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A Negotiation Protocol for Decentralised Energy Exchange Between Homes

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ABSTRACT

FACULTY OF PHYSICAL AND APPLIED SCIENCES
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A number of recent projects are focused on providing access to electricity to the remote communities in developing world. Their idea is to provide renewable energy generation units and energy storage devices to homes in these communities. These resources enable a household to generate, store and consume energy according to its needs. However, these resources operate in isolation and we envision an interconnection of homes to allow the decentralised coordination of their resources in order to exchange energy. Energy exchange offers many advantages such as improving the efficient use of energy, and therefore, is a common practice in utility companies. However, the utility-scale exchanges require several resources (e.g. human experts who manually negotiate, on behalf of their companies, to reach exchange agreement) which are not present in remote communities. In contrast, we motivate the use of an automated negotiation solution and present a novel negotiation protocol to facilitate energy exchange between off-grid homes. The negotiation over energy exchange is multi-issue, where issues are interdependent on each other, and therefore, is more complex and difficult. To deal with complexity, our protocol imposes additional constraints on negotiation such that it reduces a complex interdependent multi-issue problem to one that is tractable. We prove that using our protocol, agents can reach a Pareto-optimal, dominant strategy equilibrium in a decentralised and timely fashion. We empirically evaluate our approach with the real data and show that, in this case, energy exchange can be useful in reducing the capacity of the energy storage devices in homes by close to 40%.

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Nomenclature

u^i	Utility of agent i
d^i	Disagreement value of agent i
$\boldsymbol{k}$	Generation capability of an agent
$\boldsymbol{h}$	Load requirements of an agent
$\boldsymbol{g}$	Actual generation of an agent
$\boldsymbol{w}$	Wasted energy of an agent
$\boldsymbol{l}$	Link flow between two agents
s	Maximum storage capacity of a battery
c_{max}	Maximum charging rate of a battery
d_{max}	Maximum discharging rate of a battery
$\boldsymbol{q}$	Stored energy in a battery
$\boldsymbol{c}$	charging profile of a battery
$\boldsymbol{d}$	discharging profile of a battery
$\boldsymbol{p}$	Energy allocation
r_1, r_2 and r_3	Restrictions of our protocol
$\boldsymbol{l}^i$	Link flow offer of an agent

Chapter 1

Introduction

It is estimated that 1.6 billion people live without access to electricity; mostly in Sub-Saharan Africa and the Indian subcontinent (IEA, 2008). This population is divided into small communities scattered over large areas and thus, providing them with centralised power distribution has not been justified to date due to the capital cost of such infrastructure and the lack of demand. However, demand cannot become established if there is no supply. To address this dilemma, a number of initiatives have begun to provide these communities with off-grid renewable microgeneration infrastructure such as solar panels, and electric batteries for storage. These microgeneration units, coupled with storage devices, have been shown to be effective for satisfying the basic energy needs of these communities.[1]

At present, these microgeneration units operate in isolation. Each unit generates energy during the course of a day for a single household, where it is either consumed immediately or stored for later use. However, energy generation from these units varies with the time of day depending on the type of microgeneration unit (e.g. solar panel or wind turbine), their power output (e.g. 1kWh or 2kWh) and the local weather condition. In addition, demand for energy in each households varies depending on the personal preferences (e.g. using a electric shower early in the morning or late in the evening) of the residents and the type of appliances it contains. The fact that these resources are heterogeneous, and operate in isolation, raises a question: can such heterogeneous resources coordinate and exchange energy between the connected homes so that their energy demands are met more efficiently? If so, through what process or method can these resources come to an energy exchange agreement when each household is only interested in its own benefit (or utility)? This is the research question we aim to address in this research endeavour.

Ultimately, we envision that such interconnection and coordination of resources can lead to the creation of a grid from the "ground up", allowing these communities to take an evolutionary

[1] See the Solar Homes program in Bangladesh (`http://www.gshakti.org`), the Rural Solar Homes in India (`http://www.tatabpsolar.com`) and the Solar Village program in Ethopia (`http://www.solarsenegal.com`).

jump straight to the smart grid; an intelligent electricity supply network where electricity as well as information are exchanged to use energy more efficiently (USDOE, 2003), which is the contemporary vision of the future electricity grid.

The coordination of resources to facilitate energy exchange between homes in a community, has many benefits to offer. Energy exchange can be useful when there is a temporary shortage in generation. For example, a home with a wind turbine may experience a temporary power shortage on a calm day and can borrow some energy from a home with a solar panel, and this energy can be returned at some agreed stage. Also, when a home generates more energy (e.g. due to continuous windy days) than required for its immediate use, and also exceeds the storage capacity, it can utilise the storage capacity of another home to save this energy. Of course, both homes should benefit in this exchange for it to be sustainable.

Energy exchange is also useful to reduce the loss of energy in storage. This loss is referred to as the energy storage loss and it occurs when some part of the energy being stored is emitted as heat by the storage devices. For example, it is a common phenomenon that an electric battery heats up when charged and thus loses some energy in the form of heat. This loss can be up to 24% (Stevens and Corey, 1996) in some cases. Households can exchange energy to reduce the need for storage and, in this way, they can reduce the storage losses.

As outlined by our research question, our aim is to investigate the process or method through which homes in a remote community can exchange energy to meet their demands more efficiently. These remote communities have certain characteristics which must be taken under consideration in order to address our research question. For example, these communities lack the banking/payment systems and infrastructure which are commonplace in urban areas. In the next section, we discuss these characteristics along with other issues to identify the requirements to address the problem of energy exchange in these communities.

1.1 Research Requirements

In this section, we explore the research requirements that any solution to the problem of energy exchange should meet. We can identify two types of requirements based on their origin. First, those requirements that originate from the characteristics of remote communities. Second, those that relate to the interaction of the households in these communities.

We identify three requirements, relevant to the problem of energy exchange, that originate from the characteristics of remote communities. The first is the absence of a centralised power distribution system due to the capital and maintenance costs, as we mentioned earlier. In the absence of a centralised entity, the energy exchange must take place in a *decentralised* fashion where homes decide the power flow between them by themselves. Therefore, a decentralised solution is an essential research requirement for this problem.

Unlike the urban communities, remote communities may not have the online banking/payment systems. This characteristic hinders the possibility of automatic financial payments between homes. One way to address this shortcoming is to assume no financial transactions between homes as part of the energy exchange, which is another research requirement in this case. Finally, a remote community may consist of hundreds of homes, which indicates that scalability is another important factor that a solution must offer.

Now, in addition to the requirements inspired by the characteristics of these communities, there exists a number of requirements that are inspired by the characteristics of the individual households and their interactions to each other. Foremost, the households are interested only in maximizing their own benefit (i.e. they are self-interested) and therefore, households will only participate in an energy exchange if it increases their own utility. In other words, for any energy exchange to take place it must be beneficial to all participants. In addition to this, the benefit to each participant should be comparable or fair to others' in some regard. A solution that favours a particular participant will not be acceptable to other participants.

The households in a community can coordinate to come up with a number of different ways to exchange energy. Since the households are self-interested, each will prefer the exchange which gives it the highest utility. This leads to a conflict when the households prefer different energy exchanges. However, their interests are generally not mutually exclusive and there may be some exchange agreements that can give some utility to all participants, which may not be their preferred highest utility but more than when they do not participate in an exchange. In these cases, the households can *negotiate* and agree on an exchange agreement from this set of possible exchange agreement. Although, it is possible for humans to negotiate in simple scenarios, the negotiation over energy exchange is fairly difficult and computationally complex (as discussed in Section 1.2) and a better approach is to automate the negotiation process, thus requiring minimal or no human input. This need for *automatic negotiation* is another essential requirement.

We can identify several desirable properties for this automated negotiation process between households. For example, the negotiation process should be well-defined, simple and guaranteed to terminate in a timely manner. Also, since the participants are self-interested individuals, there is always a possibility of that they will misreport/cheat if doing so results in greater utility to them. A negotiation process that assumes that participants will be honest and willing to share their requirements truthfully, will not be appropriate in this scenario. Similarly, in negotiation processes where participants can lie and gain benefits, a great deal of efforts are required by the participants to plan and tackle dishonest behaviour of other participants and avoiding being a victim. This complicates the negotiation process for participants. One way to avoid this problem is to engineer the negotiation process so that dishonest behaviour is not rewarded. This greatly reduces the complexity of negotiation since the participants exhibit honest behaviour and there is no need for them to plan for dishonesty. This kind of negotiation processes are said to be *strategy-proof*.

It is also important to consider that even when the participants have incentives to be honest in negotiation, they may not be certain about their private information. For example, the power output from a wind turbine depends on the local weather conditions and, therefore, can only be predicted with a certain accuracy. This introduces uncertainty into the negotiation process as the participants will not be certain of their generation or demands (and thus their offers). A desirable property of the solution is for it to be *adaptable* in such scenario.

Finally, the basic motivation of energy exchange is to ensure energy is used more efficiently. Thus, negotiation should always yield an efficient outcome. One related measure in this context is whether the outcome is *Pareto-optimal*. An outcome is called Pareto-optimal when no participant can get more utility without reducing another participant's utility. For example, if there is some unused energy that 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-optimal solution.

The following list summarizes this section and presents our research requirements:

REQ 1. **Automated Negotiation**
We are interested in automated negotiation with minimal or no human input.

REQ 2. **Beneficial to all**
A solution must be beneficial to all those participating in an exchange. Participants are self-interested and will not take part in an exchange if it is not beneficial for them.

REQ 3. **Fair**
The benefit each participant receives should be fair according to a pre-agreed criteria. The fairness property ensures that a society remains just.

REQ 4. **Decentralised**
The solution must be applicable in decentralised settings, i.e. it should not require a centre or mediator.

REQ 5. **Scalable**
The solution must be scalable from a minimum of two homes to a few hundred.

REQ 6. **Adaptable**
The power output 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.

REQ 7. **Timely**
Negotiation must be guaranteed to terminate in a timely manner.

REQ 8. **Pareto-optimal**
The solution must lead to a Pareto-optimal outcome.

REQ 9. **No Payment Mechanism**
The solution must not depend upon payments between participants.

REQ 10. **Strategy-proofness**
The solution should discourage the participants from strategising over a large number of outcome. It must ensure that participants are not rewarded for their dishonesty.

These research requirements bring some research challenges with them which we discuss in the next section.

1.2 Research Challenges

In this section, we discuss the key challenges in addressing the research requirements detailed in Section 1.1. In so doing, we identify the knowledge domains where such requirements are common. We introduce and discuss such candidate disciplines and describe their relationship with our research requirements.

The first requirement states the need of automation in negotiation [REQ 1] which suggests the use of software agents. A 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. These agents exhibit autonomous and goal-driven behaviour (Jennings et al., 1998). Agents pursuing a goal or some desirable 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* (MAS).

The multiagent systems paradigm is a natural fit for the modelling our research problem. For instance, each household can be modelled as a self-interested agent and therefore, a community can be represented as a multiagent system. Multiagent systems are naturally decentralised [REQ 4], which is another desired requirement of our solution. MAS are scalable [REQ 5] because a single MAS may contain hundreds or even thousands of agents, and robust because there is no single point of failure and, in general, an individual agent's failure does not undermine the whole system function (Wooldrige, 2009). These characteristics make multiagent systems a strong candidate to model our problem.

The interactions between agents in a multiagent system can be very complex. Agents are self-interested entities and they pursue their own goals. In order to achieve their goals, they *strategically* interact with other agents. The dynamics of these strategic interactions have been studied in 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) (Luce et al., 1958, p. 9). In this sense, game theory provides an ideal platform to systematically study such interactions in multiagent systems. More specifically, game theory provides solution concepts (e.g. Nash equilibrium) to predict the outcome of the interactions between agents and to analyse the properties of the outcomes. For example, dominant strategy equilibrium is a solution concept that states that when each player has a strategy that gives it the best utility regardless of what the opponents play (i.e. when a player has a *dominant strategy*), then the players will play this strategy (Mas-Colell et al., 1995, p. 217). Another solution concept is the Nash equilibrium (Nash, 1950b), which states that a game is in an equilibrium state if none of the players wants to change its strategy given the strategy of other players.

A sub-field of game theory is *bargaining theory* which focuses on the bargaining aspect of interaction between agents. Agents bargain with each other over some resource (energy in our case) to reach an agreeable outcome (Muthoo, 1999, p. 15). Our research requirements of fairness [REQ 4] and Pareto-efficiency [REQ 8] are common topics in this field. Bargaining theory can be divided into two types, axiomatic bargaining and strategic bargaining. Axiomatic bargaining associates the outcomes with certain axioms such as Pareto-efficiency and invariance to utility scales. In this type of bargaining, the emphasis is on reaching outcomes associated with axioms but not the process that is used to reach these outcomes (Rubinstein, 1982). The Nash bargaining solution (Nash, 1950a, 1953) and the Kalai-Smordinsky model (Kalai and Smorodinsky, 1975) are examples of axiomatic bargaining solutions. On the other hand, strategic bargaining is focused on the bargaining process and strategies used in bargaining. Perhaps the most influential work in strategic bargaining is Rubinstein's work (Rubinstein, 1982), which explores the strategic bargaining between two players who need to reach an agreement over a shared resource. They propose a bargaining model (known appropriately as the Rubinstein's bargaining model) where agents make offers to each other and under some assumptions (e.g. the utility or discount rate of agents are public knowledge) this bargaining leads to an equilibrium state.

These two types of bargaining provide two extremely useful insights to our problem. Firstly, using axiomatic bargaining, we can explore the possible outcomes of our energy exchange problem that satisfy certain axioms. For example, we can use the axiomatic approach to specify outcomes which satisfy our requirements of fairness and Pareto-efficiency. Secondly, using strategic bargaining, we can study the strategies and protocols that are useful in negotiation over energy exchange. For example, we can investigate whether a particular protocol is strategy-proof.

Although the above bargaining approaches seem very promising, there are challenges in using them to solve our problem. For example, the axiomatic bargaining focuses on the bargaining outcome only and not the bargaining process and therefore, the axiomatic bargaining solutions may not be applicable when agents are self-interested and employ different strategies for their own benefit (Roth, 1979). The study of bargaining process becomes crucial in such scenarios. The strategic bargaining is helpful here as it focuses on the bargaining process and provides a good direction to study the players' strategies. However, the existing strategic bargaining models are applicable in simple settings with strong assumptions such as that of complete information (agents know the private information of their opponents) or the assumption that the utility functions are linear (Gerding, 2004, p. 32). In reality, such assumptions are generally absent and, as a consequence, it becomes extremely complex to carry out a systematic game-theoretic analysis.

One approach to deal with this complexity is to simplify the settings in which agents interact with each other. For example, Rosenschein and Zlotkin (1994) studied automated negotiation between self-interested agents and the effect of the environment on their interactions. They formulate a principled framework within which they study the interactions of agents under different *rules of encounter*. They seek to design the rules of interaction for these negotiations such that a society of agents, as a whole, exhibits desirable properties such as stability (e.g. Nash equilibrium), efficiency (Pareto-efficiency) and strategy-proofness [REQ 10]. Careful design of such rules prevents the agents from being able to exploit the system and also reduces the overall complexity of interaction for the agents. They show examples of such rules for some domains and prove that negotiation lead to certain properties. Although, this idea of simplifying settings is applicable in some cases, there are factors which hinder the straightforward application of this idea to our problem. For example, Rosenschein and Zlotkin conclude in their study (Rosenschein and Zlotkin, 1994) that there is no universal set of rules for general encounters and, therefore, a specific set of rules is required for a specific domain. The domain of energy exchange has not been studied in this regard and thus there are no rules for this domain yet. This motivates the need for studying the domain of energy exchange under this approach.

The domain of energy exchange is more challenging than those which Rosenschein and Zlotkin studied. The negotiation over energy exchange involves multiple issues which are dependent on each other. The issues are multiple because a single energy exchange may consist of multiple time periods where the amount of energy to be exchanged in each time period can be different. Therefore, agents will need to decide not only the total amount of energy to be exchange but also how much of the amount will be exchanged in each time period. Moreover, these issues are interdependent as the recipient's utility for any period may depend on the energy received in earlier periods. This type of negotiation is referred to as interdependent multi-issue negotiation and is far more complex than when issues are independent and can be negotiated individually (Robu et al., 2005). This interdependency further complicates the straightforward application of Rosenschein's work in the energy exchange domain.

More recent work that addresses interdependent multi-issue negotiation is focused on two tracks. Hindriks et al. (2006) attempts to approximate the utility space to remove the interdependency between issues. However, they conclude that this technique is only applicable when the issues are not highly dependent (i.e. only a few of the issues are interdependent) and fails to yield reliable results when the issues are highly dependent. This severely limits the application of this approach to the problem of energy exchange where *all* the issues are interdependent. The second track (Hattori et al., 2007; Ito et al., 2007; Fujita et al., 2010) is focused on the use of a central authority (a mediator) to which agents report their private information. This mediator then calculates the Pareto-optimal solutions, using stochastic optimisation techniques, from which the agents negotiate to choose one. Although, this makes the negotiation easier, such solutions fail in decentralised settings where no central authority exists.

From this discussion, we can conclude that the problem of energy exchange is difficult and challenging. The existing state-of-the-art provides a good starting point to investigate this challenge but there is no off-the-shelf solution for our specific problem at present.

1.3 Research Contributions

As a first step towards addressing our research objectives, we have developed a negotiation protocol that enables energy exchange between two agents. Under our negotiation protocol, agents can make offers which must meet three key restrictions which yield the following properties:

1. The outcome (i.e. the exchange agreement) is Pareto-optimal.
2. The negotiation protocol is strategy-proof as the dominant strategy for the agents is to reveal their offers truthfully. Therefore, agents have no incentive to develop other strategies.
3. Negotiation only lasts two rounds.
4. Agents can compute their optimal offers using linear programming.

Our negotiation protocol is detailed in Section 3.2. We also evaluate our negotiation protocol against the Nash bargaining solution and show that energy exchange has the potential to reduce the storage capacity requirements.

1.4 Structure of the report

The remainder of the report is organised as follows:

- Chapter 2 describes previous work in the domain of energy exchange. In particular, we discuss microgeneration, large scale energy exchange, bargaining solutions, and work on negotiation with interdependent issue.
- Chapter 3 presents our model of two connected agents. We show how agents can optimize their use of energy using this model. We also show how agents can use this model to agree on an energy exchange via axiomatic bargaining. We present an example to show how agents can increase their utility via exchange. Finally, we show that the mechanisms that are based on such bargaining solution are exploitable.
- Chapter 4 describes the technical details of our negotiation protocol and its properties. We describe our protocol and provide mathematical proofs of its properties. We then present an example to show that our protocol has the potential to reduce the need of storage capacity.
- In Chapter 5, we summarize our findings and outline our future research direction.

Chapter 2

Background

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 homes and which are essential in energy exchange. We then discuss the practice of energy exchange on a large scale and current work in this area. This is followed by a discussion of existing work on bargaining, a technique which can be useful in energy exchange. In the final section, we summarize and discuss the shortcomings in existing work.

2.1 Technologies to Enable Energy Exchange

In this section, we introduce three technologies underpinning our vision of energy exchange between homes. We also provide an overview of the advancements and current trends in these technologies, which is necessary to understand the state-of-the-art and to explore the problem of energy exchange. We begin by identifying which technologies can enable energy generation in homes in rural communities. We then explore the storage devices in homes by considering the current research in this direction. Finally, we introduce and discuss techniques to defer loads for more flexibility in meeting the energy demands of a household.

2.1.1 Microgeneration

Microgeneration is an umbrella term for any small-scale production of heat and/or electricity from a low carbon source.[1] It includes energy generation from small wind turbines, photovoltaic solar panel, geo-thermal, micro-CHP, micro-hydro, fuel cells and biomass burners. Microgeneration units can be used for energy generation in homes and the related literature points to many obvious advantages of microgeneration over large-scale generation. For example, micro-CHP

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

units are used for on-site electricity generation in homes. These units burn gas to generate electricity and during this process heat is produce as a by-product. This heat, which is generally wasted in large-scale generation (e.g. the nuclear plants give off this heat through their iconic cooling towers), can be utilized for space heating. Microgeneration also avoids the transmission loss which occurs in large-scale generation where some energy is lost during transmission from the point of energy generation (e.g. nuclear plant) to the point of use(e.g. homes). Microgeneration equipment such as wind turbines, solar panels and micro-CHP(combined heat and power) units are reliable and need little maintenance.

Energy in homes can be generated in a number of ways. However, on-site generation of energy by renewable energy resources such as solar panels, wind turbines and micro-CHP units have received the most attention due to comparatively low installation cost and existing infrastructure (Abu-Sharkh et al., 2006). Therefore, we focus on these three resources for energy generation in homes.

A photovoltaic (PV) solar panel consists of interconnected photovoltaic cells (or solar cells) which convert solar radiation (sunlight) to electricity via the photovoltaic effect. The power output is measured in watts (W) or kilowatts (kW) and depends on many factors such as the number, size and efficiency of solar cells and their exposure to radiation. Solar panels in remote communities come in a number of power configurations depending on the primary purpose of the generated electricity. For example, for a solar panel to provide power to a low-power light source such as LEDs (light-emitting diode), the power output needs to be in order of a few watts while the solar panels used to meet the power requirements of a home would at least be a few hundred watts. [2]

Wind turbines are used to convert the kinetic energy from the wind into mechanical energy which is then converted to electrical energy using a dynamo. The power output from a wind turbine depends on the design, blade lengths, altitude and turbine efficiency (Bahaj et al., 2007). A typical domestic wind turbine can provide 400W to 5kW.[3]

Finally, micro-CHP units are another popular choice for microgeneration, especially in some urban areas. A micro-CHP unit burns gas to generate electricity and during this process heat is produced as a by-product which can be used for space heating. This ability to use heat that would otherwise be wasted makes it ideal in regions where space heating requires considerable energy. For example, 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 has resulted in significant interest in providing micro-CHP units to households in the UK. The UK government launched a microgeneration strategy in 2006 to make microgeneraton a realistic alternative.[4] There have been good signs of progress, with the number of microgeneration units installed reported to

[2] `http://www.energysavingtrust.org.uk`

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

[4] `www.decc.gov.uk/en/content/cms/uk-supply/renewable/microgen/microgen.aspx`

be more than 100,000 (BERR, 2008). In terms of power output, micro-CHP units with power output of below 15kW are categorized as domestic micro-CHP units (Dentice et al., 2003).

To give a perspective for comparison of microgeneration power output to the energy consumption in homes, an average UK person needs 18 kWh energy per day for electrical appliances (MacKay, 2007, p. 204). The exact load of an average person in remote communities is difficult to obtain because the generation or consumption data in remote communities is not available at present. However, the load data in low-income UK homes is provided by an electric company. Based on this data set, we estimate that the daily load requirements of a low-income household on average is 26.68kWh.

2.1.2 Energy Storage Devices

Microgeneration units such as solar panels and wind turbines generate energy under certain conditions. For example, solar panels can generate energy only in daytime while wind turbines generate energy when wind blows above a certain speed. For this reason, microgeneration units are often coupled with a storage device to ensure that energy is available when energy generation is not feasible. A storage battery is also useful to provide a constant and regulated output when power is intermittent. For example, the power output from a wind turbine is intermittent and varies depending on the wind speed.

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 in homes are reported to be electric batteries and thermal storage (see DTI (2004)). The projects that are focused on empowering remote communities typically use electric batteries to store electricity generated by solar panels or wind turbines.

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 is measured in kilowatts-hours (kWh). The charging/discharging rate or power of a battery is the rate of flow of energy and we measure it in kilowatts (kW).

The storage capacity and the discharging rate depends on a number of factors. For example, in a flow-cell battery which stores electrical energy in the form of chemical energy, it may depend on the underlying chemical reaction, the nature and amount of chemicals or even the size and design of a battery. Therefore, the storage capacity and power rates differ from device to device. Electrical storage devices for homes have capacities between 5kWh to 10kWh with 1-3kW power (DTI, 2004, p. 9). If electric vehicle batteries are used for this storage, the storage capacity could be up to 50kWh with 20-50kW power (DTI, 2004, p. 9). Modern vehicles such as the Tesla Roadster from Tesla Motors, the E6 from BYD and the Zhong Tai from Zotya are examples of vehicles with a battery pack of 50kWh. The storage capacity of these are comparable to the average demand of 40kWh 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 as their cost goes down. In fact, the cost of manufacturing batteries is estimated to go down by 35% from 2009 to 2020 (BCG, 2010).

In addition to capacity and power, storage loss is another important characteristic of a battery. In principle, when energy is *stored* it is converted from one form to another. For example, when electricity is stored in an electric battery it is actually converted into chemical energy and then converted from chemical to electric energy when needed. This conversion is not 100% efficient and some part of the energy is lost during this conversion (usually in the form of heat). Another type of storage loss occurs when the internal chemical reactions in a battery reduce its stored charge without any external discharge. This phenomenon is referred to as self-discharge. The storage loss in a battery, in both cases, depends on several factors and can be up to 24% in lead-acid batteries in some cases (Stevens and Corey, 1996).

Storage devices provide households with flexibility in the storage and consumption of energy. However, there are certain operational limitations such as the maximum capacity and charging/discharging rate. This raises the obvious question of what is the best way to use a battery? In other words, when and how much energy should we store and when and how much energy should we retrieve from the battery? This is a typical optimisation problem where the objective function is to use the battery so that energy is used most efficiently. We refer to such approaches as *storage-based solutions* where the main idea is to utilize storage to its full potential. The objective functions in these solutions reflect the type of the problem considered. For example, Vytelingum et al. (2010) explore a setting where the cost of energy varies with time and an agent attempts to use its battery such that the cost of energy is minimized. The same approach can be used to minimize carbon emissions or the storage losses. The emphasis here is the optimal use of battery to achieve a particular goal.

2.1.3 Deferrable Loads

The *load* of an appliance refers to the power requirement of that appliance and here we shall used the term load interchangeably with appliance. Loads can be divided into two categories, deferrable loads and non-deferrable loads. Non-deferrable loads are those that need to be immediately available when requested. Examples include lighting, television and computers. On the other hand, deferrable loads refer to loads which may not have to be immediately available. For example, washing machines and diswashers are both deferrable loads which can be powered up at a later time. Deferrable loads are of particular interest in the energy domain due to the flexibility in their execution time. For example, deferrable loads can be delayed until the energy demand is low (and therefore the cost of energy is low) for cost savings.

In the domestic energy domain, deferrable loads can be divided into four categories (Hamidi et al., 2009) as follows:

- Wet (e.g. washing machines or dishwasher).

- Cold (e.g. fridge or freezer).
- Water heating (e.g. boiler).
- Space heating (e.g. heat pumps or radiator).

Although all these types are deferrable, the precise details or deferral technique depends on the device. For example, the wet types normally involve set periods of times when they are switched on and off by a user or a device controller. Such tasks are normally preferred to be carried out atomically. For example, it is more sensible to complete the task of dishwashing in *one go* once started, without any interruptions. Deferring this kind of loads means *shifting* the load to another time in order to achieve a particular goal (e.g. cost savings). In contrast, a cold type such as a fridge operate in cycles to keep the desired temperature. The number and duration of cycles depend on several external factors, for instance, the number of times the fridge door was opened or the initial temperature of contents. A space heating system is another example. Deferring this kind of load means deciding when exactly these cycles will take place in a given time to obtain the desired deferral goal.

As with the storage-based solutions, there exists the problem of finding the best plan to defer loads. Indeed, this is an optimisation problem which is very similar to the optimisation in the storage-based solution. The main difference is that the focus here is on the deferrable load, not the battery. Ramchurn et al. (2011) explore this possibility and show that this technique can lead to significant efficiency improvements in the use of energy as well as reductions in carbon emissions.

Load-deferral is a key enabler of energy exchange because, as with storage, it provides more flexibility in meeting energy demands. Consequently, the number of ways in which a household can exchange energy increases and therefore, energy exchange can be more useful. On the other hand, in the absence of deferrable loads, the households have rigid energy demands and thus, fewer chances of reaching an energy exchange agreement.

The three technologies that we have discussed so far, play a signification role in our vision of energy exchange in homes. In the next section, we review the existing work in the field of energy exchange and discuss its shortcomings in addressing the problem of energy exchange in homes.

2.2 Large Scale Energy Exchange

Energy exchange is a common practice in utility companies. Especially in electricity companies where the relation between demand and the cost of energy generation can be linear up to a certain threshold. This threshold depends on the infrastructure (such as nuclear power plants or wind turbines) available to a company or organization - e.g. for the UK national grid, this threshold is 40GW (Vytelingum et al., 2010). When the demand exceeds this threshold, more expensive means of energy generation (such as diesel generators) kick in and therefore, the cost of generation increases rapidly in a non-linear fashion. A utility company facing high demand can reduce the use of these expensive generators by borrowing energy from another utility company for which the current demand is low. This is not only effective in terms of cost savings but it also reduces carbon emissions, as most of these reserve generators use fossil fuels.

The examples of large scale energy exchange include exchange across the cities of a country or between two countries. For example, Finland borrows electricity from Sweden during the day and returns it 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)[5] and Pakistan (Karachi and Lahore).[6]

The amount of energy that is exchanged between two participants may not be equal. If a participant lends energy in times when demand is normally high (say daytime) and therefore, energy generation is costly, and receives the same amount back in low demand times when cost of energy generation is relatively less, then it can demand some additional amount of energy to make this exchange even. This is the case in most of the energy exchanges in real world. For instance, in the example we presented earlier where Finland borrows energy from Sweden during the day, it returns the received amount of energy, plus a predetermined additional amount (normally a certain percentage of the borrowed energy also called a *fixed surcharge*) as compensation (Ruusunen et al., 1991).

In contrast to the real world exchanges where a fixed surcharge is imposed, Rusuunen and Ehtamo propose an exchange method where energy is borrowed and an *equivalent* energy is returned later. The preference and demand of energy define when two amounts of energy are equivalent. In their proposed model (Ehtamo et al., 1987, 1989b,a, 1988) and some extensions (Ruusunen et al., 1989, 1991; Ruusunen, 1992, 1994b,a), they assume a pool of energy producers where exchange takes place to exploit diversity in energy generation costs and consumption preferences. The exchange takes place according to a pre-agreed contract, which is based on a bargaining solution (more specifically, the Nash bargaining solution as described in Section 2.3.1.1).

Both these types of energy exchanges have one feature in common, they take place as per the pre-agreed contracts. These contract-based exchanges require human experts who negotiate and design contracts on behalf on their respective companies. These experts can also audit the claims of participants (e.g. the cost of energy generation) to veracity if needed which ensures that all participants remain honest in their claims. This need of human experts designing fair and optimal contracts is in sharp contrast to our requirement of an automated negotiated (REQ1 - Section 1.1) solution. Instead, software agents are envisioned to carry out negotiation, or bargaining to be more specific, and reach an agreement. There is a clear need for automation in this negotiation process. This kind of negotiation has been studied under the bargaining theory

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

(as discussed in Section 1.2). Now, we discuss related work on bargaining that can be useful to address the problem of energy exchange.

2.3 Bargaining

Generally speaking, bargaining refers to the process through which a seller and a buyer reach an agreement. Negotiation in order to divide 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: The Bargaining Problem

The 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 desirable properties (e.g. Pareto-Optimality). This solution is called a bargaining solution. A Pareto-optimal solution is a solution where no player can improve its utility without making any other player worse off. The set of all such solutions describes the Pareto-frontier of a bargaining problem.

A bargaining problem can be characterised based on a number of attributes. We describe three of these attributes here:

- **Single-issue bargaining v/s multi-issue bargaining**
  When the object under negotiation is a single issue, then the bargaining is referred to as single issue bargaining. The opposite is multi-issue bargaining. For example, bargaining over the energy price could be regarded as a single issue bargaining if the price of the energy is the only concern. However, when other issues such as time and power are under consideration too, then the bargaining is called a *multi-issue bargaining*. Also, when the bargaining process considers multiple energy exchanges in a given time then it is a case of multi-issue bargaining.

- **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 good while a coin is not. Clearly, energy is divisible. Sometimes, a small fixed amount of a divisible good is assumed to be indivisible for bargaining to proceed more easily. For example, 1kWh may be considered to be an indivisible unit for bargaining over energy exchange.

- **Independent issues v/s dependent issues**
  In multi-issue bargaining, issues may or may not be dependent on each other. Consider an example where two agents bargain for a fixed 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 the 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 outcome of a bargaining problem also depends on how players interact with each other. For example, they can make offers and counter-offers to reach an agreement or they can reach an agreement based on some agreed criteria or axioms. In this sense, bargaining can be categorised as either axiomatic, which defines axioms and solution concepts to the bargaining process, or strategic, which studies the strategies of players. In the following sections, we discuss both types of bargaining in detail and review the existing work.

2.3.1 Axiomatic Bargaining

Axiomatic bargaining is focused on the bargaining outcome and its properties but not the bargaining process (Roth, 1979). It proposes to choose an outcome based on agreed *axioms* that it must satisfy. Depending on the agreed axioms, there may be a unique solution or multiple solutions, in the set of all possible solutions, that satisfy these axioms. The most common axioms found in literature (see Roth (1977) for a comprehensive list) are as follows:

1. **Invariance to equivalent utility representations**
   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's utility should not change the bargaining solution.

2. **Pareto-Optimality**
   This axiom refers to whether a solution is Pareto-optimal.

3. **Symmetry**
   The solution should depend only on the utility function of the 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 the inclusion of another choice C, must not make B preferable to A.

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

2.3.1.1 Nash Bargaining Solution

The Nash bargaining solution (NBS) (Nash, 1950a, 1953) is an axiomatic bargaining solution to the two-player bargaining game in which each player has a personal value (i.e. utility) for some goods which is 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[7] and convex.[8] 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 than their disagreement values, therefore $(d^a, d^b) \leq (u^a, u^b)$ must hold.

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 and y denote 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 maximize 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 the solution to this equation is unique (see Nash (1953) for the proof). Figure 2.1 provides a good illustration of the Nash bargaining product. The Nash bargaining solution satisfies all the axioms defined in the last section.

2.3.1.2 Utilitarian Solution

The utilitarian solution in axiomatic bargaining theory is used to divide a shared utility between two or more players. The shares of agents are calculated by maximizing the following equation:

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

The utilitarian solution satisfies axioms 2, 3 and 4, failing the first axiom (invariance to equivalent utility representation). This can pose a problem in situations where agents have considerable difference in their utility functions because the utilitarian solution will give the goods to

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

[8] 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.

the agent that values it the most and the other agents will get no share. On the other hand, in situations where agents are not self-interested, the utilitarian solution can be a good choice as it maximizes the overall group utility by giving the goods to the agent which has the highest utility for them. For this reason, this solution is also referred to as the *social welfare* solution.

2.3.1.3 Egalitarian Solution

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

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

The egalitarian solution satisfies axioms 2, 3 and 4. Since it does not satisfy axiom as in the case of the utilitarian solution, it suffers the same problem as discussed in the previous section.

2.3.1.4 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 axiom for a solution (Roth, 1977). This axiom 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, provided that solution exists in the subset of S (Mas-Colell et al., 1995). However, it has been shown that adhering to this axiom may make a player less satisfied with its utility when the solution set is enlarged (see Luce et al. (1958, p.128) and Kalai and Smorodinsky (1975) for examples). The Kalai Smorodinsky bargaining solution (Kalai and Smorodinsky, 1975) is an extension to the Nash bargaining solution that does not conform to this axiom.

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 2.1.

The Kalai-Smorodinsky solution has been shown to be a good choice when the fourth axiom (independence from irrelevant alternatives) is not important (see Roth (1979) for a discussion and examples).

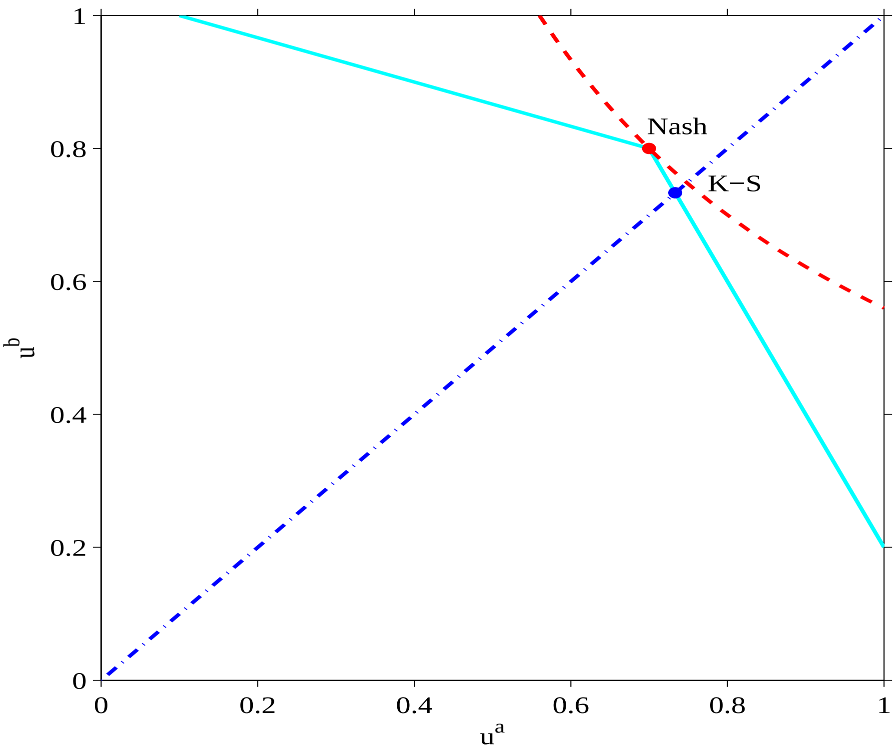


FIGURE 2.1: Nash and Kalai-Smorodinsky Bargaining Solution. The solid line is the Pareto-frontier. The origin is taken as the disagreement point (i.e. $(d^a, d^b) = (0,0)$), thus all the acceptable agreement must lie above this point. This region is called the feasible region and any point in it shows 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.

All the discussed different axiomatic bargaining solutions conform to different axioms. Depending on the choice of axioms, there may be multiple axiomatic bargaining solutions, a unique solution (e.g. the Nash bargaining solution is the only solution that satisfy the first four axioms we described, see Roth (1979)), or no solution. However, as we mentioned earlier, axiomatic bargaining describes only the outcome, not the process or strategy that players can use in bargaining. Hence, we return to strategic bargaining as as instantiation of this process and discuss it in the next section.

2.3.2 Strategic Bargaining Model

Unlike axiomatic bargaining which focuses on the bargaining outcome, strategic bargaining focuses on the strategies of the players. At a very basic level, players make offers to each other to reach an agreement. Perhaps the most influential work in strategic bargaining theory is Rubinstein's dividing pie problem (Rubinstein, 1982). The pie problem refers to the bargaining situation where two players have to reach an agreement on the partition of a shared resource (pie). 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 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 (for a detail discussion see Muthoo (1999)). 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 Rubinstein's model (see Binmore (1992) for an overview). Examples include the models with the risk of breakdown, incomplete information, or with a time deadline. In relation to our problem, Rubinstein's bargaining model provides a good opportunity to investigate the strategic interaction among agents. However, as with some game theoretic approaches, computing the equilibrium can be computationally complex, even infeasible, in some settings, which renders this approach infeasible. For example, Rubinstein's standard model assumes that players have knowledge of their opponents' utility function which is taken into account when making an offer. Indeed, this assumption rarely holds in real world scenarios. Although, some extensions (one example is (Rubinstein, 1985)) incorporate the assumption of incomplete knowledge, it is still assumed that each player has a *known probability* over the type of its opponents. Even with such assumptions, the seemingly easy task of computing counter-offers becomes complex and computationally-intensive as the number of types increases. Therefore, although these games can be analysed theoretically, such solutions are inappropriate when a finite amount of time is available. For this reason, Rubinstein's model has only been applied to simple settings until now.

One approach to deal with this complexity in strategic bargaining is to simplify the settings in which agents interact with each other and structure the interaction such that the computation needed to generate an offer is much less. In the next section, we discuss this approach and its benefits.

2.3.3 Rules of Encounter

Rosenschein and Zlotkin (1994) studied automated negotiation between self-interested agents and the effect of the environment on their interactions. They formulate a principled framework within which they study the interactions of agents under different *rules of encounter*. They seek to design these rules of interaction for these negotiations such that a society of agents, as a whole, exhibits desirable properties such as stability (e.g. Nash equilibrium), efficiency (Pareto-optimality) and simplicity in interaction. Agents interact with each other in a decentralized manner obeying the rules of encounter.

The idea of specifying rules of encounter to simplify the negotiation process, is very useful when agents are required to carry out computationally complex tasks during the negotiation (e.g. calculating the optimal offer in complex domains). Enforcing a specific set of rules can reduce this computational complexity and enable agents to interact in a timely manner. Moreover, we can design the rules of encounter to influence the strategies of agents. For instance, Rosenschein and Zlotkin (1994) present some examples of negotiations where agents cannot gain any benefits, or even lose its own utility, when they deceive their opponents (e.g. lying about their own utility or tasks). In this kind of negotiation, the dominant strategy for an agent is to be honest. Indeed, this is a very important property as it prevent agents from wasting their time in devising deceptive strategies.

Although this approach seems very promising, there are challenges in applying them to our domain. Firstly, as Rosenschein and Zlotkin (1994) conclude, there is no universal set of rules and therefore every domain must be considered in isolation. The domain of energy exchange has not been explored under this approach. Secondly, negotiation over energy exchange is much more challenging than the settings considered by Rosenschein and Zlotkin (1994). This negotiation, as we discussed in Section 1.2, is an *interdependent* multi-issue negotiation which is more challenging than the *independent* multi-issue negotiation. To the best of our knowledge, there is no work on designing rules of encounter for an interdependent multi-issue negotiation in any domain. However, there is some contemporary work on interdependent multi-issue negotiation that uses alternative approaches (discussed next). We now discuss and evaluate the usefulness of this work in the context energy exchange.

2.4 Negotiation with interdependent issues

Negotiation with interdependent issues has long been identified as very difficult and complex (Wooldrige, 2009, p. 316), (Robu et al., 2005). Some recent work takes on this problem by focusing on either eliminating the interdependence (between issues) or by utilizing a mediator to help in finding a solution. The first approach taken by Hindriks et al. (2006) attempts to approximate the utility space in order to eliminate interdependencies. The general idea is to transform the utility space of multiple interdependent issues to an approximated one with multiple independent issues. It is fairly obvious that the degree of approximation is entirely dependent on the transformation and, indeed, they conclude that their transformation technique is only reliable when the issues are not *highly dependent*. In other words, it is only reliable when merely *a few* issues are interdependent in multi-issue negotiation. This severely limits the applicability of this technique to the problem where all issues are interdependent. For example, in an exchange with multiple time period (e.g. $\{t_1, t_2, t_3\}$), the energy flow in one time period (say t_2) is dependent on the flow in *all* other time periods (i.e. t_1 and t_3). Therefore, this technique is not applicable in our problem where issues are highly interdependent.

Negotiation over interdependent issues poses another challenge; in comparison to multi-issue negotiation, it is much harder and time-consuming for agents to learn the preferences and utility of their opponents due to the complex utility space. Learning the preferences of opponents is important because it helps agents make offers which give the opponents at least some utility, which in turn increases the chances of reaching an agreement within the deadline while reducing the negotiation time and communication cost (Weiss, 1999, p. 272). Some work suggest the use of a central authority to assist in negotiation and some examples of recent work on this track is Hattori et al. (2007), Ito et al. (2007) and Fujita et al. (2010). The general idea of this work is to assume a mediator (with sufficient computing power) to which agents provide information about their utility functions. This mediator then uses stochastic optimisation to calculate a number of Pareto-optimal solutions which provide both agents some utility. The agents can then choose a solution from this set which makes it easier to negotiate. However, this approach requires the presence of an unbiased and independent mediator, capable of carrying out intensive computations. Such assumptions rarely hold in our decentralized setting where there is no centre and households are required to negotiate directly with each other. Therefore, we conclude that the contemporary work on interdependent multi-issue negotiation is not applicable to the problem of energy exchange.

2.5 Summary

In this chapter, we reviewed the literature related to the problem of energy exchange between homes. We began with the technologies that are essential for energy exchange and found that much of the needed technologies, such as microgeneration and storage devices, are already in use. Furthermore continued research in these areas is constantly improving these technologies. Indeed, the ongoing research in these areas will result in improvements in these technologies. We concludes that the building blocks of our vision of energy exchange in homes are in place, making this vision a possibility.

We discussed the existing work in energy exchange and found that energy exchange in utility companies is a common practice. However, this kind of exchange takes place after human experts bargain, on behalf of their respective companies, and prepare a contract. Such solutions are not automated and there is a clear need for automated negotiation. Automated negotiation requires software agents to bargain on behalf of a human. Bargaining theory provides two types of bargaining solutions for such situations, axiomatic and strategic bargaining. Axiomatic bargaining defines the solutions and their properties (e.g. the Nash bargaining solution and the axioms it satisfies) but not the process to reach these solutions. Strategic bargaining is focused on the bargaining process. However, the theoretical framework can be computationally-hard and is an inappropriate choice when bargaining involves interdependent issues. A solution to this is to simplify the settings in which agents interact by devising specific rules of encounter. This enables agents to interact (e.g. make offers) in situation where interactions in computationally hard otherwise. This approach has been shown to be effective and practical. However, it has only been tested in simpler settings in the absence of interdependent issues. Alternative proposals either require low-interdependence, and are therefore, not applicable in the problem of energy exchange where issues are highly dependent, or use a centralised entity, and therefore will not work in decentralised settings such as ours.

We conclude that, at present there is no off-the-shelf solution to the problem of energy exchange between homes. Despite the lack of a definite solution, the existing literature has the potential to provide us with the basic framework to build upon. Based on the presented literature, in the next chapter we present a two-agent model to analyse this problem and investigate the optimize use of energy and energy exchange via an axiomatic bargaining solution.

Chapter 3

Energy Exchange via Axiomatic Bargaining

Following the review of existing work and its shortcomings in addressing the problem of energy exchange, in this chapter we systematically analyse the energy exchange between homes. We begin by presenting a model of energy exchange between two homes. We describe how agents can use this model to optimize their use of battery in order to improve their utility. We then describe an axiomatic bargaining solution that can be used for energy exchange between agents. We demonstrate via example the use of our model and the advantage of energy exchange between homes via axiomatic bargaining. Finally, we discuss the challenges in the practical implementation of such an exchange solution in the real world and present an example to show its shortcomings. This then motivates our novel solution presented in Chapter 4.

3.1 Problem Model

This section describes our model in detail along with the basic components and assumptions that we hold. Our model consists of two connected homes where each home has a microgeneration unit, an electric battery and some loads. Figure 3.1 shows a visual illustration of this model. We use the notion of an agent to model a house. The agent has access and control of all appliances in the home along with the energy generation and storage. We also assume that this agent has all the relevant information required such as the energy generation and consumption which we describe in the following paragraphs.

3.1.1 Generation Capability and Load

The generation capability of an agent refers to the maximum power that the agent expects to be able to generate. Let $\boldsymbol{k} = (k_1, ...k_n) : \boldsymbol{k} \in \mathbb{R}_n^+$ denote the generation capability of an agent in n

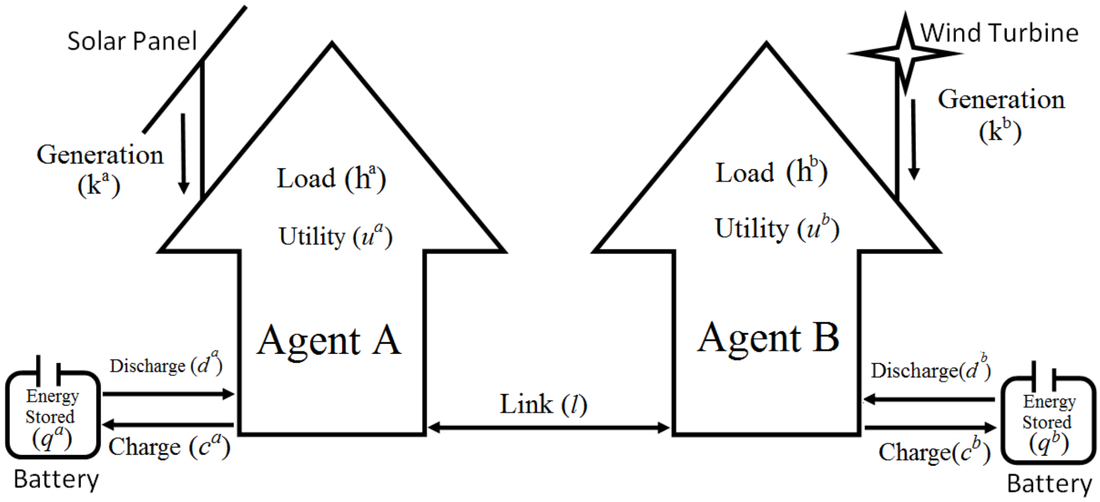


FIGURE 3.1: A visual description of the model.

time periods. A time period is an atomic unit of time (e.g. an hour) and each entry in generation shows the rate (i.e. power) in that time period. For example, if $k_1 = 5$ then it means that an agent expects to be able to generate 5kW during this (first) time period. We assume this rate to be constant during a time period, although there may be some variation in practice. However, at this stage we rule out this variability as it makes the modelling of our problem easier. We also currently ignore uncertainty in this value and we will model these factors in our future work.

We use $\boldsymbol{h} = (h_1, ..., h_n) : \boldsymbol{h} \in \mathbb{R}_n^+$ to denote the load in n time periods. Here, each entry refers to the total power required in a single time period. For example, $h_1 = 5$ denotes a constant load of 5kW in the first time period and therefore, the energy consumed in this time period is 5kWh.

3.1.2 Generation and Waste

The generation capability k denotes the energy that *can* be generated. However, an agent may reduce the amount it generates if the energy to be generated can neither be used immediately nor stored due to the limited battery flow or capacity. To capture this possibility, we use a generation, $\boldsymbol{g} = (g_1, ..., g_n) : \boldsymbol{g} \in \mathbb{R}_n^+$, to indicate the actual energy generated and wasted energy, $\boldsymbol{w} = (w_1, ..., w_n) : \boldsymbol{w} \in \mathbb{R}_n^+$, to denote the energy that was not generated or wasted. It is obvious that $\boldsymbol{k} = \boldsymbol{g} + \boldsymbol{w}$.

3.1.3 Link Flow

We assume that the homes are connected via a cable or link. The power flow over this link is denoted by $\boldsymbol{l} = (l_1, ..., l_n) : \boldsymbol{l} \in \mathbb{R}_n$. The direction of the flow is denoted by the sign of the quantity, i.e. positive quantity shows flow in a particular direction (e.g. from agent a to b) while a negative quantity shows flow in reverse direction.

3.1.4 The Battery

We characterise our battery with four parameters. The first is its maximum storage capacity, which is denoted by $s \in \mathbb{R}^+$ and refers to the maximum amount of energy that can be stored in the battery, measured in kWh. The second is the maximum charging rate of the battery which is denoted by $c_{max} \in \mathbb{R}^+$ and measured in kW. The third is the maximum discharging rate of the battery, denoted by $d_{max} \in \mathbb{R}^+$ and measured in kW. Finally, the efficiency of the battery is denoted by e and it describes the loss of energy when the battery is charged. For example, with a 90% efficient battery 1kWh of electricty may flow into it to charge it, but only 900Wh can be used (the rest being lost as heat).

While in use, the dynamic state of the battery is described in terms of energy flow into and out of it and the energy stored. We denote the energy flow into the battery (charge) by $\boldsymbol{c} = (c_1, ..., c_n) : \boldsymbol{c} \in \mathbb{R}_n^+$ and the flow going out (discharge) $\boldsymbol{d} = (d_1, ..., d_n) : \boldsymbol{d} \in \mathbb{R}_n^+$. Since the charging or discharging flows are constant in a time period, the amount of energy stored in the battery constantly changes during a time period (exceptions are the time periods where there is no inward or outward flow). Therefore, we use $\boldsymbol{q} = (q_1, ..., q_n) : \boldsymbol{q} \in \mathbb{R}_n^+$ to show the stored energy at the start of each time period.

3.1.5 Energy Allocation

A battery enables an agent to store and use energy throughout a day, which helps the agent to compute an energy allocation, $\boldsymbol{p} = (p_1, ..., p_n) : \boldsymbol{p} \in \mathbb{R}_n^+$, to allocate the generated energy g to loads h. This allocation dictates how much energy is to be consumed at what time and therefore, can be considered as an n-time periods plan to satisfy loads.

3.1.6 Utility Function

We describe the utility of an agent for a given time period, t, as the ratio of load (p_t) that is powered at time t, to the total load required (h_t) at time t. The overall utility for an agent is the sum of these ratios given by:

$$u^a = \sum_{t=1}^{n} \frac{p_t}{h_t} \tag{3.1}$$

It is evident that the more the load is powered, the greater the utility. Therefore, the goal of a utility-maximizing agent is to power as much of its loads as possible. In other words, the goal of an agent is to use its battery to store its generated energy such that it can meet the maximum possible load in order to obtain maximum possible utility. This corresponds to seeking an energy allocation ($\boldsymbol{p}$) that maximizes the utility, which we discuss next.

3.2 Optimal Energy Allocation

As we discussed, the goal of an agent is to seek an optimal energy allocation that maximizes its utility. Formally, a utility-maximizing agent will seek the energy allocation, $\boldsymbol{p}^{*}$, that maximizes its utility as given by:

$$\boldsymbol{p}^{*} = \underset{p_t \,\in\, \boldsymbol{p}}{\operatorname{argmax}} \sum_{t=1}^{n} \left(\frac{p_t}{h_t}\right) \tag{3.2}$$

This can be transformed into a linear program. The objective function here is Equation 3.2 subjected the following constraints:

Constraint 1: At any given time t, the allocated power $p_t \in \boldsymbol{p}$ must be equal to the generated power g_t, battery charging flow c_t, discharging flow d_t and link flow l_t:

$$p_t = g_t - c_t + d_t + l_t \tag{c_1}$$

Constraint 2: The current battery state, q_t, depends on the last battery state, $q_{(t-1)}$, charge $c_{(t-1)}$ and discharge $d_{(t-1)}$. The charge flow $c_t \in \boldsymbol{c}$ is subjected to the battery efficiency e. Also, the first state of the battery, q_1, must equal the last battery state of the battery q_n to ensure there is no net change of battery charge over the day so that the utility remains dependent only on the energy generated in n time periods:

$$q_t = \begin{cases} q_{(t-1)} + e \times c_{(t-1)} - d_{(t-1)} & , \; t > 1 \\ q_n + e \times c_n - d_n & , \; t = 1 \end{cases} \tag{c_2}$$

Constraint 3: The allocated power p_t must not exceed load h_t :

$$p_t \leq h_t \quad \forall \, t \tag{c_3}$$

Constraint 4: The battery state, q_t, must not exceed the maximum capacity, s. Also, the battery state cannot be negative, i.e. energy must be stored before it is drawn:

$$0 \leq q_t \leq s \quad \forall \, q_t \in \boldsymbol{q} \tag{c_4}$$

Constraint 5: In any time period, t, the battery charge flow, c_t, must not exceed the maximum charge limit c_{max}. Also charge flow is always positive:

$$0 \leq c_t \leq c_{max} \quad \forall \, c_t \in \boldsymbol{c} \tag{c_5}$$

Constraint 6: In any time period, t, the battery discharge flow, d_t, must not exceed the maximum discharge limit, d_{max}. Also discharge flow is always positive:

$$0 \leq d_t \leq d_{max} \quad \forall \, d_t \in \boldsymbol{d} \tag{c_6}$$

Constraint 7: The wasted energy, w_t, is always positive and cannot exceed the energy, k_t, that can be generated at time t:

$$0 < w_t < k_t \quad \forall\, t \tag{c_7}$$

Constraint 8: The battery efficiency must be between 0 to 1 (i.e. 0% to 100%):

$$0 \leq e \leq 1 \tag{c_8}$$

Now, an agent can compute an energy allocation $\boldsymbol{p}^*$ which maximizes its utility via Equation 3.2 and constraints $\{c_1, ..., c_8\}$.

This completes our discussion of the model of an agent and its utility maximization. So far, we have discussed how a single agent can maximize its utility. An agent can further increase its utility by exchanging energy with a connected agent. Given the model we described, this corresponds to finding a link flow, $\boldsymbol{l} = (l_1, ..., l_n)$, that must be agreed by both agents. However, finding this agreed link flow is challenging for two reasons. First, the set of all possible link flows (i.e. all link flows that provide each agent with greater utility than when disconnected, i.e. when $\boldsymbol{l} = 0$, because a self-interested agent will never agree on a link flow which gives it lesser utility than when its disconnected) is exponential in the number of time periods and secondly, each agent will prefer the link flow that maximizes its own utility. In the next section, we elaborate on a game theoretic solution to find an agreed link flow between agents.

3.3 Energy Exchange Between Two Agents

As we discussed in Section 2.3.1, axiomatic bargaining facilitates the bargaining process between self-interested agents by defining a number of solution concepts. Here, we describe how an axiomatic bargaining solution, the Nash bargaining solution (Section 2.3.1.1), can be used as a solution concept to help agents agree on a link flow.

The Nash bargaining solution is the solution, in the set of all possible solutions, which maximizes the product of gains in utility. In the context of energy exchange, the set of all possible solutions is essentially the set of all possible link flows which gives *both* agents more utility than when there is no exchange. The *gain in utility* comes from the fact that via exchange an agent can avoid energy storage losses and the limit imposed by the maximum capacity of the battery. In this way, an agent can utilize energy that will be unused otherwise. To be clearer on this point, if an agent has 100% efficient battery and infinite storage, it cannot increase its utility via exchange.

Finding the Nash bargaining solution in the energy exchange problem involves finding the link flow between agents that maximizes the product of gains in their utility. Assuming two agents a and b, let d^a and d^b be the utilities that agents can gain when they are disconnected or when they do not agree on a link flow (also called *disagreement utilities*). These disagreement utilities are the maximum utilities that a and b can get when the link flow $\boldsymbol{l} = 0$ (i.e. no exchange) , as we explained in Section 3.2. Let the solution set S_{NBS} be the set of all feasible link flows between a and b. Nash (1953) requires this set to be compact[1] and convex[2] for the solution to be unique. Since agents will only exchange energy if they get more utility than their disagreement utilities, $\forall\ \boldsymbol{l} \in S_{NBS} : (u^a(\boldsymbol{l}), u^b(\boldsymbol{l})) > (d^a, d^b)$. Given the set S_{NBS}, the Nash bargaining solution, $\boldsymbol{l}_{NBS}$, is obtained by:

$$\boldsymbol{l}_{NBS} = \underset{\boldsymbol{l}}{\operatorname{argmax}} \quad [u^a(\boldsymbol{l}) - d^a] \times [u^b(\boldsymbol{l}) - d^b] \tag{3.3}$$

This equation is subjected to constraints $\{c_1, ..., c_8\}$ listed in Section 3.2 for both agents.

When S_{NBS} is compact and convex, the optimal solution to Equation 3.3 is unique (Nash, 1953) and can be computed using convex optimisation. We note that when agents are negotiating over n-issues, S_{NBS} will be n-dimensional. However, the Nash bargaining solution will remain unique as long as the solution set S_{NBS} remains compact and convex.

When the solution set S_{NBS} is not convex (i.e. non-convex), the uniqueness of the Nash bargaining solution can not be guaranteed. This is the case when negotiation involves interdependent issues, since the interdependency between issues gives rise to a non-convex solution set with multiple Nash bargaining solutions (Fujita et al., 2010). In such cases, stochastic optimisation techniques can be used to find the Nash bargaining solution. Since the negotiation over energy exchange has interdependent issues (Section 1.1), we use simulated annealing (see Kirkpatrick et al. (1983) for an overview) which is a stochastic optimisation technique, to find the Nash bargaining solution in our case.

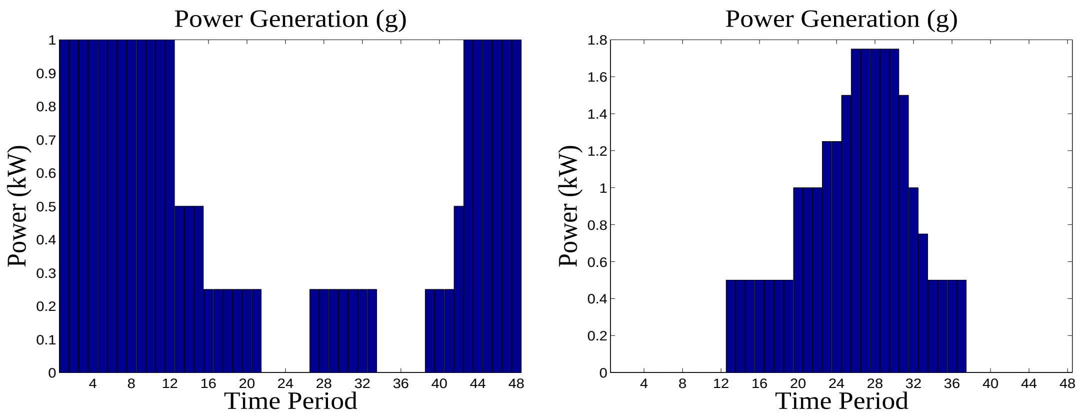
Having defined the utility maximization function for a single agent and the use of the Nash bargaining solution for energy exchange between two agents, we have now completed our theoretical part of the discussion. In the next section, we present an example to show how this works in practice. This example will also serve as an argument to show the advantages of energy exchange between agents. In the next chapter, we will further build on this example to illustrate the use and comparison of our energy exchange protocol.

3.4 Experimental Setup

Let us consider an example of energy exchange between two agents, a and b, where each agent has a microgeneration unit, an electric battery and some loads. We assume that agent a has a 1.5kW wind turbine and agent b has a 1.75kW solar panel. These power ratings are in line with our discussion on existing microgeneration technologies in homes (Section 2.1.1). Furthermore, we assume that both agents have identical loads and identical batteries. We now describe the origin of data for their power outputs, loads and battery specification.

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

[2] 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.



(a) Power output of a 1.5kW wind turbine

(b) Power output of a 1.75kW solar panel

FIGURE 3.2: Power output of a 1.5kW wind turbine (agent a) and a 1.75kW solar panel (agent b).

3.4.1 Energy Generation

The energy generation data for the wind turbine of agent a comes from a wind farm near Lugo, Northwest Spain.[3] We use the data for July 2010, estimate the average generation for a day, which we then scale to match the output of a 1.5kW wind turbine. This provides us with an estimate of the half-hourly power (and hence 48 time periods in a day) output of a typical domestic wind turbine on a typical day as shown in Figure 3.2(a). We can see that the energy generation is spread unevenly over the day. There are peaks in the early morning and late night (time periods 1-12 and 43-48) and some time periods where output is very low or none (e.g. time periods 22-26). The total energy generated in a day is 24kWh.

To estimate the power output of the solar panel of agent b, we use the daily solar irradiance for the same region since the power output of a solar panel is directly proportional to the solar irradiance.[4] We use the data for the same month (July 2010), estimate the average power output for a day and scale it to match the output of a 1.75kW solar panel. In this way, we can estimate the half-hourly daily power output of a 1.75 kW solar panel in that region. This estimated generation is shown in Figure 3.2(b). It is evident that the generation is limited to day time only (time periods 13-37 which corresponds to 06:30-18:30 in real time) with most of the energy produced from 1100 to 1600 (time periods 22-32). The total energy generated is 24.5kWh (0.5kWh more than that of agent a).

[3] `www.sotaventogalicia.com`

[4] Available at `www.re.jrc.ec.europa.eu/pvgis/apps/radday.php`

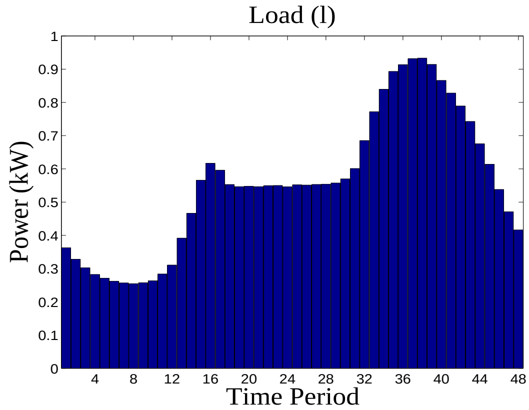


FIGURE 3.3: Daily load requirements of a low-income home.

3.4.2 Loads

As discussed in Chapter 1, our current focus are the homes in remote areas and, at present, the load requirements of such homes are not available. Therefore, we use the load data in low-income homes equipped with smart meters. This data is recorded and provided by a UK electric company and cannot be disclosed for data protection reason. This enables us to estimate the daily load requirements of an average low-income home. Figure 3.3 shows this load over the course of a day. We observe that there are two peaks: one in the morning time (time periods 15-17 which corresponds to 07:30-08:30) perhaps when the households get ready to leave for school or work, and the second peak in the evening (36-42 which corresponds to 18:00 to 21:00) when the households come back and power-hungry devices (such as the TV or electric kettle) are switched on. The total load for a day is 26.68kWh. This load requirement is assumed to be identical for both agents.

3.4.3 The Battery

Following our discussion on contemporary electric batteries in Section 2.1.2, we assume that both agents have identical batteries that have a maximum capacity, s=20kWh, a maximum charging rate, c=4kW, maximum discharging rate, d=4kW and efficiency e=90%.

Given this data, agents can maximize their utility without exchange (as described in Section 3.2) and via exchange by computing the Nash bargaining solution (Section 3.3). In the following, we first discuss the optimisation results for each agent without exchange, followed by results of energy exchange via the Nash bargaining solution. It is important to note that the only difference between agent a and b is the energy generation. The load and the battery specifications for both agents are the same.

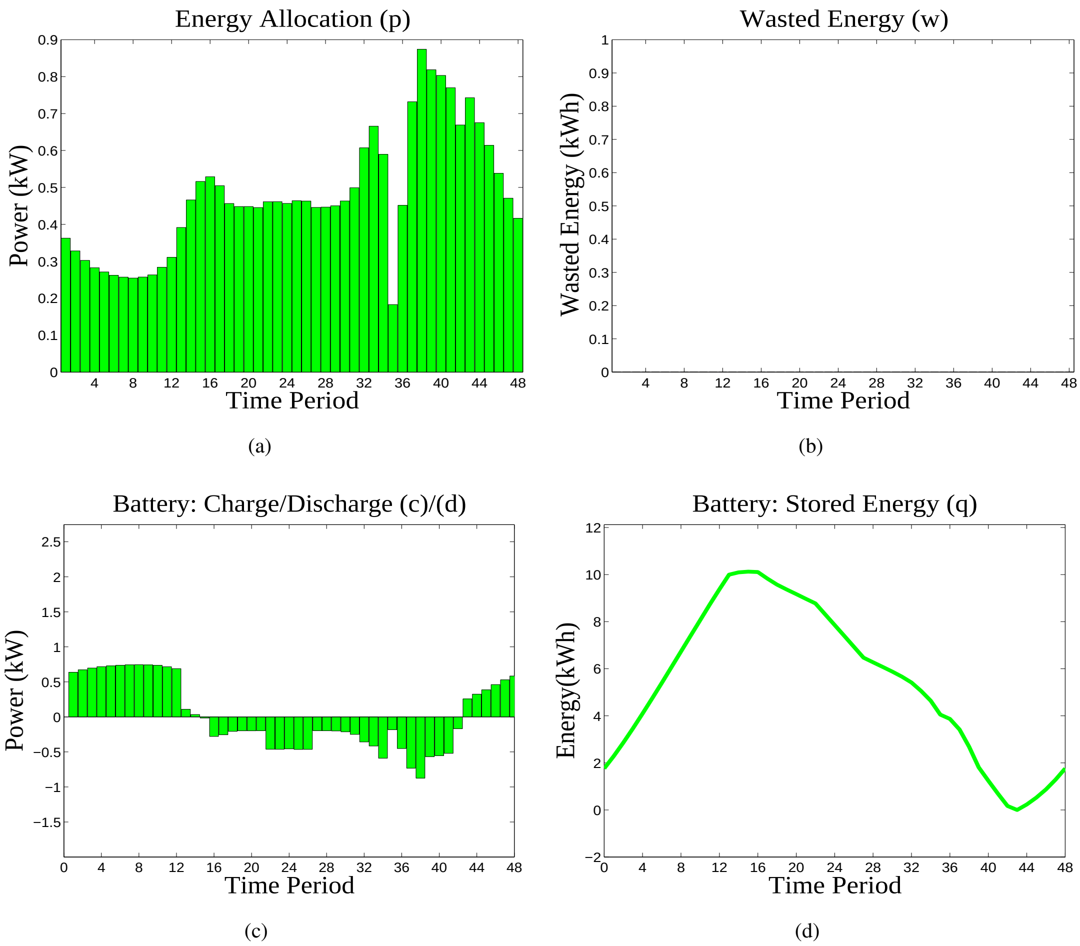


FIGURE 3.4: Agent a: Results of utility maximization without energy exchange.

3.4.4 Optimisation results - Without Energy Exchange

Figure 3.4 shows the optimisation result without exchange for agent a. All the data presented is half-hourly, hence 48 time periods in a day.

Figure 3.4(a) shows the optimised energy allocation ($\boldsymbol{p}^*$) which maximizes the utility of agent a (i.e., u^a). We observe that this allocation is very similar to the load (Figure 3.3). This optimal allocation utilizes 95% of generated energy (22.88kWh out of 24kWh). We note there is no waste in Figure 3.4(b) which means that at no point was the energy generation not fully used due to the limited storage or charging capacity of the battery. Therefore, the 5% of energy that was lost, is entirely due to the energy storage loss (the battery is 90% efficient).

Figure 3.4(c) and 3.4(d) show the dynamic state of the battery during the day. More specifically, Figure 3.4(c) shows the charging (positive values) and discharging rates (negative values) over the time periods. We observe that the battery is charged early in the morning (time periods 1-12) and late at night (time periods 43-48) when the demand is low and generation is high. In contrast, the battery is discharged throughout the afternoon and the evening (time periods 15-42) because the energy generation is low and cannot meet the load during this time. It is also notable

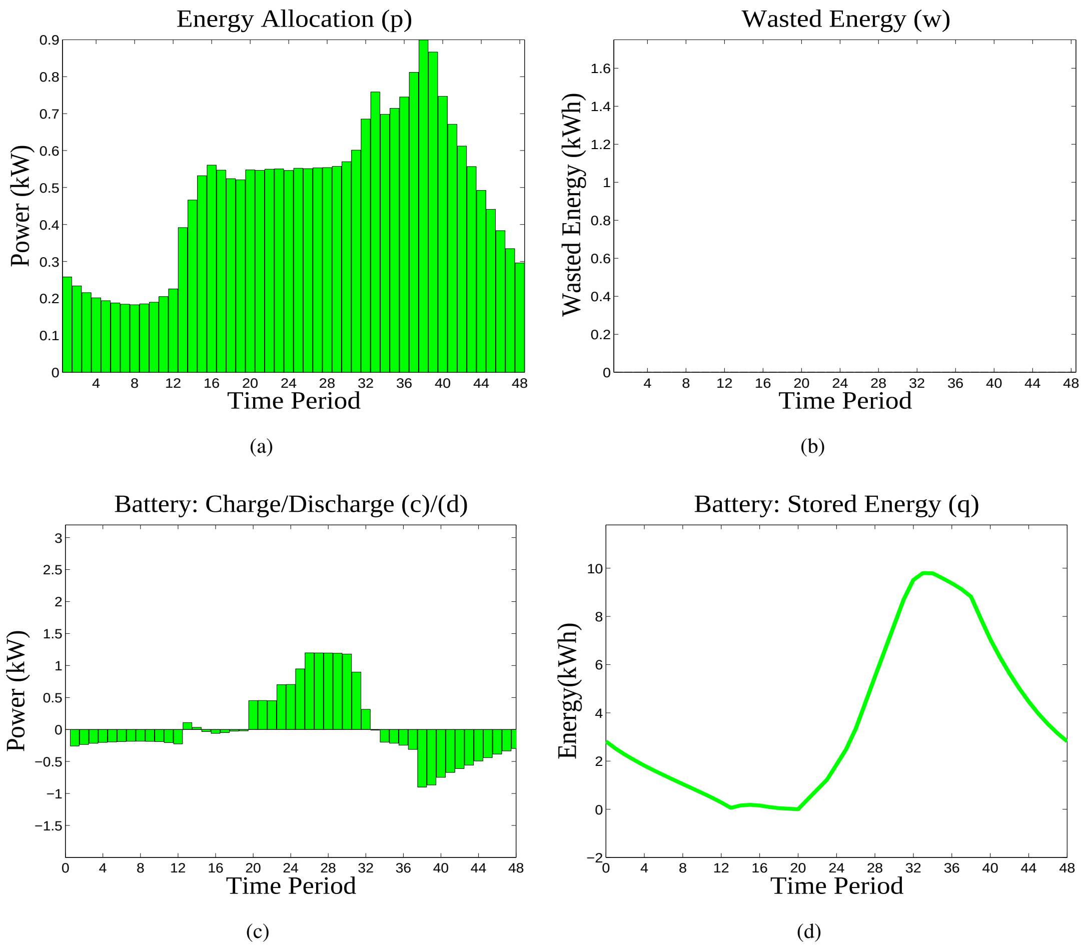


FIGURE 3.5: Agent b: Utility maximization without energy exchange.

that the charging/discharging rate is well under the maximum rate of 4kW and 4kW respectively, which confirms that no energy is wasted due to limited charging/discharging rate.

Figure 3.4(d) shows the energy stored throughout the day. We see that the graph goes upward twice (time periods 1-15 and 43-48) which corresponds to the charging of battery as shown in Figure 3.4(c). Also, it is obvious that the amount of stored energy drops when the battery is discharged (time periods 15-42) as show in Figure 3.4(c). We note that the maximum amount of energy stored at any point is 10.12kWh which is well below the 20kWh maximum capacity of the battery. Again, it confirms that no energy is wasted due to the lack of storage capacity.

In summary, the ratio of powered load to the total load is 0.86 (i.e. 22.88/26.68) via optimisation without any exchange. This means that agent a can achieve a utility of 0.86 (i.e. $u^a = 0.86$).

Figure 3.5 shows the optimisation results for agent b. Figure 3.5(a) shows the optimised energy allocation ($\boldsymbol{p}^*$) which maximizes the utility of agent b. This allocation is similar to the load and utilizes 96% of the generated energy (23.4kWh of the generated 24.5kWh). The remaining 4% of the generated energy is lost due to the storage loss. This allocation satisfies 88% of the load (23.4/26.68) and therefore, $u^b = 0.88$.

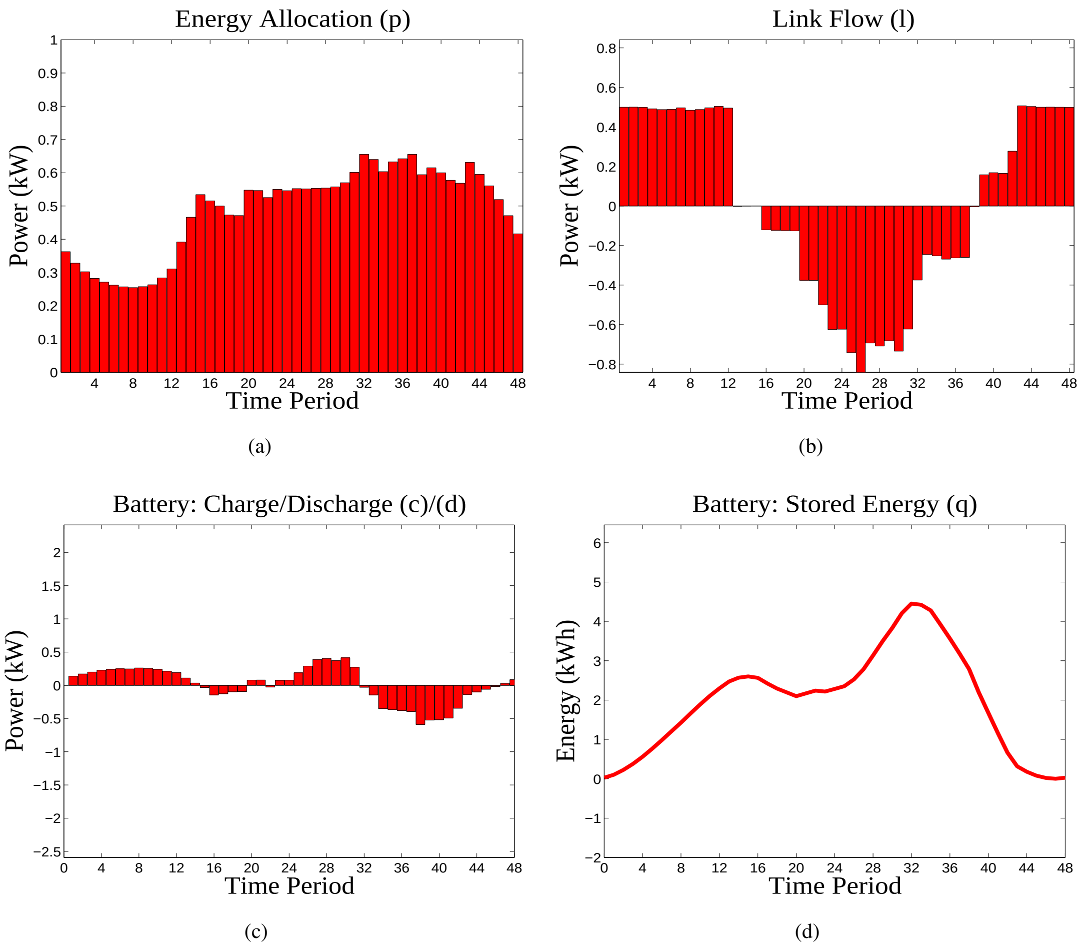


FIGURE 3.6: Agent a: Utility maximization with exchange.

Figure 3.5(c) and Figure 3.5(d) show the charging/discharge rate and stored energy in the battery over 48 time periods. The peak in the middle of Figure 3.5(c) is easy to explain as the battery is charged mainly during the day time (time periods 20-32) and discharged in other time periods. Figure 3.5(d) also reflects this charging and discharging as the amount of energy increases during the time periods 20-32 (when it is charged) and decreases otherwise. Another important point to note is that neither the maximum charging/discharge rate nor the maximum battery capacity is reached, which tells us that no energy is wasted due to limited charging/discharging or lack of storage space. This is also evident in Figure 3.5(b) where there is no energy waste.

We can see that agents a and b can attain the maximum utilities of $u^a = 0.86$ and $u^b = 0.88$ respectively, without any exchange. In the next section, we discuss the possibility of energy exchange via computing the Nash bargaining solution.

3.4.5 Optimisation results – With Energy Exchange

Figure 3.6 shows the results for agent a when energy exchange is agreed with agent b via computing the Nash bargaining solution. Figure 3.6(a) shows the optimal energy allocation for

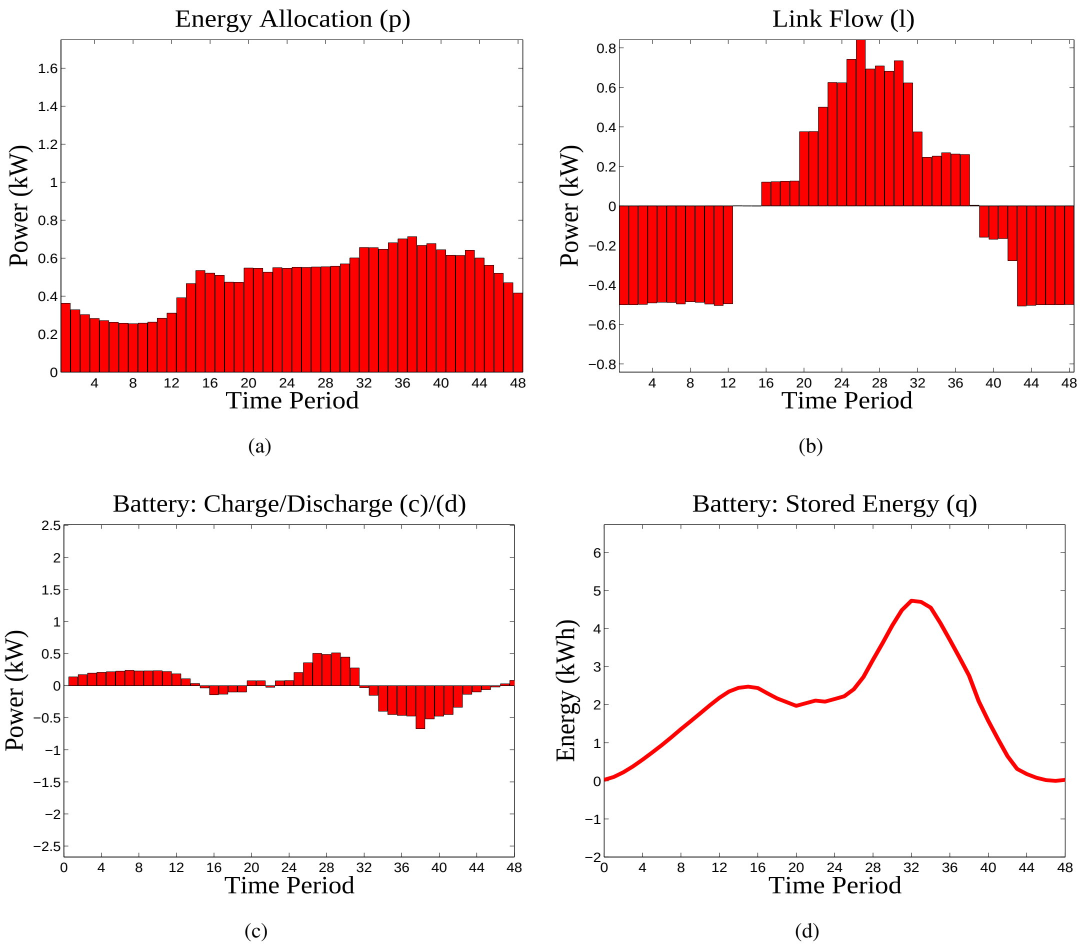


FIGURE 3.7: Agent b:Utility maximization with exchange.

agent a which maximizes its utility via exchange. This energy allocation satisfies 88% of its load which is 2% more higher than without exchange. Consequently, u^a increases from 0.86 to 0.88. Also, due to energy exchange agent a can utilize 23.42kWh of the 24kWh generated energy, comapared to 22.88kWh without exchnage. This means that only 2.5% of the generated energy is wasted, which is half the amount lost without exchange. The cause of this reduction in energy loss is the fact that the agent can exchange energy rather than store it and therefore, can avoid the storage loss.

Figure 3.6(b) shows the link flow between agents. The negative flow indicates power outwards to the other agent and positive flow represents flow inwards. We observe that agent a sends energy downlink early in the morning and late at night (time periods 1-12 and 39-48) during peak energy generation times (Figure 3.2(a)). This trend is reversed during the day (time periods 16-38) when the generation is low and agent a receives energy from the other agent.

Figure 3.6(c) and Figure 3.6(d) show the state of the battery at every time period. The battery usage is evidently reduced compared to when agent a does not exchange energy. More specifically, Figure 3.6(c) shows that the total amount of energy stored in the battery is 5.43kWh compared to 11.25kWh with no exchange. Consequently, the maximum amount of energy stored in the battery at any time is 4.15kWh (Figure 3.6(d)) instead of 10.12kWh with no exchange (Figure 3.4(d)). This reduction in the use of battery leads to reduced energy losses which in turn, increases the amount of energy available to the agent, thus, increasing its utility.

Figure 3.7 shows the results for agent b with energy exchange. The optimal energy allocation which maximizes u^b is shown in Figure 3.7(a). This allocation satisfies 90% of load which is 2% more than that of without exchange. Therefore, u^b increases to 0.90. Also, agent b can utilize 23.94kWh of the 24.5kWh generated energy, compared to 23.4kWh without exchange. Again, this increase is the result of reduced use of the battery.

Figure 3.7(b) shows the link flow from agent b to agent a and it is essentially the inverted graph of Figure 3.6(b). The battery flow and battery storage are shown in Figure 3.7(c) and Figure 3.7(d), respectively. It is obvious that the battery is charged less compared to when there is no exchange (Figure 3.5(c)) which results in reduced use of the battery.

We note that both agents can increase their utility when they exchange energy. Although, this utility increase is small, an important observation here is the reduction in use of the battery at the same time. This leads to the possibility that agents can reduce the size of their battery when they exchange energy. Battery size is important here because the relation between the cost of a battery and its size is linear (e.g. a Lithium iron phosphate battery may cost $ 500/kWh). In the next chapter, we quantify the reduction in battery size when our developed protocol is used for energy exchange.

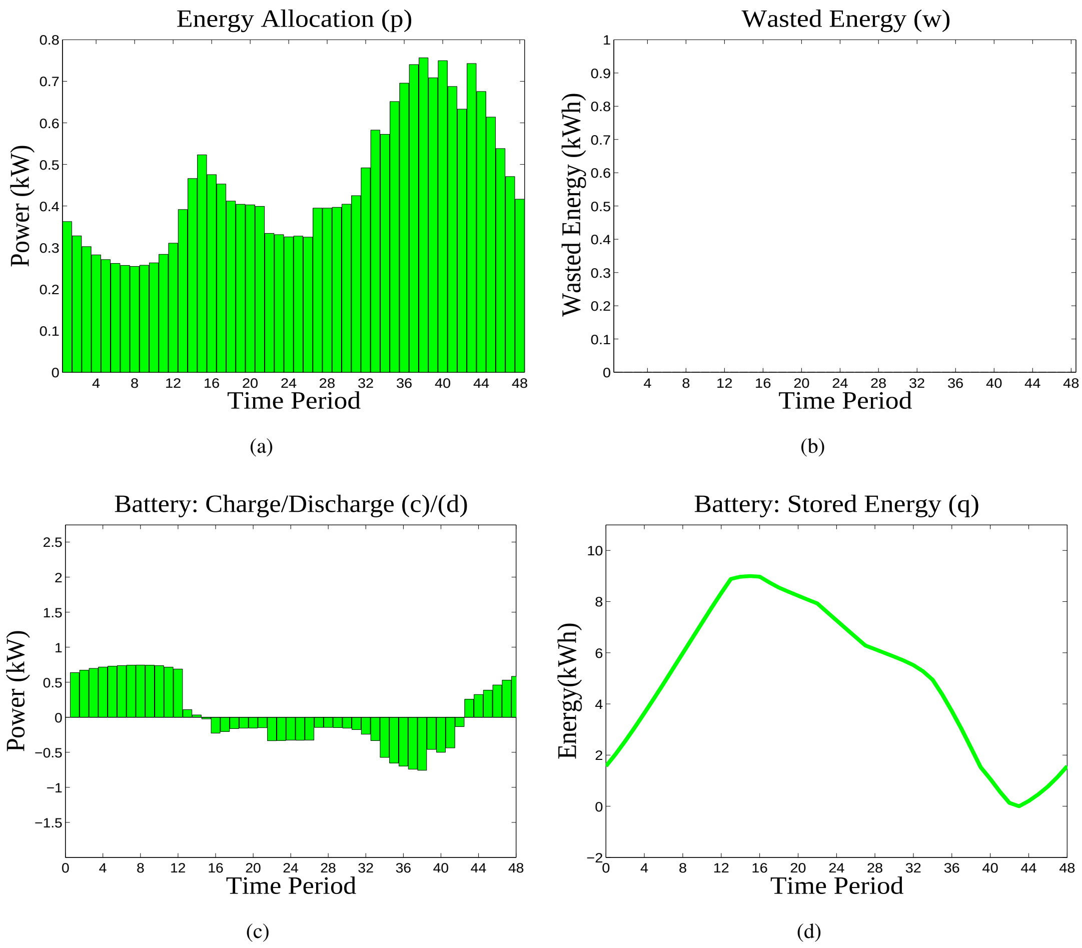


FIGURE 3.8: Effect of Misreporting: Optimisation result for Agent a without exchange (with an 80% efficient battery).

3.5 Mechanism to Compute the Nash Bargaining Solution

We have shown how agents can increase their utility by exchanging energy via computing the Nash bargaining solution. However, we intentionally left out the practical implementation details such as where the actual computation takes place and how the agents exchange the information about their generation or loads. In reality, we must establish a well-defined mechanism that outlines all these details. For example, one simple mechanism is to assume the presence of a mediator to whom agents report their private information and have it computed the Nash bargaining solution. However, given that the agents are self-interested, it may not be reasonable to assume that they will report truthfully. If there is a possibility of gaining more utility by misreporting, agents will. Indeed, this is the case in energy exchange where agents can obtain more utility by misreporting. In the next section, we explore this possibility and its effect on the utilities of agents.

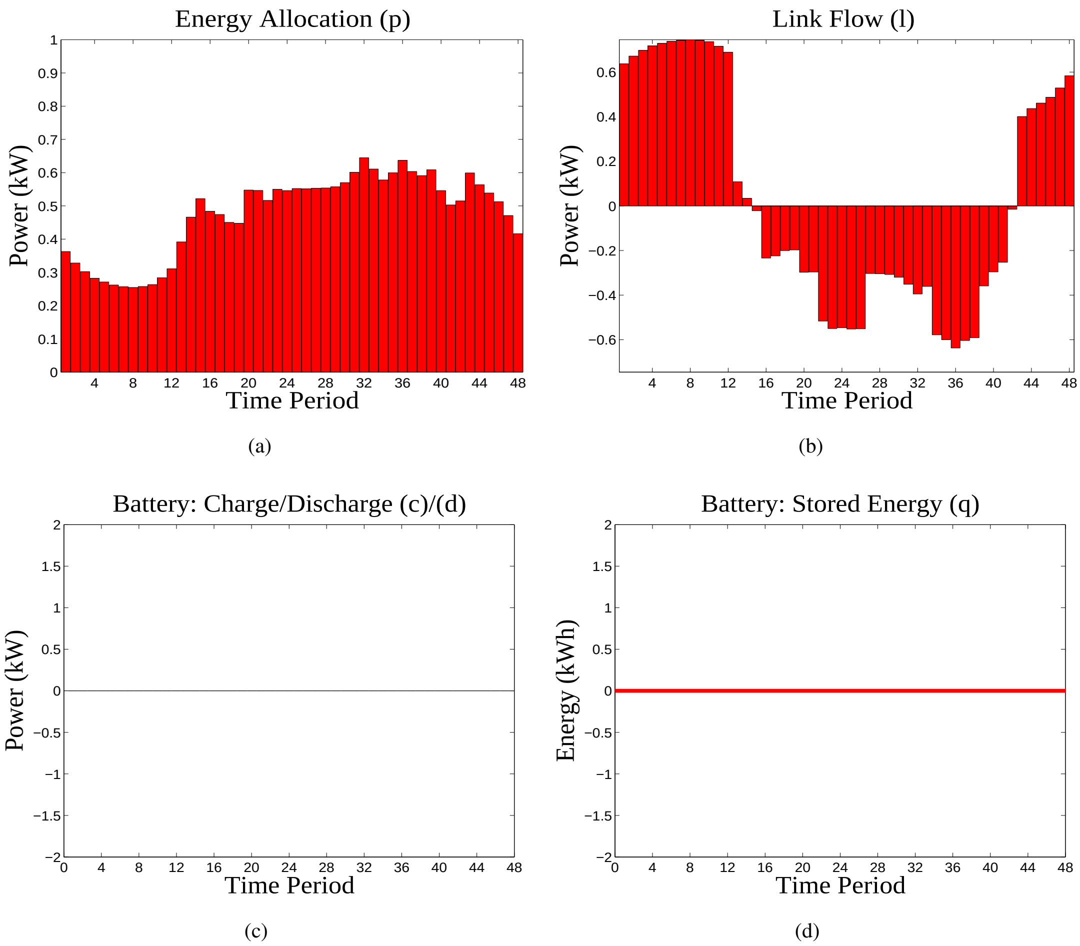


FIGURE 3.9: Effect of Misreporting: Optimisation result for Agent a with exchange when it reports truthfully.

3.6 Effects of Misreporting

We present a simple example to show that an agent can *misreport* to obtain more utility in the above mentioned mechanism. Consider agents a and b with generation, load and battery as outlined in Section 3.4 with one exception: the battery efficiency of agent a is 80% instead of 90%. There is no other change in data. Now, we consider two cases: (i) when agent a reports its battery efficiency truthfully (i.e. 80%) and (ii) when it misreports its efficiency to be at 89%.

One aspect of the Nash bargaining solution that is important in understanding the effect of misreporting, is that the choice of a solution (in the set of all possible solutions) is greatly dependent on the disagreement utilities of agents. The disagreement utility of an agent is the utility that it can obtain without cooperation (or exchange in this case) as discussed in Section 2.3.1.1. A self-interested agent will never participate in an exchange if it does not offer more utility than when there is no exchange. This means that if an agent can somehow show a higher disagreement utility (than the actual), it is guaranteed to obtain more than this utility if there exists an exchange solution. This is the kind of exploitation that we show in the following sections.

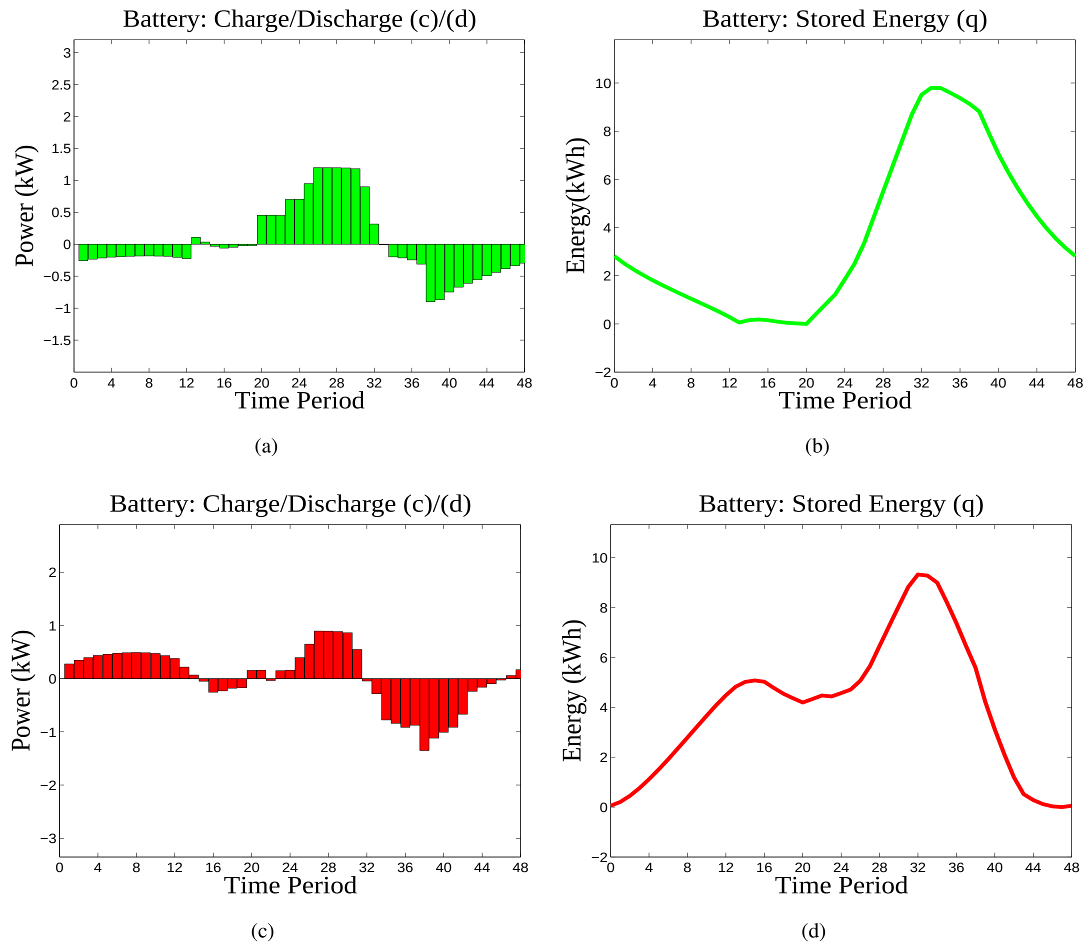


FIGURE 3.10: Increased use of the (90% efficient) battery of agent b when agent a reports a less efficient battery (80%).

3.6.1 Case 1: Agent a is truthful

Imagine that agent a reports all of its information truthfully to the mediator including the fact that its battery is 80% efficient. The mediator computes that a can utilize 21.75kWh of its 24kWh generated energy and therefore the disagreement utility of a is $u^a = 0.90$. The optimisation results for this computation are shown in Figure 3.8.

Once the mediator has computed the disagreement utility of a (and agent b), it can compute the Nash bargaining solution. Figure 3.9 shows the results of this computation. We note that with exchange, agent a can increase its utility by 0.05 to $u^a = 0.95$ compared to without exchange. We also note that the mediator computes an exchange which does not use the battery of agent a, as evident is Figure 3.9(c) and Figure 3.9(d). This is because the battery of b is more efficient (90% compared to 80%) and has sufficient capacity to store the energy for both agents (see Figure 3.10). If both batteries had the same efficiency then the mediator may compute an exchange that involves both batteries. Indeed, this is the case in Section 3.4.5 where agent a and b have identical batteries and therefore, both are used during exchange (see Figure 3.6(d) and Figure 3.7(d)).

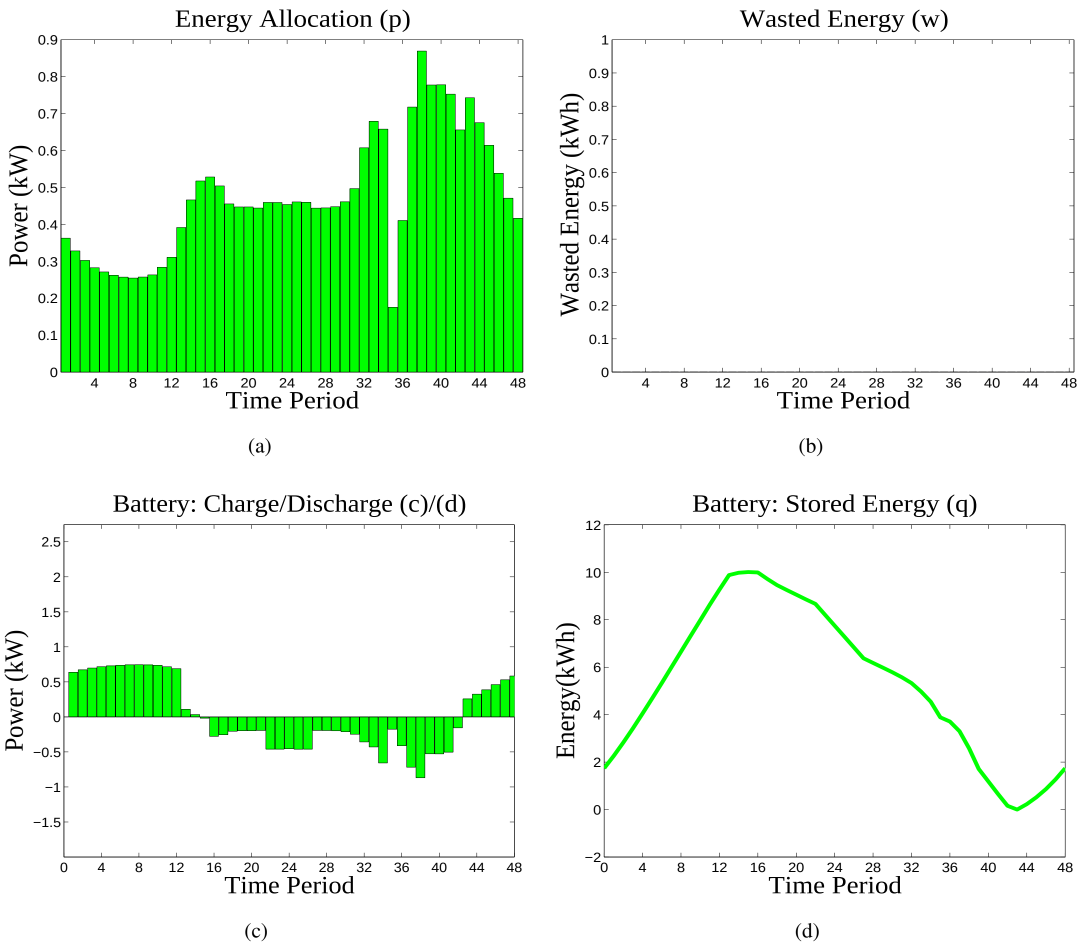


FIGURE 3.11: Effect of Misreporting: Optimisation result for Agent a without exchange when it misreports.

3.6.2 Case 2: Agent a misreports

When the battery efficiency of agent a is 80%, its utility without exchange is 0.90 as shown in the last section. However, imagine that agent a misreports its battery efficiency to be 89% to the mediator. The mediator then calculates that agent a can utilitze 22.76kWh of the 24kWh generated energy and thus, it computes the disagreement utility of agent a to be $u^a = 0.95$, instead of 0.90 had a been honest. The result of this computation is shown in Figure 3.11.

Now the mediator computes the Nash bargaining solution. Figure 3.12 shows the results of this computation. This shows that the utility of agent a, $u^a = 0.97$ with exchange. This clearly shows that agent a gets better utility, $u^a = 0.97$, by misreporting its battery efficiency to be 89% than when it reports truthfully and gets $u^a = 0.95$ with exchange.

This simple example demonstrates that the implementation of the Nash bargaining solution can be challenging in real world, especially where agents have incentives to misreport.

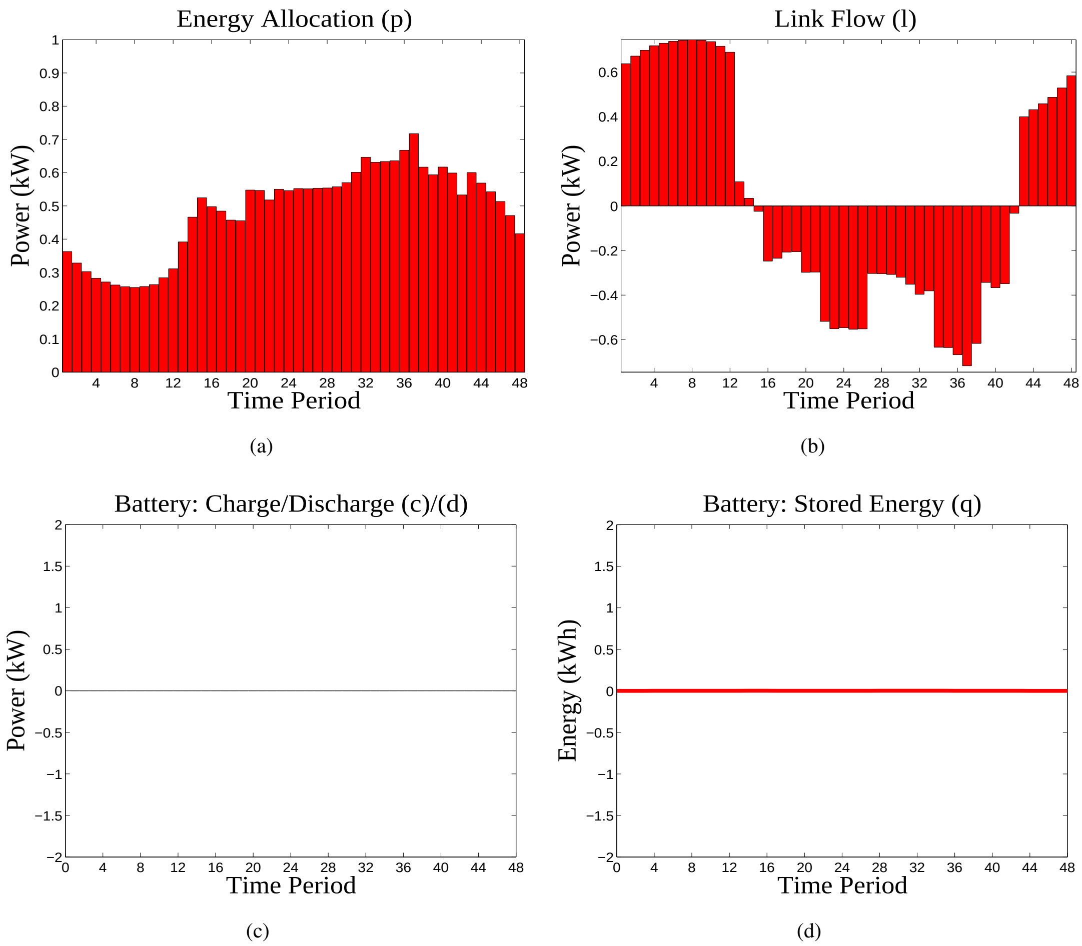


FIGURE 3.12: Effect of Misreporting: Optimisation result for Agent a with exchange when it misreports.

3.7 Summary

In this chapter, we first outlined our model of two connected homes and discussed the optimised use of energy without exchange. We elaborated on energy exchange between agents via the Nash bargaining solution and presented a practical example with real data to demonstrate that energy exchange has the potential for improving the energy management. We also discussed the challenges of energy exchange via computing the Nash bargaining solution and showed that a mechanism based upon a mediator calculating this solution may be exploitable. In the next section, we present an energy exchange protocol that can be used to exchange energy while avoiding the shortcomings discussed above.

Chapter 4

A Negotiation Protocol for Decentralised Energy Exchange

In the last chapter, we outlined a model of the setting we consider and demonstrated the benefits of energy exchange between agents. We also discussed the challenges of implementing an NBS-based mechanism. Building on this model, we now present an energy exchange protocol that agents can use to agree on the link flow between them. Our protocol places restrictions over the offers that agents can make to each other, in order to reach an agreed flow. The novelty of our approach is that these restrictions are engineered in such a way that the negotiation results in certain desirable properties. We begin this chapter by defining our terminology and assumptions, followed by our protocol and its properties. We then present our mathematical proofs for these properties. Finally, we show that our solution has the potential to reduce the required capacity of the batteries used for energy exchange. We also provide a comparison of energy exchange via our protocol and via computing the Nash bargaining solution.

4.1 Preliminary

Before we define our energy exchange protocol, we define the terminology used. Unlike the mechanism in Section 3.5 where agents report to a mediator which computes a link flow between them, our energy exchange protocol (EEP) allows agents to make offers to each other in order to reach an agreement on the link flow between them. We call these offers *link flow offers* and the agreement, an *exchange agreement*. Our protocol requires these link flow offers to adhere to three restrictions and dictates that whichever offer minimizes the total flow over the link, is selected as the exchange agreement. The restrictions on the offers reduce the set of feasible solutions between agents to ensure that the solution is reached with certain properties (listed in Section 4.3).

We consider each exchange agreement in isolation, independent of the past and future exchange agreements. Also, we consider exchange over a finite period of time (e.g. a day), which can be divided into *exchange periods*. An exchange period is a unit of time for energy exchange and consists of at least one *time period*. A time period is an atomic unit of time and each entry in a profile (e.g. energy generation, load) is described against a single time period, as detailed in Section 3.4. With this terminology in place, we now describe our energy exchange protocol.

4.2 Energy Exchange Protocol

Let us assume two agents a and b, with utility functions u^a and u^b, disagreement utilities d^a and d^b respectively, and let S_p be the set of possible link flows between them, i.e. $\forall\ \boldsymbol{l} \in S_p$: $(u^a(\boldsymbol{l}), u^b(\boldsymbol{l})) \geq (d^a, d^b)$, the same set as defined in Section 3.3. Let us also assume that a initiates the negotiation by making an offer to b. The energy exchange protocol (EEP) dictates that this offer must meet two restrictions, namely r_1 and r_2 (Figure 4.1 describes r_1 and r_2). Now, agent b has three options; it can either accept or reject this offer in which case the EEP terminates, or it can make a counter offer. If b decides to make a counter offer, then this counter-offer must meet r_3, in addition to r_1 and r_2. On receiving the counter offer, a can either accept or reject at which stage the EEP terminates. Figure 4.1 describes the EEP in detail.

4.2.1 Computing the Valid Link Flow Offers

Given the protocol, we now define how agents compute valid link flow offers. As discussed in Section 3.3, each agent will prefer the link flow that maximizes its own utility. In order to compute this link flow, we can alter Equation 3.2 (which finds the energy allocation that maximizes utility) as the following:

Given Equation 3.1, substituting for p_t from c_1:

$$u^a = \sum_{t=1}^{n} \left(\frac{g_t - c_t + d_t + l_t}{h_t} \right) \tag{4.1}$$

The objective is to find the optimal link flow $\boldsymbol{l}^*$, such that Equation 4.1 is maximised:

$$\boldsymbol{l}^* = \underset{l_t\, \in\, \boldsymbol{l}}{\operatorname{argmax}} \sum_{t=1}^{n} \left(\frac{g_t - c_t + d_t + l_t}{h_t} \right) \tag{4.2}$$

subjected to all constraints $\{c_1, ..., c_8\}$ as listed in Section 3.2. Now, an agent making an offer can compute a valid link flow offer which maximizes its utility by using Equation 4.2 with two more constraints, $\{r_1, r_2\}$ (in addition to $(\{c_1, ...c_8\})$), and an agent making a counter-offer needs to include a further constraint r_3. In fact, agents can offer *any* link flow provided it is

Energy Exchange Protocol (EEP)

1. Agent a submits a *valid* link flow offer $\boldsymbol{l^a}$ to agent b. An offer is valid if it meets the following criteria.

   - The offer must have exactly two exchange periods. Each exchange comprises of an equal number of consecutive time periods. The sum of magnitude of energy in time periods of an exchange period must be equal to other exchange period.

   $$\boldsymbol{l} = (l_1, ...l_n) \in S : \left|\sum_{t=1}^{n/2} l_t\right| = \left|\sum_{t=n/2+1}^{n} l_t\right| \qquad (r_1)$$

   - The amount of energy in each time period is equal.

   $$\boldsymbol{l} = (l_1, ...l_n) \in S : \ \forall\, l_t \in \boldsymbol{l} : |l_t| = |l_{t+1}| \qquad (r_2)$$

2. On receiving the offer $\boldsymbol{l^a}$, Agent b has three options:.

   - Reject: b can reject an offer, e.g. when exchange is not beneficial to b. It happens when $\neg\exists\, \boldsymbol{l} \in S : u^b(\boldsymbol{l}) > 0$. Agent b indicates its rejection by sending the REJECT message. The agreed link flow is $\boldsymbol{l^{ex}} = 0$. The EEP terminates.
   - Accept: b can accept $\boldsymbol{l^a}$ by sending the ACCEPT message. The agreed link flow is $\boldsymbol{l^{ex}} = \boldsymbol{l^a}$. The EEP terminates.
   - Counter-offer: Finally, b can make a counter-offer $\boldsymbol{l^b}$ which meets above criteria (r_1,r_2). In addition, it must ensure that:

   $$\boldsymbol{l^b} < \boldsymbol{l^a} \qquad (r_3)$$

3. On receiving the counter-offer, $\boldsymbol{l^b}$, Agent a has two options:

   - Accept: It can accept $\boldsymbol{l^b}$ and send the ACCEPT message to b. The agreed link flow is $\boldsymbol{l^{ex}} = \boldsymbol{l^b}$. The EEP terminates.
   - Reject: It can reject $\boldsymbol{l^b}$ and send the REJECT message to b. The link flow is not agreed, $\boldsymbol{l^{ex}} = 0$. The EEP terminates.

FIGURE 4.1: The Negotiation Protocol

valid, not just the one that maximizes its utility. However, in Section 4.3, we prove that the dominant strategy for agents is to offer the link flow that maximizes its utility, leaving no need for them to strategize.

Before we explain the properties of the EEP, we give an intuitive example to show how it will work in action:

Example 4.1. *Imagine that in a society of agents, the following is the already agreed conventions:*

1. *The total time of an exchange is 24 hours. The exchange starts at 0600 hours local time and ends at 0600 hours next day.*
2. *A day is divided into 2 exchange periods, each consists of 6 two-hours-long time periods.*

Given these conventions, an agent a computes a valid link flow offer, $\boldsymbol{l^a} = (2,2,2,2,2,2,-2,-2,-2,-2,-2,-2)$*, which maximizes its utility. Agent a makes this offer to agent b. However, Agent b finds that its utility is maximised with the link flow,* $\boldsymbol{l^b} = (1,1,1,1,1,1,-1,-1,-1,-1,-1,-1)$*. Since* $\boldsymbol{l^b} <^3 \boldsymbol{l^a}$*, b makes this offer to a. Agent a accepts this offer and exchange takes place as per* $\boldsymbol{l^b}$*.*

Case	**Agent a reports $\hat{\boldsymbol{l}}^a$**		**Agent a reports $\boldsymbol{l^a}$**		**Result**
	Chosen Link $min(\hat{\boldsymbol{l}}^a, \boldsymbol{l^b})$	u^a	Chosen Link $min(\boldsymbol{l^a}, \boldsymbol{l^b})$	u^a	
$\hat{\boldsymbol{l}}^a \geq \boldsymbol{l^a} \geq \boldsymbol{l^b}$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$u^a(\boldsymbol{l^b}) = u^a(\boldsymbol{l^b})$.
$\boldsymbol{l^a} \geq \hat{\boldsymbol{l}}^a \geq \boldsymbol{l^b}$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$u^a(\boldsymbol{l^b}) = u^a(\boldsymbol{l^b})$.
$\boldsymbol{l^a} \geq \boldsymbol{l^b} \geq \hat{\boldsymbol{l}}^a$	$\hat{\boldsymbol{l}}^a$	$u^a(\hat{\boldsymbol{l}}^a)$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$u^a(\hat{\boldsymbol{l}}^a) \leq u^a(\boldsymbol{l^b})$ $\because \hat{\boldsymbol{l}}^a \leq \boldsymbol{l^b} \leq \boldsymbol{l^a}$ (monotonicity).
$\boldsymbol{l^b} \geq \boldsymbol{l^a} \geq \hat{\boldsymbol{l}}^a$	$\hat{\boldsymbol{l}}^a$	$u^a(\hat{\boldsymbol{l}}^a)$	$\boldsymbol{l^a}$	$u^a(\boldsymbol{l^a})$	$u^a(\hat{\boldsymbol{l}}^a) \leq u^a(\boldsymbol{l^a})$ $\because u^a(\boldsymbol{l^a}) > u^a(\boldsymbol{l}) \; \forall \, \boldsymbol{l} \in S : \boldsymbol{l} \neq \boldsymbol{l^a}$.
$\boldsymbol{l^b} \geq \hat{\boldsymbol{l}}^a \geq \boldsymbol{l^a}$	$\hat{\boldsymbol{l}}^a$	$u^a(\hat{\boldsymbol{l}}^a)$	$\boldsymbol{l^a}$	$u^a(\boldsymbol{l^a})$	$u^a(\hat{\boldsymbol{l}}^a) \leq u^a(\boldsymbol{l^a})$ $\because u^a(\boldsymbol{l^a}) > u^a(\boldsymbol{l}) \; \forall \, \boldsymbol{l} \in S : \boldsymbol{l} \neq \boldsymbol{l^a}$.
$\hat{\boldsymbol{l}}^a \geq \boldsymbol{l^b} \geq \boldsymbol{l^a}$	$\boldsymbol{l^b}$	$u^a(\boldsymbol{l^b})$	$\boldsymbol{l^a}$	$u^a(\boldsymbol{l^a})$	$u^a(\hat{\boldsymbol{l^b}}) \leq u^a(\boldsymbol{l^a})$ $\because u^a(\boldsymbol{l^a}) > u^a(\boldsymbol{l}) \; \forall \, \boldsymbol{l} \in S : \boldsymbol{l} \neq \boldsymbol{l^a}$.

TABLE 4.1: Reporting the link, $\boldsymbol{l^a}$, which maximizes its utility, is the dominant strategy for agent a.

4.3 Properties of Our protocol

Before outlining the properties of the EEP, we describe our notation. Let S be the set of *valid link flows* between a and b obeying the rules defined by the EEP. If $\exists \; \boldsymbol{l} \in S : u^a(\boldsymbol{l}) > 0$ then $\forall \; \boldsymbol{l'} \in S : 0 < \boldsymbol{l'} < \boldsymbol{l}, \; u^a(\boldsymbol{l'}) > 0$. For example, if agent a prefers an exchange $(2,2,-2,-2)$, then $(1,1,-1,-1)$ is also a feasible link flow for a, since $(1,1,-1,-1) \in S$ and $(1,1,-1,-1) < (2,2,-2,-2)$, although $u^a[(1,1,-1,-1)] < u^a[(2,2,-2-2)]$. It actually follows that given a link $\boldsymbol{l^*} \in S : \; u^a(\boldsymbol{l^*}) > u^a(\boldsymbol{l}) \; \forall \; \boldsymbol{l} \in S : \boldsymbol{l} \neq \boldsymbol{l^*}$, then all $\boldsymbol{l} \in S : 0 < \boldsymbol{l} < \boldsymbol{l^*}$ are feasible and u^a is a strictly monotonically increasing function on this range. This monotonicity arises from the fact that the negotiation has been reduced to a single-issue, i.e. the amount of flow in one time period (since the amount of energy in each time period must be equal - see r_2 in Figure 4.1). Now we prove the properties.

1. **Dominant Strategy Equilibrium**

[3]The inequality here is the *vector inequality*.

Theorem 1. The agent making an initial offer has a dominant strategy which is to offer the link that maximizes its own utility.

Proof. Assume that there are two agents a and b, and $\boldsymbol{l}^a \in S$ is the link that maximizes the utility of agent a. Imagine that a wants to manipulate the protocol by reporting some other link $\hat{\boldsymbol{l}}^a \in S$ to agent b. Table 4.1 lists all possible scenarios that a faces in this case. It is evident that reporting $\boldsymbol{l}^a$ weakly dominates reporting $\hat{\boldsymbol{l}}^a$. Specifically, when both $\hat{\boldsymbol{l}}^a$ and $\boldsymbol{l}^a$ are less than $\boldsymbol{l}^b$, agent a gets the same utility for reporting $\hat{\boldsymbol{l}}^a$ as that of reporting $\boldsymbol{l}^a$. Thus, reporting $\boldsymbol{l}^a$ weakly dominates $\hat{\boldsymbol{l}}^a$. However, in rest of the four cases, reporting $\boldsymbol{l}^a$ strictly dominates reporting $\hat{\boldsymbol{l}^a}$ (unless $\hat{\boldsymbol{l}}^a$=$\boldsymbol{l}^a$). Thus, an agent maximizes its utility by reporting $\hat{\boldsymbol{l}}^a = \boldsymbol{l}^a$. □

Theorem 2. An agent making a counter-offer has a dominant strategy to offer the link that maximizes its own utility.

Proof. Imagine that agent a has received an offer $\boldsymbol{l}^b$ from agent b. Agent a needs to make a counter-offer to b. It can either report the link $\boldsymbol{l}^a \in S$ which maximizes its utility or some other link $\hat{\boldsymbol{l}^a} \in S$. Then Table 4.1 lists all the possible values of $\hat{\boldsymbol{l}^a}$. Again, reporting $\boldsymbol{l}^a$ weakly dominates $\hat{\boldsymbol{l}}^a$. □

It is evident that revealing the link that maximizes its utility, is a weakly dominant strategy for both initial-offer and counter-offer making agents. As a by-product, this property also renders the order, in which agents make offers to each other, irrelevant. The solution is the same no matter which agent commences the negotiation. The result is always a dominant strategy equilibrium.

2. **Pareto-Optimality**
Imagine that $\exists\ \boldsymbol{l} \in S : u^a(\boldsymbol{l}) > 0$ and $u^b(\boldsymbol{l}) > 0$. As proved above, agent a and b will reveal truthfully the links $\boldsymbol{l}^a$ and $\boldsymbol{l}^b$, that maximize their utilities u^a and u^b. Assume that $\boldsymbol{l}^a > \boldsymbol{l}^b$, then the EEP dictates that $\boldsymbol{l}^b$ is the agreed link flow. Since $\boldsymbol{l}^b$ maximizes u^b and it is unique (u^b is strictly monotonic), any other link flow which increases u^a will decrease u^b, hence the protocol is Pareto-optimal.

3. **Beneficial to all**
The EEP is beneficial to all participants. Consider a self-interested agent which is making the first offer. This implies that there is at least one valid link flow offer that increases its utility (more specifically, the valid link flow offer that maximizes its utility [Theorem 1]). A self-interested agent that has no such offer will not make an offer. Now, consider the other agent that needs to make the counter-offer. Given the EEP, this agent has three options: decline, accept or make a counter-offer. A rational agent will only decline an exchange if it has no *valid counter-offer* (counter-offer is valid if it satisfies $\{r_1, r_2, r_3\}$) that increases its utility. An agent will only accept those offers that give it more (or equal) utility than that of any valid counter-offer, otherwise, it will make that counter-offer. In

both cases (i.e. accepting the offer or making a counter-offer), it is evident that the agent must be able to increase its utility, otherwise, it could decline the offer in the first place.

Now reconsider the agent that makes the first offer. It will make the offer only if it gives it more utility. Once it has made the offer, it can expect three cases as listed in Figure 4.1. First, its offer can get rejected and, thus, no exchange takes place. Second, its offer can get accepted which implies that agent will increase its utility. Finally, it can receive a counter-offer, in which case, this agent can either decline it (when it gives absolutely no gain in utility) or accept it (if this offer gives *any* gain in utility since the other option, i.e. declining, will give it no gain in utility). Thus, if the agent agrees to an exchange by accepting the counter-offer, it will gain some utility.

Therefore, it is evident that whenever an energy exchange is agreed, *both* agents will increase their utility.

4. **Equal Exchange of Energy**
Besides benefiting all participants, our protocol also ensures that amount of energy exchange remains the same for every participants. In other words, an agent will lend and receive the same amount of energy (see r_1 in Figure 4.1).

5. **Scalable**
Our protocol enables one to one negotiation between agents. However, a single agent can exchange energy with multiple agents using our protocol. Consider three agents, a, b and c which are connected together. Let us assume that $\boldsymbol{l^a} = \{1, -1\}, \boldsymbol{l^b} = \{2, -2\}$ and $\boldsymbol{l^c} = \{-3, 3\}$ are the links that agents a, b and c prefer respectively. Now, imagine that agent c offers $\boldsymbol{l^c}$ to a. Since a prefers $\boldsymbol{l^a}$ and $\boldsymbol{l^a} < \boldsymbol{l^c}$, therefore $\boldsymbol{l^a}$ is chosen as the exchange agreement. However, agent c still requires $\boldsymbol{l^c} - \boldsymbol{l^a} = \{-2, 2\}$. Imagine it offers this exchange to b. Since $\boldsymbol{l^b} = \boldsymbol{l^c}$, therefore, the exchange agreement takes place. In this way, agent c can exchange energy with a and b simultaneously. Also, it is evident that the order in which exchange agreement between a and c and b and c are reached is irrelevant.

6. **Tractability**
Our solution is tractable as each agent needs to make at most one offer. Also, an optimal offer can be computed using a standard linear programming solver (Section 4.2.1).

4.4 Importance and Implication of These Properties

Having proven the properties of our protocol, we now elaborate on the importance and implications of these properties. The first property states that, with the restrictions imposed, each agent has a weakly dominant strategy which is to offer the link that maximizes its utility. This dominant strategy for both agents leads to a dominant strategy equilibrium, which is the strongest form of equilibrium in game theory and a highly desirable outcome for it simplifies the design of the agents. When an agent has a strategy that dominates all other strategies regardless of the opponents' strategy, there is no need to devote time or efforts to devise or evaluate other strategies; the dominant strategy is the best and most rationale choice. This also eliminates the need of *strategising*, i.e. to employ a strategy taking into account the opponent's current strategy. As a consequence, designing agents for protocols which have a dominant strategy equilibrium is a comparatively simple task.

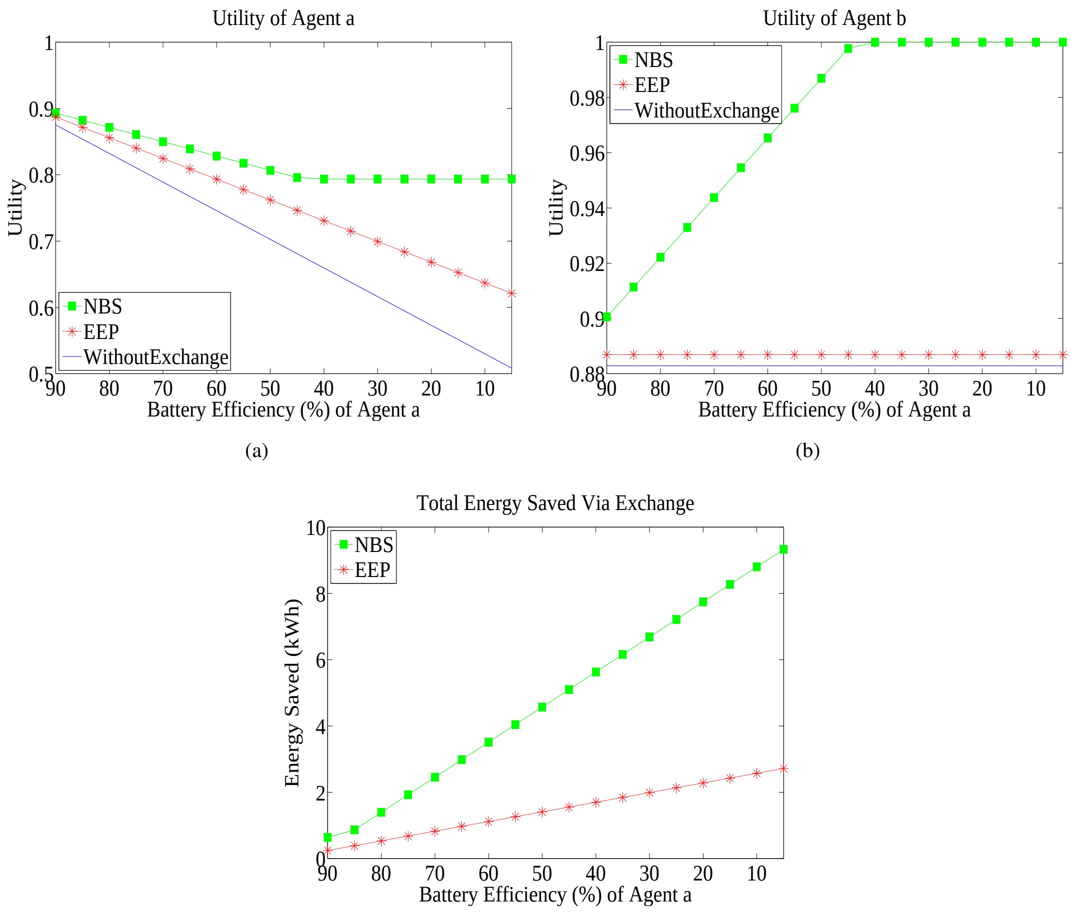
The second property states that the outcome of the negotiation is Pareto-optimal. This is also a very sought-after property in negotiation as it ensures that the outcome is efficient (i.e. that no agent can get more utility without reducing another agent's utility see Section 1.1). Some other negotiation protocols result in outcomes which are not Pareto-optimal and further steps (sometimes called *Pareto-improvement*) are required to make them Pareto-optimal. However, this is not the case with our protocol, which requires no further steps as the outcome is already guaranteed to be Pareto-optimal.

The third property of our protocol ensures that all the agents can increase their utility compared to when they do not participate. This property is essential to ensure that self-interested agents take part in the exchange. We have also mentioned in Section 1.1 that this benefit should be comparable or *fair* to other agents' in some regard. A solution that favours a particular agent will not be regarded as fair and thus will not be acceptable to other participants. We have also pointed out in Section 1.1, the notion of fairness is contentious among researchers (and philosophers) and there is no agreed definition of fairness. One line of argument from evolutionary psychology suggests that humans have evolved to favour agreements which propose equal division of goods among participants (Alexander, 2000; Binmore, 2009). Some debate that even when participants get equal shares, the value that they associate with their share (i.e. utility) can be different and, thus, despite getting equal share they will end up with different utilities. However, we lean towards the side of equal division of goods as a measure of fairness for two main reasons. First, this criterion has been used extensively in research across many domains (Binmore, 2009). Secondly, equal division of goods is easy to define and verify in practice. This equality is reflected as the equal amount of exchange in our protocol. All agents send and receive the same amount of energy.

Finally, the property of tractability is related to the negotiation process. It guarantees that negotiation will stop in two steps. An agent can make at most only one offer and this offer is can be computed using standard linear programming solver. Therefore, there are only two computations (offers) at maximum. This makes our negotiation protocol ideal for negotiations where outcome must be reached within a short time period.

4.5 Empirical Evaluation

Having discussed the properties of our protocol, we now provide an example to empirically evaluate it and compare it against the Nash bargaining solution, presented in Chpater 3. Let us



(a) (b) (c)

FIGURE 4.2: Utility of agents and total energy saved verses *battery efficiency* of agent a.

imagine two agents, a and b, with energy generation, load and battery specifications as laid out in Section 3.4. We compute the utilities that they get:

1. With no exchange (as described in Section 3.2)
2. With exchange via the Nash bargaining solution (Section 3.3)
3. With our energy exchange protocol (Section 4.2)

Moreover, we consider how these utilities vary as we reduce the battery flow and storage capacity of agent a as shown in Figure 4.2 and Figure 4.3.

Consider first Figure 4.2, which shows the utilities of agent a and b, and the total energy saved via exchange, as the battery efficiency of agent a is reduced. All the other factors, (including the battery efficiency of agent b) are kept constant. We can see that agents can increase their utilities via exchange. The amount by which their utility increases depends on the type of solution used and the battery efficiency. The *total energy saved via exchange* is the energy which would otherwise be lost (either in storage loss or due to limited battery flow or storage - Section 3.3)

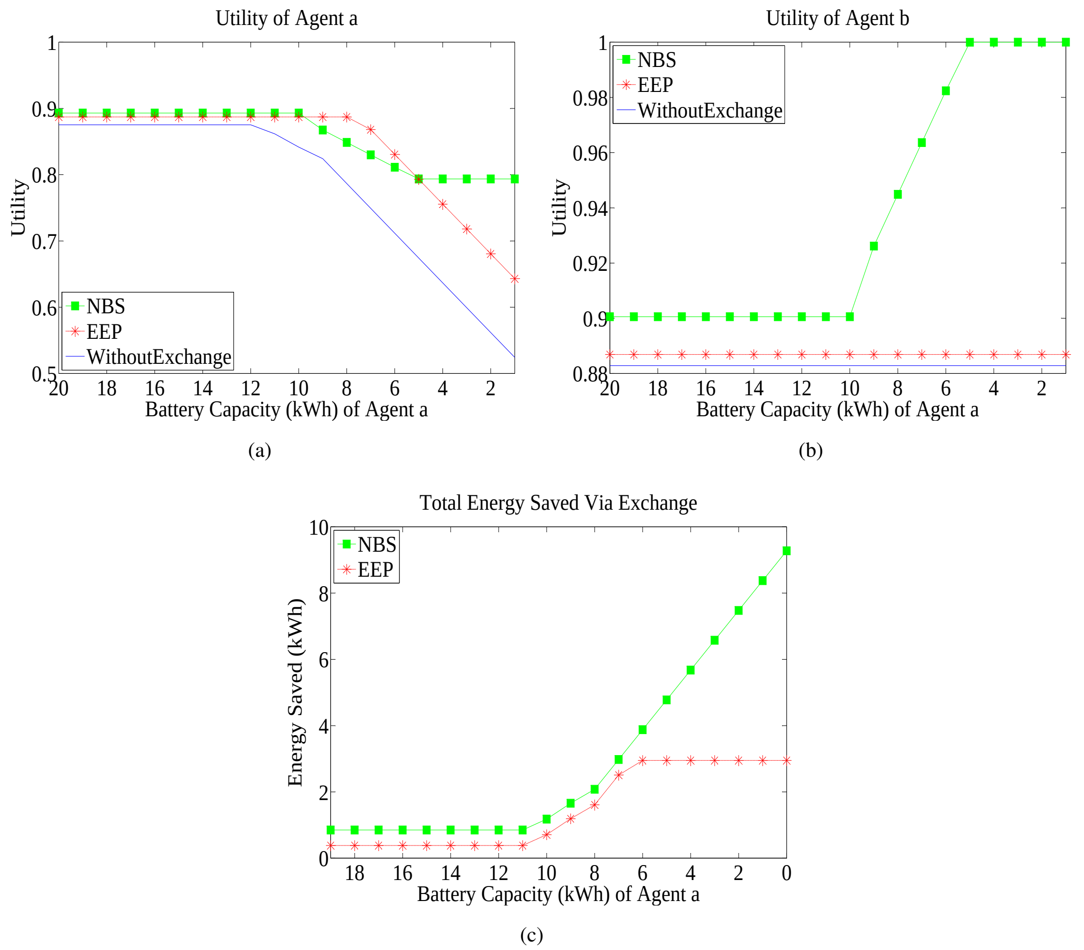


FIGURE 4.3: Utility of agents and total energy saved versus *battery capacity* of agent a.

without exchange. We also see that as the battery efficiency of agent a is reduced, so does its ability to meet its load, therefore, its utility reduces.

For b, this reduction in the battery efficiency of a does not affect its utility in scenarios without exchange or with the EEP. However, for the NBS its utility increases. The reason for this is that when we increase the storage loss for agent a, the amount of energy that can be saved via exchange increases, as shown in Figure 4.2. However, this saved energy is the result of cooperation between agents and the NBS divides it between both agents and hence, the increase in utility of b. Thus, with reduction in the battery efficiency, the energy exchange becomes more beneficial as agents can reduce their storage losses by exchanging energy.

We also note that the NBS gives both agents better utilities compared to the EEP. However, its computation comes with the challenges discussed in Section 3.5. To compare the EEP against the NBS, we measure the difference in the energy saved using these solutions. We observe that this difference depends on the battery efficiency of a and that the EEP can save from 29% to 84% (Figure 4.2(c) and Figure 4.3(c), respectively) compared to the energy saved with the NBS.

Figure 4.3 shows the utilities of the agents as the battery capacity of agent a is reduced. Again, as in Figure 4.2, agents can get better utilities with exchange. Also evident is the fact that as storage is reduced, energy exchange becomes more useful as agents can exchange energy instead of storing it. An important observation here is that an agent can maintain the same level of utility with a smaller battery via exchange that it obtains otherwise. For example, we see that a maintains the same level of utility in exchange via our protocol with a 7kWh battery that it gets without exchange with an 11kWh battery. This corresponds to almost a 37% reduction in battery size. Though, the same phenomenon can be seen for battery efficiency, what makes battery capacity more interesting here is the strongly correlated relationship between the battery capacity and cost, and thus, reducing the battery size will significantly reduce its cost.

4.6 Summary

In this chapter, we presented a negotiation protocol, the energy exchange protocol, that can be used to enable energy exchange between homes. We showed that by imposing three key restrictions on the offers that agents make, we can drive the negotiation towards a dominant strategy equilibrium and a Pareto-optimal outcome. Moreover, negotiation lasts only two rounds and each agent can make only one offer. We provided mathematical proofs to prove these properties. Following our example of energy exchange in the last chapter to show that it results in better energy management, we have demonstrated via an example in this chapter that it also has the potential to reduce the required storage capacity by up to 37% less. In addition to that, we use the Nash bargaining solution as the benchmark to provide a comparative analysis of our protocol. More specifically, we showed that the energy saved using the EEP can be up to 84% of the energy that can be saved using the NBS.

Although we have demonstrated the usefulness of our protocol, there are some limitations in the practical implementation of our protocol. For example, one limitation of our current protocol is that we do not model uncertainty in energy generation. In the next chapter, we discuss such limitations along with our research requirements and describe our future work.

Chapter 5

Conclusions and Future Work

We present our conclusions and future work in this chapter. We begin by evaluating our presented work against the requirements set out in Section 1.1 to enable energy exchange between homes in rural communities. We arrive at the conclusion that our developed energy exchange protocol meets all but one of these requirements. We then draw general conclusions based on our work. Finally, we point out to the current shortcomings of our work and lay out our plan to address them in our future work.

5.1 Conclusion

The problem of energy exchange between homes is an interdependent multi-issue negotiation problem. Such problems are complex and computationally expensive to negotiate over. The game-theoretic framework and bargaining techniques (e.g. strategic bargaining) are difficult to utilize due to the complexity of analysis. In order to reduce the complexity and be able to systematically analyse, one approach is to simplify the settings that these problems are studied in. We applied this approach to the problem of energy exchange between homes and developed a novel energy exchange protocol (EEP). We showed that this protocol guarantees certain properties to address the research requirements mentioned in Section 1.1. In the following section, we analyse each requirement against our protocol:

REQ 1. **Automated Negotiation**

We are interested in automated negotiation with minimum or no human input.

Our presented work assumes the role of software agents and does not require the human engagement. Thus, the negotiation is automated.

REQ 2. **Beneficial to all**

A solution must be beneficial to all those participating in an exchange. Participants are self-interested and will not take part in an exchange if it is not beneficial for them.

In Section 4.3, we have proven that the EEP is beneficial to all participants.

REQ 3. **Fair**

The benefit each participant receives should be fair according to a pre-agreed criteria. The fairness property ensures that a society remains just.

As mentioned in Section 4.4, we define the notion of fairness as the equal amount of energy exchange between agents. Our protocol imposes this as a precursor to any exchange agreement as shown in Figure 4.1.

REQ 4. **Decentralised**

The solution must be applicable in decentralised settings, i.e. it should not require a centre or mediator.

The EEP enables agents to make offers to each other and does not require an entity to assist in negotiation.

REQ 5. **Scalable**

The solution must be scalable from a minimum of two homes to a few hundred.

In Section 4.3, we showed that a single agent can use our protocol to simultaneously exchange energy with multiple agents.

REQ 6. **Adaptable**

The power output 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.

We will consider this possibility in our future work as discussed in Section 5.2.

REQ 7. **Timely**

Negotiation must be guaranteed to terminate in a timely manner.

In Section 4.3, we proved that the EEP allows each agent to make utmost one offer and these offers are computable via standard linear programming solvers. This shows that negotiation will only last two rounds.

REQ 8. **Pareto-Efficient**

The solution must lead to a Pareto-efficient outcome.

In Section 4.3, we proved that the outcome from our EEP is Pareto-efficient.

REQ 9. **No Payment Mechanism**

The solution must not consider payments between participants.

We do not assume financial payments between agents. The negotiation depends solely on the exchange of energy.

REQ 10. **Strategy-proofness**

The solution should discourage the participants from putting their efforts into developing strategy. It must ensure that participants are not rewarded for their dishonesty.

In Section 4.3 [Theorem 1 and 2], We proved that our protocol leads to a dominant strategy equilibrium which implies that our protocol is strategy-proof.

In Chapter 3, we presented an example of two agents to show that energy exchange between homes is a viable and useful option to improve energy efficiency. We demonstrated via example and concluded that via exchange, agents can reduce energy storage loss which results in more efficient use of energy. Furthermore, in Chapter 4 we extended our model and showed that energy exchange is also useful in reducing the need for storage. Agents can maintain the same level of utility with less storage when they exchange energy. This result is important as the cost of battery is fairly linear with the storage capacity. We presented an example to show that such reduction in storage could be up to 40%. We also note that all the examples we presented had diversity only in terms of energy generation while consumption and battery specifications were the same among agents. In reality, such diversity will exist in a varierty of ways such as in energy consumption, storage, preference over energy use and types of loads. As this diversity will increase, so will the number of different ways in which an exchange can take place. Also, we have only considered cases where loads were non-deferrable. With deferrable loads, agents are more flexible in energy allocation which also increases the possiblity and usefullness of energy exchange.

As we mentioned in Section 2.3.3, our work is an example of the rules of encounter approach. We also stated that this approach is domain specific, i.e. there is no universal set of rules (of encounter) for all domains and every domain should be analysed individually for its own set of rules. In this regard, our work can been seen as designing a set of rules for the energy domain, similar to the works in other domains (such as postmen or bidding for phone calls), for more examples see Rosenschein and Zlotkin (1994)). However, what makes our work unique is the fact that, to the best of our knowledge, their is no work on designing the rules of encounter for an interdependent multi-issue negotiation in *any* domain. In this regard, our work is the first example of designing rules of encounter for an interdependent multi-issue negotiation. Therefore, based on our work, we conclude that this approach is also applicable to the interdependent multi-issue negotiation in general.

5.2 Future Work

Although our presented protocol for energy exchange addresses most of the requirements, as outlined in Section 1.1, it still lacks the property of *adaptability*. We define the requirement of adaptability as the ability to cope up with uncertainty in energy generation. As stated earlier, our focus is the generation from renewable resources, such as solar panels and wind turbines, which are weather-dependent and thus the power output can be predicted to a certain degree. At present, our protocol is inflexible in that it does not consider the possibility that an agent may not be able to keep the agreed link flow due to the uncertainty in its power generation. This is an important hindrance in the implementation of our energy exchange protocol in the real world and, therefore, our very next task in the future work.

Although our developed model in Chapter 3, is realistic and practical, we have not considered the possibility of deferrable-loads in homes. As we mentioned in Section 2.1.3, deferrable loads provide more flexibility in allocating energy as some loads can be moved to times when it is more efficient to power them. This flexibility in allocating energy increases the number of ways an agent can power its load which in turns, increases the number of possible ways an agent can exchange energy. In future work, we will also incorporate deferrable-loads in our model to investigate the effect of deferrable-loads on exchange agreements.

Figure 5.1 shows our planned future work.

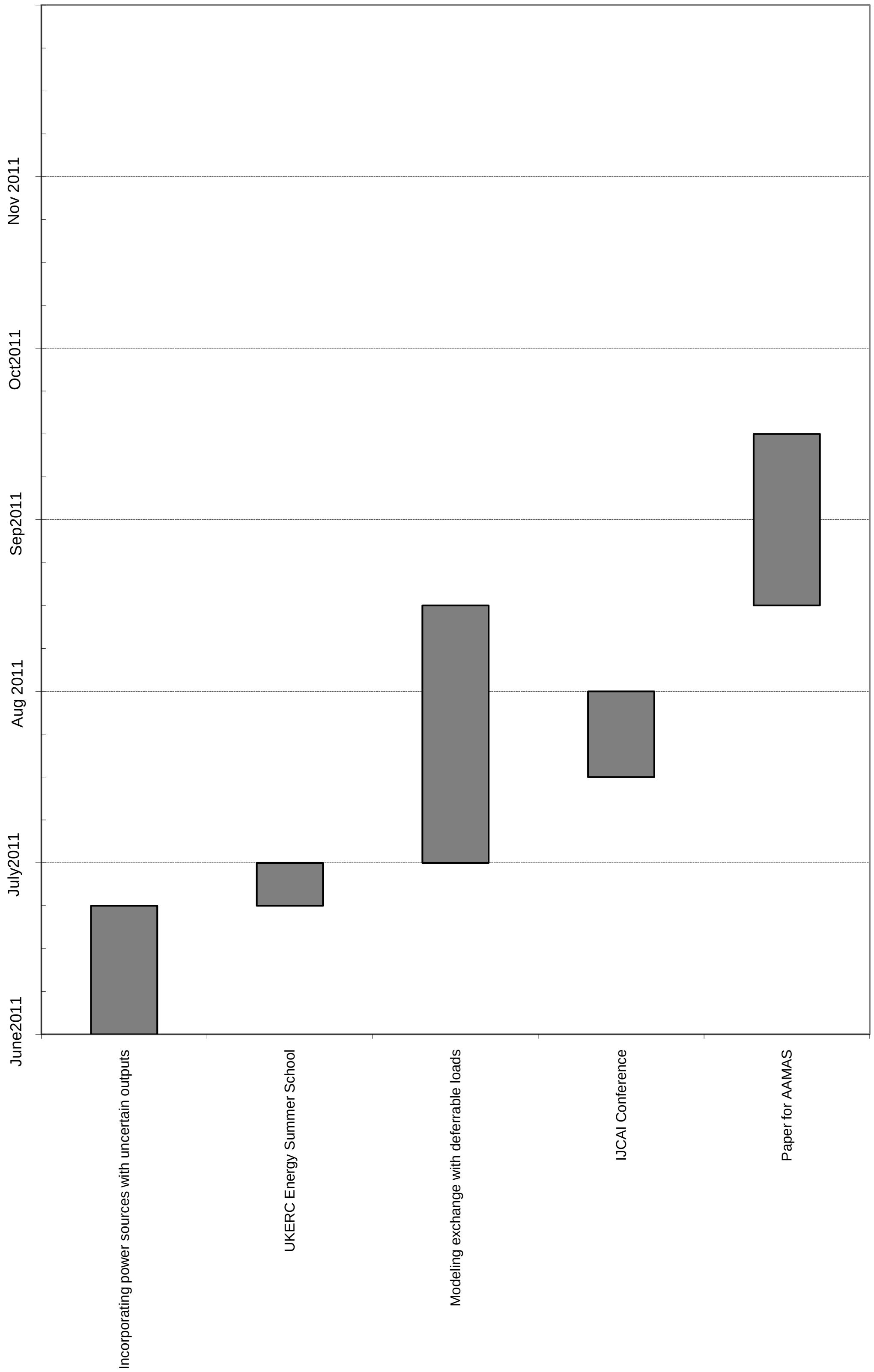


FIGURE 5.1: Gantt chart of our planned work.

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