.

Before indulging further into discussion, we describe a common approach in the domain of energy management for using energy efficiently. In many scenarios, it is assumed that reducing demand peak can help to use energy resources more effectively and can bring the price of energy down. For example in terms of electricity, the price of electricity generation increases rapidly after a certain threshold is reached as more expensive generators are switched on to meet this demand. Figure 2.2 shows this threshold to be 40 GW for the UK national grid. If this peak in demand is somehow reduced then electricity generation can be cheaper which is good for the suppliers and consumers. One way of doing it is to spread the demand across the day to avoid daily peaks. This is also referred to as *flattening* the demand curve. Many papers target this approach from different multi-agent techniques. Here, we focus on three aspects such as negotiation, coordination and coalition.

Negotiation is the process of reaching an outcome via arguing. In multiagent systems for energy management, negotiation can be used between agents for load balancing i.e. to reduce peaks in demands (Brazier et al., 2002; Praça et al., 2008). Agents negotiate with other agents to reach an outcome where demands are spread in nearly uniform distribution to avoid peaks. However, these negotiation are price-based negotiation and are not applicable in payment-free settings.

Coordination is another multiagent technique that can be used for the same purpose of using energy efficiently. Coordination is a problem of *managing inter-dependencies between the activities of agents* (Wooldrige, 2009). Based on coordination, we can divide multiagent systems into three categories. Firstly, a *full-cooperative* multiagent system

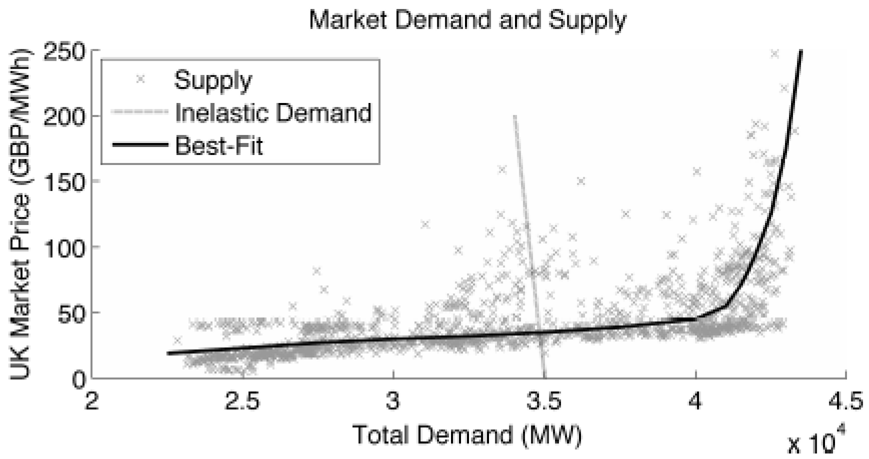


FIGURE 2.2: Energy Demand against the generation cost. Each cross represent a half-hour reading. Source - Vytelingum et al. (2010)

where agents are *selfless* and have a *common goal*. The cooperation is explicit as agents cooperate to maximize overall system utility. Secondly, a *cooperative system* where agents are *selfish* and interested in achieving their *personal goals*. In these games, cooperation is not explicit; agents cooperate only when it leads to better utility for them. Thirdly, a *non-cooperative system* is a multiagent system where agents are strictly competitive.

In cooperative systems where agents are selfish, coordination emerges when agents interact while pursuing their self-interest (Searle, 1983; Wooldrige, 2009, p. 79-111, 116). Searle gives an example of people running towards a tree when it suddenly rains to describe coordination in self-interested agents. This type of emergent cooperation is also evident in Vytelingum's work (Vytelingum et al., 2010). In this work, selfish agents store electricity when the demand is not high and thus electricity is cheap. However, when they all attempt to store simultaneously, demands increases rapidly driving prices up. Thus, these agents learn not to store electricity in a synchronized manner. In other words, a cooperation emerges whereby demand peaks are kept lower. This is an implicit result of selfish agents interacting with each other, they have no intentions and no communications to cooperate.

Li et al. (2010) identifies the following four types of coordination approaches for the management of energy resources along with their merits and demerits.

1. **Price-Based Control**
   Consumers' energy appliances are controlled indirectly by asking the human owner of the resources to respond to a varying price. Thus, at peak-times the price could be set high to motivate owners to reduce consumption. Owners reduce their consumption for their own benefits and an overall reduction in peak reduces the energy generation cost. Though, each agent acts in its own interest, their

coordination leads an efficient use of energy. Pitfalls are dependence on the human owners who may not be available sometimes or even not exists for some resources (Hopper et al., 2007).

2. **Direct Load Control**
   Using special equipment, consumers appliances can be directly controlled and can be switched on or off when needed by the energy suppliers. The savings are passed onto consumers based on their level of participation.[3] Demerits are insensitive intervention in the operation of appliance which may cause inconvenience sometimes. Some companies may consult the human owner before switching appliances on or off but this approach introduces the problems discussed above.

3. **Market-Based Control**
   Agent-based, market-oriented algorithms are used where a broker agent negotiates with resource agents to fix usage and price (Kamphuis et al., 2006; Carlsson and Andersson, 2005). This can involve virtual or real money or tokens. This approach has two scalability problems. First in terms of number of players and secondly regarding the interdependency in the participants' demand over time. One commercial implementation of this approach is PowerMatcher. [4] It is a market mechanism where energy resources are allocated via auctions.

4. **Planning Algorithms**
   A number of planning algorithms to induce explicit coordination in agents have been proposed (Clement and Barrett, 2003; Muller et al., 2001). These algorithms can be divided into centralized or decentralized and long-term or short-terms algorithm based on the architecture and scope of optimization. However, it has been identified that there are two types of issues with such algorithms (Li et al., 2010). Firstly, the lack of scalability in terms of number of resources. Secondly, there is no room for adaptation and thus the lack of ability to respond to unexpected events.

The final approach is the coalition approach where agents form a coalition to be able to get a better deal (Hamalainen et al., 2000). Here a group of agents coordinate to use energy. This coordination may involve negotiation and/or cooperation for efficient use of energy within the group. This approach provides a good way of reducing energy cost within a group, however the overall effect on the system is not mentioned.

Up to this point, we have summed up all the contemporary multiagent techniques applied to energy resource management domain. One noticeable point is the fact that all of these approaches are price-based mechanisms. We also notice that there is no published work on the idea of energy exchange in multiagent system for energy efficiency. As we stated

[3]For example: http://www.energex.com.au/environment/energy_efficiency.html

[4]http://www.powermatcher.net

in the last chapter, we can use bargaining theory for the energy exchange in multiagent systems. In the following section, we explore literature on bargaining theory, particularly bargaining solutions that can be used for energy exchange.

2.3 Bargaining

Generally speaking, bargaining refers to the process through which a seller and buyer reach an agreement. Also, the negotiation over dividing the result of a cooperation between participants is also called bargaining. Bargaining is a very well studied topic in game theory and consequently there have been many bargaining solutions proposed (Muthoo, 1999; Mas-Colell et al., 1995). We next define the bargaining problem and discuss related concepts in the following paragraph.

Definition 1: Bargaining Problem

In cooperative game theory, a bargaining problem refers to the problem of selecting an *appropriate solution* from a *solution set*. The solution set is the set of all feasible solutions or agreements. An appropriate solution is a solution with some desired properties. This solution is called a bargaining solution. A Pareto-solution is the solution where one player can not improve her utility without making any other player worse off. The set of all such solutions describes the Pareto-frontier of a bargaining problem.

A bargaining solution can also refer to the method used to reach this solution. Throughout this report, the same term will be used for both the solution and the method, however, the context will reveal the nature of use.

2.3.1 Characteristics of Bargaining Problems

The type of a bargaining problem can vary depending on the number of issues or the type of issues involved. Below we discuss these characteristics.

- **Single-issue bargaining v/s multi-issue bargaining**

  When the subject under consideration is a single issue, then the bargaining is called single issue bargaining. The opposite is multi-issue bargaining. Here, issue does not refer to the number of items and therefore, the single-issue negotiation does not necessarily refer to bargaining over a single item. For example, bargaining over the energy price could be regarded as a single issue bargaining if price of the energy is the only concern. However, when other issues such as time and power are under consideration too then it is a multi-issue bargaining. Also, when the bargaining is considering multiple energy exchanges in a given time then it is a case of multi-issue bargaining as the issues under consideration (i.e. the number of energy exchanges) are multiple.

- **Divisible goods v/s indivisible goods**

  A good is divisible if it can be divided into smaller parts. For example, a cake is a divisible goods while a vehicle is not. In context of energy, energy is divisible as any given amount of energy can be divided into smaller parts. For example, 10kWh of energy can be divided into 10 smaller parts, each of 1 kWh. Sometimes, a small fixed amount of a divisible goods is assumed to be indivisible for bargaining to proceed more easily. For example, 1kWh may be considered to be an indivisible unit in our case.

- **Independent issues v/s dependent issues**
  In multi-issue bargaining, issues may or may not be independent of each other. An example is the bargaining for a fix amount of energy for two hours. If the energy is required to watch two unrelated hour-long programs on TV, then the issues (energy in each hour) can be considered to be independent as watching the second program does not depend on whether energy was secured for the first hour. On the other hand, if this power is required to power an oven for two hours to bake a dish, then these issues are dependent as the energy is required in both hours to cook the dish properly.

The type of the bargaining issues play a significant role in selection and complexity of bargaining solutions proposed in literature. For example, bargaining over single issues which are independent and divisible is easier than indivisible, interdependent multi-issue bargaining (Wooldrige, 2009, p. 316).

Apart from the type of issues, the choice of bargaining solution also depends on how players interact with each other. For example, if bargainers solve the dispute by offer and counter-offer proposals, then it is said to be strategic bargaining. On the other hand, if bargainers interact via a mediator or arbiter which sets several axioms and then finds a bargaining solution for them, then it is said to be axiomatic bargaining. Here, in the following paragraph, we discuss both approaches in detail.

2.3.2 Axiomatic Bargaining

Apart from the number, type or relationship of bargaining issues, a significant part of the bargaining literature is focused on the optimality and fairness of bargaining solutions. The notion of optimality in bargaining refers to Pareto-optimality, described below. However, there is no agreed definition of a fair solution (Binmore, 2009; Bereby-Meyer and Niederle, 2005). One way to get around this lack of definition is to agree on some characteristics of the outcome, i.e. some criteria that the solution should meet. For example, in game theory the problem of dividing goods amongst players is called *fair division* (Brams and Taylor, 1996). Here, fairness criteria can be the exact division, envy-free division or proportional division (see Brams and Taylor (1996) for a full discussion). Thus, some division of goods are associated with having some or all of these properties. In this sense, players may agree on a division given that it has certain agreed properties.

In the context of bargaining theory and multiagent systems, the bargaining outcome or solution is reached in a similar way. Given a set of bargaining outcomes, some solutions are associated with having certain properties or axioms. This kind of bargaining is referred to as the axiomatic bargaining (Nash, 1953; Roth, 1979).

Before discussing the axiomatic bargaining solutions, we list the most common axioms found in literature (see Roth (1977) for a comprehensive list):

1. **Invariance to equivalent utility representation**
   This axiom is also known as invariance to affine transformation or scale-freeness. This refers to the characteristics that the bargaining outcome should be invariant to how each agent values its share. In other words, rescaling an agent utility should not change the bargaining solution.

2. **Pareto-Optimality**
   This axiom means that the solution can not be improved in any particular direction without making another player's payoff worse. In other words, no agent can improve its utility without making another agent's worse.

3. **Symmetry**
   The solution should depend only on the utility function of agents, not on the identity of agents. In other words, symmetric utility functions should result in symmetric payoffs.

4. **Independence from irrelevant alternatives**
   This axiom states that if a certain choice A is preferred over B in a choice set S then inclusion of another choice C, must not make B preferable to A.

In the next sections, we discuss some axiomatic bargaining solutions and discuss the axioms they satisfy.

2.3.2.1 Nash Bargaining Solution

In cooperative game theory, the Nash bargaining solution (NBS) (Nash, 1950, 1953) is a solution to the two-player bargaining game. Each player has a personal value, i.e. utility, for some goods which are to be divided. Furthermore, the players have a disagreement value which represents their utility if no cooperation takes place (i.e. when players fail to reach an agreement).

Assuming two players A and B, the set of all solutions is a plane while the set of feasible solutions S is a subset, or graphically, a subplane within this plane. The subplane S has the pair of disagreement values (d^a, d^b) as one vertex and Nash assumes this set to be compact[5] and convex.[6] Any point (u^a, u^b) in the set S describes the individual shares of agents and since agents will only cooperate if they get more utility then their disagreement values, therefore $(d^a, d^b) \leq (u^a, u^b)$.

If x and y are the shares of agent A and B respectively, then the Nash bargaining solution is obtained by

$$\underset{x,y}{\operatorname{argmax}} \quad [u^a(x) - u^a(d^a)] \times [u^b(y) - u^b(d^b)] \tag{2.1}$$

where x, y and denotes shares of A and B respectively and d^a, d^b are the disagreement value of agents A and B respectively. The solution to equation 2.1 (i.e. the values of x and y which maximizes this equation) are the shares of agents A and B respectively. Equation 2.1 is also called the *Nash Product*. If the feasible solution set S is convex and compact then this solution to this equation is unique (see Nash (1953) for the proof). Figure 2.3 provides a good illustration of the Nash bargaining product.

The Nash bargaining solution satisfies all the axioms defined in the last section.

2.3.2.2 Utilitarian Solution

The utilitarian solution in cooperative game theory is used to divide a shared utility between two or more players. If (x, y) shows the shares of agent A and B, (u^a, u^b) are the utilities, and (d^a, d^b) are the disagreement values respectively, then we find the point which maximizes the following equation.

$$\underset{x,y}{\operatorname{argmax}} \quad [u^a(x) + u^b(y)] \tag{2.2}$$

The utilitarian solution satisfies the axioms 2, 3 and 4, failing the first axiom in Section 2.3.2 of invariance to equivalent utility representation. This can pose a problem in situation where agents have considerable difference in their utility functions because the utilitarian solution will give the goods to the agent which values it the most and the other agents will get no share. Thus, though it maximizes the overall group utility by

[5] A set is compact if it is closed and bounded.

[6] A set C is convex if for all x and y in C and all t in the interval $[0, 1]$, the point $(1 - t)x + t(y)$ is in C.

giving the goods to the agent which has high utility for them, it can be argued whether it is a fair solution.

2.3.2.3 Egalitarian Solution

The egalitarian solution attempts to grant equal payoff to both players. It proposes that in a given feasible solution space S, solving the following equation will divide the shared utility equally between two players (Mas-Colell et al., 1995):

$$(u^a(x) - d^a) = (u^b(y) - d^b) \tag{2.3}$$

Here x, y, u^a, u^b and d^a, d^b are the shares, utilities and disagreement values of players A and B respectively.

The egalitarian solution satisfies the axioms 2, 3 and 4. Since it satisfies the same axioms as the utilitarian solution does, it is hindered by the same problem discussed in the last section.

2.3.2.4 Kalai-Smorodinsky Bargaining Solution

The fourth axiom (independence from irrelevant alternatives) has been a topic of controversy as it has been described as a very restrictive axioms for a solution (Roth, 1977). This property describes that if two players prefer a solution in a solution set S then they must prefer the same solution in a subset of S (Mas-Colell et al., 1995). However, it has been shown that adhering to this axioms may make some players worse off when the solution set is reduced (Kalai and Smorodinsky, 1975). The Kalai Smorodinsky bargaining solution (Kalai and Smorodinsky, 1975) is an extension to the Nash bargaining solution which does not conform to this axiom, instead it introduces an alternative axioms called monotonicity, as defined below:

5. **Axiom of Monotonicity**
   For every utility level that player 1 may demand, the maximum feasible utility level that player 2 can simultaneously reach is increased, then the utility level assigned to player 2 according to the solution should also be increased (Kalai and Smorodinsky, 1975).

To compute the Kalai-Smorodinsky solution, we need to form a rectangle in the solution space S. The rectangle is formed such that one point is the set of disagreement values (d^a, d^b). The other point is the the maximum utility that the first player can make, i.e. $u^{a^*} = max(u^a : (u^a, u^b)) \in S$ denoted as u^{a^*}. The third point is the maximum utility for the second player i.e. $u^{b^*} = max(u^b : (u^a, u^b)) \in S$. Given that three points of the rectangle are known, the last point is just the intersection of projections, one from point u^{a^*} in the direction of u^b and the other from the point u^{b^*} in the direction of u^a. We call this point (x^*, y^*). Then a line is sketched from the point (d^a, d^b) to (u^{a^*}, u^{a^*}). The Kalai-Smorodinsky solution is the point where it intersects the Pareto-frontier, as shown in Figure 2.3.

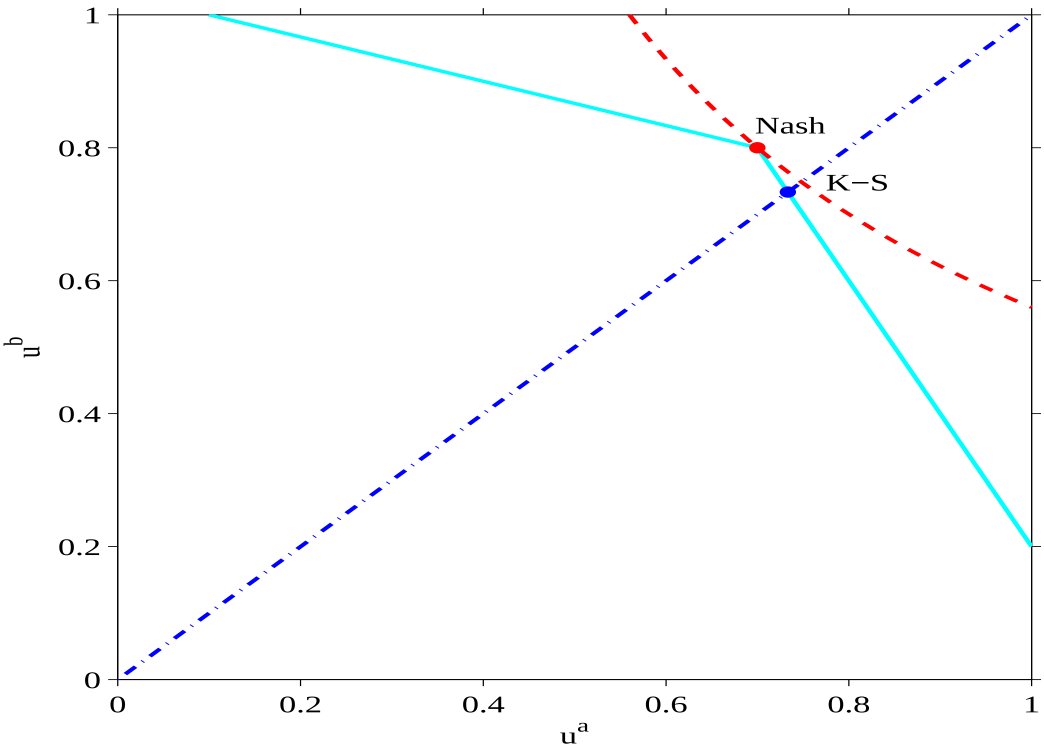


FIGURE 2.3: Nash and Kalai-Smorodinsky Bargaining Solution. The solid line is the Pareto-frontier. The origin is taken as the disagreement point (i.e. $(d^a, d^b) = (0, 0)$), thus all the acceptable agreement must lie above this point. This region is called the feasible region and any point in it shows the player utility, i.e. (u^a, u^b). The dashed line represents the Nash product of the players utility (i.e. $(u^a \times u^b)$ since $(d^a, d^b) = (0, 0)$). Kalai-Smorodinsky Bargaining Solution (K-S) is the dashed-dotted line. The maximum utility that agent A can get is at the point $(1, 0)$ while the maximum utility for agent B is at $(0, 1)$. Thus, $u^{a^*} = max(u^a : (u^a, u^b)) = 1$ $u^{a^*} = max(u^b : (u^a, u^b)) = 1$ and the point (u^{a^*}, u^{b^*}) shows the maximum utilities of agent A and B which is the end point of K-S line. The K-S solution lies at the point where this line intersects Pareto-frontier.

The Kalai-Smorodinsky solution has shown to be a good choice when the fourth axioms (independence from irrelevant alternatives) is not important (see Roth (1979) for a discussion and examples). Apart from this, the Kalai-Smorodinsky solution satisfies the axioms 2, 3 and 4 and the additional axiom 5.

2.3.3 Strategic bargaining Model

Seminal work in strategic bargaining theory is Rubinstein's dividing pie problem (Rubinstein, 1982). The pie problem refers to bargaining situation where two players have to reach an agreement on the partition of a pie of 1. Both players make offers and counter-offers to suggest how it should be divided. When a player makes an offer, the other player must either accept it or reject it and continue with the bargaining. Rubinstein assumes that players have complete information and can make unlimited alternating offers. It is further assumed that the delays are costly for both parties.

Rubinstein's bargaining process can be modeled as a dynamic game and solved by using the backward induction method. The general idea of the backward induction method is to determine the optimal strategy of the player who makes the last move of the game. Then, the optimal action of the next-to-last moving player is determined taking the last player's action as given. The process continues in this way backwards in time, until it determines the Nash equilibrium of each subgame of the original game.

There are many different variations of the Rubinstein's model (see Binmore (1992) for an overview). Examples include the models with risk of breakdown, incomplete information or with a time deadline. As mentioned in Section 1.5 the ultimate goal of our research is to develop a software-based solution where agents can negotiate to each other directly by making offers for energy exchange. In relation to our model, the Rubinstein's bargaining model provides a good opportunity to investigate the strategic interaction of agents. However, the seemingly easy task of computing counter-offers can be very complex. For this reason, the Rubinstein's model has been applied to simple settings until now.

2.3.4 Which bargaining solution is appropriate for the energy exchange problem?

We have discussed utilitarian, egalitarian, the Nash bargaining and the Kalai-Smorodinsky models in the above sections. Each model has its own properties and satisfies some of the axioms defined above. The question here is whether each of these models is applicable in the energy exchange. This question can be answered by analyzing the required properties of our solution listed in Section 1.4. In particular, we note that one property requires the solution to energy exchange problem to withstand the effect of false reporting. Though there can be many ways of reporting false information, one way is to report exaggerated utility for a given energy allocation. An appropriate solution must withstand this effect and it should not let an agent influence the outcome in its favour by reporting a false utility function. In other words, the solution should be irrelevant to utility representation of the agents or more precisely, irrelevant to equivalent utility representation which is our first axiom listed in Section 2.3.2. Thus, all the solutions which do not conform to the first axiom are exploitable. This leaves only the Nash bargaining solution as it satisfies all four axioms. Indeed, it is the only bargaining solution which satisfies all four axioms (Roth, 1979). Therefore, in the energy sharing problem where selfish agents need to reach a solution, the Nash bargaining solution is the most appropriate choice.

The discussion so far focuses on the two players games and the obvious question is whether the Nash bargaining solution is applicable in multi-player games. Indeed, extension of the Nash bargaining to multi-player scenario has been shown to be robust and straightforward (Waslander et al., 2003; Sang-Chul and Wen, 2006; Ruusunen, 1994b) which again confirms the appropriateness of the Nash bargaining solution in energy exchange problem.

However, one key requirement of our model which is to enable agents to negotiate directly to each other can not be modeled using the Nash bargaining solution. Nash bargaining solution is an axiomatic bargaining solution and it requires a mediator to which agents can report. This mediator then computes a solution. The presence of a mediator makes this process a centralized solution which is against our requirement. This leads us to strategic bargaining where agents can negotiate directly. We note that the Rubinstein's model can be a good choice. The standard Rubinstein's model can be extended to include our requirements of timeliness, robustness and adaptability (Binmore, 1992) which makes it a good choice for our problem. However, the Rubinstein's model cannot always be solved as the standard model assumes full information. Also, as said earlier, it can be computationally complex to compute the counter-offer.

2.4 Energy Exchange

In this section we summarize the literature on energy exchange. Most of the literature can be divided into two categories based on whether fairness is a criterion in the solution. Thus, one category deals with energy exchange which is purely cooperative and where fairness is not a criterion. In such systems, the objective is to maximize overall system utility, i.e. a utilitarian approach. These problems arise frequently in systems where all agents have a common goal. Examples are power management on a naval ship where different components coordinate and exchange power to conserve power (Ganesh, 2005) or intelligent buildings where different agents coordinate to reduce peak (Abras et al., 2010; Davidsson and Boman, 2000). Since the overall performance, not fairness, is the prime objective, these approaches are not feasible in our case.

The other part of the literature on energy exchange consider fairness criteria in some respect. We can divide this literature into further four subcategories.

2.4.1 Fixed-surcharge energy exchange

As mentioned in the first chapter, the energy cost varies with the demand. In some cases, when energy exchange is to take place in periods where energy demand is different, an extra amount of energy may be demanded to make this exchange even. For example, Finland borrows electricity from Sweden during the day and returns the received amount of energy, plus a predetermined additional compensation at night (Ruusunen et al., 1991). In some countries, the same exchange method is employed for electricity exchange between cities. Examples are India (New Dehli and Madhya Pradesh) [7] and Pakistan (Karachi and Lahore)[8].

2.4.2 Market-based energy exchange

Market-based environments are simulated by trade between multiple buyers and multiple sellers (Carlsson and Andersson, 2005; Clearwater, 1996; Clement and Barrett, 2003). Broadly speaking, it is an auction-based model where the sellers list the availability of energy. The buyers then submit their bids for this energy. The highest bid wins the auction and thus the buyer with the highest bid is allocated the energy. The roles of seller and buyer are not permanent. For example, a buyer who has won multiple auctions and has extra energy may become a seller to sell the extra energy.

A majority of contemporary approaches for energy exchange are market-based (examples are Jia-hai et al. (2005); Gnansounou et al. (2004); Li et al. (2007)). Although, it is sometimes referred to the energy exchange it is a market model and exchange takes place in the form of money, not pure energy. Furthermore, in some cases this may be virtual money (Li et al., 2010). Fairness is imposed by establishing a free market where buyers and sellers can decide over price. A participant may walk away from an auction if she feels the price is not fair.

Despite their popularity, market-based approaches does not provide us with a good solution to the energy exchange in peer-to-peer networks. Firstly, market-based approaches involve currency and are not applicable in payment-free system. One way to get around this problem is to use virtual money or tokens. However, perhaps what makes market-based unseemly is the fact that all market-based approaches assume a central entity which is responsible for maintaining the market or auctions and thus leading to a centralized solution. Such centralized solutions are not applicable in decentralized environments which is one the requirement (Section 1.4) in our problem.

2.4.3 Pure Barter

Energy barter refers to energy exchange where energy is the only medium of payment. Energy is borrowed and an *equivalent* amount is returned later. This equivalence is measured in some agreed way before the exchange (Ruusunen et al., 1991). The difference in fixed-surcharge energy exchange defined above and energy barter is that in energy barter there is no additional surcharge, instead the preference and demands for the energy defines when two amount of energy are equivalent.

[7] Times of India, October 10, 2006
[8] Pak Tribune (Newspaper), July 04, 2006

Surprisingly, apart from Rusuunen's and Ehtamo's work (Ehtamo et al., 1987, 1989b,a, 1988; Ruusunen et al., 1989, 1991; Ruusunen, 1992, 1994b,a), this area has not been much explored. Rusuunen's work provides a good basis for fair and optimal barter in electricity exchange. In his proposed model, energy producers form a pool where barter takes place to maximize cost savings. This saving is then divided between participants using the Nash bargaining solution. These savings are recorded in terms of energy saved and the exchange takes place in terms of electricity only; thus, a pure barter. Apart from being a centralized solution, this work provides a good example for our problem.

2.4.4 Barter with side payments

This approach is a modified form of pure barter. Here, barter takes place in the form of energy exchange, as mentioned above, but in cases where only energy exchange may not be conceived as a fair solution, a side-payment is introduce to make up for someone losses. Such approaches are again not applicable in payment-free settings.

We have summarized energy exchange methods in literature. Based on the nature of solutions, energy exchange may or may not be required to be fair. We are interested in fair solutions. However, the contemporary energy exchange approaches are either centralized and/or payment based which make them improper in distributed and payment-free settings. Energy barter, however, provides a window of opportunity and can be applicable where distributed control and payment-free energy exchange.

2.5 Peer-2-Peer Energy Networks

As we mentioned earlier in Section 1.4, the idea of P2P energy networks is not novel but it has not received the attention it deserves. Two references in literature are in hydrogen distribution network (Amoretti, 2009) and in power grid (Beitollahi and Deconinck, 2007). Amoretti (2009) proposes that owners of distributed generation resources can be connected in a peer-to-peer network and can buy and sell energy (hydrogen in this case). He provides an overview of feasible network overlays schemes in such energy networks. An overlay scheme defines how peers are connected and how messages are propagated among nodes. Several overlay schemes such as unstructured, structured, hierarchical schemes, in context of energy distribution, are discussed in this study. He assumes that each peer is a consumer and as well as a producer of energy. When a peer has some demands which it is unable to meet, it sends a message to the network which is propagated by all peers to find a peer which can provide energy. When found, the price of the energy (including the transmission cost) is negotiated and then this peer buys this energy.

This study provides a good case for the peer-to-peer energy network. However, his idea is in a preliminary stage and there are a couple of directions that must be explored before it can be applied in real world. Firstly, it abstract away the negotiation details. It is assumed that peers are able to negotiate over price and reach a decision. Also, there is no study on how the message passing mechanism scales and how payments are divided if two peers are connected through another peer and energy transfer involves this peer.

Another study on the P2P energy networks by Beitollahi and Deconinck (2007) discusses advantages of different network overlays schemes, in a network of distributed generation. It advocates the idea of dissolving the traditional power grid into smaller distributed units which can then exchange energy. Though, it promotes the idea of P2P energy networks, it does not provide any details on implementation neither any empirical data.

The topic of P2P energy networks has yet to be studied comprehensively. In particular, there is no study to explore energy exchange in houses.

2.6 Summary

Microgeneration and smart houses are the inevitable part of future vision of energy. Given the intermittent nature of renewable energy resources and the need to integrate distributed energy resources, energy exchange is a component of this vision. Energy exchange between utility companies has been studied by Rusuunen, however, this work is not applicable to our more general problem of energy exchange for two reasons. First, it makes use of axiomatic concepts and thus assumes a centralized system. Second, it does not consider energy storage or issues with renewable generation. In multiagent systems, the idea of energy sharing has only been studied in terms of energy trading, with most of the literature focused on market-based approaches. These approaches again propose centralized systems which are not applicable in one-to-one energy exchange.

Axiomatic bargaining solutions are centralized and assumes that participants reveal their true information which may not be the case when selfish agents are involved in bargaining. Strategic bargaining models are decentralized and allow one-to-one bargaining between selfish agents. However, it can be hard to use strategic models in real world for two reasons. Firstly, some of them require players to have complete information, e.g. Rubinstein's model. Secondly, it can be computationally complex for players to compute offers and counter-offers in multi-issue negotiation.

Although, certain outcomes can be labelled as fair in axiomatic bargaining, strategic bargaining models can not be measured on this criteria. However, a bargaining problem can be modeled using both axiomatic and strategic approaches to benchmark the strategic approach against the axiomatic approach.

Chapter 3

Cooperative Energy Barter in Microgrids

As the first step towards a decentralized bargaining solution for energy exchange, we develop an axiomatic bargaining model. Axiomatic bargaining models, as we mentioned earlier, are centralized which is against our requirements. However, the purpose of developing an axiomatic model is two-fold. First, we can identify the energy exchanges which can said to be fair, based on some axiomatic criteria. Second, we can use the outcomes from axiomatic bargaining to compare with the outcomes from strategic bargaining and then benchmark the strategic approach against the axiomatic approach.

3.1 Problem Model

This section describes our model in detail along with the basic components and assumptions that we hold. We discuss the power generation, load, preference, utility, storage and constraints in our model. We also show all the attributes and notations of our model.

We begin with Figure 3.1 which shows a visual model of two houses connected together. Each house has some microgeneration units (a solar panel and a wind turbine), a battery and a house controller device (circles: A and B). A house controller device is responsible for controlling all appliances, microgeneration units, battery and power flows in the house.

We now discuss each profile and notation in detail.

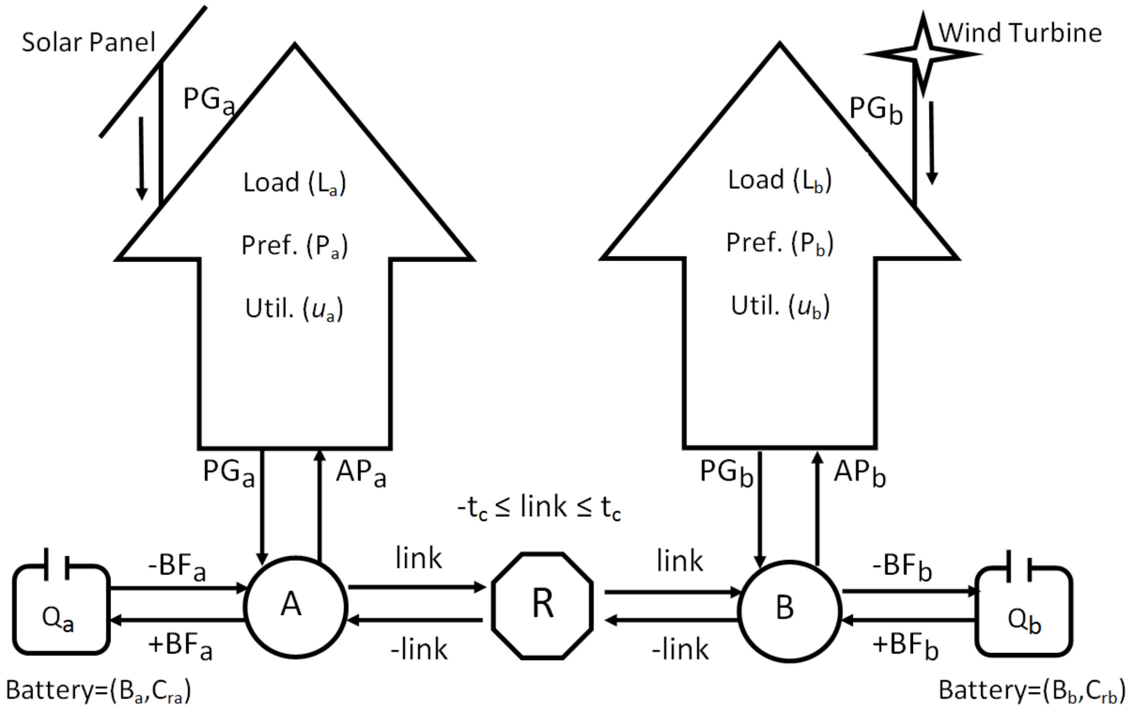


FIGURE 3.1: A visual description of the model.

3.1.1 Agents

As stated in Section 1.5, in our problem an agent represents the energy controller device in a house. The house energy controller is assumed to have access and control of all the microgeneration units and appliances in a house. Also, the controller has all the information regarding a house such as the power generation, preference and load profiles which are described in the later sections.

3.1.2 Time periods

We divide a day into 24 discrete periods corresponding to 24 hours in a day. This leads to three implications. First, the least amount of time for which an exchange can take place is an hour. Second, the rate of energy exchange during this unit time remains constant. For example, an exchange of 1 kWh energy for a single time period implies that this exchange takes place in one hour and 1 kW was the power maintained during the exchange. Third, all the profiles are based on unit times. At this stage, this atomicity is assumed to keep our model simple but at a later stage, we can relax these constraints. A unit of time is denoted by t such that $t \in T$ where T is the set of all time unit and $|T| = 24$.

An additional assumption regarding the time periods is that they are circularly linked, i.e. the last time period of a day is connected to the first time period of the next day i.e. $t_1 = t_{24} + t$.

3.1.3 Power Generation Profile

The energy generation profile for an agent shows the total generation capacity in a unit time by the microgeneration units. We assume that the power in a unit time remains constant. For example, a 5 kW entry in the power profile shows that the energy can be generated at a constant rate of 5 kW for an hour. This assumption of constant power is valid for two reasons. Firstly, the agent can use a combination of microgeneration units (e.g. a micro-CHP with a wind turbine) to ensure a constant output. Secondly, this assumption rules out the uncertainty associated with renewable energy resources and thus, makes the modeling of our problem easier. We will model this uncertainty factor in our future work.

Microgeneration units are characterized as low-power generators and we assume that agents in our model have a maximum power generation capacity of 8 kW which is available only in certain times of a day.

We denote the set of power generation as PG and pg_t shows the generation at time t. Since $|T| = 24$ therefore $|PG| = 24$. Also, since the time periods are linked, the profile is repeatable (i.e. $pg_{24+t} = pg_t$).

3.1.4 Load Profile

Load profile shows the required power in each unit time. As with the power generation, we assume energy consumption rate to be constant in a unit time. For example, a load of 2 kW in a unit time corresponds to a constant requirement of 2 kW in that time unit and the energy consumed is 2 kWh.

The load profile is represented by a set L and a member of this set is denoted by l_t at time t. Also, since the time periods are linked, the profile is repeatable (i.e. $l_{24+t} = l_t$).

3.1.5 Available Power Profile

Unlike the load profile which is a set of an agent's demands, the available power profile is the set of the actual power available or allocated to an agent. For example, an agent may need 10 kW power for a unit time (load) but gets 2 kW from a microgeneration unit and 3 kW from a battery, a total of 5 kW power for that time unit; thus, 10 kW is the required power or load while 5 kW is the available power for that time period. Available power profile is represented by AP and ap_t is the available power at time t. Also, this profile is repeatable, i.e. $ap_{24+t} = ap_t$.

3.1.6 Preference Profile

For every load per unit time, an agent has a preference. This shows the comparative degree to which an agent regards this demand important. In other words, preference is a function which associates the load l_t at time t with a real number. The preferences are assumed to be independent i.e. a preference for a single time period depends only on that particular period and not on any other time period. For example, the preference to watch an hour-long TV program in a given time period depends only on this time period. This assumption of independent preferences reduces the complexity in computation. We will consider interdependent issues later in our future work.

The preference profile is represented by P and p_t denotes the preference at time t. Also, since the time periods are linked, this profile is repeated for every day.

3.1.7 Utility Function

The utility function of an agent is a linear function which maps a member of the available power profile to a real number. It is computed as the following:

$$u_t = p_t \times \frac{ap_t}{l_t} \tag{3.1}$$

subjected to $0 \leq ap_t \leq l_t$, where u_t is the utility of an agent at time t, p_t is the preference at time t, l_t is the load at time t, ap_t is the available power at time t.

More specifically, the utility of an agent at a particular time period is the percentage of demand (load) met multiplied by the preference for that load. This implies that u_t can never be greater than p_t, (i.e. $u_t \leq p_t$). Also, Equation 3.1 implies that when the ratio between ap_t and l_t equals 1 then u_t is equal to p_t and thus, the maximum utility for a time slot is the preference for that time slot. Equation 3.1 also implies that the ratio between ap_t and l_t is never greater than one,(i.e. $\frac{ap_t}{l_t} \leq 1$) since available power should not exceed the load at any time. Also, since the preferences are assumed to be independent, the overall utility is a linearly-additive function. [1] Therefore, the overall utility of an agent for a given preference, load and available power set is

$$u = \sum_t p_t \times \frac{ap_t}{l_t} \tag{3.2}$$

[1]Let $f : V \to \mathbb{R}$ be a function on a real vector space V. We say that f is additive if $f(x + y) = f(x) + f(y)$

3.1.8 Battery Model

Although the current state of storage technologies make a 50kWh battery storage a valid assumption as described in Section 2.1.2, for our model, we assume that each house has a 30kWh energy storage capacity with a 5kW maximum charge and discharge rate. This is more than current storage devices in homes, which are reported to be somewhere between 5kWh to 10kWh with power ratings of 1-3kW power (see Section 2.1.2), for two reasons. First, the current use of energy storage devices is limited in houses. Storage is either used for stabilizing the intermittent renewable energy or for storing some energy when it is cheaper (a storage heater is an example). This indicates that storage is not being used to its full potential in houses. Second, in the near future, energy storage will cost less and will be more appealing to people.

We denote the maximum capacity of this battery by B, i.e. $B = 30$kWh. Also, the maximum rate of energy flow or power of the battery is denoted by C_r and $C_r = 5$kW. C_r is assumed to be positive when charging and negative when the battery is discharged.

During operation, the dynamics of battery states can be defined by two variables. Firstly, by the flow of energy in and out of the battery at each time slot. The rate of this energy flow is measured in kW and we denote it with $bf_t \in BF$ where t is the time period and BF is the set of battery flows. As the maximum flow at any given time is C_r, it implies that $-C_r \leq bf_t \leq +C_r$. The second variable is the state of a battery describing the amount of energy stored. It is measure in kWh, denoted by the set Q and a member in this set is identified as q_t where t is the time period. This implies that $q_t = 0$ means that the battery is not charged while $q_t = B$ shows that the battery is fully charged. Note that $0 \leq q_t \leq B$ (i.e. the battery cannot store energy greater than its capacity and it can only provide energy which has already been stored). Finally, as mentioned above in Section 3.1.2, the last state of the battery is linked with the first state of the next day, i.e. $q_1 = q_{24} + bf_{24}$. These all attributes are modeled as constraints in our model.

3.1.9 Wasted Energy

There may be some cases where an agent is unable to use its full energy generation capacity. For example, an agent may decide to miss or reduce some energy generation opportunity when the battery is full and the load is already met. We want to model this phenomenon to measure the amount of energy that could be generated but the agent does not opt to due to the limited battery or low demand. We call this *wasted* energy and denote it by a set W where each element w_t denoted the amount of energy that was not generated at time t. Since this waste comes from power generation only, the waste at any time is always less than the generated power at that time, i.e. $w_t \leq pg_t$. Also, since the time periods are linked, $w_{24+t} = w_t$.

3.1.10 Transmission Line

So far the discussion is around an agent, i.e. a single house. However, when we extend our model to two agents, we need a transmission line and a regulator between these agents. The transmission line is a physical link which can transfer power. The power on transmission line is denoted by $link_t$ at time t and it is positive or negative depending on the direction of flow. The capacity of the transmission line to transfer power is denoted by $link_{cap}$ and it constant, i.e. $link_{cap} = 5$kW. Since the power on the transmission line can never exceed the capacity of the transmission line therefore $link_t \leq link_{cap}$ where $link_t \in \mathbb{R}$.

3.1.11 Regulator

In order to regulate energy flow between houses and to facilitate negotiations, we require a regulator between houses. Agents who wish to participate in an energy exchange send the details of their profiles and utility functions to the regulator who then computes an optimal and fair energy exchange solution.

3.1.12 Summary of the Model

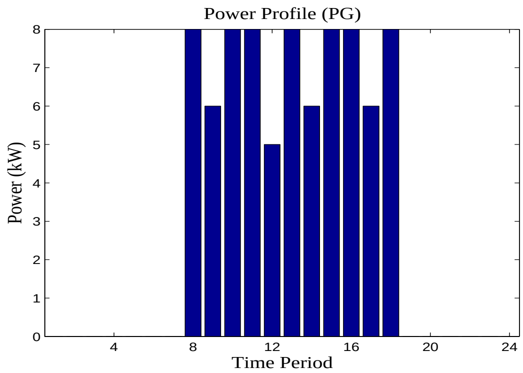
We now present a review of all sets and notations we used so far in our model in Table 3.1.

Name	Type	Notation	Notation for an element	Value/ Boundary
Time periods	Set	T	t	$1 \leq t \leq 24$
Power Generation Profile	Set	PG	pg_t	$0 \leq pg_t \leq 8$
Load Profile	Set	L	l_t	$0 \leq l_t$
Available Power Profile	Set	AP	ap_t	$0 \leq ap_t \leq l_t$
Preference Profile	Set	P	p_t	$0 \leq p_t$
Battery States	Set	Q	q_t	$0 \leq q_t \leq B$
Transmission Power	Set	Link	$link_t$	$-link_{cap} \leq link_t \leq link_{cap}$
Waste	Set	W	w_t	$0 \leq w_t \leq pg_t$
Utility Function	Function	u	u_t	$0 \leq u_t \leq p_t$
Storage Capacity	Constant	B	-	30 kWh
Battery Charging rate	Constant	C_r^+	-	5 kW
Battery Discharging rate	Constant	C_r^-	-	5 kW
Transmission Capacity	Constant	$link_{cap}$	-	5 kW

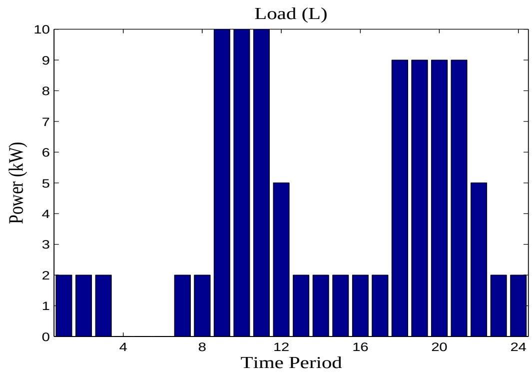
TABLE 3.1: An overview of the model attributes and notation.

3.2 Optimal Energy Use Without Energy Exchange

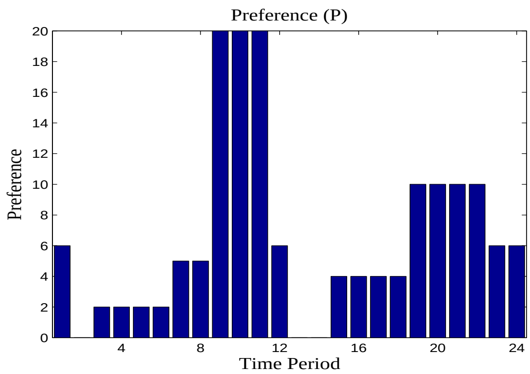
In this section, we discuss an optimization approach where energy exchange is not an option. In such case, the prime objective is to allocate the available power to meet demand on time. This allocation is computed so that the overall utility is maximized. Demands are prioritized based on the associated utility and the demands with higher preferences are met first. We give an example of such optimization in the section below.



(a)



(b)



(c)

FIGURE 3.2: Power, load and preference profile of the agent.

Suppose an agent has some microgeneration units and a battery. This agent has a power, load and preference profile as shown in Figure 3.2. The data here is synthetic and it is based on our literature review (see Enabling Technologies - Section 2.1).

We can see that power generation is restricted to daytime only, i.e. from 0800 to 1800 (10 hours), simulating generation from solar panels. Also, the power generation is not constant, as the case with the renewable generation. Figure 3.2(b) shows the load profile. We can see that there are some peaks (0800 - 1100 and 1800 - 2200) which show the times when the demand is high. These times roughly correspond to times in a typical house when household wakes up and gets ready to leave for office and schools. Generally, this preparation involves taking a shower, having a breakfast and watching TV for which power-hungry devices such as the electric shower, electric kettle, microwave oven and toaster are used and hence the demand peaks in the morning. The second peak is in the evening time when the household returns. The typical activities at that time include space-heating, use of oven, microwave oven, watching TV and using computers . This again results in the demand peak. Also, it can be seen that the demand for power is nominal very early in the morning when household is asleep and in times other than peak times.

Figure 3.2(c) shows the preferences for the each time period. We can see that preference are high when the tasks are intensive and very desirable. For example, the preferences for power in the morning is very high which can reflect the household's wish to be ready in time for the office and school. Also, the preferences are higher for the time when household returns and needs energy to carry out activities such as space-heating and watching TV.

The objective of this agent is to obtain the maximum preferences possible with the given power generation profile. Since it is equipped with a battery, it can store and use energy later to achieve its goal more effectively. The overall utility is defined in Equation 3.2 and the objective is optimal energy allocation for maximum utility, therefore:

$$AP^* = \underset{ap_t}{\operatorname{argmax}} \sum_t u_t \tag{3.3}$$

Substituting for u_t from Equation 3.1

$$AP^* = \underset{ap_t}{\operatorname{argmax}} \sum_t p_t \times \frac{ap_t}{l_t} \tag{3.4}$$

subjected to the following constraints:

1. $ap_t = pg_t + fb_t - w_t$
   Available power at time t must not exceed the total power in the house (i.e. the power generated, flow from the battery and waste) at time t.

2. $ap_t \leq l_t$
   Available power at t must not exceed the load at time t.

3. $q_{t+1} = q_t + bf_t$
   The next battery state depends on the current battery state and the current battery flow.

4. $q_1 = q_{24} + bf_{24}$
   The last battery state for this day is the first battery state for the next day.

5. $0 \leq q_t \leq B$
   The boundaries for battery states. B is the maximum storage capacity of the battery.

6. $C_r^- \leq bf_t \leq C_r^+$
   The boundaries for battery flows. C_r^+ is the maximum flow while C_r^- is the minimum flow.

7. $w_t \leq pg_t$
   Waste cannot exceed the power generated in that time period.

Since the objective function and all the constraints are linear, the optimization is a linear programming problem which can be solved using the simplex algorithm. [2] The following plots show the summary of optimization.

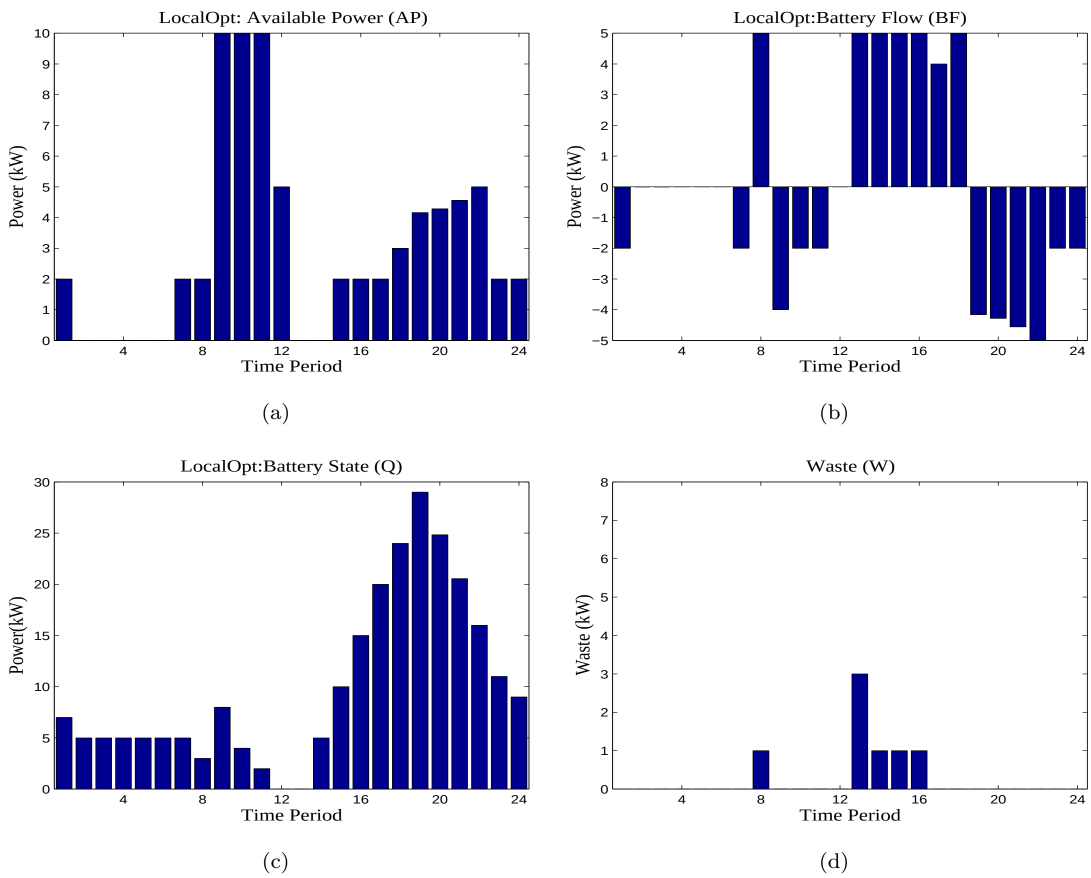


FIGURE 3.3: Optimization without energy exchange.

Figure 3.3(a) to Figure 3.3(d) show the results of optimization for this agent. There are a couple of interesting results. Firstly, as expected, we can see that the energy is made available for the time periods for which preference per unit power is higher. For example, the time periods 9-11, 19-23 have higher preference (Figure 3.2(c)) and thus

[2] See *Applied Optimization with MATLAB Programming* by P.Venkataraman, for more information

the maximum possible energy is available to these periods, as shown in the available power plot (Figure 3.3(a)). Also, the time periods where preference is low are allocated the least power. The extreme cases are time periods number 2 and 13-14 where the preference is zero for each period (Figure 3.2(c)). We see that these periods do not get any energy (Figure 3.3(a)) which conforms the intuition.

Secondly, for the battery flow, Figure 3.3(b) shows that the battery is charged during time periods 13-18 (positive power indicates charging and negative power indicates discharging) when power is available (Figure 3.2(a)). It is discharged later in the evening (periods 19-23) when the preferences for energy are higher.

The figure for the battery states (Figure 3.3(c)) shows the stored energy at each time period. This again conforms with our intuition as the energy is gradually stored in the later part of the day (time periods 13-18) up to the maximum capacity of the battery (30 kWh) and then discharged later in the evening and early morning. Some slightly counter-intuitive duration is the time period 9-11 when the battery is discharged in hours when the power is available. However, this effect is due to the fact that the battery is slightly charged in time period 8, and then it is discharged in time period 9-11 to augment the generated power. This is done as the generation profile is known and the optimizer knows that the battery can still be charged up to the maximum capacity in the following time periods, as evident in Figure 3.3(c) where the battery is again charged from time period 14-19, achieving the maximum storage capacity (30kWh) in time period 19.

A quick look may raise a question about the stored energy in the early periods when the agent is not producing any energy (Figure 3.2(a), time period 1-8). This is due to the fact that the battery states are linked, i.e. the last state of the battery is linked to the first state of the battery. In other words, the last state of the battery is the first state for the next day, as mentioned in Section 3.1.2.

Figure 3.3(d) shows the *wasted* energy. This is actually the energy that could have been generated but the generation opportunity was intentionally missed as the storage was not available. Comparing this figure with Figure 3.3(b), we can see that in all periods where the energy is wasted, the demand is already met and the battery flow (charging) is maximum and thus the opportunity to produce energy is missed as this energy is extra.

Table 3.2 provides another view of the optimization results. Here, we can also see profiles, utility and the wasted power for each time period. We observe that the amount of wasted energy is 7kWh out of 79kWh (8%). The battery flows sum up to zero, indicating that all the energy that is stored is withdrawn later. We can also see that the agent achieves a utility of 131.75 out of 158 (83.3%) using 72 kWh energy. To make sense of this number, we can compare it with the overall utility when this agent has no battery. Figure 3.4 shows the comparison of utility per time period for this agent. We can immediately see that the agent gets utility only in the time period when the energy

Time	Pref	Load	Power Gen.	Battery Flow	Available Power	Utility	Waste	Battery charge
00:00	6	2	0	-2	2	6	0	7
01:00	0	2	0	0	0	0	0	5
02:00	2	2	0	0	0	0	0	5
03:00	2	0	0	0	0	0	0	5
04:00	2	0	0	0	0	0	0	5
05:00	2	0	0	0	0	0	0	5
06:00	5	2	0	-2	2	5	0	5
07:00	5	2	8	5	2	5	1	3
08:00	20	10	6	-4	10	20	0	8
09:00	20	10	8	-2	10	20	0	4
10:00	20	10	8	-2	10	20	0	2
11:00	6	5	5	0	5	6	0	0
12:00	0	2	8	5	0	0	3	0
13:00	0	2	6	5	0	0	1	5
14:00	4	2	8	5	2	4	1	10
15:00	4	2	8	5	2	4	1	15
16:00	4	2	6	4	2	4	0	20
17:00	4	9	8	5	3	1.33	0	24
18:00	10	9	0	-4.16	4.16	4.62	0	29
19:00	10	9	0	-4.28	4.28	4.75	0	24.83
20:00	10	9	0	-4.55	4.55	5.05	0	20.55
21:00	10	5	0	-5	5	10	0	16
22:00	6	2	0	-2	2	6	0	11
23:00	6	2	0	-2	2	6	0	9
Total	**158**	**100**	**79**	**0.00**	**72**	**131.75**	**7**	**-**

TABLE 3.2: Optimization results with the utility breakdown and wasted power.

is generated (Figure 3.2(a)) as it has no battery to store this energy for later use. In terms of numbers, without the battery this agent an overall utility of 76.55 out of 158 (48.44%) while with the battery it is 83.3% as mentioned earlier in this section.

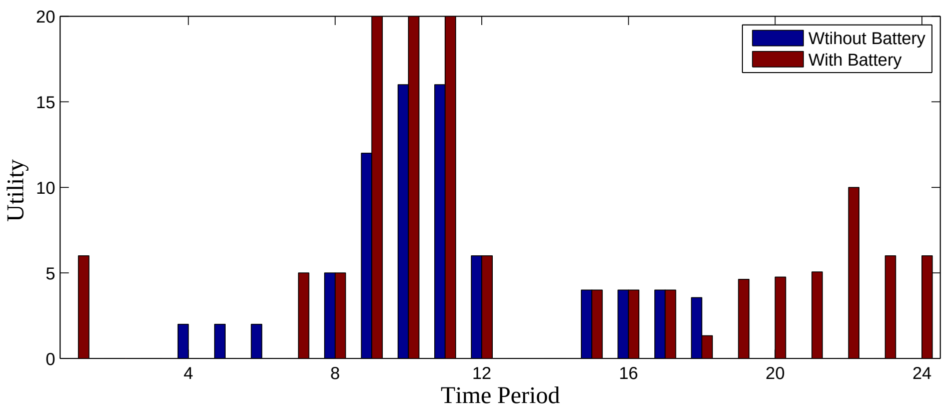
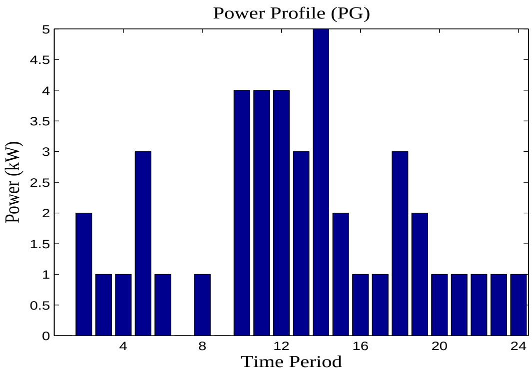


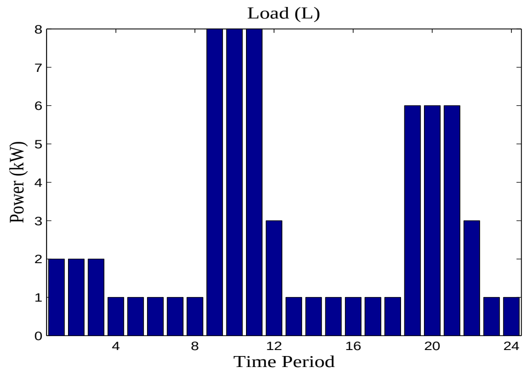
FIGURE 3.4: Utility comparison for the agent: with and without a battery

3.3 Optimal Energy Use With Energy Exchange

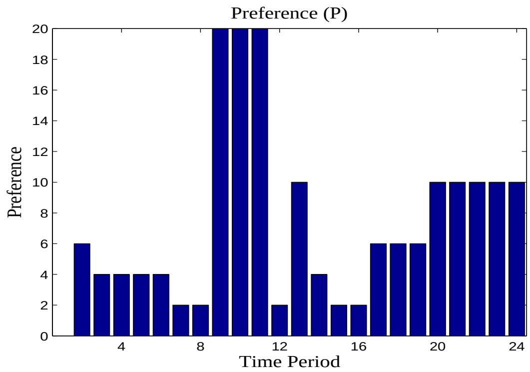
As we argued in the first chapter, energy exchange between agents can lead to more efficient use of energy. Let us imagine that there are two agents A and B each acting as the energy controller device for a house. These agents have their own power generation profiles, loads and preferences as detailed in Figure 3.2 for agent A and Figure 3.5 for agent B. We assume that agent A has some solar panels while B has a wind turbine for power generation and that the houses are linked so that electricity can flow in either direction as shown in Figure 3.1.



(a)



(b)



(c)

FIGURE 3.5: Power, load and preference profile for agent B.

A classical problem in cooperation is to decide about dividing the obtained utility from cooperation. We have discussed some approaches in Section 2.3 and concluded that the Nash bargaining solution is the most suitable solution in our problem. Therefore, we use the Nash bargaining solution for a fair and optimal energy exchange.

In order to compute the Nash bargaining solution, agents are required to report their information to the regulator between houses. Since this regulator decides about the energy flow, agents must inform it about their energy generation and storage capabilities. Furthermore, since these agents are rational and selfish, they will only cooperate with each other if this cooperation results in higher utility for them. In other words, agents will only participate if they get a higher utility than what they obtain when they work individually. In our case, agent A and B can do no better than optimizing the energy allocation using their batteries. We have already shown the optimization for agent A in Figure 3.3. Here, in Figure 3.6 shows the equivalent optimization results for agent B.

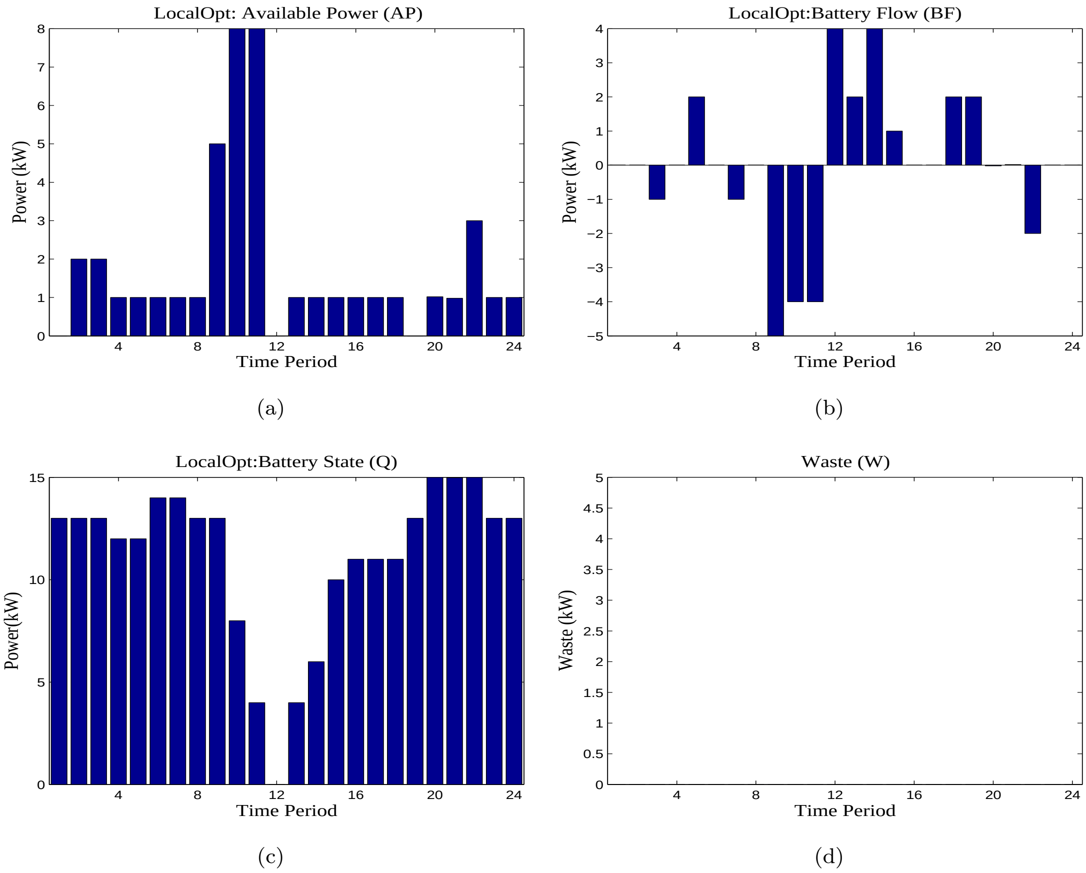


FIGURE 3.6: Local Optimization (without energy exchange) results for agent B.

Firstly, we discuss these optimization results for B. Figure 3.6(a) shows the available power to agent B. We can see that power is again allocated to time periods where preference per unit power is higher. Figure 3.6(b) shows the battery flow. We can see that the battery is charged and discharged throughout the day. This is due to the fact that power is available most of the time as agent B has a wind turbine. Figure 3.6(c) shows the battery states.

One noticeable result is that the maximum energy stored is 15kWh (time periods 20-22) despite the fact that the maximum storage capacity was twice as much (30kWh). This, again, is due to the fact that wind turbine generates low-power over almost all periods which is then used immediately, as opposed to agent A which produces more power but only in certain times of a day. In this way, we can observe that agent B is not using the battery to its full potential.

We can also see that agent B does not miss any opportunity to generate energy, hence

Time	Pref	Load	Power Gen.	Battery Flow	Available Power	Utility	Waste	Battery charge
00:00	0	2	0	0	0	0	0	13
01:00	6	2	2	0	2	6	0	13
02:00	4	2	1	-1	2	4	0	13
03:00	4	1	1	0	1	4	0	12
04:00	4	1	3	2	1	4	0	12
05:00	4	1	1	0	1	4	0	14
06:00	2	1	0	-1	1	2	0	14
07:00	2	1	1	0	1	2	0	13
08:00	20	8	0	-5	5	12.5	0	13
09:00	20	8	4	-4	8	20	0	8
10:00	20	8	4	-4	8	20	0	4
11:00	2	3	4	4	0	0	0	0
12:00	10	1	3	2	1	10	0	4
13:00	4	1	5	4	1	4	0	6
14:00	2	1	2	1	1	2	0	10
15:00	2	1	1	0	1	2	0	11
16:00	6	1	1	0	1	6	0	11
17:00	6	1	3	2	1	6	0	11
18:00	6	6	2	2	0	0	0	13
19:00	10	6	1	-0.01	1.01	1.68	0	15
20:00	10	6	1	0.01	0.98	1.63	0	14.98
21:00	10	3	1	-2	3	10	0	15
22:00	10	1	1	0	1	10	0	13
23:00	10	1	1	0	1	10	0	13
Total	**174**	**67**	**43**	**0**	**42.99**	**141.81**	**0**	**-**

Table 3.3: Agent B: Optimization results (without energy exchange) with the utility breakdown and wasted power

the empty plot for waste energy(Figure 3.6(d)).

In terms of utility, Table 3.3 shows the utility breakdown for agent B. The overall utility for agent B is 141.8 out of 174 (81.4%).

3.3.1 Nash Bargaining Solution

Table 3.2 and Table 3.3 show that the overall utility is 131 and 141 for agent A and B respectively, when they work alone or, in other words, when no energy exchange takes place. As described in Section 2.3, the Nash bargaining solution requires disagreement values, or the least utilities for which agents will be willing to cooperate. Since, agent A and B can gain the utilities of 131 and 141 respectively, on their own, they will only be willing to cooperate if they get more utility than these utilities. Therefore, we take these utilities as the disagreement values in the Nash bargaining solution and formulate this problem as an optimization problem as the following:

$$AP^{a^*}, AP^{b^*} = \underset{AP^a, AP^b}{\operatorname{argmax}} \quad [u^a(AP^a) - u^a(d^a)] \times [u^b(AP^b) - u^b(d^b)] \tag{3.5}$$

Where u^a is the utility function of agent A, $u^a(d^a)$ is the disagreement utility of agent A which we have already computed to be at 131, AP^a is the power allocation profile for the agent a, and therefore, $u^a(AP^a)$ computes the overall utility for the given available power profile AP^a, u^b is the utility function of agent B, $u^b(b^d)$ is the disagreement utility of agent B which we have already computed to be at 141, AP^b is the power allocation profile for the agent B and finally $u^a(AP^b)$ computes the overall utility for a given available power profile AP^b.

Equation 3.5 is subjected to the constraints number 2 to 6 listed in Section 3.3.Here we list one modified constraint (constraint number 1 in Section 3.3) and an additional constraint below:

1. $pg_t = ap_t + bf_t + w_t + link_t$
   The power generated equals the sum of power used immediately, the battery flow, the waste and the power sent towards the other agent (i.e. link).

8. $-link_cap \leq link \leq link_cap$
   The flow on the link cannot exceed the maximum transmission capacity.

We can use the interior-point algorithm [3] to solve this problem. Below, we discuss the optimization results for both agents.

3.3.2 Optimization results via the Nash bargaining solution: Agent A

Figure 3.7 shows the result of optimization for agent A when energy exchange is an option. Figure 3.7(a) shows the available power profile using the Nash bargaining solution.

[3] Applied Optimization with MATLAB Programming by P.Venkataraman, for more information

We can compare it with the Figure 3.3(a) for the optimized allocation of power when no energy exchange takes place. Some obvious changes are in the pattern in the evening. We can see that with the energy exchange, agent A gets more power in evening where its preferences are higher. Before the energy exchange, the maximum power available for agent A was 5kWh which is the maximum flow allowed from the battery. However, with the energy exchange it can also get power from agent B in evening to meet its highly preferred demands. The power that comes from agent B can be seen in Figure 3.8(e). The negative readings show the power coming from agent B to agent A and the positive readings show the power from agent A towards agent B. We see that there is a significant amount of power coming from agent B during the late evening while a good amount of power goes from agent A during the afternoon which ensures that both agents meet their demands with high preferences.

Another aspect is the energy waste analysis. We can see that around 7kWh energy is wasted in a day with no energy exchange (see Figure 3.3(d)) due to the limited battery of agent A(30kWh). However, the energy exchange enables agent A to send this power to agent B which stores it. Thus, via energy exchange agent A not only reduces its energy loss but also get some of this energy back later in the evening as evident in Figure 3.8(e).

Figure 3.3(c) and Figure 3.7(c) show the battery states without and with energy exchange respectively. We can immediately observe that the battery stores more energy when the energy exchange is allowed than when it is not allowed. Obviously, the extra energy comes from agent B and is returned later. Therefore, we can deduce that when the energy exchange is allowed, agents can make more efficient use of their storage.

In terms of utility, Table 3.4 shows the comparison of utilities for agent A with and without energy exchange. We can see that that there is a negative change of utility in time period 18 when agent A gets a utility of 1.33 with local optimization but with energy exchange it gets zero in this time period. However, there are positive changes in time periods 19-21 when agent A gets more utility from energy exchange than local optimization. Indeed, the overall utility of agent A with local optimization is 131.78 while with the energy exchange it rises to 136.94, a net change of 5.16 or 3.91%.

One interesting point here is that agents can provide their disagreement utilities in two ways. They can either provide a single number representing their overall utility (i.e. u^d) or they can provide a set of disagreement utilities for each time period (i.e. u_t^d). When an agent provides just the overall utility, it will cooperate as long as it gets a better overall utility. In this case, it does not care about the utility in each period. On the other hand, if an agent provides a set of disagreement utilities, then it is will cooperate only if it gets a better utility in *each* time period. This approach may be useful where agents have some minimum loads requirements (such as critical loads) in some or all time periods.

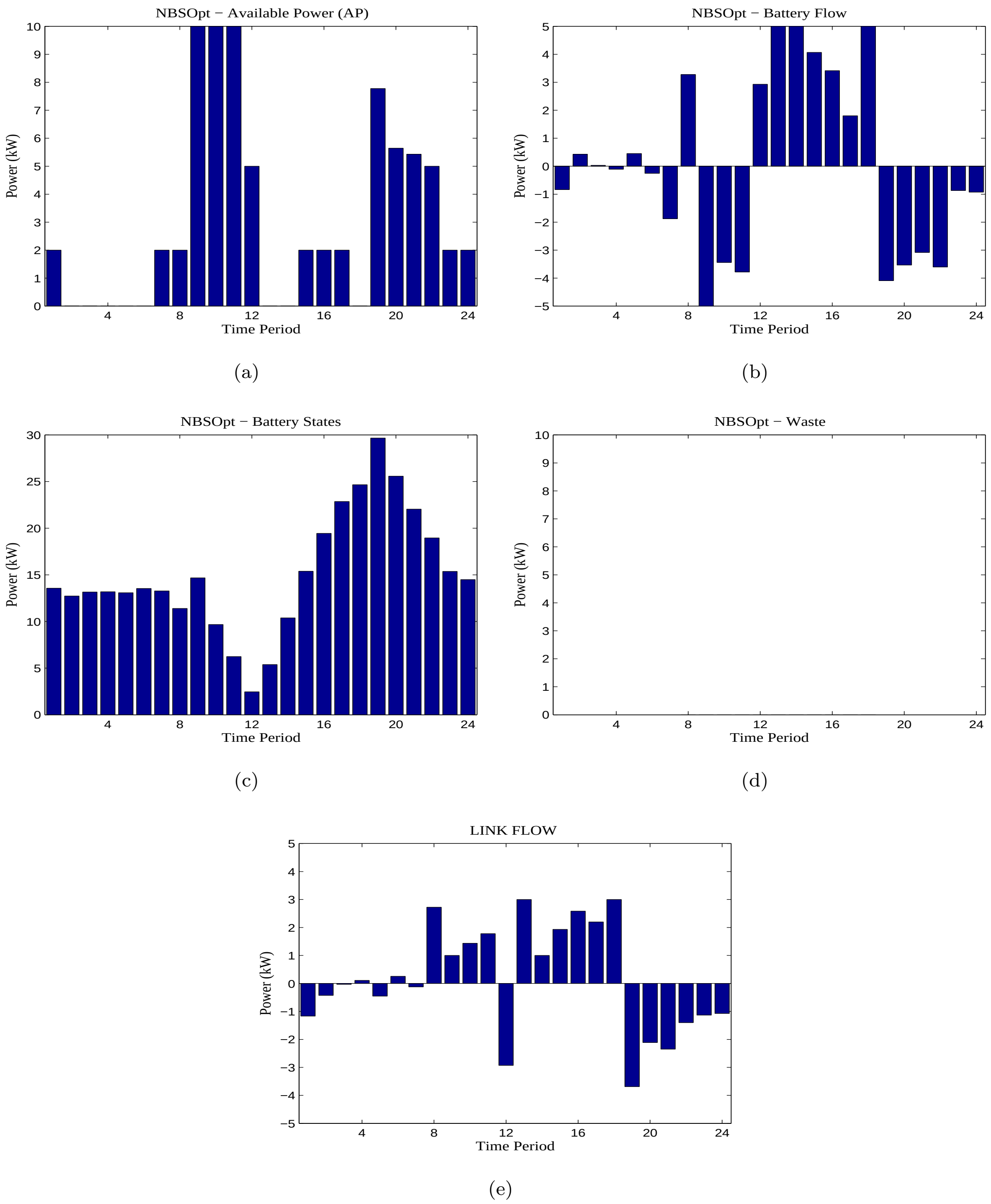


FIGURE 3.7: Agent A: Optimization via the Nash bargaining solution. In Figure (e), the negative readings show the power coming from agent B to agent A and the positive readings show the power from agent A towards agent B.

3.3.3 Optimization results via the Nash bargaining solution: Agent B

Figure 3.8 shows the optimization result for agent B when energy exchange is an option. We can see that the pattern for the available power changes (Figure 3.8(a) as compared to the Figure 3.6(a)) particularly in evening time. This is the time of the day when the power is preferred, as evident in the preferences of agent B (Figure 3.5(c)). The plots for the battery flow and for the battery states (Figure 3.8(b) and Figure 3.8(c))

	Without Energy Exchange			With Energy Exchange			
Time	**AP**	**Utility**	**Waste**	**AP**	**Utility**	**Waste**	**Link**
00:00	2	6	0	2	6	0	-1.16
01:00	0	0	0	0	0	0	-0.42
02:00	0	0	0	0	0	0	-0.03
03:00	0	0	0	0	0	0	0.1
04:00	0	0	0	0	0	0	-0.45
05:00	0	0	0	0	0	0	0.25
06:00	2	5	0	2	5	0	-0.12
07:00	2	5	1	2	5	0	2.72
08:00	10	20	0	10	20	0	1
09:00	10	20	0	10	20	0	1.43
10:00	10	20	0	10	20	0	1.77
11:00	5	6	0	5	6	0	-2.92
12:00	0	0	3	0	0	0	3
13:00	0	0	1	0	0	0	1
14:00	2	4	1	2	4	0	1.93
15:00	2	4	1	2	4	0	2.58
16:00	2	4	0	2	4	0	2.1
17:00	3	1.33	0	0	0	0	3
18:00	4.16	4.62	0	7.77	8.64	0	-3.68
19:00	4.28	4.75	0	5.64	6.27	0	-2.11
20:00	4.55	5.05	0	5.43	6.03	0	-2.34
21:00	5	10	0	5	10	0	-1.4
22:00	2	6	0	2	6	0	-1.13
23:00	2	6	0	2	6	0	-1.07
Total	**71.99**	**131.75**	**7**	**74.84**	**136.94**	**0**	**4.05**

TABLE 3.4: Utility comparison for Agent A: with and without energy exchange

show the comparative increase in the battery use when energy exchange is not an option (Figure 3.6(b) and Figure 3.6(c)). This again supports our argument that agents can utilize their storage more effectively when energy exchange is allowed. Another interesting point is that there is no energy waste in optimization, both with and without the energy exchange (Figure 3.6(d) and Figure 3.8(d)). This implies that agents do not necessarily need to have waste energy in order to obtain better results in energy exchange. A simple exchange of energy to match agents' preferences in a better way can result in better utility for both agents.

Table 3.5 shows the comparison of utilities for agent B in optimization with and without the energy exchange. We can see that, due to an optimal allocation of energy, there are some positive changes in few periods (19-21). In fact, the overall utility for agent B increases by 5.46%, from 141.83 to 149.58.

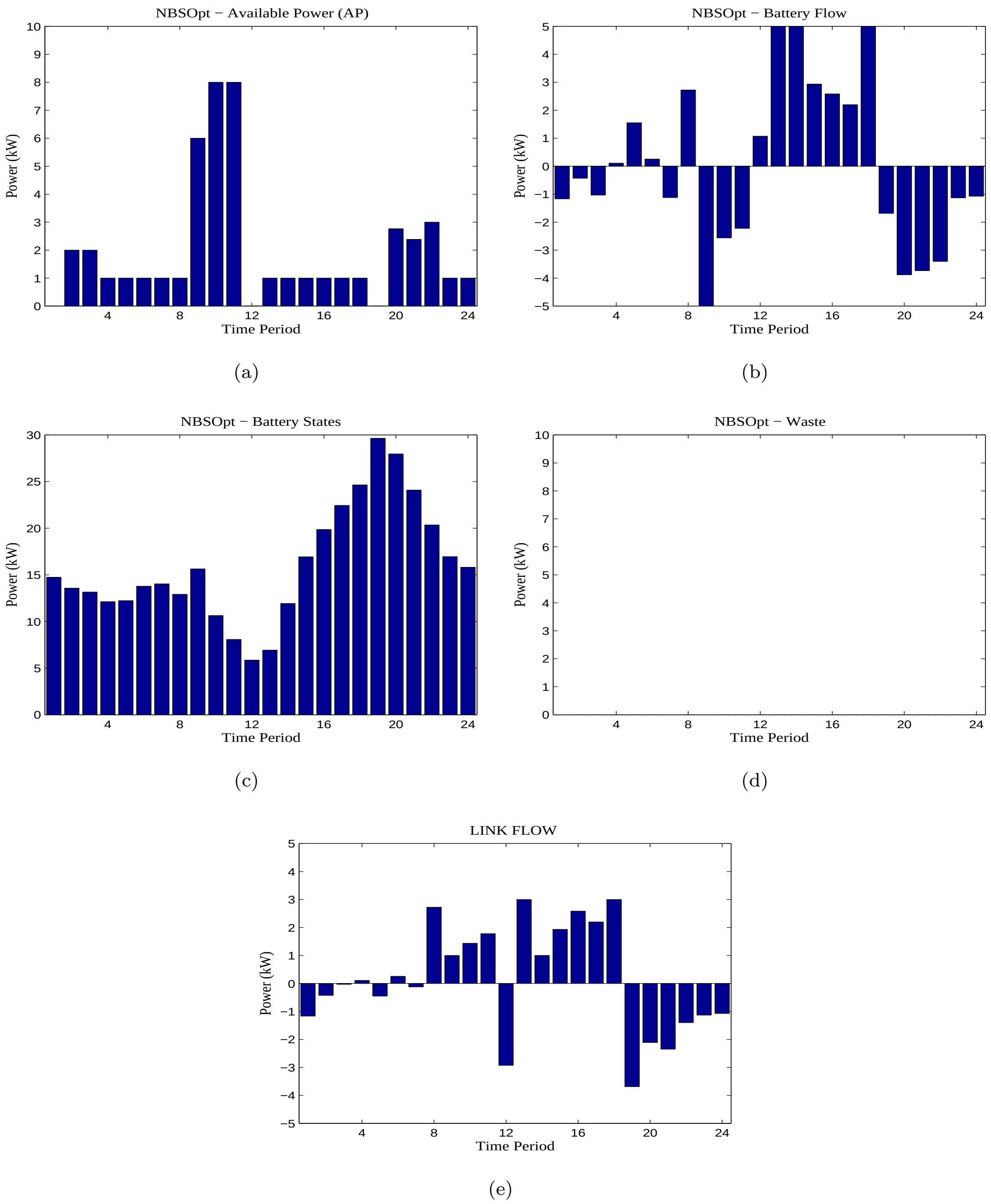


FIGURE 3.8: Agent B: Optimization via the Nash bargaining solution. In Figure (e), the negative readings show the power coming from agent B to agent A and the positive readings show the power from agent A towards agent B.

3.4 Conclusion

In this chapter, we described our model and experiments and showed how an energy exchange can lead to better use of energy and higher utilities for the participants. We observed that both agents in our example increased their utilities by 4% to 5 % via energy exchange. It can be argued that such exchange does not offer a great deal of improvement. However, this improvement depends on the diversity in preferences, power

Time	Without Energy Exchange			With Energy Exchange			
	AP	**Utility**	**Waste**	**AP**	**Utility**	**Waste**	**Link**
00:00	0	0	0	0	0	0	-1.16
01:00	2	6	0	2	6	0	-0.42
02:00	2	4	0	2	4	0	-0.03
03:00	1	4	0	1	4	0	0.1
04:00	1	4	0	1	4	0	-0.45
05:00	1	4	0	1	4	0	0.25
06:00	1	2	0	1	2	0	-0.12
07:00	1	2	0	1	2	0	2.72
08:00	5	12.5	0	6	15	0	1
09:00	8	20	0	8	20	0	1.43
10:00	8	20	0	8	20	0	1.77
11:00	0	0	0	0	0	0	-2.92
12:00	1	10	0	1	10	0	3
13:00	1	4	0	1	4	0	1
14:00	1	2	0	1	2	0	1.93
15:00	1	2	0	1	2	0	2.58
16:00	1	6	0	1	6	0	2.1
17:00	1	6	0	1	6	0	3
18:00	0	0	0	0	0	0	-3.68
19:00	1.02	1.68	0	2.76	4.6	0	-2.11
20:00	0.98	1.63	0	2.39	3.98	0	-2.34
21:00	3	10	0	3	10	0	-1.4
22:00	1	10	0	1	10	0	-1.13
23:00	1	10	0	1	10	0	-1.07
Total	**43**	**141.81**	**0**	**47.15**	**149.58**	**0**	**4.05**

Table 3.5: Utility comparison for Agent B: with and without energy exchange

and load generation of agents. With more agents, this diversity is likely to increase and therefore it can give better improvements over utilities. Besides gain in utility, we have also shown the energy loss can be reduced and agents can use their appliances and storage devices more efficiently.

At this stage, our model assumes a mediator (i.e. the regulator) between houses. This is against the requirement of a decentralized solution. Our next step is to remove this mediator to enable agents to negotiate directly with each other. We can then use this solution to benchmark the decentralized solution and measure its performance.

Chapter 4

Conclusions and Future Work

4.1 Conclusions

In this report, we discussed the ever-increasing need of energy and the problems of reliance on fossil fuels. We reviewed some contemporary proposals to address these issues such as microgeneration, smart houses, microgrids and smart grids and we noted that these proposals open up the possibility of energy exchange which is a common practice for efficient use of energy in larger networks such as between utility companies. We presented a scenario of a small network of smart houses and then discussed the benefits of energy exchange such as the efficient use of energy, reduction in carbon emissions, better management of intermittent resources, reduction in energy storage loss and more efficient use of storage etc. We then discussed the challenges and requirements of such energy exchange between houses. We noted that these requirements are common in domains of multiagent systems, game theory, bargaining theory and peer-to-peer networks and we identified specific topics of interest in these domains for literature review.

We then presented a model of two agents representing two houses. We optimized the use of energy for both agents when energy exchange is an option. We observed that in some cases, agents may miss the opportunity to generate energy due to limited storage capacity. We then used the Nash bargaining solution to compute an energy exchange between agents. We noted that such an exchange is beneficial to both agents as they gain more utility than when they work individually. We also noted that agents can use their storage more efficiently when exchange is an option. Thus, we concluded that energy exchange between houses can result in efficient energy use and efficient use of energy resources.

4.2 Future Work

At this stage, we have a centralized solution. Our model needs a mediator between houses which computes the energy exchange. Since it is against our requirements as we need a decentralized solution, it is essential that we remove this mediator. This requires us to consider a strategic bargaining model and as we discussed in the Section 2.3, we choose the Rubinstein's model to proceed our investigation. As discussed earlier, this model assumes full information and may not provide a fully-fledged solution for energy exchange. However, we use this model as the point of our departure and we will consider such shortcomings along our path.

We are also interested in the case, where agents negotiate via mediator and misreport their information to this mediator. We would like to see if such settings are exploitable and if an agent can manipulate the bargaining outcome in their favour by reporting false information.

Another direction of future work is to model uncertainty in energy generation. Renewable energy generation weather-dependent and therefore their output is uncertain. Agents must consider this uncertainty when they make offer to other parties. One way to achieve this is to ensure that agents express their belief about uncertainty in their offers. For example, if an agent believes that it can generate 5kWh in a particular time period with a probability of 0.8, then it must pass this probabilistic measures in its offer to other agents. Also, We also need to consider what circumstances where an agent fails to meet his committed offers.

In the mini-thesis which is due in January, 2011, we intend to include a reasonably real-world model of strategic bargaining for energy exchange between houses.

The following figure shows the planned future work.

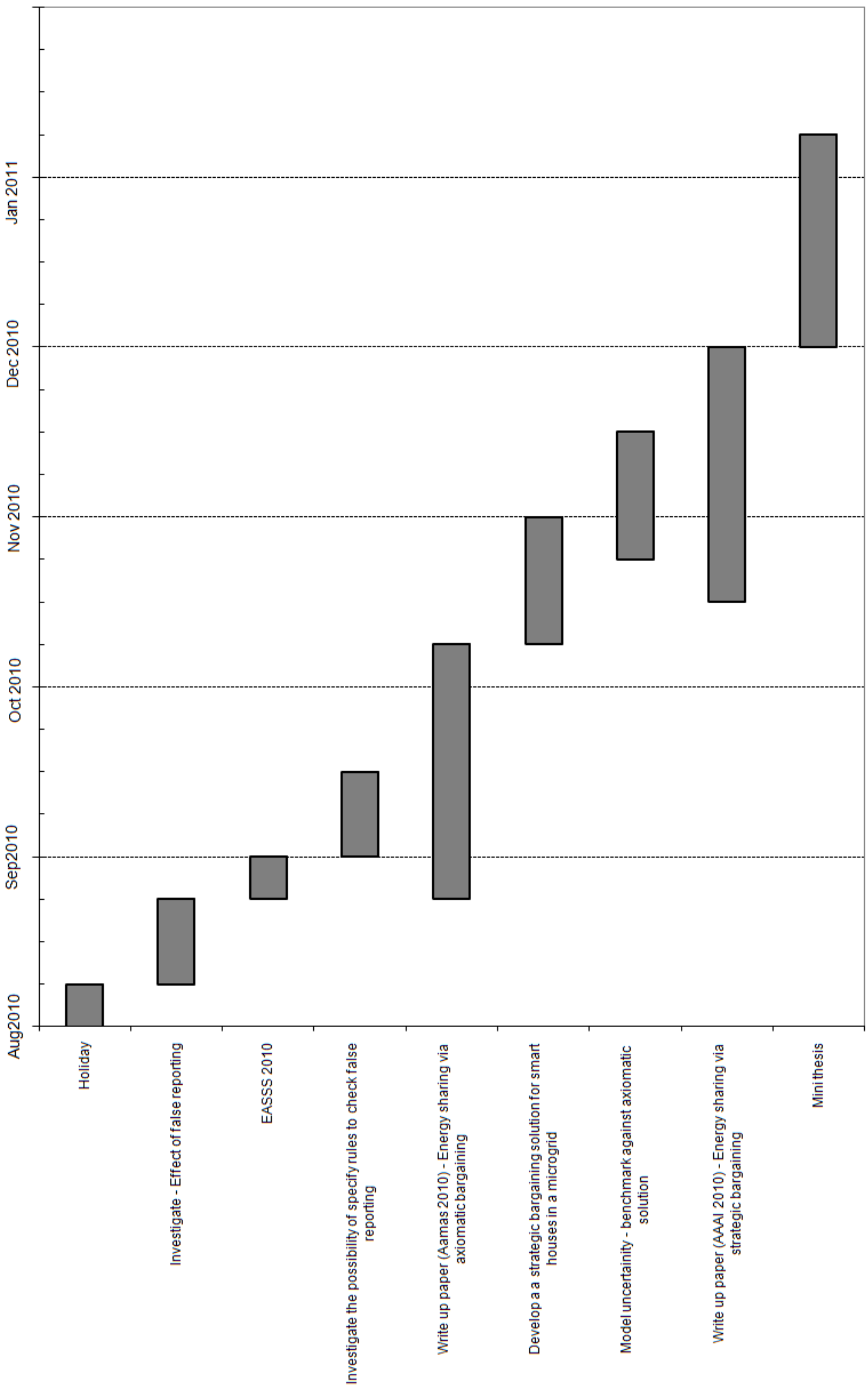


FIGURE 4.1: Gantt chart of planned work until Minithesis.

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