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THE IMPACT OF SOCIAL NETWORKS ON ENERGY EFFICIENCY PROJECTS: THE INFORMATION PROPAGATION APPROACH

by

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Submitted in partial fulfilment of the requirements for the degree

Philosophiae Doctor (Electrical Engineering)

in the

Department of Electrical, Electronic and Computer Engineering
Faculty of Engineering, Built Environment and Information Technology
UNIVERSITY OF PRETORIA

September 2015

SUMMARY

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Keywords:	social network, energy efficiency, information transmission, probability, information entropy, energy savings

There are many reasons why energy efficiency projects are carried out; to reduce electricity and water usage, cut greenhouse gas emissions and to promote the conservation of biodiversity. A common factor is that humans are the ones that make a major contribution towards achieving goals set for energy efficiency projects. As such, humans should be targeted when campaigning for a change of any policy concerning energy efficiency. It is often assumed that the "end use" technology is what achieves energy efficiency. This is not true; people and "use of the technology" consume energy and therefore determine the viability of the energy efficiency of the project.

In most researches, the human aspect is not taken into consideration and the behaviour of people is assumed to be generic towards thinking of energy efficiency projects. Generalising how energy efficiency projects affect the entire population is a mistake and as such, the actual targets of the projects may be missed. Studying the social structures of society will reveal the actual impact each individual has on his/her society when an energy efficiency project is

carried out.

It is therefore important to determine the expected energy savings by dividing the savings into two categories; direct and indirect savings. Mathematical models to determine the impact each individual has on his/her neighbours within a social network are formulated. The models are derived from the study of energy, information theory and social networks. From these models, the expected energy saved indirectly through information propagation of the energy efficiency project is determined. The advantages of this research can be extended to the identification of potential customers in residential mass roll-out programs and the adoption of demand response programs.

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OPSOMMING

DIE IMPAK VAN SOSIALE NETWERKE OP ENERGIEPROJEKTE: DIE INLIGTINGVOORTPLANTINGBENADERING

deur

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Sleutelwoorde:	sosiale netwerk, energiedoeltreffendheid, inligtingoordrag, waarskynlikheid, inligtingentropie, energiebesparing

Daar is verskeie maniere waarop energiedoeltreffendheid bewerkstellig word om elektrisiteit- en watergebruik, sowel as kweekhuisgasvrystelling, te verminder; en biodiversiteit te bewaar. Die gemeenskaplike faktor is dat mense die grootste bydrae lewer tot die bereiking van doelwitte vir enige energieprojek om die gewenste resultate te bereik. Daarom, is mense dus die teiken wanneer verandering van enige aard met betrekking tot energiedoeltreffendheid gepropageer word. Daar word dikwels aanvaar dat "eindgebruiktegnologie" die belangrikste rol speel in energie-doeltreffendheid. Dit is n denkfout; mense; en die gebruik van die tegnologie, verbruik energie en bepaal gevolglik die lewensvatbaarheid van die energie-doeltreffendheid van enige projek.

In die meeste navorsing word die menslike aspek nie in ag geneem nie en word daar aanvaar dat menslike gedrag generies is of dat mense gestruktureerd is in hulle denkwyse of aanvaarding van enige energiedoeltreffendheidprojek. Veralgemening oor hoe energiedoeltreffendheidprojekte die algehele bevolking raak, is ’n fout wat daartoe kan lei dat die werklike doelwit van projekte nie bereik word nie. Bestudering van die sosiale structure van die

gemeenskap sal die werklike impak wat elke individu op die gemeenskap het, blootlê wanneer ’n energiedoeltreffendheidprojek aangepak word.

Dit is daarom belangrik om die verwagte energiedoeltreffendheidbesparing te bepaal deur die besparing te verdeel in direkte en indirekte besparings. Wiskundige modelle om die impak van alle individue op hulle bure in ’n sosiale netwerk te bepaal, word geformuleer. Die modelle is afgelei van die studie van energie, informasieteorie en sosiale netwerke. Deur die modelle te gebruik, word die verwagte indirekte energiebesparing deur informasieverspreiding oor die energiedoeltreffendheidprojek bepaal. Die voordele van hierdie navorsing kan uitgebrei word om potensiële kliënte in residensiële massa-implementeringsprogramme en die aanvaarding van aanvraagresponsprogramme te identifiseer.

LIST OF ABBREVIATIONS

kW	Kilowatt
kWh	Kilowatt-Hour
DSM	Demand side management
TOU	Time of use tariff
EPS	Expected power savings
CFL	Compact fluorescent light
POET	Performance, operational, equipment and technology
EU	European Union
GNP	Gross National Product

LIST OF PUBLICATIONS

The information propagation approach to examine the impact of social networks on energy efficiency projects is the research that was undertaken during the study. The following articles were published in journals or presented at international conferences during the research. The content of these publications are the research content of this study and as such are represented in the thesis. The publications are as follows:

1. U. E. Ekpenyong, J. Zhang, X. Xia, "How information propagation in social networks can improve energy savings based on time of use tariff", *Sustainable Cities and Society*, vol 19, pp. 26-33, 2015.

2. U. E. Ekpenyong, J. Zhang, X. Xia, "Mathematical modelling for the social impact to energy efficiency savings", *Energy and Buildings*, vol. 84, pp. 344-351, 2015.

3. U. E. Ekpenyong, J. Zhang, X. Xia, "Social influence and energy efficiency savings", in *Proceedings of IEEE AFRICON Conference*, Mauritius, 9-12 September, 2013.

4. U. E. Ekpenyong, J. Zhang, X. Xia, "Social impacts for energy efficiency savings based on time of use tariff", in *Proceedings of 5th International Conference of Applied Energy ICAE 2013*, Pretoria, South Africa 2-4 July 2013.

5. U. E. Ekpenyong, J. Zhang, X. Xia, "The approaches to social impact of energy efficiency projects", in *Proceedings of International Energy Program Evaluation Conference*, Rome, Italy, 12-14 June, 2012.

ACKNOWLEDGEMENT

I thank God who has been my help and strength throughout the duration of my studies.

I am grateful to my supervisor Prof. Xiaohua Xia for his support and guidance throughout my postgraduate studies. He has been patient and his knowledge of research has been a great motivation for my research.

I am grateful to all other professors and friends who have supported me throughout my PhD study; their encouragement kept me on track. Finally, I am extremely grateful to my family for all their support especially to my parents Mr & Mrs Ekpenyong (and my sisters Enobong and Egho) who have been my greatest supporters throughout this journey.

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CHAPTER 1

INTRODUCTION

The complex energy challenges facing the world today requires different measures to reduce an ever increasing use of energy while still providing the same services. Some of these measures are the introduction of renewable energy, conservation of energy and energy efficiency projects. Energy efficiency is a fast growing activity that is taking over the world. There are many ways in which energy efficiency is carried out, with the aim being to reduce electricity and water usage, cut greenhouse gas emissions and to conserve biodiversity. The common factor is that humans are the major contributors towards achieving the goals set for any energy efficiency project. As such, humans are the ones to target when campaigning for change of any kind concerning energy efficiency.

It is often assumed that the "end use" technology is what achieves the energy efficiency. This is not true; people and the use of the technology consumes energy and therefore determines the viability of the energy efficiency of any project. In order to quantify the effect of an energy efficiency project, money saved can be used to determine the success of the project. However, energy efficiency projects affect the environment via a reduction in greenhouse gas emissions and also have economic and social benefits. The main focus of the research, is on how one individual's energy efficiency project can influence his/her neighbours to save energy and thus save money.

In most researches, the human aspect is not taken into consideration and the behaviour of people is assumed to be generic in their acceptance of any energy efficiency project. Generalising how energy efficiency projects affect the entire population may be a mistake and as such, the actual target of the projects may be missed. Studying social structures of the society will reveal the actual impact each individual has on his/her society when an energy efficiency project is done.

Lifestyle plays a big role in the acceptance or success of energy efficiency projects and people are likely to make energy efficiency changes because their neighbours or friends made those changes. Hence, different lifestyles have differing consumptive requirements and environmental impacts.

In the lifestyle concept, energy efficiency technologies have different meanings in different cultural context. For example, people from a particular social group may be involved in the project to "save the planet", another group may be involved to reduce expenses due to electricity consumption. It is therefore important to determine the expected savings by dividing the energy efficiency savings into two categories; direct and indirect savings.

Direct savings are savings that can be measured or calculated and quantified by means of measurement and verification. They are savings related to the energy efficiency technology that is installed or measures that were taken, for example; by changing from incandescent light bulbs to compact florescent light (CFL)bulbs. The indirect savings are savings that result from social interactions in a network. Indirect savings are derived from the social impact of energy efficiency projects through calculation based on the knowledge of information theory and social networks.

Mathematical models to determine the impact each individual has on his/her neighbour within a network are formulated. The models are derived from the study of energy, information theory and social networks. From these models, the expected energy costs saved indirectly through information propagation of the energy efficiency project are determined. The advantages of this research can be extended to identify potential customers in residential mass roll out programmes and the adoption of demand response programmes.

1.1 PROBLEM STATEMENT

As energy efficiency is at present one of the major topics in energy research, it is therefore important to know how people will become aware or take advantage of this situation. There is much information available however, it is sometimes difficult for people to communicate their ideas to other people. This can complicate the energy planner's decisions.

However, if the energy planner understands the flow of information within a social network, he/she will be able to determine the key people who will spread the information faster within that network, it will save time and money; rather than trying to convince every individual to adopt energy efficiency and reduce his/her electricity demand.

It is because of the fact above that this research is aimed at determining the advantages of information transmission within a social network that helps propagate energy efficiency from an individual to his/her neighbours within the network.

The challenge therefore, lies in how the quantity of information is estimated from the source of information to the receiver considering time intervals and the influence of the source on the receiver.

1.1.1 Context of the problem

To fully understand the impact individuals have on their neighbours in terms of information transmission of energy efficiency measures, the type of network, information and influence the individual has on his/her neighbours needs to be studied. This will enable the energy planner to determine the people to target in the quest for greater awareness of energy efficiency and demand side management.

This research is therefore focused on addressing the estimation of the quantity of information transmitted across a network using information entropy and social networks as tools for this study.

1.1.2 Research gap

The motivation of this research is the need to quantify the energy cost savings related to non-technical factors. These are related to the social interactions of people in societies or communities. The interaction of people results in information transfer, the information transferred regarding energy efficiency projects helps in saving energy because it encourages more people to adopt the energy efficiency projects.

Quantifying the non-technical savings related to social impact is achieved by formulating mathematical models of expected energy cost savings. The models contain all the necessary variables and the constraints needed to achieve the indirect savings. The models are optimised using research from social networks and information theory.

1.2 RESEARCH OBJECTIVES AND QUESTIONS

The objective of this research is to formulate models that quantify the social impact of energy efficiency projects. The social impact of the energy efficiency projects examine the non-technical savings or indirect savings that past literature did not quantify.

The research questions include:

- How does social impact relate to energy efficiency savings?
- How does a social network affect the progress of energy efficiency projects?
- How does calculating the transfer of information within a network benefit energy efficiency projects?

1.3 HYPOTHESIS, TASK AND APPROACH

The social impact a person has on his/her network can be quantified by the information he/she transfers within the network. The relationships among people in a social network can affect how they respond to energy efficiency projects and thus affect the energy efficiency savings.

The research approach will first identify the problem, choose the research design then formulate mathematical models, and finally engage in the research using different case studies. The case studies give evidence that the impact an individual has on his/her network in terms of energy efficiency can be quantified via information propagation.

To achieve the desired objectives the following steps have been undertaken sequentially:

1. The first step is to perform a study on social networks and information theory. This is to identify how they relate to energy efficiency.

2. The next step is to conduct a study of the existing research on the social impacts of energy efficiency projects using the POET (performance, operation, equipment and technology) system of classification of energy efficiency components, with a major focus on performance efficiency aspects. The POET system of classification refers to a broad scope of definitions of the different components which consist of many branches of science and engineering with the aim of understanding the different facets of energy efficiency.

3. The third step is formulating mathematical models which calculate the expected energy cost savings that comprise of direct and indirect savings. The formulation of the models will be divided into three stages.

    - The first stage is to consider instant savings on a network.

    - The second stage is to consider savings that will be obtained over a period of time.

    - The third stage is to consider the savings based on the influence of people within the network. This stage shows that influence can affect an individual's impact in the network.

4. The models are applied to some case studies with unweighted and undirected networks and the results of the networks are analysed. The reason for using the undirected networks is because these networks ensure that when any two people are connected, they have a mutual acknowledgement of their connections. The reason for the unweighted graph is that the research does not place importance on any particular person in the social network.

1.4 VALIDATION OF THE PROPOSED RESEARCH

All models formulated in this study have been solved using social network data, this is to provide evidence of the expected energy savings. The solution methodology for each model in chapters 3, 4 and 5 is explained within the chapters. The results prove that information propagation is important for energy efficiency project adoption. All the results show that information propagation can increase the expected energy savings of people within a social network. The models can be applied to other fields that involve information propagation in social networks.

1.5 RESEARCH CONTRIBUTION

The contribution of this research is to make available the ability to quantify the non-technical savings of energy efficiency projects through social influences. This research can help determine the acceptability of any energy efficiency projects by people within a network. The calculations on the expected energy savings based on social impact are achieved from the study which can help determine optimal placements of energy efficiency projects that will yield maximum savings. This study validates the theory that information propagation can enhance increased adoption of energy efficiency projects within a social network.

1.6 OVERVIEW OF THE STUDY

The outline of this thesis is as follows, Chapter 1 presents the research problem, goals and contribution to this particular study. Chapter 2 highlights the background literature, the rationale for the study and the in-depth contribution and limitation of the study. In Chapter 3, the initial information transmission model is formulated while Chapter 4 enhances it to include time intervals. In Chapter 5, a mathematical model that explores the effect of the influence a person has on his/her neighbour is formulated. Chapter 6 compiles all the case studies from all three mathematical models from Chapters 3, 4 and 5 with their results and discussions. The conclusion and further research ideas are given in Chapter 7.

CHAPTER 2

LITERATURE STUDY

2.1 CHAPTER OBJECTIVES

In this chapter, the background literature is provided in order to understand the overall structure of the research. The background literature starts with energy efficiency and demand side management in South Africa, then proceeds to explain complex networks focusing on studies in social networks and what has been accomplished. The rationale for this study is given together with the limitations and contributions to the research community.

2.2 RESEARCH METHODOLOGY

The research methodology used in this study is as follows:

1. Literature study: This research combines three different areas and compresses it into one unique research output. The three different areas are social networks, information theory and energy efficiency.

    - Social networks: The first approach was to understand the meaning of a network and how it can be applied to human behaviour. Research on different complex networks was conducted, followed by in-depth studies on the different research works pertaining to social networks. The "small world" network was then identified as the type of network that represents real-life human interactions and from these findings the mathematical interpretations of small world networks were explicated and formulated to understand the connectivity of people in networks.

- Information theory: The information theory framework used in this thesis is based on Shannon's information theory research. Existing literature on information entropy was also perused and analysed.

- Energy efficiency: The human contribution towards energy efficiency is a fairly new area and the combination of how social interactions affect energy efficiency is yet to be explored and, this is what this research intends to do.

2. Mathematical formulation: From the literature study, the mathematical models for expected energy cost savings are formulated incorporating the findings from all the necessary studies such as network degree, information entropy, social impact, social influence, etc.

3. Case study: After the mathematical models are formulated, three case studies are applied to the obtained models to determine if these models depict real life situations. In each case study, a medium sized small world network is used where all the members of the network are connected to at least one other person in the network. The networks used in this study are physically connected networks (not through internet social media).

4. Results and conclusion: The results of each case study are analysed and discussed. The conclusion of the study highlights the findings of the research and details future expansion of this research endeavour.

2.3 BACKGROUND OF THE STUDY

Whilst examining energy efficiency in a large society, the authors of [1] explained that the measurement of energy efficiency refers to the "efficiency with which societies convert commercial energy resources - generally inanimate energy - into socially useful production and consumer goods". Therefore, any country which requires a high amount of energy to meet it's per capita Gross National Product (GNP) is not an energy efficient nation when compared with other nations with similar GNP levels but lower energy consumption. Therefore, reducing energy consumption use is beneficial to both nations and individuals. There are many avenues through which energy efficiency is carried out mostly to reduce electricity and/or water usage. However, in recent years the reduction of greenhouse gases has become more pronounced when energy efficiency is mentioned [2]. Also there is an increasing focus on the conservation of biodiversity in certain areas of the world because of the exploitation of natural resources. The common denominator with all these measures is that humans are the ones who make a major contribution towards achieving the set goals of the energy efficiency project. As such, it is advisable to focus on humans when the adoption of an energy efficient lifestyle is concerned. In [2] the authors show that the impact of energy efficiency is varied and dependent on the type of event, but also on the particular cultural orientation and the social aspects.

This is why in [3], the authors characterised the sites for any energy efficiency project within the energy system with several parameters to identify the different indicators of energy efficiency. These indicators describe how the impact of energy efficiency affects the dynamics of the energy system in that environment whether directly or indirectly. This type of evaluation is done by weighing each impact indicator against the different environmental indicators that have been listed. In an attempt to consider both direct and indirect effects, the authors [4] found a means to define the site and energy system characteristics, they refer to this as a form of dynamic weighting. In this regard, the environmental measures are then used to evaluate the impact energy policies have had on the country. They do this by applying boundary limits to each environmental measures and depending on where the impact lies on that limit, an optimal solution for the system defining the environmental impact can be obtained [4]. However, the human influence or impact was not quantified.

Characterising the human impact would improve the spread of information about different energy efficiency measures. One way in which the human impact of energy use can be observed is through lifestyle. As [5] highlights many researchers have used lifestyle to understand and explain the variations in energy use. This is why [5] proposed a general definition of lifestyle intended to provide a starting point for further research in this area. In [5] lifestyle is defined as "distinctive modes of existence that are accomplished by persons and groups through socially sanctioned and culturally intelligible patterns of action", this definition is supported by [6], [7] and [8].

However, when considering individuals in a society and how they perceive energy efficiency, [9] explains that saving money was the primary reason people participated in energy efficiency measures. They also found out that there are non-energy related benefits that gave these people the power and ability to create or increase awareness in others. This has led to different demand response programmes such as "high price notification" programmes. Demand response programmes as defined by [9] are often characterised as shifting, but not necessarily reducing, electricity use and high price notification help keep energy use "top of mind". The authors of [9] highlighted that savings on electricity bills have a relatively greater impact on lower income consumers, so there are benefits to facilitating these consumers' successful participation in real-time pricing programmes [9]. Therefore, educating the public about energy efficiency is important but has not been sufficient. There is the need for behavioural changes that will greatly increase the adoption or penetration of energy efficiency.

This is why in [9] the authors concur that energy efficiency means "doing the same amount of work with less energy and can have clear environmental benefits, including reduced carbon and sulphur emissions and less demand for new power plants". In [9], the author argues that the energy efficiency community does not take into account the human impact but just the technologies and this can affect the decisions of the policy makers. Furthermore, he states that the research community does not fully understand what the energy efficiency market entails from the "processes of innovation or adoption of different technologies (to be more precise everything that one would want to know about in order to make significant changes in technology), behaviour and finally the consumption" [9]. If these facets are clearly understood, then it will be seen that throughout the process there is human involvement as such, and that quantifying the human impact of energy efficiency is important.

Understanding the human impact of energy efficiency should therefore be studied through the people who understand how to use energy efficiently and also have the ability to transfer their knowledge to their immediate neighbours. In [10], the authors highlight what is needed for a lifestyle change through applying energy efficiency. The posit:

- "A person needs to be aware of the impact or influence of their own behaviour on others or the environment (awareness of consequences).
- A person needs to have a sense of responsibility personally for these behavioural consequences (ascription of responsibility)" [10].

To support their points, the authors in [10] add that people who feel responsible towards their energy use will be more obligated to reduce their own usage and assist in helping others reduce their energy consumption.

This leads to how a social network of people functions. How does one reach his/her neighbours and transfer this knowledge that he/she has? [11] and [12] pose several questions that may be important to answer when considering the transmission of information within a network. The questions proposed by [12] are listed as follows:

1. "How many people does an individual know?
2. What is the distribution of acquaintance volumes, the mean and the range between the extremes (lowest and highest)?
3. What kind of people are those who have many contacts and whether those people are also influential?
4. How the lines of contact are stratified; what is the structure of the network?"

These questions give rise to the formation of the network equations needed to understand how people interact in their networks. To have answers to the questions above, one must understand and analyse the distribution of people within the network and study the social influence and the characteristics of individuals in that network.

Once these questions have been answered, the information can be used to calculate the probability that any two persons within a network would know each other, have a common friend, or identify what is the shortest path between these two people. People do not necessarily know who they are connected to and their impact in the network. Identifying the people most likely to motivate their neighbours to adopt energy efficiency measures can be most helpful in an energy efficiency project. As [12] analyses, the knowledge of these questions can determine the exact influence a person has with regards to his/her contacts.

This is why the study of complex networks is important in this research, as [13] states "many complex networks display strong heterogeneity in the distribution degree". This can reduce the average distance between nodes but does not guarantee that once an individual makes a decision, the rest of the network will follow. According to [13] the shorter distances between nodes "may suppress synchronisation in networks of oscillators coupled symmetrically with uniform coupling strength". Therefore, [7] proposed a model that shows how to add random short cuts in a network that may tend to improve network synchronization. In terms of social networks this means that one can easily determine the person who influences the rest of the network to adopt the energy efficiency measure he/she has implemented. Thinking in terms of small-world networks (which depict real-life networks), [7] implies that the "small-world route produces synchronization more efficiently than standard deterministic graphs, purely random graphs, and ideal constructive schemes".

It is imperative therefore, that people interact among themselves to promote energy efficiency within networks as [6] highlights that interpersonal interactions among individuals in the same group are stronger than interactions among individuals from different groups. They further explained that the smaller a group is, the greater the chances are of an individual's influence on the members of his/her group. Take the spread of an epidemic as an example, family members and close friends are more likely to contract the disease from an individual than a random person. However, random contacts are important too because these could be present in an individual's life even though he/she is not aware of them. For example, this includes an individual's co-workers, bus commuters, shopping in the same stores and so forth. In addition, due to the world becoming a "global village" one does not necessarily need to have physical contact with another individual to have a probability of association with the person, this is pointed out in [6].

Spreading information can also be viewed as a form of epidemic but in our research we take it further to indicate that the quantity of information passed from an individual to the rest of the network is important and this is based on his/her connection within the network. If one considers media spread in social networks, [14] proves that it is best to go through individuals known as "opinion leaders", these people have the most influence in their network. It is their example that others will likely follow. As [14] explains, opinion leaders are viewed as the middlemen between the followers and the media. Putting it back in the energy efficiency context, the opinion leader is the person between the energy efficiency project planner and his/her neighbours. It is this individual that convinces his/her neighbours to either adopt or reject the project. However as [14] explains, this is not just a "two-step" level of communication within networks but involves multiple steps, their description leads to the infamous diffusion of innovation model designed by [15].

In this regard, studying the role of influence should not just be based on surveys as [16] explains but also by incorporating real energy consumption data in order to understand the underlying mechanisms driving conservation efforts. This is why the authors of [17] introduced the eco-feedback model which provides a platform to capture such energy consumption data, and provided some methods to analyse this data required to gain a deeper understanding of the role of social influence in energy efficiency. However, they did not take into account how an individual's social connections can influence his neighbours to adopt energy efficiency options. In the next few sections, an in-depth explanation of social networks, energy efficiency and information is explained in relation to the research of how information transmission can enhance energy efficiency savings.

2.4 ENERGY EFFICIENCY IN SOUTH AFRICA

Energy efficiency projects involve the implementation of a technology or process that uses less energy to achieve the same quality and quantity of output. In South Africa, the aim of energy efficiency projects is to be able to reduce the total energy consumption in the medium or long term [3]. An example of an energy efficiency project is replacing incandescent light bulbs with energy saving compact fluorescent light (CFL) bulbs. This will save energy and cost while maintaining the quality of service. For mass roll out of energy efficiency projects, it is beneficial for governments or utility companies to minimise the cost of the project while maximising the number of people who adopt this project. The propagation of information within a social network can speed up the rate of adoption of a project.

Demand side management (DSM) of energy is a method of curtailing the demand for electricity when the supply is low. DSM has to consider the technical, organisational and behavioural solutions that will help decrease energy consumption and demand. These measures are implemented mostly for the short term which reduces the shut down and start up generating plants to meet demand. The benefits of DSM include but are not limited to the reduction of customer bills, air pollution, heavy investment in power plants and grid congestion [18], [19], [20]. The measures also create job opportunities through innovation and technology to produce energy efficient appliances. The tools used in DSM measures are real time pricing, time of use (TOU) tariff, smart metering and web-based communication systems [18]. The authors of [21] show that the success of energy efficiency begins with information and insight into the efficiency process involved. An example of such is the HomeFlex TOU tariff which is targeted for medium to high income suburb households with the aim to encourage them to reduce their electricity consumption [22].

2.5 COMPLEX NETWORKS

A network is a representation of items called nodes with connections between them called edges. Networks with irregular and complex structures that are dynamically evolving with time are known as complex networks. Network studies started as far back as 1732 by a Swiss mathematician Leonhard Euler when he solved the Konigsberg bridge problem [23]. However, back then, the networks studied were small, structured and were only studied in a branch of mathematics known as graph theory. The development of social networks started as far back as in the 1920s where relationships among social groups, trades among nations and economic transactions among companies were studied [24]. Some examples of networks studied are the scientists collaboration network [25], [26], transport network [26], cellular network [27], Internet and the World Wide Web [28], [29] and ecological networks [30], [31] and so forth.

These studies enable one to understand the behaviour of a system. For example investigating the structure of a social network, where the nodes represent the humans and the edges are their social relationships, one can predict what information to send to such a network and the people to whom to give the information. The entire topography of the network, the individual connections among the nodes and the type of relationships among the nodes has to be studied in order to understand how to control what information is transferred within the network. A recent study from [29] shows that due to the fact that the world has become a "global village" the degree of separation has reduced from six to four (this was determined through the experiments they performed on over 10 million Facebook users. This is about one sixth of the world's population. There are many applications of complex networks in real life case studies. Examples of such applications are the spread of epidemics, rumour spreading opinion formation and so forth.

2.5.1 Social networks

The authors of [12] and [32] show that there is connectivity among people even though they are not aware of such connections. This is where the exclamation "it's a small world!" originates, that is, "when two people meet who previously did not know each other but have a mutual acquaintance" [32]. An example that shows social networks can promote energy efficiency savings is given in [17] .

Three properties have been used to describe real-world networks they are; small-world, clustering and degree distribution [28], [31]. Small-world describes the real network as having short distances between nodes despite the fact that the network could actually be large. For social networks, Stanley Milgram discovered an interesting trait when he performed an experiment and concluded that there are six degrees of separation between any two individuals in the United States of America [33], [34]. Rapoport and Horvath in [35] conducted empirical studies that relate to small-world problems which examine the sociometric networks in a junior high school of 861 students. Their tracing procedure was quite different from that of Milgram although it has some relationship to the small world problem.

The small world characteristics of a network can be quantified by the characteristic path length L which is defined as "the average number of edges that must be traversed in the shortest path between any two pairs of nodes in the graph and it is a measure of the global structure of the graph" [28]. The characteristic path length L is given in [28], [31] as,

$$L = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} d_{i,j}, \tag{2.1}$$

where N is the total number of nodes in the network, $d_{i,j}$ is the distance between node i and j.

Clustering represents the cliques formed by friends or acquaintances where every node is connected to another [23]. Watts and Strogatz discovered that "if node A is connected to node B and node B is connected to node C there is a high probability that node A is connected to node C" [24], [28], [31], [36]. Clustering coefficient C is defined from [28], [31] as,

$$C = \frac{1}{N} \sum_{i \in N} c_i, \tag{2.2}$$

$$c_i = \frac{2e_i}{k_i(k_i-1)}, \tag{2.3}$$

where c_i is the local clustering coefficient of node i, k_i is the node degree of i, which is the number of nodes linked to i, and e_i is the number of edges in the subgraph of the neighbours of i. The node degree shows the interactions of nodes within the network. The degree distribution D of any network gives the average node degree of all the nodes in the network. It is defined from [11], [28] and [31] as,

$$D = \frac{1}{N} \sum_{l=1}^{N} k_l = \frac{2E}{N}, \tag{2.4}$$

where E is the total number of edges in the network.

Having established that small world networks depict real-world connectivity of people in social networks, the characteristic path length, clustering coefficient and degree of distribution is used to study the topology of the social network. The research focuses on social networks which are a type of small-world network. This is because when considering the spread of information about energy efficiency and calculating the energy saved social networks best fit the criteria for the type of network to be studied. There are many applications of complex networks in calculating the spread of any given entity in the networks. Some examples are the spread of epidemics [37], rumour spreading [38]-[41] opinion formation and marketing [42] and so forth.

Rumour spreading is an epidemic-like propagation process studied in small world networks. In the rumour model there are three states a node takes, spreader (S), ignorant (I) and stifler (R). The I nodes have not heard the rumour, S nodes have heard the rumour and are willing to transmit and finally the R nodes have heard the rumour but have grown tired of it and are not willing to pass it along. In the literature, for the initial stage of evolution in the rumour model, only one node is 'infected' with the rumour and willing to share, after a while all the nodes become stifler this means the rumour has penetrated into the entire network. The rumour-spreading model has been used in marketing campaigns such as viral marketing [42], spread of scientific ideas [41], spread of rumours [38]-[40] and so forth. The rumour spreading fits into the field of research to be studied however, the quantity or quality of the rumour spread within the network is not calculated. It is assumed that the information passed from person A to person B is the full information and B understands the information. In a real life situation, this is not the case as there is always some information missing. However, just applying the rumour model will not portray real-life situations and may produce unrealistic results. Furthermore, the influence an individual has on his/her neighbours is not taken into consideration.

2.5.2 Social influence

As human beings we affect one another in different ways, some positively or some negatively. There is always some level of influence we have on each other. To place it in a better context, Latané summarises that "we are influenced by the actions of others, entertained by their performances and sometimes persuaded by their arguments. We are inhibited by the surveillance of others and made less guilty by their complicity. We are threatened by the power of others and angered by their attack. Fortunately we are comforted by the support of others and sustained by their love" [43]. This long definition of social impact given by Latané, gives a glimpse to the reason why people do things the way they do. He further explains that "social impact means the great variety of changes in physiological states and subjective feelings, motives and emotions, cognitions and beliefs, values and behaviour, that occur in an individual, human or animal, as a result of the real, implied or imagined presence or actions of others" [43].

In [43] the author presents three major factors that affect social impact, these are: strength, immediacy and the number of sources present. Strength means "the intensity or importance of a given source to the target of influence" [43]. Immediacy means "the closeness in space or time and absence of intervening barriers or filters" [43]. Number means "the amount of people present within that circle of influence" [44]. Putting these definitions in a social network context, the source of information is in the same social network as the receiver of that information and the number of people in that network affect how much influence the source has on the receiver. Therefore, "in a network, the number of people connected to a source directly affects how much information he can transfer throughout the entire network and the influence he/she has on those neighbours can determine the impact he/she has on all the people in his network" [44].

Studies show that people of the same age group have stronger bonds than when the age difference becomes greater [32], [42], [45]. There is also a tendency for an individual to divulge information to someone who is within the same age bracket as themselves. There are other forms of relationships people have not just age groups such as co-workers, kinship (family) or friendships and so forth. These relationships can also determine who an individual will turn to depending on the type of situation and information needed as explained in [32], [42], [45].

2.5.3 Types of relationship

Humans are social animals; we always want to belong to a certain group. People who have similar characteristics or prefaces tend to have a short distance of connectivity between them.

This short distances reduces the length at which information has to be transmitted between two individuals [46]. As [47] explains "any social entity that depends to a substantial degree on networks for its transmission will tend to be localised in social space and will obey certain fundamental dynamic as it interacts with other social entities in ecology of social forms". This means that peer groups are a key factor to social influences in networks.

There are different types of relationships that are observed in a social community, they are ethnicity, race, education, occupation, age, sex, religion or behavioural patterns [47]. In this research, there is a focus on how relationships affect the influence an individual has on his/her social network. To be more specific the age differences and how that can impact on one's expected savings. The basis of this assumption with regard to age stems from the research conducted by [32], [47], [48].

2.6 INFORMATION PROPAGATION

Spreading of information is a key ingredient in the propagation of the usefulness of energy efficiency across different platforms. The diffusion of information/rumour depends on the strength of the new idea, the type of channel it is communicated through, the time it takes for that idea to saturate the network and the members of the social networks [12], [15], [32]. The rumour spreading model in social network fits into the field of research to be studied however, the quantity or quality of the rumour spread within the network is not calculated in the literature.

The diffusion of information depends on the "new idea" and the members of the social network [12], [15], [32]. In the literature [39], [40], [41], it is assumed that the full information is transmitted among people. However, in the real world this is not the case, there is always some information that is lost during transmission. The application of the entropy of information has been successfully used in different fields of complex networks such as water supply [50], [51], ecology [30], [52], evaluation of alternative measures of new energy saving technologies [53] and it shows the possibility of defining and quantifying information transfer among people.

The influence an individual has on his/her network is determined by the connections of people in that network. This influence can determine the amount of information transferred from him/her to his/her neighbours. The influence through information transfer is therefore obtained using the entropy of information theory. The entropy of information theory is defined as "measures of information choice or uncertainty" [49]. The entropy of information transfer then functions through three different probabilities; functional, conditional and joint probabilities.

The functional probability $p(i)$ is proportional to the ratio of the node degree k_i of i to the total number of edges E in the network. This gives the probability that a node is in the network and connected to other nodes. The conditional probability $p_i(j)$ refers to the probability that node i is connected to node j through at most four intermediaries. The reason for this is because, from recent research in [29] it shows that people are connected by at most four intermediaries between them. The joint probability $p(i,j)$ is the probability that the information regarding an energy efficiency project has been transferred from the end user i who performs the project to his neighbour j.

The relationship between $p(i)$, $p_i(j)$ and $p(i,j)$ in [49] is given as:

$$p(i,j) = p(j,i) = p(i)p_i(j), \tag{2.5}$$

$$\sum_{i=1}^{N} p(i) = \sum_{1\leq i,j\leq N,\ j\neq i} p_i(j) = \sum_{1\leq i\leq N} \sum_{1\leq j\leq N,\ j\neq i} p(i,j) = 1. \tag{2.6}$$

The entropy $H(i)$ for a single source of information is defined in [49] as,

$$H(i) = -\sum_{1\leq j\leq N,\ j\neq i} p(i,j)\log_2 p_i(j), \tag{2.7}$$

More explanation of the different probabilities is given in the subsequent chapters.

2.7 RATIONALE OF THE STUDY

The motivation of this research is the need to quantify the energy savings due to non-technical factors. The non-technical factors are caused by the social interactions of people in societies or communities. The interaction of people results in information transfer, the information transferred regarding energy efficiency projects helps in saving energy because it encourages more people to adopt the energy efficiency projects. Quantifying the non-technical savings due to social impact is achieved by formulating mathematical expected energy saving models.

The models contain all the necessary variables and the constraints needed to achieve the indirect savings. The models are formulated using the research from social networks and information theory.

2.8 CONTRIBUTIONS OF THE STUDY

The contribution of this research is in establishing a framework to quantify the non-technical savings of energy efficiency projects through social influences. This type of research has not been conducted in the energy efficiency field and would benefit researchers by means of increasing the public's awareness of energy efficiency. This research will help determine the acceptability of any energy efficiency project by people within a network. The calculation of expected energy savings from social impact is achieved from the study and enables one to determine optimal placements of energy efficiency projects that will yield maximum savings.

This study can be leveraged to other applications because it is not just limited to energy efficiency studies. Fields that require the participation of humans will also benefit.

2.8.1 Deliverables

At the end of this research the following deliverables were obtained:

1. Expected energy efficiency saving models were formulated;
2. A complete report that documented all the research and formulations regarding this study was written;
3. Journal articles on this study were published.

2.9 LIMITATION OF THE RESEARCH

Due to the diverse applications of this research and time constraints, the research is only focused on the physical social networks of communities. However, the fundamental contribution of the research can be applied to different forms of social networks. Also, the networks used in the case studies are medium sized, small-world human networks because of the complexity and computational time needed for large networks.

2.10 CHAPTER SUMMARY

This chapter gives a background study of the research topic. The role of individuals in a network is highlighted and the corresponding literature on social networks have been explored. The reason information transmission is important to energy efficiency has been explained. Literature providing evidence that identification of the people with the highest influence will benefit energy efficiency projects. The research methodology has been explained with regards to the contribution to the research community is given. The limitations of the research have also been explained. The deliverables achieved from this research have also been listed. In the next chapter the first mathematical model of information propagation in a network is formulated.

CHAPTER 3

INFORMATION TRANSMISSION MODEL

This chapter describes the information transmission model, case study and solution methodology. Excerpts from this chapter have been published on [58].

3.1 INTRODUCTION

In all energy efficiency projects, humans are always invovled and they play a major role towards the realisation of any project. It is therefore vital that humans are the ones to target when campaigning for change of any kind concerning energy efficiency. The authors of [54] recommend that interactions among residents in a network lead to an increase in energy savings which may be more cost effective than physical renovations of their buildings. There are several studies that show that social networks contribute to the reduction of energy consumption [17], [55], [56], [57].

Energy savings consist of two parts: direct and indirect savings. Direct savings refer to savings that are measurable or observable and can be determined by various measurement and verification techniques [61]. Indirect savings refer to the mathematical expectation of the savings additional to direct savings, which are achieved by social interactions of people in a community within the boundaries of probability theory. This social interaction is classified under the performance, operational, equipment and technology (POET) classification [62].

These indirect savings can help identify people with the most influence in their network through the transfer of information about their energy efficiency projects. It can also help estimate the expected power saved from an energy efficiency project, the economic importance of a project, predict the optimal location for an energy efficiency project in the residential sector that will yield maximum expected savings and calculate the acceptability of a project within a residential community.

The mathematical model proposed in this chapter (known from here on as the expected power saving model) is loosely related to the pinning control of complex networks. Pinning control is when a network cannot synchronise on its own and some controllers are applied to selected nodes in the network to force the network to synchronise [63], [64], [65].

Physically this means the model identifies people who, after they implement energy efficiency projects in their homes, will encourage other people in their community or network to implement those projects. This helps to save money and encourages free riding. Free riders are defined as those people in an energy efficiency programme who would have installed the same energy efficiency measures even if there had been no programme [66], [67].

The outline of the chapter is as follows; section 3.2 gives the expected power mathematical model. Sections 3.3 gives the limitations of the model while the solution methodology is found in section 3.4. The case study, assumption and chapter summary are given in section 3.5, 3.6 and 3.7 respectively.

3.2 MATHEMATICAL MODEL FOR EXPECTED POWER SAVINGS

Energy efficiency projects in the residential sector are performed by humans, therefore quantifying the social impact through social communication will give the total expected power saving in every energy efficiency project. The social effect of an individual is dependent on their peer-to-peer interactions; this can pinpoint the most influential people in a community and thus reveal to energy planners the people to target in spreading information about the energy efficiency projects. Identifying people who will spread the information about the energy efficiency project to the network fastest is significant because this will help change people's behaviour towards energy conservation and thus increase energy savings at little or no cost.

The mathematical model of the expected power savings calculates the combined direct and indirect savings of the energy efficiency project. In the model, the physical distance between two people is not ignored, two people are said to be connected if there is a mutual acknowledgement of acquaintance between them. The nodes represent the households and the edges represent the connection between two households. The mathematical model of the expected power savings considers two scenarios; when there is a focus on one or multiple end users to transfer information to the rest of the network. This model will try to dispute the instinctive belief that people with the highest node degree have the ability to spread the most information in the network.

Assume that the i-th end user is the only one in the network who performs an energy efficiency project, the expected power saving is calculated as:

$$EPS = S_i + \sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}, \tag{3.1}$$

where S_i is the direct savings from the energy efficiency project that the i-th end user implements. The calculation of direct savings is not a major contribution of this research hence in the case study, the direct savings are given. $S_{j,i}^{indirect}$ is the indirect saving of the j-th end user that is affected by the social impact of the i-th source node. The source node is a representation of an end user that performs an energy efficiency project and is able to transfer information about the project to other nodes.

Now consider the case where the network has more than one end user implementing energy efficiency projects. The expected power saving for multiple sources is calculated as:

$$EPS = \sum_{i \in I} S_i + \sum_{i \in I} \sum_{1 \leq j \leq N, j \notin I} S_{j,i}^{indirect}, \tag{3.2}$$

where I is the set of source nodes in the network. Note that the summation $\sum_{1 \leq j \leq N, j \notin I} S_{j,i}^{indirect}$ excludes the case that one source is influenced by another source. This is because a source node already has its direct saving therefore, any information that is transferred from another source will have no effect and hence no indirect savings

The entropy of information theory is applied to information sharing of energy efficiency projects within a network. The higher the entropy the more information about the energy efficiency project is expected to be transferred within the network. With this knowledge, the expected indirect savings for a single source case is defined as:

$$\sum_{1\leq j\leq N, j\notin I} S_{j,i}^{indirect} := H(i)S_i, \tag{3.3}$$

where $H(i)$ is defined as the entropy in equation (3.4).

$$H(i) = -\sum_{1\leq j\leq N,\ j\neq i} p(i,j)\log_2 p_i(j). \tag{3.4}$$

In the case where more than one end user performs energy efficiency projects, the indirect saving for the multiple sources follows easily from (3.3)

$$\sum_{i\in I}\sum_{1\leq j\leq N, j\notin I} S_{j,i}^{indirect} := \sum_{i\in I} H(i)S_i. \tag{3.5}$$

Formulae (3.3) and (3.5) are applied in (3.1) and (3.2) for the single and multiple sources respectively.

In the multiple sources case, $H(i)$ in (3.5) is calculated similarly as the single source case. That is,

$$H(i) = -\sum_{1\leq j\leq N,\ \ j\notin I} p(i,j)\log_2 p_i(j). \tag{3.6}$$

From (3.4), (3.6) can also be written as

$$H(i) = -\sum_{1\leq j\leq N,\ \ j\notin I} p(i)p_i(j)\log_2 p_i(j). \tag{3.7}$$

It turns out that the single source case in equation (3.1) is a special case of equation (3.2) for multiple sources. Therefore, from henceforth in the chapter, the single and multiple source cases will not be distinguished for the following calculations of $p(i)$ and $p_i(j)$.

The functional probability $p(l)$ for any node l gives the likelihood that the node has a node degree k_l out of the network degree distribution in N total number of nodes in the network. The functional probability l is defined as

$$p(l) = \frac{k_l}{DN}, \text{ for } l = 1,\ 2,\ \ldots,\ N \tag{3.8}$$

where D is give in equation 2.4. Now consider the calculation of $p_i(j)$ where $i \in I$ and $j \notin I$, note that $p_i(j)$ is the quantitative value for the connectivity of nodes within the network.

As people grow further apart from one another, the influence of their information transferred is reduced, as shown in Figure 3.1 where the boxes represent the information transferred from the source. As the boxes move further away from the source, the colour representing the information transfer becomes lighter as this means the impact on the receiving node is reduced. The greater the path length between the receiver of the information and the source node, the smaller quantity of the information transferred. In the calculation of $p_i(j)$ for a medium sized network, the only cases considered are when j is connected to the source node i with degree of connection of at most four. This is a good approximation of the latest research on social networks that an "individual is separated from anyone in the world by an average characteristic path length $L = 4.74$ people" [29].

In a network, the conditional probability $p_i(j)$ that an information source node i can transfer information to another node j is dependent on how the two nodes are connected to each other and to other nodes in the network. Note that information transferred along shorter paths are always dominant when compared to the information transferred along longer paths. Therefore, it is reasonable to consider only information transferred along the shortest paths when considering the definition of $p_i(j)$. Meaning, information transferred along further paths will be disregarded, and if the shortest path between i and j is not singular, then information transferred along all the shortest path will be added together to give the full conditional probability.

Explaining this in practical terms, it means that the more a person hears about the benefits of a product (for example the use of CFLs) from more than one friend, the more probable it becomes that he/she will be convinced to obtain that product. Therefore, the conditional probability does not only focus on the source node who transfers the information but also on the receiver's different access to the information. The following cases are explained in the description of $p_i(j)$.

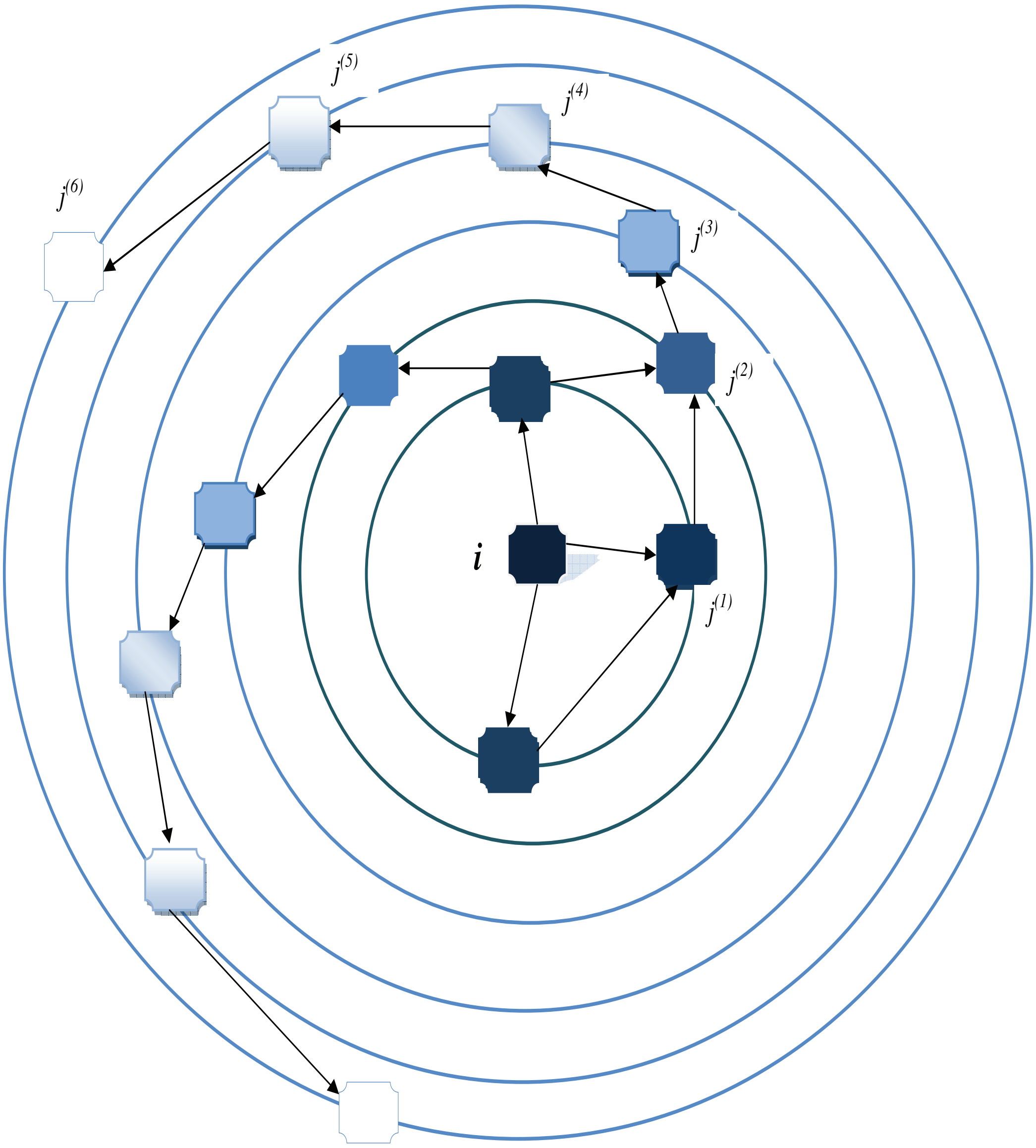

Figure 3.1: Information transfer

Case I: Assume that j is directly connected with node i, $d_{i,j} = 1$. This means that their degree of connectivity is equal to 1. Then $p_i(j)$ is defined as

$$p_i(j) := \frac{1}{k_i k_j}. \tag{3.9}$$

Case II: For the degree of connectivity equal to 2 $d_{ij} = 2$, that is j has an intermediary between him/her and node i, that is $j \notin M_i$. Now we define the $p_i(j)$ as

$$p_i(j) := \frac{1}{k_i k_j} \sum_{q \in M_i \cap M_j} \frac{1}{k_q}. \tag{3.10}$$

In (3.10) the second degree of information transfer is dependent on the information already transferred from the source node to the first degree node $q \in M_i \cap M_j$. The second degree node j treats the first degree node q as its source of information which is dependent on the amount of information that is passed to q from the source node i. This implies that q transfers the information he/she obtained from i to j. This shows the continuity of information transfer among nodes in the network. The addition of the probability of total number of nodes q between i and j indicates that when one hears about a lifestyle change from several friends the higher the chances of that person adopting that lifestyle change.

This can also been viewed from the receiver's side, for example, the more people tell him/her about their savings through the retrofitting of their home, the more likely this person will change in order to obtain those savings. If j decides to implement this lifestyle in order to save, it does not mean that j will buy the retrofits that her friends tell her, as this may be unrealistic or not cost effective.

This means that the more information j obtains about savings from his/her friend the more probable he/she will be willing to adjust to that lifestyle. Furthermore, it confirms that the social impact i has on j through information transfer is less than the impact i has on q and this depicts real life scenarios where the influence of one's friends are bigger than the impact of a friend of a friend [17] . Case III and IV follow the same thought pattern as case II.

Case III: If $d_{i,j} = 3$, then $p_i(j)$ is defined as

$$p_i(j) := \frac{1}{k_i k_j} \sum_{(q,r)} \frac{1}{k_q k_r}, \quad q \in M_i,\, r \in M_j,\, q \in M_r. \tag{3.11}$$

Case IV: Assume that the degree of connection of node j with node i is four that is $d_{i,j} = 4$, then $p_i(j)$ is defined as

$$p_i(j) := \frac{1}{k_i k_j} \sum_{(q,r,s)} \frac{1}{k_q k_r k_s}, \quad q \in M_i,\, r \in M_q \cap M_s,\, s \in M_j. \tag{3.12}$$

Case V: Assume that the degree of connection of node j with node i is greater than four, the conditional probability is assumed to be negligible and therefore

$$p_i(j) := 0. \tag{3.13}$$

Practically, equations (3.9) - (3.13) implies that when a person performs an energy efficiency project, the information he/she transfers to the network is dependent on the number of neighbours he/she has and on the number of neighbours his/her neighbours have too. The conditional probabilities measure the quantity of information moved from the source i to his/her neighbour j. As information is never fully transferred, the quantity of information transferred between i and j is diminished when there are many people between them. The conditional probability ensures that all the people who could possibly receive information from the end user do receive it. And it helps in the calculation of the information entropy that determines the influence a person has on the rest of the network. The expected energy savings model therefore incorporates the quantity of information transmitted within the network that evaluates the indirect savings of an individual and in turn determine the expected energy savings.

3.3 LIMITATIONS OF THE PROPOSED MODEL

The following are the limitation of this mathematical model;

1. The model assumes that there is an instant connection between these people in the network. How these relationships are formed is outside the scope of the study.

2. The model assumes an instantaneous indirect saving without the consideration of a time interval. This is possible because the focus is on the power saved and not the energy or cost over time.

3.4 SOLUTION METHODOLOGY

We assume that it is cheaper for neighbours of j to obtain information from i because it is free rather than find information about energy efficiency measures through other means that may cost money and time. The model is solved with the use of the Java programming language on a 32-bit processor. The reason for using Java is because it can process a large network. The solution methodology is as follows;

For a single source of information in the network;

1. Assume that general external information is available to the whole network and this information is complete.

2. Obtain the direct savings S_i, of each node. Calculate the functional $p(i)$, conditional $p_i(j)$ and joint $p(i,j)$ probabilities and entropy $H(i)$. Calculate the indirect savings obtained from the entropy and direct savings. Calculate the expected power cost savings for all i as the sum of the direct and indirect savings.

3. Find the node i with the maximum expected power cost savings $\max(F_i)$ output solution.

For multiple sources of information in the network;

1. Assume that general external information is available to the whole network and this information is complete.

2. Find all the possible combinations for the number of sources required using a brute force search algorithm. The brute force search algorithm exhaustively searches through all the possible combinations until the optimal solution is found. For example, if we assume a multiple source network of 3 households in a 56 household network, then there will be $\binom{3}{56} = 27720$ different combinations.

3. Obtain the direct savings S_i, of each of the sub-networks. Calculate the functional $p(i)$, conditional $p_i(j)$ and joint $p(i,j)$ probabilities and entropy $H(i)$ accordingly. Calculate the indirect savings obtained from the entropy and direct savings. Calculate the expected power cost savings for all i as the sum of the direct and indirect savings.

4. Find the sub-network i with the maximum expected power cost savings $\max(F_i)$ output solution.

3.5 CASE STUDY I

The South African government has partnered with the local utility company Eskom to provide some limited, free low-pressure solar water heaters to residential houses within South Africa. When the household to receive the free solar water heaters are chosen, a member of the household has to be present while the installation is carried out. After the installation, a brief description of the solar water heater and lessons on how to use the heaters are given. The benefits of the solar water heater are highlighted to the member of the household [68]. This is done with the expectation that the person talks about the efficiency of the heater to his/her friends. The transfer of such information leads to more people purchasing the solar water heaters for their houses and as such reduce electricity costs and save energy.

People are connected to each other through various means and as such information is transferred from one household to another. The reasons any two households are connected to each other are based on different factors such as environmental proximity, members of the same organisation, have children in the same school or work at the same office. In this research, a survey was carried out on a group consisting of fifty-six households from the same church organisation to obtain data for the social network graph. Each household is given a questionnaire to write out the names of other households they consider as friends within the group. After the necessary information has been collected, an adjacency matrix is constructed. The criterion for the graph is that two households must acknowledge that they are friends with each other before an edge can be drawn between them. The network graph is given in Figure 3.2.

There are two examples presented in this case study, the first example is when there is only one person to be given a new solar water heater and when there are more people to be given solar water heaters. The aim of the installation of the solar heaters is to promote renewable technology and to encourage people to buy the solar water heaters. The use of the solar water heaters reduces the electricity bills and electricity consumption of the entire community. In order to maximise the indirect savings due to social impact, the criteria for houses to receive

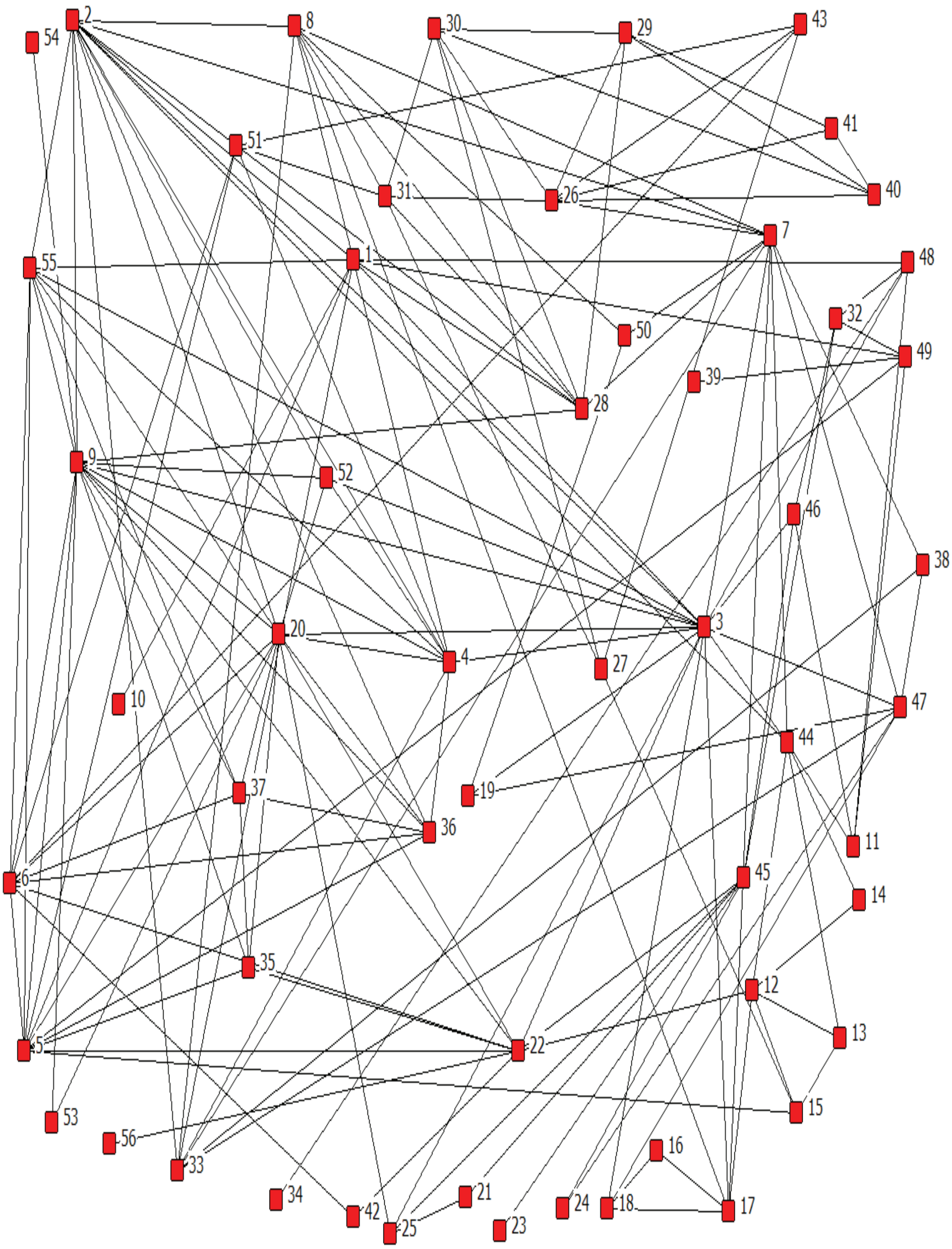

Figure 3.2: Network graph of the 56-household community

free solar water heaters will be based on how much power is saved and how much impact these households have on their community. As the direct savings is fixed, the indirect savings will determine the person who has the most expected power savings.

3.6 ASSUMPTIONS

In order to calculate the expected power savings, the following assumptions are made:

1. Each household is assumed to use their electric heaters at about the same time throughout the community, for example at both the morning and evening peak hours, which is between 08:00 - 10:00 and 18:00 - 20:00 hours respectively. These peak hours are adopted from the HomeFlex Eskom TOU tariff [69].

2. Installation of each solar water heater will save at least 2kW of power when compared with turning on an electric water heater [69]. This means that the direct savings for this case study is $S_i = 2$.

3. The distance and type of relationship between each household is not considered in this problem and hence the network problem is considered to be unweighted and undirected.

4. There are no new members introduced into the network and none of the members leave the network.

3.7 CHAPTER SUMMARY

In this chapter, a mathematical model is formulated to quantify the social impact an individual has on his/her community when he/she adopts an energy efficiency project and transmits that information to his/her neighbours. This model is called the expected power savings model; it combines direct and indirect expected power savings of the energy efficiency project for each individual within the network. The indirect savings are quantified through the social interactions between people in the network. The example used in this chapter illustrates the effectiveness of the model by identifying the households who should have free solar water heaters installed in their residential houses based on their influence through interactions in their community. The results of the case study in this chapter are discussed in Chapter 6.

CHAPTER 4

EXPECTED ENERGY COST SAVINGS MODEL WITH RESPECT TO TIME

This chapter describes the expected energy cost saving model, case study used and solution methodology developed. Excerpts of this chapter have been seen published in [60].

4.1 INTRODUCTION

Rewarding people for the effort they have made to reduce electricity consumption not only encourages them to continue applying their energy efficiency measures, but also enables them to tell their friends about their rewards. Human interaction increases the success of energy efficiency measures in the residential sector at reduced cost to the utility company or government where the spread of information about energy efficiency is concerned. Therefore, propagation of information about energy efficiency measures among members of a social network can lead to a greater reduction in electricity usage within that network. This is because people are more likely to change to more efficient lifestyles because their friends or family have changed [17], [54], [55], [56] and [57].

Rewarding people for the information they have transmitted to their neighbours has been discussed in [58] and [59] and the previous chapter, using the expected power saving model. The expected power saving model consists of two components; direct and indirect savings. The direct savings are referred to as the "energy cost savings directly measurable or observable and can often be determined by various measurement and verification techniques" [62]. The indirect savings refer to as the "savings additional to direct savings which are achieved by the social interaction of people in a network" [58]. In [58], the results show that the household with maximum expected power saving is identified using only the indirect saving because the direct saving is assumed to be the same for every household.

This chapter continues the research on rewarding people for their effort in not just reducing electricity usage but also their influence that encourages other members of the community to reduce their electricity consumption. This is done by considering the time interval where the potency of the information reduces as time increases. In chapter 3, only the immediate power saved on an appliance is considered however, this chapter takes the mathematical model further to include energy consumptions of households using the time-of-use tariff. This gives a clearer prediction when considering energy efficiency of the overall electricity usage of a household.

The advantage is that the results obtained from the mathematical model, can be used to encourage people to save more energy when they are presented with their energy savings and that of their neighbours or the savings of the entire community at large. Although a similar study has been done by [17], [56], [55] there has not been literature that uses information entropy to determine the influence of people with respect to energy efficiency savings.

Similar to the model in [58], the proposed model makes use of the knowledge of complex networks [11], [31]-[34], [70], [35], [34] and information entropy [49]. One advantage of this model is that it includes the reduction of the quality of information as time increases; this gives the duration the neighbours of a person with the energy efficiency information can free ride on that information. Free riders in energy efficiency are people who would have performed energy efficiency projects if they had the knowledge about the savings they could effect, even if no energy efficiency programme was in place [66], [67], [71].

An individual who shares his success stories about energy efficiency measures to his neighbours, provides them with free information that they would have otherwise have had to spend some effort (either money or time) in obtaining the information [67]. The free rider aspect of this model refers to the information received by neighbours when they adopt the actions of the person who undertakes an energy efficiency project. This human interaction is not always highlighted when the calculations of energy cost savings are performed; however it has a high impact on the success of energy efficiency projects.

The outline of the chapter is as follows: section 4.2 gives a brief background on previous work done. Section 4.3 gives a brief study on demand side management. Section 4.4 gives the expected energy saving cost model and section 4.5 gives the solution methodology. In section 4.6, a case study for the model is provided. In section 4.7 the limitations of the model are listed and section 4.8 gives the chapter summary.

4.2 DEMAND SIDE MANAGEMENT

In this chapter, the expected energy saving model is formulated that determines the energy saved through direct and indirect savings over time, using the Homeflex time-of-use (TOU) tariff. The model depicts the real-life situation where people in a community apply different types of energy efficiency measures and consequently save varying amount of energy. The energy saved is dependent on an individual's personal effort as well as the connections he/she has in the network. Therefore it is important to identify the people who will transmit the most information within their network. Since people are not compensated for the information they provide to others when they propagate the usefulness of energy efficiency measures, this model continues the research from chapter 3 to bridge that gap.

Demand side management (DSM) is a method of curtailing the demand for electricity when the supply is low. Demand side management has to consider the technical, organisational and behavioural solutions that will help decrease energy consumption and demand. The benefits of DSM include the reduction of customer bills, air pollution, heavy investment in power plants and grid congestion as discussed by [18], [19] and [20]. The tools used in DSM measures are real time pricing, TOU tariff, smart metering and web-based communication systems [18]. [21] points out that the success of energy efficiency projects begin with information and insight into the efficiency process involved. This means the more a customer is informed or aware of energy efficiency measures, the more likely the success of that project. The TOU tariff, which is a tool that offers customers different electricity rates at different times of the day, is used in the proposed model to calculate the direct savings of customers.

Because of the increasing rate of electricity demand over the years, Eskom (the South African utility company) has introduced a new type of TOU tariff, the Homeflex tariff. This tariff is targeted at residential consumers of electricity. In South Africa, the residential sector accounts for 17% of the total electricity use (kWh) and 30% of the peak demand (kW) [72]. The TOU tariff is designed to be an incentive for customers to reduce their electricity usage during peak periods. The tariff is to be implemented voluntarily.

The energy rates differ according to high-demand (June, July and August) and low-demand seasons, with a higher active charge during the high-demand season. The tariff for the low-demand season (between September and May) consists of the active energy charge (peak period = 0.75 R/kWh, off-peak period = 0.50 R/kWh), network access charge = 4.20 R/day, service charge = 3.37 R/day, and environmental levy charge = 0.02 R/kWh, where R represents the South African rand equivalent to 0.1USD (as at May 2015) [72]. The daily peak periods are 08:00 - 10:00 and 18:00 - 20:00 and the off-peak periods are 0:00 - 07:00, 11:00, 17:00, and 21:00 - 23:00. Figure 4.2 gives an illustration of an average daily load profile for one of the households in the study. The load profile gives a general profile illustration of households' electricity consumption per day of an average South African home.

For a day the Homeflex TOU cost is given as

$$EU = 5EC_p + 19EC_o + SC + NC + 24EL, \tag{4.1}$$

where EU is the energy cost per day, EC_p is the active energy charge at peak period, EC_o is the active energy charge at off-peak period, SC is the service charge, NC is the network charge and EL is the environmental level.

Since this new incentive tariff in South Africa is applied on a voluntary basis, it is wise to identify people in a community (network) who will save more energy by using this TOU tariff and spread the news about the advantages of the tariff. This chapter identifies the people who will be more likely to accept the new tariff and encourage their neighbours to

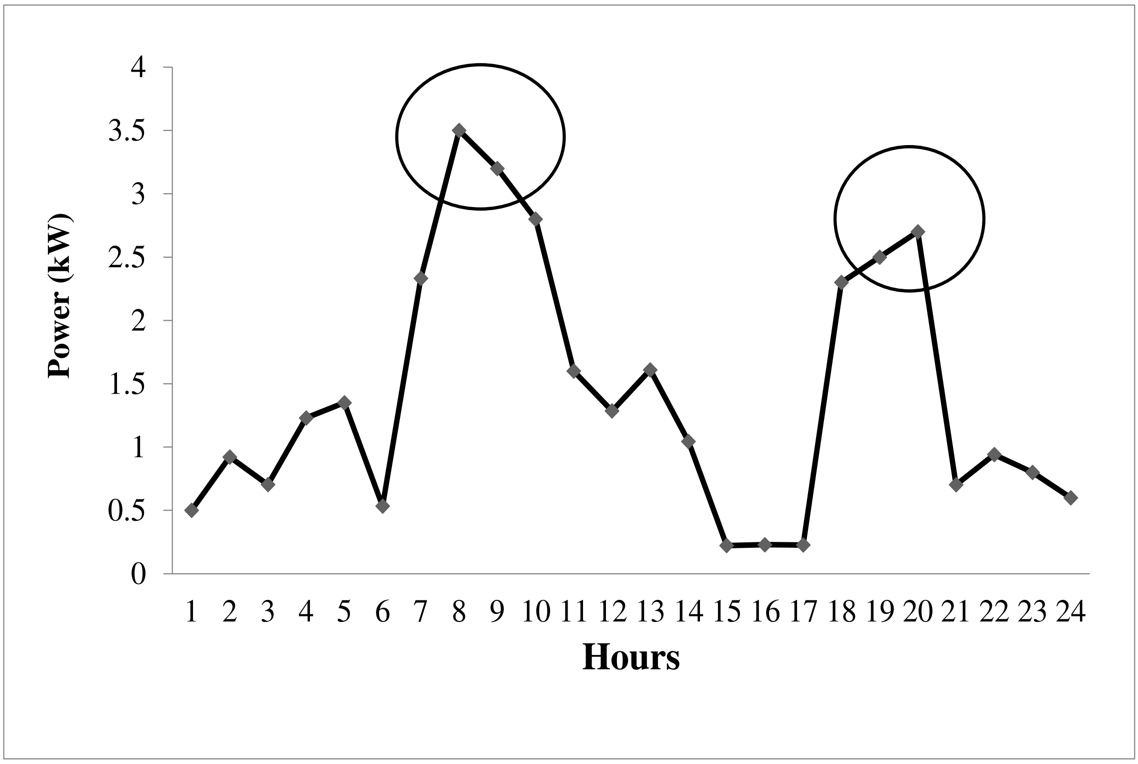

Figure 4.1: An example of an average 24-hour load profile of a typical household in the network

adopt the tariff, which will enable Eskom to identify the people to target in their campaign to promote the Homeflex TOU. This is carried out by showing that interaction of people within their network makes people more aware of energy efficiency and may increase savings. The Homeflex TOU tariff is used to calculate the direct savings of the expected energy cost savings model described in section 4.3.

4.3 MATHEMATICAL MODEL OF EXPECTED ENERGY COST SAVINGS MODEL

In this section, the expected energy cost savings mathematical model is formulated. The network is explained, the probabilities and their differences with respect to chapter 3 are explained and finally the expected energy cost savings is formulated.

4.3.1 The network

A community with N households can be represented by N nodes on a network. The interactions between the nodes are represented by edges on the network. The physical distance between each household is not considered in this research, however two households are said to be connected when there is a mutual acknowledgement of friendship between them. We consider an undirected network where the path between two nodes is represented with $d_{i,j} = d_{j,i}$ and there is no self connection, that is $d_{i,i} = 0$. Within the network, the set of nodes directly connected to i is represented with M_i. The network topology is represented by an adjacency matrix B, N^2 matrix with entries; $B_{i,j} = \left\{ \begin{array}{ll} 1 & \text{, if } i \text{ and } j \text{ are connected} \\ 0 & \text{, otherwise} \end{array} \right\}$.

For any network, the connectivity distribution is the network degree D defined from [11] as $D = \frac{1}{N}\sum_{i=1}^{N} k_i$, where $k_i = \sum_{j=1}^{N} b_{i,j}$ is the *node degree* of i. The connectivity distribution is used to calculate the functional probability of any node i.

4.3.2 The probabilities

The functional probability $p(i,t)$ is the ratio of the node degree k_i of i to the connectivity distribution of the network, it is modified from [58] to include the discrete time interval $t = 1, 2, \ldots, T$. So at every time step $p(i,t)$ is calculated for every node in the network. The functional probability is given as

$$p(i,t) = \frac{k_i(t)}{D(t)N}, \text{ for } i = 1,\ 2,\ \ldots,\ N. \tag{4.2}$$

The functional probability in the scope of this study represents the strength of i relative to the entire network, where the functional probabilities for all i's $\sum_{i=1}^{N} p(i,t) = 1$. The functional probability represents the value in terms of information transmission a person has in the network when compared to all people in that network.

The conditional probability $p_i(j,t)$ as defined in [58] and [59] is the probability that node i is connected to j with at most three nodes between them. In practical terms this refers to the probabilistic quantity of information that i can transfer to j when there are at most three nodes between them. It gives a realistic view of the information exchange within a community and highlights the influence i has on his neighbour j with respect to information diffusion of energy efficiency measures.

Conditional probability of nodes with five different path lengths $d_{i,j}$ are presented below. The conditional probability in [58] is modified to incorporate time intervals. The incorporation gives a more accurate description of the influence a person has on his neighbours in comparison to the conditional probability of [58], where influence is measured on an instance of connection identification of households.

When two nodes are directly connected to each other, their path length $d_{i,j} = 1$ and the corresponding conditional probability is given as,

$$p_i(j,t) := \frac{1}{k_i(t)k_j(t)}. \tag{4.3}$$

This calculates the probability that at time t, the influence i has on j with respect to information transmission is a function of the node degrees of both nodes. The reason the inverse of the node degree is used is because the probability that i is connected to j is the inverse of i's node degree that is $1/k_i$. The same goes for the probability that j is connected to i, therefore the conditional probability that i is connected to j is given above when their path length $d_{i,j} = 1$.

The conditional probabilities for the different measures of path length $d_{i,j}$ are given below.

For $d_{i,j} = 2$

$$p_i(j,t) := \frac{1}{k_i(t)k_j(t)} \sum_{q \in M_i(t) \cap M_j(t)} \frac{1}{k_q(t)}. \tag{4.4}$$

For $d_{i,j} = 3$

$$\begin{gathered} p_i(j,t) := \tfrac{1}{k_i(t)k_j(t)} \textstyle\sum_{(q,r)} \tfrac{1}{k_q(t)k_r(t)}, \\ q \in M_i(t),\, r \in M_j(t),\, q \in M_r(t). \end{gathered} \tag{4.5}$$

This means that r and q are directly connected to i and also directly connected to j. This is a case of j obtaining information from two different sources (r and q), where r and q obtain their information from one source i.

For $d_{i,j} = 4$

$$p_i(j,t) := \frac{1}{k_i(t)k_j(t)} \sum_{(q,r,s)} \frac{1}{k_q(t)k_r(t)k_s(t)}, \quad q \in M_i(t),\ r \in M_q(t) \cap M_s(t),\ s \in M_j(t). \tag{4.6}$$

As the number of people between i and j increases the information transferred to j from i becomes insignificant and may even be lost during transmission, therefore for $d_{i,j} = 5$,

$$p_i(j,t) := 0. \tag{4.7}$$

The conditional probabilities calculates the quantity of information transmitted from the source of information i, typically the end user of an energy efficiency project to his/her neighbours j. As shown in [58] "information is never fully transferred, the more people between i and j the less the quantity of information transferred," the conditional probabilities give the possible degree to which a neighbour j can receive information from the end user. Similar to chapter 3 the conditional probability is a key factor in the calculation of the information entropy.

The joint probability $p(i,j,t)$ is the probability that the information regarding an energy efficiency project has been transferred from the end user i who performs the project to his neighbour j. Inspired by the joint probability of [49], $p(i,j,t)$ is given as

$$p(i,j,t) = p(i,t)p_i(j,t) \tag{4.8}$$

The joint probability combines the influence a node has on his/her neighbours and the entire network with regards to information propagation. The functional $p(i,t)$, conditional $p_i(j,t)$ and joint $p(i,j,t)$ probabilities are used to calculate the information entropy of node i in the network. The entropy of information theory is defined as the level of information transfer or influence one individual has to the rest of the network. Similar to [35] and [58], the formula for entropy of information is defined in equation 3.4.

4.3.3 The expected energy cost savings model

The mathematical model calculates the combined direct and indirect savings of energy efficiency measures. Assume the i-th end user is the only person that implements any energy efficiency measure in his/her community, the expected energy cost savings i over a period is calculated as:

$$F_i = \sum_{t=1}^{T} \left(S_i(t) + \sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t) \right), \tag{4.9}$$

where $S_i(t)$ is the direct savings of the i-th end user at time t that implements the energy efficiency measure. $S_{j,i}^{indirect}(t)$ is the indirect saving in addition to $S_i(t)$ because of the energy efficiency information he transmitted to his community. The indirect saving $S_{j,i}^{indirect}$ from [58] is given as,

$$\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect} := H(i) S_i. \tag{4.10}$$

In order to ensure that people will likely follow an individual's energy efficiency measure, it is important to fashion the indirect savings as a function of the direct savings. This means that the total expected energy cost savings of an individual is dependent on his/her personal effort and his/her connections in the network. The indirect savings $S_{j,i}^{indirect}$ give the savings of the j-th end user that is affected by the information transmission of the i, where i can be seen as the source of information to the rest of the network. This gives a representation of an end user that performs an energy efficiency measure and is able to transmit that information to others in his/her network.

However, at time $t = t+1$, $t \neq 0$ the indirect savings of an individual reduces because the value of the information depreciates, this means people are more likely to forget that they have been told after some time or choose not to implement the energy efficiency measures they heard. As time increases, i may choose to interact with the same neighbours or change the people he/she interacts with about his/her energy efficiency measures however the potency of his/her information would have decreased. The decrease of information with respect to time is incorporated into the mathematical model through the indirect savings. Therefore, at time $t = t+1$ the indirect savings is $\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t+1)$ is given as,

$$\begin{aligned} &\textstyle\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t+1) = \delta H(i,t+1) S_i(t+1) - \textstyle\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t), \\ &\text{for} \quad t = 1, \ldots T, \end{aligned} \tag{4.11}$$

where δ is the forgetting rate. The forgetting rate enables the depreciation of the effect of information from time t to $t+1$. The forgetting rate is used in advertisements to calculate the information diffusion of adverts over a given time [73], [74] and [75]. In this research, the information on energy efficiency measures can be said to be diffused within the community through social interactions. The forgetting rate borders between 0 and 1, that is $0 < \delta < 1$. In literature, the forgetting rate is always close to 1 and is expected to be stable and sometimes constant over time [73], [74] and [75]. For simplicity, the forgetting rate is assumed to be constant for all nodes and is chosen to be 0.9 according to the research conducted in [75]. Equation (4.11) ensures that the influence of i on t is not included with the influence he has on the network at $t+1$.

Incorporating both the quantity (through entropy $H(i,t)$) and quality (through the forgetting rate $delta$) of information transferred within the network at every time interval is used to evaluate the indirect savings of an individual and in turn determine the expected energy cost savings.

4.4 SOLUTION METHODOLOGY

The assumption is that it is cheaper for the neighbours of i to obtain information from i because it is free rather than find information about energy efficiency measures through other means that may cost money and time. The model is solved with the use of the Java programming language on a 32-bit processor. The reason for using Java is because it can process a large network. The solution methodology is as follows;

Step 1: At time $t = 0$ assume that general external information is available to the whole network and this information is complete without any loss of information. The information that is referred to in this chapter are the different measures one can take to reduce electricity usage in their homes while still enjoying similar comfort as if they did not perform any energy efficiency measures.

Step 2: At $t = 1$ obtain the direct savings S_i, of each node. Calculate the functional $p(i,t)$, conditional $p_i(j,t)$ and joint $p(i, j,t)$ probabilities and entropy $H(i,t)$ using equations (4.2)-

(4.10). Calculate the indirect savings obtained from the entropy and direct savings using equation (4.11). Calculate the expected energy cost savings for all i as sum of the direct and indirect savings.

Step 3: At $t = t+1$, $t \neq 0$ calculate the direct savings and indirect savings

$\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t+1)$ that is relative to

$\sum_{1 \leq j \leq N, j \neq i} S_{j,i}^{indirect}(t)$, then calculate the expected energy cost savings of i.

Step 4: Continue *Step* 3 until $t = T$, then obtain the sum of total expected energy cost savings of i for total period.

Step 5: Find the node i with the maximum expected energy cost savings $\max(F_i)$.

The case study and results for the mathematical model and solution methodology of sections 4.4 and 4.5 respectively are given in chapter 6.

4.5 CASE STUDY II

Consider a network of thirty-six people where a rebate is to be given to a limited number of people based on their implementation of energy efficiency measures to reduce the cost of electricity consumption every month. The rebates are given to people who have saved 10% and above of their electricity consumption in response to the information they received from Eskom (the utility company in South Africa) [76].

The rebate is determined by the total expected energy cost savings of the household. The rebate pricing is not covered in the scope of this work (as it has already been predetermined by the utility company); however, this study will enable the utility company to identify the people who are more likely to encourage their neighbours to reduce their electricity usage within the community.

Energy consumption data is gathered through a household inventory and actual electricity use during a period of three months in each household.The energy consumption for all 36 households over the three months are given in Table 4.1.

Table 4.1: Monthly energy consumption (kWh) of 36 households

Household	Month 1	Month 2	Month 3
1	16467.7	16094.8	15748.1
2	34764.3	30790	26070.5
3	27740.7	25091.2	24077
4	24331.8	22460.1	23840.2
5	20862.2	15674.9	11818.2
6	24812.2	22657.4	21110.2
7	14152.4	13157.3	13101.2
8	19720	20469.4	22833.1
9	12990.3	13162.8	12137.4
10	30781.2	37989.2	31817.7
11	24133.3	21247.4	20063.6
12	13761.4	12908.3	13712.5
13	11170.3	11105.9	11380.7
14	16108.1	15590.5	14417.2
15	8347.1	8841.6	8653.3
16	25495	27368.5	27490.2
17	29843.4	24615.2	23426.6
18	8958.9	8398.7	8815.6
19	11037.2	11875.1	10712.5
20	21606.5	20275.3	22787.3
21	9821.4	9955.5	9775.9
22	15233.6	15094.4	14603.9
23	18946.4	18741.5	20176.7
24	12204.6	11332.1	14482
25	8784.2	9299.7	9645
26	14981	15139.4	12944.4

27	7388.7	8356.6	8378.6
28	30971	28924	27543
29	15578.8	16536.2	17310.3
30	8241.3	8316.3	9036.6
31	11732	12378.4	12561.6
32	10067.9	10422.9	9777.9
33	16971.7	16554.2	16814.9
34	24359.3	23677	22408.4
35	24857.8	23743.3	22533.3
36	23915.3	20012	23211.4

The first month is a blind baseline measurement, to determine electricity usage before any energy efficiency measure has been taken. Households are educated on simple energy efficiency measures. The simple energy efficiency measures that they implement include changing incandescent bulbs to CFL bulbs, switching off geysers and switching off unused lights. The aims of these interventions are to promote energy efficiency awareness, to reduce electricity costs and thus reduce electricity usage in the community.

The measures are voluntary and there is no penalty for people who do not implement the efficiency measures nor have effected any savings. In the remaining two months the electricity usage is measured to determine the direct savings. In this case study, the direct savings $S_i(t)$ are calculated as a percentage of electricity cost after implementation relative to the electricity cost before implementation. For this study the direct savings for each household is calculated as,

$$S_i(t) = \frac{\sum_{c=1}^{30} EU_b - \sum_{c=1}^{30} EU_a}{\sum_{c=1}^{30} EU_b} \times 100 \tag{4.12}$$

where c represents the time in days, EU_a and EU_b are the energy cost after and before implementation of energy efficiency measures respectively. The direct savings are calculated in this way because different types of households are used in this study and each saves a different amount of electricity. Comparing the exact amount of electricity saved will not show the true effort of a person's energy efficiency implementation. For illustration purposes, consider two households A and B in the network that implements energy efficiency measures. The first household saves R200 while the second person saves R50. However, before the implementation, household A used to spend R 2500 on its electricity bills while B spent R500. This shows that in actual fact household B saved more, with a 10% decrease, and household A had only an 8% decrease in the electricity bill and therefore in electricity consumption. Therefore using a percentage decrease in energy cost depicts the actual results people have achieved in saving. The assumptions made are:

1. Every individual uses electricity and the savings are based on the average electricity consumption peak periods only, which are from 08:00 to 10:00 and from 18:00 to 20:00 for morning and evening peaks respectively. These peak periods are determined by Eskom HomeFlex TOU tariff [72].

2. The calculations and determination of the rebates are not within the scope of this research.

3. The criteria for giving the subsidy are based on the percentage of energy cost saved and how much influence each individual has in the community.

4. The rebate is given to a household that has saved at least 10% of energy costs after two months. The energy cost savings are based on the morning and evening electricity consumption peak and off-peak periods given by the Homeflex TOU tariff.

5. The network is undirectional. This means an edge is drawn between both individuals (i and j) when they both acknowledge that they know one another.

The relationships among members of a network is used to establish a social network graph. In this chapter, the relationship is based on mutual acknowledgement of friendships among households in the network. The network graph is constructed from nodes (households) and edges (relationships). Household i and j must agree that they know each other and are friends before a link (edge) is made between them. The network graphs of Figure 4.2 and 4.3 are based on the adjacency matrix of the 36 members of the community. The graph is an unweighted and undirected graph, that is when two households are connected $d_{i,j} = d_{j,i} = 1$. The network graphs showing the connections among households in a community after information about energy efficiency is introduced into the network is given in Figure 4.2 and 4.3.

4.6 LIMITATIONS

As with mathematical models, some assumptions have been made. There has also been a limitation of the time of use tariff to the Homeflex tariff. The reason for this is because this is the tariff currently used by Eskom to support energy efficiency and demand side management.

4.7 CHAPTER SUMMARY

The importance of implementing energy efficiency measures that will reduce energy consumption is due to the high demand for electricity. Therefore, it is essential to know which people or households in a community to target that will spread information about energy efficiency measures to their neighbours and in doing so encourage their neighbours to reduce their electricity usage.

In this chapter, an expected energy cost savings model is formulated. The model shows how the information obtained reduces in value over time but still motivate people to adopt energy efficiency measures based on their connectivity. This means that an individual can spread the information about energy efficiency to a friend but the friend may only be influenced to adopt the measures the following month. The effect of that information would depreciate over time and is represented in this model. The model is applied with a time of use tariff. The next chapter explores how an individual's level of influence affects his/her neighbours to adopt to energy efficiency changes.

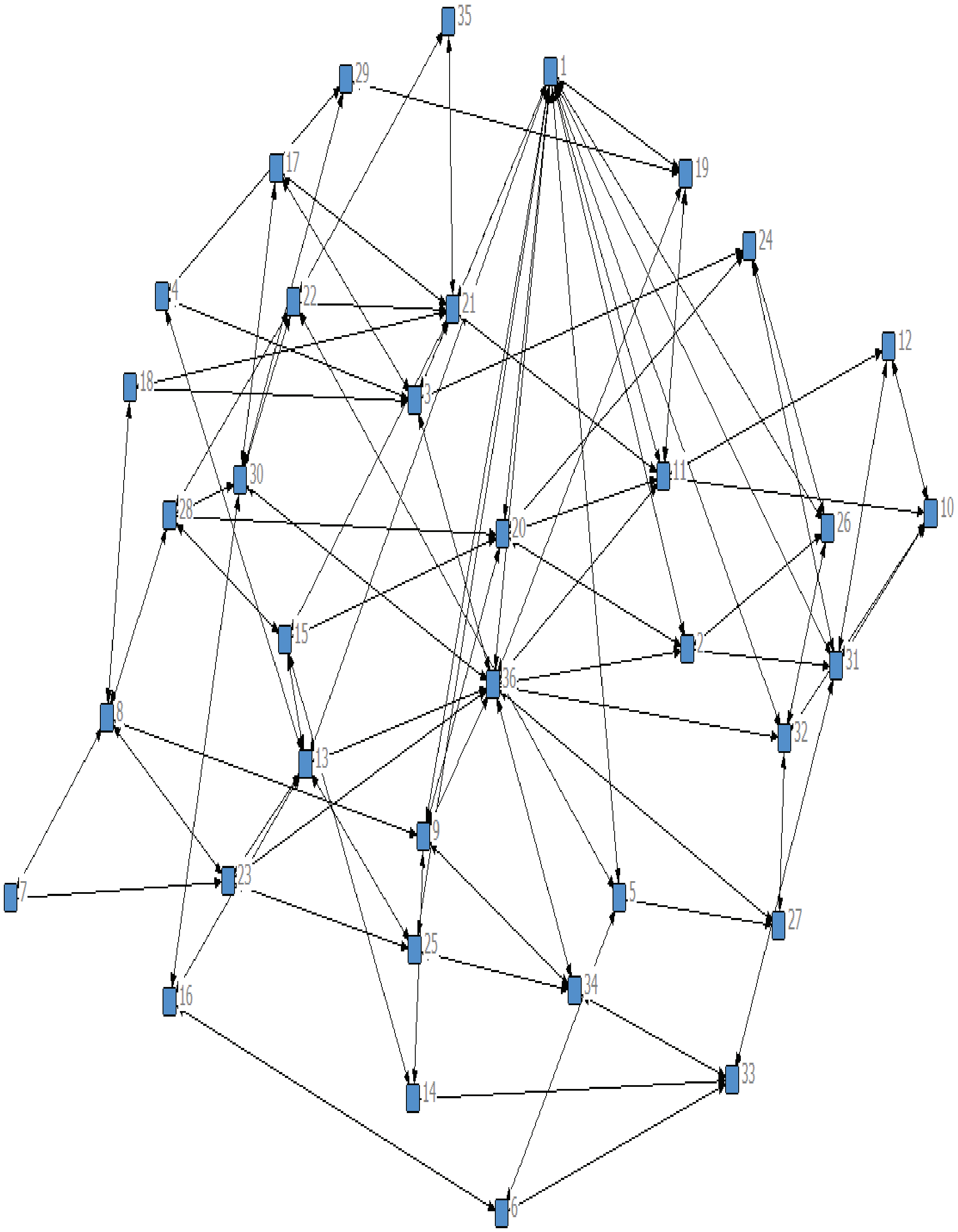

Figure 4.2: First month network graph

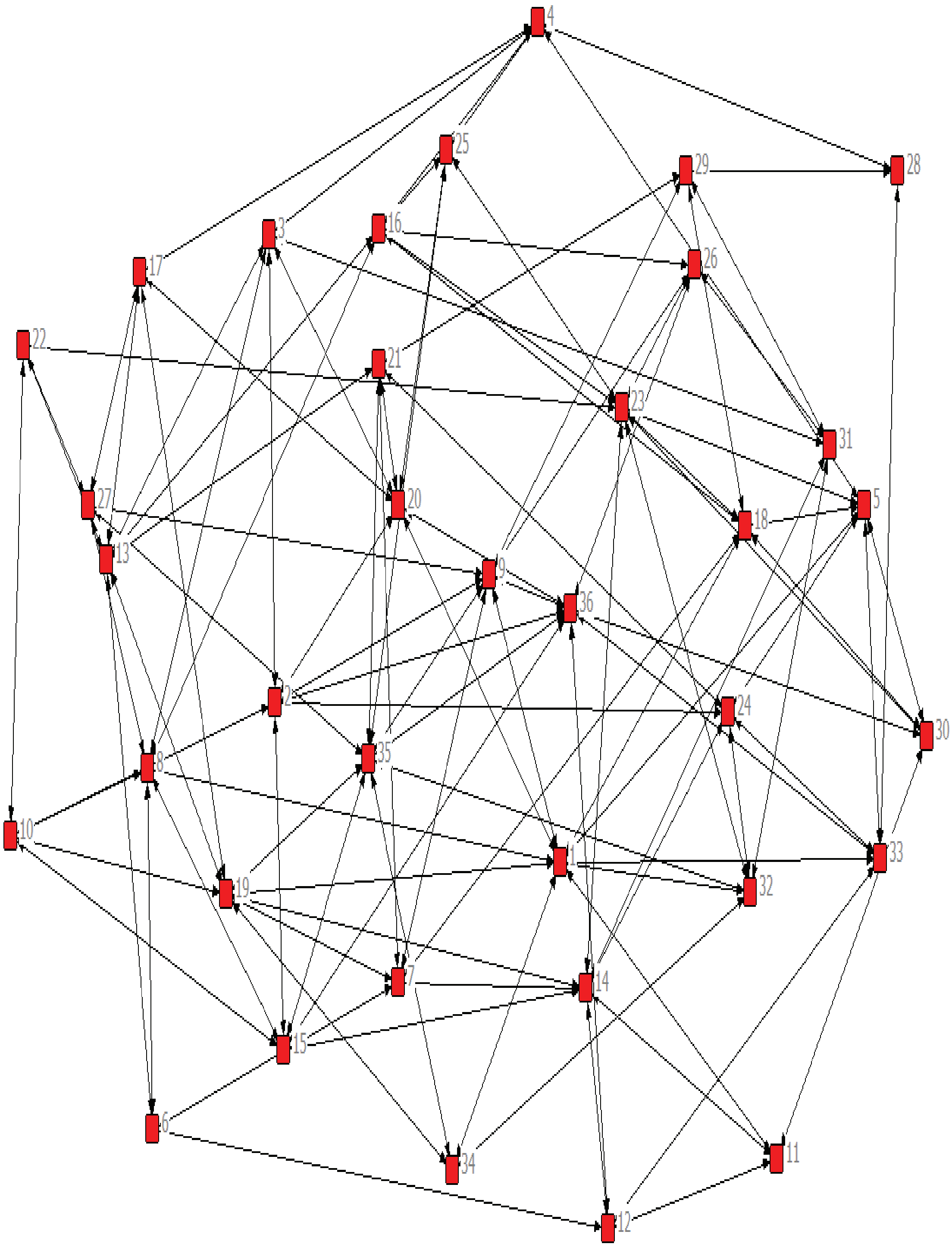

Figure 4.3: Second month network graph

CHAPTER 5

SOCIAL INFLUENCE AND ENERGY EFFICIENCY SAVINGS

This chapter describes the expected energy cost saving model based on social influence, followed by a case study and the solution methodology. Excerpts from this chapter have been published in [78].

5.1 INTRODUCTION

Human beings are the common denominator when sustainable development of energy efficiency projects are concerned. Therefore, before any energy efficiency project is carried out it is important to know the people that will give the highest amount of savings within their network. The calculation of energy saved due to an energy efficiency project is divided into two, technical or direct savings and the non-technical or indirect savings [58]. The direct savings are savings that can be measured or calculated and quantified through measurement and verification means [61]. The indirect savings are savings that are a result of social interactions in a network [58]. In this chapter, an extension of the mathematical models in Chapter 3 and 4 is formulated that quantifies the monthly energy saved due to the social influence an individual has on the rest of his/her network.

There have been studies that give levels of impact that an energy efficiency project has on a community [77], [79], [80] but no one has quantified the role social interaction plays in energy saving especially the non-technical or indirect savings until [58]. The authors of [56] explain that people are more likely to make energy efficiency changes because their neighbours or friends made those changes. Therefore, it is essential to quantify the energy saved due to the non-technical activities or human activities such as social interactions in a network.

The layout of this chapter is as follows. In section 5.2 a mathematical model is formulated to calculate the expected energy savings of an energy efficiency project. Social influence is discussed in section 5.3 and section 5.4 gives the solution methodology. The limitation of the model is given in section 5.5 and in section 5.6 the chapter summary is given.

5.2 THE EXPECTED ENERGY SAVING MODEL BASED ON INFLUENCE MATHEMATICAL MODEL

In this chapter, an extension of the mathematical model of the social impact of energy efficiency projects in chapter 3 and 4 is given. The mathematical model of the final expected energy savings calculates the combined direct and indirect savings of the energy efficiency project.

The probabilities that are used to calculate the information entropy are improved probabilities used in [58]. This is because the probabilities in this chapter include the level of influence an individual has on his/her neighbours.

5.2.1 Functional probability

The functional probability is defined as,

$$p(l) = \frac{\sum_{j=1}^{N} d_{l,j} y_{l,j}}{\sum_{l,j}^{N} d_{l,j} y_{l,j}}, \text{ for } l, j = 1,\ 2,\ \ldots,\ N, \tag{5.1}$$

where $d_{l,j}$ is the direct connection of l to j $d_{l,j} = 1$ when there is a connection and 0 otherwise, $y_{l,j}$ is the influence l has on j. The influence of a node in relation to its neighbour is directional therefore $y_{i,j} \neq y_{j,i}$ for $(j \neq i)$. The functional probability definition is a generic one however for this research, the level of influence is based on Table 5.1. The functional probability $p(l)$ gives the distribution of an individual node within the network.

5.2.2 Conditional probability

Conditional probability $p_i(j)$ is defined in [58] as "the calculation of the quantitative value for the connectivity of nodes within the network". In a network, the conditional probability that the source of information or end user who has performed an energy efficiency project i has transferred information to his/her neighbours j depends on how many intermediaries are between i and j. Therefore, only connections along the shortest paths between i and j are considered. Following the recent theory that any two people are connected with a degree of separation of 4.74 [29], the following cases are identified when defining $p_i(j)$,

Case I: Assume there are two nodes connected directly, that is node i influences node j on a certain level, the conditional entropy is given as,

$$p_i(j) := \frac{y_{i,j}}{k_i k_j}. \tag{5.2}$$

Case II: When there is one intermediary q between the source node i and its neighbour j the conditional entropy is given as,

$$p_i(j) := \frac{1}{k_i k_j}\left(\sum_{q\in M_i\cap M_j} \frac{y_{i,q}\cdot y_{q,j}}{k_q}\right) \tag{5.3}$$

Case III: Assuming i and j have two people between them, then case III is used. This means that j is influenced not just by i but also by the other two people r and q who are connected to each other before connecting to i. This means that there is a long chain before the information reaches j and this affects the quantity of the information that had been transferred from i in the first place. The conditional probability for such a case is therefore defined as:

$$\begin{aligned} &p_i(j) := \tfrac{1}{k_i k_j}\left(\textstyle\sum_{q,r} \tfrac{y_{i,q} y_{q,r} y_{r,j}}{k_q k_r}\right), \\ &q \in M_i, r \in M_j, q \in M_r. \end{aligned} \tag{5.4}$$

Case IV: Assuming i and j have three people between then, the conditional probability is:

$$\begin{aligned} &p_i(j) := \tfrac{1}{k_i k_j}\left(\textstyle\sum_{q,r,s} \tfrac{y_{i,q} y_{q,r} y_{r,s} y_{s,j}}{k_q k_r k_s}\right), \\ &q \in M_i, r \in M_q \cap M_s, s \in M_j. \end{aligned} \tag{5.5}$$

Case V: For more than three people between i and j then, the conditional probability in this research is assumed not to exist between the two nodes. The reason for this is because the probability that the information has been transferred is negligible and thus can be assumed to be non-existent. As such, the conditional probability for this case is defined mathematically as:

$$p_i(j) := 0. \tag{5.6}$$

5.3 SOCIAL INFLUENCE

In this section an example of relationship (age group) is discussed. This gives an example of how different relationships influence people and move them towards adopting what their neighbours have already adopted.

From the discussion in chapter 2 on the types of relationships, it can be noted that age groups play a role in the transfer of information among members of a community [47]. Households are divided into different groups depending on their age groups to illustrate that the level of influence an individual has on his/her neighbours can determine how much information he/she can transfer based on probability definitions in section 5.2.

The relationships can be based on different factors such as geographical locations, political views, family ties, age groups, common behavioural interactions and economic class [47], [48]. In this chapter, two households are connected when there is a mutual acknowledgement of friendship between them, that is $d_{i,j} = d_{j,i}$ (this is what is referred to as an undirected network) and this can be found in the network graph in Figure 4.2. The influence level $y_{i,j}$ each household has on its neighbour is considered in this chapter using Table 5.1.

In this chapter, the households are divided into four groups they are, single, newly weds, mixed family and older households. Each of the households have different levels of influence on the other households. The influence of each household that is proposed is given in Table 5.1.

Table 5.1 is used to depict the influence people have on their neighbours using age groups.

Table 5.1: Level of Influence for every age class $y_{l,j}$

	Level of influence			
	Single	Newly weds	Mixed family	Older
Single (age 19 - 35)	4	3	1	1
Newly weds (age 22 - 40)	3	4	3	2
Mixed family (age 0 - 60)	2	2	4	3
Older (age 60 - above)	1	1	2	4

From the table it can be seen that people who are within the same age bracket have more influence on one another when compared to the other age groups. The influence directly affects how information is transferred in the network. This in turn affects the expected indirect savings of the energy efficiency projects. It is assumed that in the mixed family, the breadwinner of the family makes decisions when it concerns energy usage.

The households are arranged from 1 to 36 as follows: household 1-9 are single households, 10-18 are newly wed households, 19-27 are family households and 28-36 are pensioner households. Each household is required to identify whom they know among the group. However, details of how they know the person or how they are related are not included in this study.

The reason for choosing this set of influences is based on the literature [47] that provides evidence that people within the same age group are most likely to influence each other than people from a different age group. To validate the reason for choosing these numbers, a brief comparison between three different scenarios is presented, where the first scenario is the proposed one in Table 5.1. That is people influence all other age groups but they influence those in their age group *only*. The second is the assumption that a household influences only people of the same age group. The third is when there is a lower level of influence from each age group in Table 5.1 assigned to people in the network. For example, where household 1 had influence over household 9 with a level of 4, and that level has now been reduced to 3. Also, it should be noted that the entropy of information is not only dependent on the level of influence but also on the connectivity within the network, therefore even if households within the same age group would have a lot of influence on themselves but when they are not connected directly to each other, their impact on each other is reduced. This study shows that taking influence into consideration enhances the real-life implications of information propagation of energy efficiency projects which in turn affects the savings.

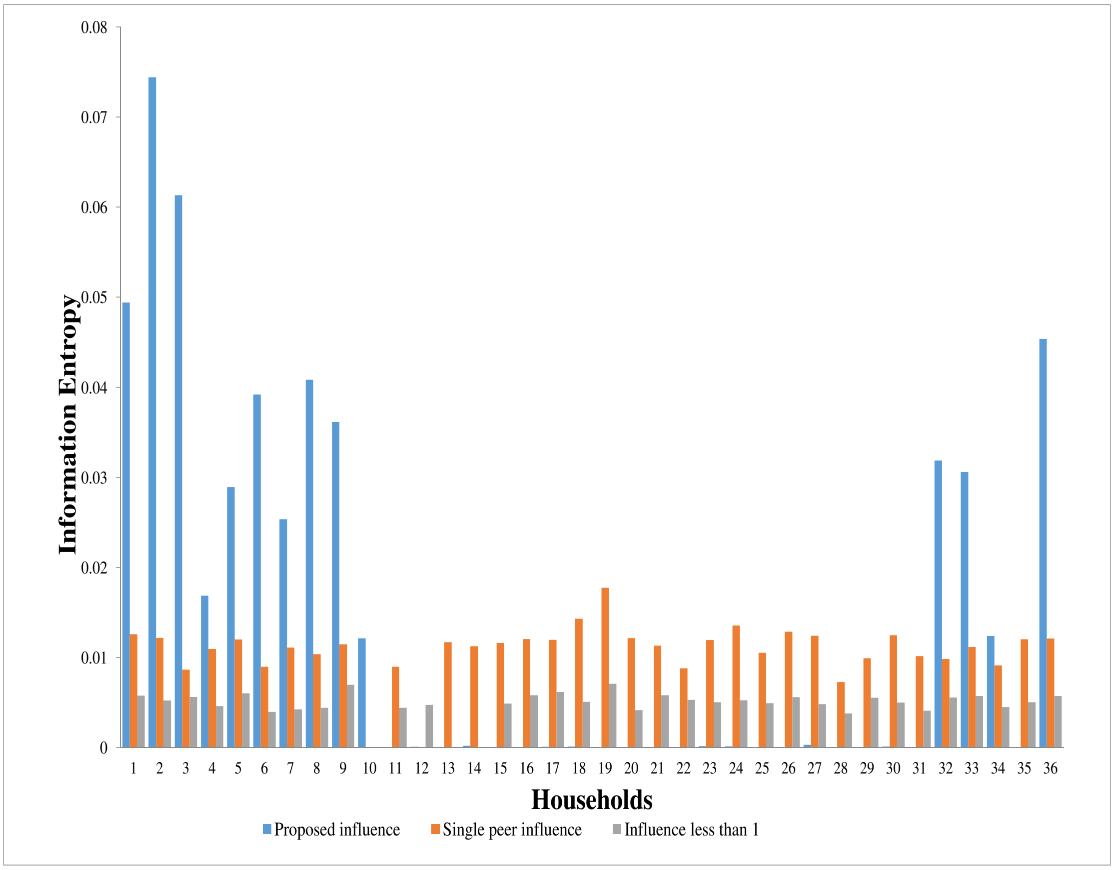

Figure 5.1: Comparison of different influence levels

The results of the information entropy given in figure 5.3 are as follows; the proposed influence of Table 5.1 is represented in blue, the assumption that a household influenced only its peers is represented by the orange bars while the gray bars represent the scenario where the influence levels are reduced on the table. This means that if the level was 4, it is reduced to 3, level 3 is reduced to level 2, but level 1 remains the same because it means there is no influence between the two households even when they are connected.

This concept is known in research circles as sensitivity analysis and seeks to determine the effect of a reduction in influence levels on the savings. Interestingly, it is observed that when the level of influence reduces by 1 from the proposed level of influence, the single and pensioners age groups have reduced information entropy. The same occurs when they only have to influence members of their age group. However, the reverse is the case for the newly weds and mixed family age groups. However, it is worth noting that their information entropy is still very low with a maximum of 0.016 information entropy from household 19 who had who had personally achieved direct savings below 50kWh.

Household 10 doesn't have any influence no matter the level of influence given, this could be due to the number or the type of age groups of households connected to that household. The reason for the comparison of different levels of influence is to show that in a social network the impact an individual has on his/her neighbour is quite sensitive to his/her level of influence which in turn can enhance the chances of increased adoption. Identifying the people who would motivate their neighbours to adopt energy efficiency projects can improve savings.

5.4 CASE STUDY III

A case study of thirty-six households is used to illustrate the impact an individual has on the rest of his/her network based on his/her level of influence. To calculate the direct cost savings we use one of the TOU tariffs in South Africa. The aim is to monitor a 10% reduction in electricity consumption due to some daily practices based on category I of energy savings given by Eskom in [76]. Examples of activities that would induce savings include changing from incandescent light bulbs to compact fluorescent lamps (CFL), switching off electric water heaters at peak times and switching off appliances when they are not in use. A few assumptions are made for this case study and they are;

1. The network is undirected
2. Every individual uses electricity and the savings are based on the electricity consumption peak periods only which are from 08:00 to 10:00 and from 18:00 to 20:00 for

morning and evening peaks respectfully. These peak periods are determined by the Eskom HomeFlex TOU tariff [69].

The criteria for giving the subsidy is based on how much direct and indirect energy is saved and how much influence each individual has on his/her community.

5.5 SOLUTION METHODOLOGY

Just as in the case of the last two chapters, the assumption is that, it is cheaper for neighbours of i to obtain information from i because it is free rather than find information about energy efficiency measures through other means that may cost money and time. The model is solved with the use of the Java programming language on a 32-bit processor. The reason for using Java is because it can process a large network. The solution methodology is as follows;

1. Assume that general external information is available to the whole network and this information is complete. The information that is referred to in this research are the different measures people can take to reduce electricity usage in their homes while still enjoying similar comfort if they do not perform any energy efficiency measures.

2. The direct savings represented by S_i, of each node. Calculate the functional $p(i)$ from equation (5.1), conditional $p_i(j)$ from equations (5.2) - (5.6) and joint $p(i,j)$ from equation (2.5) probabilities and entropy $H(i)$ from equation 3.4. Calculate the indirect savings obtained from the entropy $H(i)$ in equation 3.3. Calculate the expected energy cost savings for all i as sum of the direct and indirect savings as given in equation 3.2.

3. Find the node i with the maximum expected energy cost savings: $\max(F_i)$.

The case study and results for the mathematical model and solution methodology of section 5.2 and 5.4 respectively are given in chapter 6.

5.6 LIMITATIONS

As with all mathematical models, some assumptions have been made. There have also been limitations to the type of relationship used (age groups). The model is generic and can be used for different relationships and can be adjusted to suit the relationships portrayed. The reason age group was used is because research shows [57], that people will most likely do what other people in their peer group do. Thus, the focus of the study is on the mathematical modelling and not necessarily the type of relationship.

5.7 CHAPTER SUMMARY

This chapter explores the mathematical modelling of how information is propagated within a social network using age groups as an example of influence class. This model sums up the models of the two previous chapters as it combines the connectivity of people and the expected energy savings obtained by people who have adopted the energy efficiency measures.

From this model, an energy planner can understand who to target in a community when introducing energy efficiency projects to that community by using criteria for the level of influence he/she wants. The level of influence is not always based on age but on different factors such as proximity, friendships, families and so forth. Those types of relationships are not covered in this research as it is not part of the scope of the research. In chapter 6, the results of the case study presented in this chapter are explained.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 INTRODUCTION

This chapter examines all the results of the three case studies to validate the practicality of the mathematical models presented in chapters 3, 4 and 5. The case studies give practical interpretation to the mathematical models and validate the problem statement presented in Chapter 1. The results from the first model details in chapter 3 prove that the most influential person is not necessarily the person with the most connections in a network. The second case study proves the hypothesis from chapter 4 that information flow over time can enhance savings, however information potency can be reduced over time. The third case study in chapter 5 brings to perspective the influence of people. The third case study proves that the level of influence a person has on his/her neighbour will affect his/her information entropy which in turn affects the expected energy savings of that individual. These three case studies aid the explanation of information propagation of energy efficiency and how this information enhances savings within a network. All the network graphs are drawn using the software of [81], which is a network analytical software. Excerpts from in this chapter are published in [58], [60] and [78] which describe the results and discussions for each of the case studies.

6.2 RESULTS OF CASE STUDY I

In general, a social network graph can be referred to as an expression of patterns with regards to relationships among people within a network. How each friendship is formed and the level of friendship such as close, very close and acquaintances are not within the scope of this research. The network graph of Figure 3.2 is based on the adjacency matrix of the 56 members of the community. The graph is an unweighted and undirected graph, that is when two households are connected $d_{i,j} = d_{j,i} = 1$.

The average number of nodes to which any node is connected to, which is the network degree D of (2.4), is 5.66. This means that a person is connected to one-tenth of the total population of the network on average. This shows that people are heavily connected to one another in this network. The average degree of connection of the network is L = 2.75, this corresponds with the definition of the assumptions of the conditional probability formula (3.13) and the latest findings that any two people chosen at random will have at most 4 intermediaries between them. The network used in the case study shows that it is a real-life small work network in with a small mean path length and large network degree.

6.2.1 Example I

Assume that there is only one solar water heater to be given out for free. In order to identify the best household that will qualify for the free heater, the expected power savings for single source nodes of all the 56 people are calculated using the entropy, the indirect savings and total expected power savings equations (3.4), (3.3) and (3.1) respectively. The person with the highest total expected power savings is therefore the person who will transmit the information about the solar water heater most effectively and through his/her broadcasting about the advantages solar heaters will encourage other people to buy their own heaters. The results of the household expected power savings and information entropy from the highest to the lowest are shown in Table 6.1 and Figure 6.1 respectively.

The results show that node 3 has the highest entropy, this means that it has the highest possibility of transmitting the most information about the solar water heater to the rest of

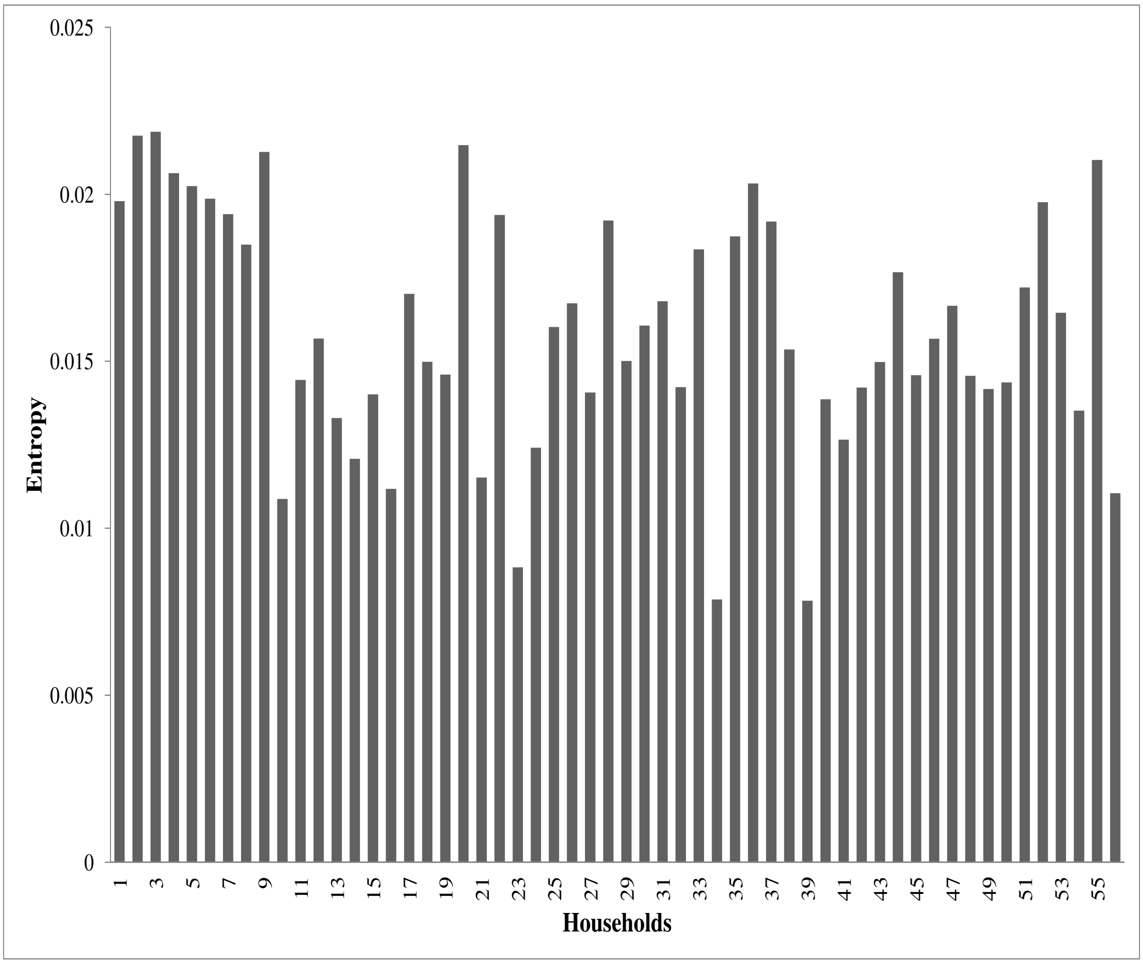

Figure 6.1: Entropy of all nodes

the network. Node 3 has 17 connections and the highest entropy $H = 0.022$ compared to node 9 with 15 connection and the entropy $H = 0.02$. This means that node 3 has the highest influence within the network and thus has the highest social impact on the community. From Table 6.1, household 2 who has 13 people connected to it has higher expected power savings than household 20 and 9 that have 14 and 15 connections respectively.

Since the power saving for every solar water heater is the same, the household with the highest entropy is also the household with the highest expected power saving value. From the results, it is seen that the individual having a high number of people connected to him/her does not automatically ensure he/she will have the most influence in his/her community through social interactions that will prompt people to save energy. By using the expected power savings model the energy planner has knowledge to some degree of the people who are more likely to spread information in a network and thus aiding him/her in establishing how to encourage those significant people to save energy, which in turn will encourage the rest of the network to save energy.

Table 6.1: Node degrees and expected power savings for single source of information

Household/node	3	2	20	9	55	4	36	15
Node degree (k_i)	17	13	14	15	9	10	7	11
EPS (kW)	2.055	2.054	2.054	2.053	2.053	2.052	2.051	2.051
Household/node	6	1	52	7	22	28	37	35
Node degree (k_i)	10	11	5	10	8	6	5	
EPS (kW)	2.05	2.049	2.049	2.049	2.048	2.048	2.048	2.047
Household/node	8	33	44	51	17	31	26	47
Node degree (k_i)	8	7	7	5	6	6	7	7
EPS (kW)	2.046	2.044	2.043	2.043	2.043	2.042	2.042	2.042
Household/node	53	30	25	12	46	38	29	18
Node degree (k_i)	2	6	4	6	4	3	5	4
EPS (kW)	2.041	2.040	2.040	2.039	2.039	2.038	2.038	2.037
Household/node	43	19	45	48	11	50	32	42
Node degree (k_i)	4	3	7	5	4	3	4	2
EPS (kW)	2.037	2.036	2.036	2.036	2.036	2.036	2.036	2.036
Household/node	49	27	15	40	54	13	41	24
Node degree (k_i)	5	4	4	4	1	3	3	2
EPS (kW)	2.035	2.035	2.035	2.035	2.034	2.033	2.032	2.031
Household/node	14	21	16	56	10	23	34	39
Node degree (k_i)	2	2	2	1	1	1	1	1
EPS (kW)	2.030	2.029	2.028	2.028	2.027	2.022	2.022	2.020

6.2.2 Example II

If more than one household has the highest number of connections, it becomes difficult to determine which household has the most influence in the network. This is where the EPS model gives the best possible solution for the household with the most influence in its community in terms of information transfer. The EPS from each subnetwork consisting of 3 households must be calculated so that the maximum EPS can be identified. The expected saving from a 3-household subnetwork is calculated by using formula (3.6).

A search of all the possible 3-household subnetwork combinations is done using the brute force search algorithm. The brute force search algorithm exhaustively searches through all possible combinations until the optimal solution is found. In this example, the optimal solution is the 3-household subnetwork that has the highest expected power network. The total number 3-household subnetworks search equals $\binom{3}{56} = 27720$ different combinations. Table 6.2 lists the expected power savings of the 10 best and 10 worst subnetworks. The combination of households 4, 8, 50 gives the highest expected power savings, which is 6.4kW and 38.4kWh energy saved during the peak periods on an average day. These savings are 6.7% higher than the worst household combinations. It is worth noting that household 3, 9 and 20 are the top 3 households which have the highest connections as individual nodes. However, their combination as a 3-household subnetwork has only 6.3kW expected power saving. Households 39, 55 and 56 with the lowest connections have expected power savings of 6.2kW which is higher than household 33, 48 and 53 with the worst expected power savings. Therefore, in the multiple source case, if households have high connections it does not imply that the expected power savings of those households as a subnetwork will be high too.

The multiple source case study also concludes what the single case study revealed; that people with higher connections do not automatically influence their neighbours any more than people with lower connections have the least influence, hence the need for the EPS model.

Table 6.2: Expected power savings (EPS) and expected energy savings (EES) of the best and worst combinations

	Best Combinations			Worst Combinations		
S/n	Combination	EPS (kW)	EES (kWh)	Combination	EPS (kW)	EES (kWh)
1	4, 8, 50	6.400	38.40	6, 23, 52	6	36
2	4, 8, 51	6.398	38.391	9, 38, 42	6	36
3	5, 10, 40	6.398	38.386	11, 27, 34	6	36
4	4, 10, 33	6.395	38.372	13, 22, 32	6	36
5	4, 9, 17	6.395	38.372	17, 21, 38	6	36
6	4, 10, 32	6.395	38.371	19, 24, 55	6	36
7	2, 25, 38	6.394	38.365	21, 31, 53	6	36
8	5, 16, 37	6.394	38.364	26, 39, 50	6	36
9	4, 8, 20	6.394	38.363	29, 46, 54	6	36
10	2, 19, 36	6.394	38.361	33, 48, 53	6	36

6.3 RESULTS OF CASE STUDY II

The results of the case study from chapter 4 are discussed in this section. The network graph of Figures 4.2 and 4.3 are built using the connections of households and the UCIENT software [81]. Similar to [58], the graphs are unweighted and undirected graphs, that is when two households are connected $d_{i,j} = d_{j,i} = 1$. The average number of nodes that any node i is connected to, which is the network degree D is 3.

The percentages of the total expected energy cost savings are given in Figure 6.3. Figure 6.3 shows the percentage savings for the two months (i.e. T = 2) after energy efficiency measures have been implemented in each household. The results show that household 5 has the highest percentage of expected energy cost savings; however, the savings of the second month are higher than the savings of the first month. The increase in savings is due to the personal effort of the individual (direct savings), the increase in the node degree of that individual and the type of connections. The reward for the information-sharing among members of the network through indirect savings encourages them to save more and thus increases awareness of energy efficiency in the community.

It can be seen that household 5 interacted with four people about energy efficiency measures after the first month and seven people after the second month. The increase in interactions among people enables households to spread information and by doing so, awareness of energy efficiency is increased. The households with the highest percentage of savings are household 5 with 30% savings, followed by households 17, 2 and 11 with percentage savings of 15.1%, 14% and 10.7% respectively. The results show that in the 36-member network, only four households had expected energy savings of above 10%. They not only endeavoured to reduce their energy consumption but they also transmitted information about their energy efficiency measures to the rest of the network.

These results show that savings depend not only on the personal effort of an individual, but also on the connections and his/her influence on his/her neighbours to transmit information about energy efficiency. For example, household 2 has only seven connections after the second month, as can be seen in Figure 4.3. However his neighbours (households 3, 15, 8, 24, 20 and 36) have higher node degrees k_i because of this, household 2 is able to obtain a high level of influence when calculating the indirect savings of household 2 that are used to evaluate the total expected energy cost savings. This model acknowledges the hard work of individuals in the network to save energy, as well as the ability of those individuals to transfer the information to the rest of the network based on their influences.

Although there are some negative percentages in terms of savings, it shows in Figure 6.2 that most households consumed less electricity in the second month compared to the first month. For example households 10, 19, and 21 went from negative percentages to positive. Even though we have ensured in our model that the effect of the information diminishes over time, these households still reduced their electricity consumption which led to energy cost savings. Further analysis from Table 4.1 shows that when the total community energy use is combined, there are savings of 22881.9kWh and 35922.03kWh for the second and third month respectively. This means that there was a 3.51% and 5% reduction of energy use in the

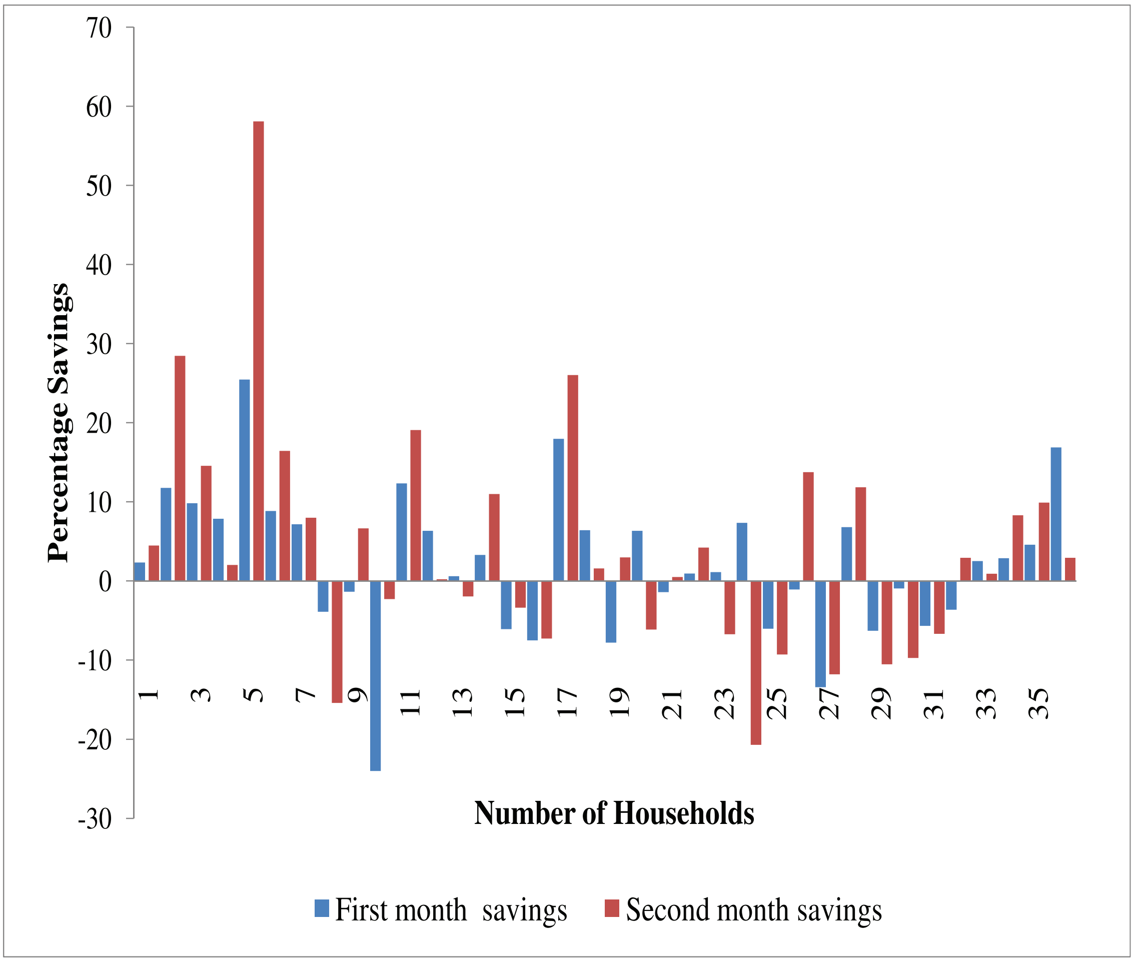

Figure 6.2: Percentage of energy cost savings for each household after two months

second and third month respectively and this shows a general increase of savings by people just interacting with each other with each other at no cost to the utility company.

Understanding why people use more electricity after they have established some savings as in the case with households 8 and 23 is still a subject of research in many fields and it can be due to a number of reasons. Looking at the rebound effect of energy efficiency as one of the possible reasons which is explained in [82] as "greater energy efficiency results achieved can lead to an even greater energy use because it can cause people to use more energy". For example, some households may already have some energy efficient appliances and when they obtain information about energy efficiency realise that they are already saving, as such they decide to use or purchase more electricity products. As [82] explains, "it is challenging to quantify rebound effects" although [83] and [84] have tried estimating the rebound effect in households they advise that rebound effects should not be the only tool used to identify a household's response to energy efficiency.

Another reason for negative percentages could be the fact that the households are willing to make energy efficiency improvements but have financial constraints. This is where the model comes in, because information is dependent on people interacting with one another, a person can have the knowledge of energy efficiency measures and transfer that knowledge to his/her neighbour although he/she doesn't reduce his/her electricity usage but his/her neighbour does because of the information that he/she gave. However, the reasoning behind why there are negative savings are not within the scope of this study.

This case study is intended to illustrate the usefulness of the expected energy cost savings model in identifying people who influence their community by propagating information about energy efficiency. The model captures the personal effort of the individuals (direct savings) and also their social effort (indirect savings) in the reduction of their energy usage. This will in turn help reduce the energy consumption of the entire community and in a wider scope the energy production by the utility company. This model is useful for providing information to members of the community about their energy usage. Such information can trigger greater effort from the community members to be more conscious about energy usage.

The results depict a real-life scenario and show that although some people do not save even though they have been informed about the energy efficiency measures, more than 50% of the people in the network show significant savings. This demonstrates that human interaction can indeed help in the reduction of energy usage and thus motivate energy cost savings for that individual without incurring any extra cost to the utility company. This type of research provides the end users with information about energy efficiency measures as such, informed decisions can be made on how they utilise electricity. If an individual is willing to reduce his/her electricity consumption, the utility company also wins through the reduction of electricity demand at no additional cost. The reduction is achieved through various means of transmitting such information such as, television, radio, social media and so forth.

6.4 RESULTS OF CASE STUDY III

This section discusses the case study of chapter 5 where the expected energy savings model is formulated based on social influence. The results of [58] (case study I example I) show that when considering a single source of information, the household with the highest connections automatically has the highest expected power savings due to the magnitude of the neighbours it has. However, the results of case study III show that when the level of influence is taken into consideration, it can influence how much of the expected energy is saved. The results show that four households out of the 36 actually saved more than 10% of their electricity costs after performing some energy efficiency measures in their homes.

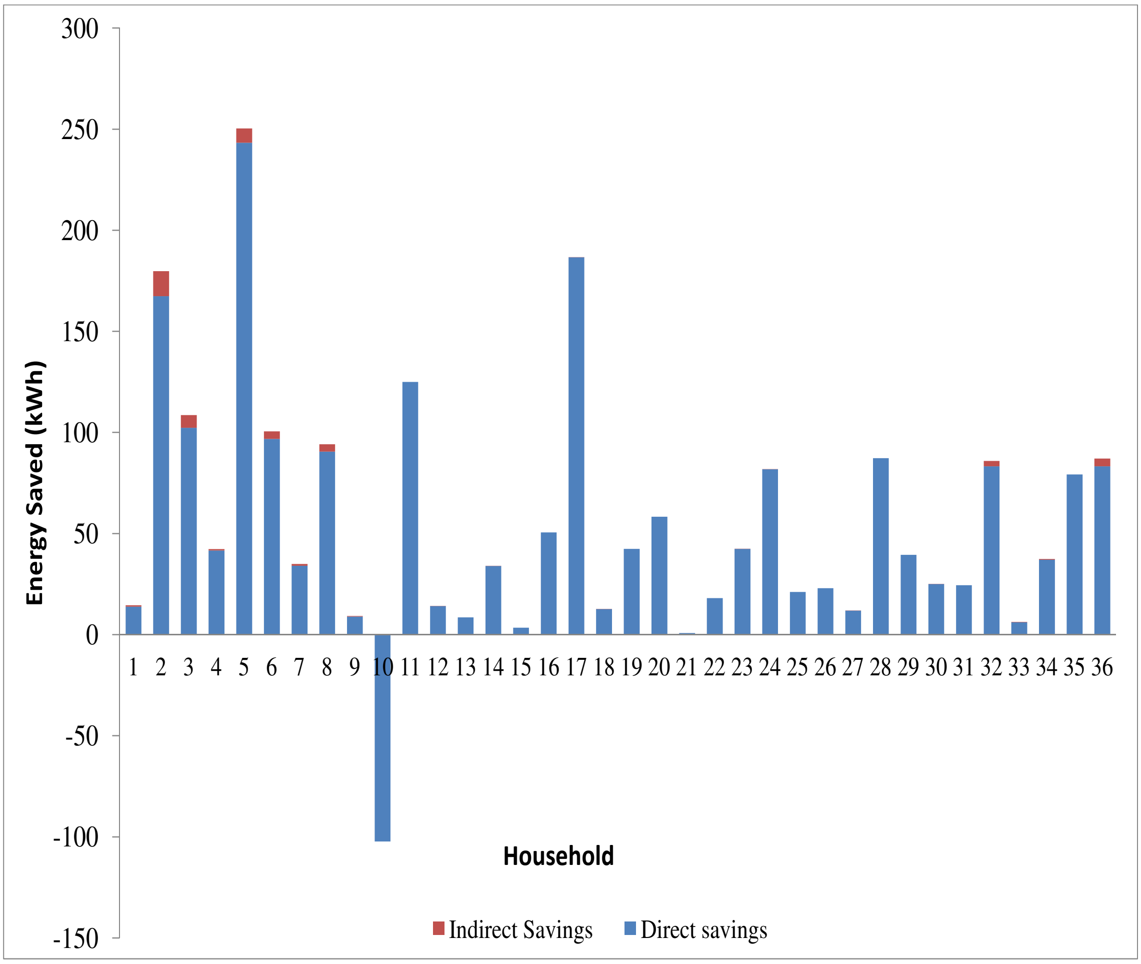

Figure 6.3: Expected energy savings of a thirty-six household network

From the calculation of the expected energy savings, household 5 emerges as the household with the most influence and ability to transfer information to the rest of the network as seen in Figure 6.3. Household 10 does not have any influence on its neighbours because it does not have any direct energy savings, in fact more electricity is consumed. Household 10 experiences what is referred to as the so called "rebound effect", however this a broad topic and is not covered in this research.

Household 5 has the highest total expected energy savings of 250kWh, followed by household 17 and 2 with savings of 186kWh and 179kWh respectively. If three rebates were to be handed out, the three households mentioned above are recommended to receive them. Household 1, with the highest number of connections, has only achieved savings of 14kWh. These results show that energy savings not only depend on an individual but also on the connections and influence he/she has. This model acknowledges the hard work of individuals to save energy as well as the ability of that individual to transfer the information to the rest of the network based on his/her influence in the community.

6.5 REPRODUCIBILITY OF THE RESULTS PRESENTED

The first step in obtaining the data can be through existing social networks or by conducting a survey. In this research, a survey was conducted to identify the connections of individuals in the networks used. For case study I (as explained in chapter 3), a survey was conducted from 56 households whose members were part of a church. These people were given questionnaires to fill and indicate who they knew in the church. From the data, an adjacency matrix was built where an edge was drawn between two households if and only if, they both acknowledged they knew each other, hence the social network used is undirectional.

The network data used in case study II and III was obtained using a similar method to case study I; however, a gated-community was selected where the households allowed the capturing of their monthly electricity consumption. Energy consumption of each household was recorded in the first month. Questionnaires were given out in the second month and the energy consumption of that month recorded. Finally, questionnaires were distributed in the third month and the energy consumption recorded once again.

The next step was to input this adjacency matrix into the UCINET software (an Analytic Technologies Software developed by Borgatti et al. in 2002 [81]) that can perform some basic network analysis to determine if the network is really a small world network. The collection of data and obtaining the adjacency matrix is in itself part of a broader research field, instead the study was focused on information propagation and not on the reason people form the bonds they do with other people in their network. UCINET is also responsible for drawing the network diagrams presented in all the network figures within this report. The graph provides the connectivity of households in the network (where each household is represented by a number).

Depending on the model required the solution methodology presented for each model in chapter 3, 4 and 5 respectively are applied. Therefore, by following the step-by-step approach of each solution methodology, the solutions presented in this report can be reproduced. Java was used to solve the models because of the large size of the networks. Further research can be done with larger networks, however collecting data for a large group of more than 50 can be tedious and time consuming. Although Java programming was used to solve all the case studies, by following the solution methodology steps, any software that can analyse mathematical models can be used.

6.6 CHAPTER SUMMARY

This chapter presents the results and discussions of the case studies for the three models presented. Case study I provides two examples on what to expect if there are single or multiple sources of information. The examples illustrate that the person with the highest expected energy savings is not necessarily the person who is connected to the greatest number of people in the network.

Case study II focuses on the degradation of information over time and its effect on energy efficiency cost savings based on time of use tariff. This case study further confirms the fact that it is not the person with the most connection who will provide the most expected energy efficiency cost. It is therefore imperative for the energy planner to identify the people to target when trying to implement energy efficiency projects in different communities or networks. This will ensure that the effort towards external injection of information such as television advertisements are curtailed.

Case study III spotlights the impact of social influence towards energy efficiency adoption. From the results, it can be seen that people within the same age group are able to influence their peers more efficiently. Furthermore, the case study shows the age group of people who are likely to be more influential within a community. However, this is just a case study for one example and this model can be used for different types of social influence categories. In conclusion, this chapter highlights the advantages of the mathematical models when applied to the case studies and validates the mathematical models formulated in chapters 3, 4 and 5.

CHAPTER 7

CONCLUSION

7.1 SUMMARY OF RESEARCH

The aim of the research is to formulate expected energy saving mathematical models, which are useful in identifying individuals in a network who would convince or influence their neighbours to adopt energy efficiency projects. From the research, the expected savings can be divided into two categories; direct and indirect savings. Direct savings are calculated from different measurement and verification methodologies, (this is not the focus of this research) while the indirect savings are the additional savings which have never been quantified in the literature. The indirect savings are a function of the direct savings and the information transmitted within a social network. The indirect savings are therefore the main contribution of this study to the energy efficiency research community.

Through the indirect savings, the influence one has within the social network can be recognised and this can help identify the people who need to be educated and convinced about energy efficiency projects. The targeted people are the ones who will encourage their neighbours and by so doing, the rest of the network. This will potentially save money by mobilising and increasing the number of people who would join in a mass roll out project, thereby assisting the utility company with the goal of reducing electricity consumption.

After the study of how social networks and energy efficiency intertwine, three mathematical models were formulated to depict information transmission among members of a network.

The first stage, chapter 3, assumes that there are multiple information sources in an undirectional network with no weighting. The model is then tested on a 56-household community. The results from the simulation show that it is not necessarily the person with the most connections that will provide information to the rest of the network when considering multiple sources of information. However, if one is considering just a single source of information chances are that the person with the highest connectivity may be able to spread the most amount of information to the rest of the network depending on the number of connections his/her neighbours have. It is essential to identify the people within a network who have the highest level of influence in terms of information transfer because this leads to a faster transmission of energy efficiency ideas to the community which in turn leads to faster adoption.

The second stage focused on the difference time intervals made in the expected energy saving model as explained in chapter 4. From the mathematical model, time was incorporated into the expected power model of chapter 3 and the results show that the more people are connected in the network, the higher the possibility of potential for an increase in energy cost savings over time. Allowing individuals to know how much energy they are saving can lead to more potential savings and that can be drawn from the results where it shows that that the indirect savings actually increases the total expected energy cost savings of an individual. This can be one of the ways to broadcast the benefits of energy efficiency. When individuals see how much their information about energy efficiency has enabled them to increase their savings, the information is bound to spread faster.

The third stage focused on how the different levels of relationships influenced savings in the social network in chapter 5. Quantifying the social impact each individual has on his/her network shows the expected energy saved by the individual within the network. The influence an individual has is reflected in the functional and conditional probabilities of that node. The functional and conditional probabilities are defined for different cases in the model and these probabilities are incorporated in the expected energy saving model. The model is tested using an example of a thirty-six household community, where rebates are to be given to a limited number of households. The results show that the level of influence a person has on his/her neighbour can determine how much expected energy savings he/she can obtain. The results also validate that the number of connections a person has does not always determine how much influence he/she has in the network.

7.2 LIMITATIONS OF THE STUDY

The major limitation to this study is the time constraint. A vast amount of time is needed to study human patterns of behaviour. However, this research relied on studies conducted by various top researchers on human behaviour to formulate and solve the mathematical models presented. The fundamental contributions of the research can still be applied to different forms of social networks. Furthermore, if the network sizes for the case studies were increased, the complexity and computational time required for large networks would be enormous. Therefore, using a medium-sized network gives a general overview of what to expect within a larger network.

7.3 FURTHER STUDIES AND RECOMMENDATIONS

This is a new step toward understanding information transmission within social networks with the aim of increased adoption of energy efficiency projects. The main focus of the research was to identify the people who would influence their neighbours to adopt energy efficiency projects through the expected energy efficiency models that have been formulated.

Further studies that can be done for this research include:

1. Extension of the study in order to understand the relationship between external information sources and internal sources. This means how information obtained from sources such as television and radio directly affect an individual in his/her network which in turn will affect his/her neighbours. Also how this information received accelerates adoption of energy efficient initiatives.

2. How information can be propagated strategically to people with the aim to encourage

them to adopt an energy efficient lifestyle.

3. Further studies on different social networks and how they can be applied to energy efficiency and demand side management.

4. Further studies on the different types and levels of influences should be conducted.

5. Reduction of optimisation time can be implemented by the application of different search algorithms; if a larger network is to be studied, a brute force algorithm suffers from combinatorial explosion.

REFERENCES

[1] F. H. Buttel, "Social structure and energy efficiency: A preliminary cross-national analysis", *Human Ecology*, vol. 6, pp. 145-164, 1978.

[2] R. Capata, V. Naso, F, Orecchini, "Social impacts of energy systems", *Renewable Energy*, vol. 9, pp. 1291-1294, 1996.

[3] F. Orecchini, A. Zuccari, A. Santiangeli, "Social impact method of energy analysis: improvements and results" , in *Proceedings of IEEE International Symposium on Technology and Society*, pp 235-224, 2000.

[4] Y. J. Wu, M. A. Rosen, "Assessing and optimizing the economic and environmental impacts of cogeneration/district energy systems using an energy equilibrium model", *Applied Energy*, vol. 62, pp. 141-154, 1999.

[5] L. Lutzenhiser and S. Lutzenhiser, "Looking at lifestyle: The impacts of American Ways of Life on energy/resource demands and pollution patterns", in *Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings*, pp. 163-176, 2006.

[6] A. Grabowski and R. A. KosiÃśski, "Epidemic spreading in a hierarchical social network", *Physical Review E*, vol. 70, 031908, 2004.

[7] M. Barahona and L. M. Pecora, "Synchronization in small-World systems", *Physical Review Letters*, vol. 89, 2002.

[8] L. Lutzenhiser , M. Gossard, "Lifestyle, status and energy consumption", *Consumer*

Behaviour and Non-Energy Effect, vol. 8, pp. 207-221, 2000.

[9] M. Isaacson, L. Kotewa, and A. Star, "Changing how people think about energy", in *Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings*, pp. 127-140, 2006.

[10] W. Abrahamse, L. Steg, "How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings?", *Journal of Economic Psychology*, vol. 30, pp. 711-720, 2009.

[11] M. E. J. Newman, D. J. Watts, S. H. Strogatz, "Random graphs model for social networks" in *Proceedings of the National Academy of Sciences*, vol. 99, pp. 2566-2572, 2002.

[12] I. S. Pool, M. Knochen, "Contacts and influence", *Social Networks*, vol. 1, pp. 5-51, 1978.

[13] A. E. Motter, C. Zhou, and J. Kurths, "Network synchronization, diffusion, and the paradox of heterogeneity", *Physical Review E*, vol. 71, 016116, 2005.

[14] I. N. Athanasiadis and P. A. Mitkas, "Social influence and water conservation: an agent-based approach", *Computer Simulation*, vol. 7, pp. 65-70, 2005.

[15] E. M. Rogers, *Diffusion of Innovation* The Free Press, 1983.

[16] A. Pina, C. Silva, P. Ferrão, "The impact of demand side management strategies in the penetration of renewable electricity", *Energy*, vol. 41, pp. 128-137, 2012.

[17] R. K. Jaina, R. Gulbinasb, J. T. Taylor, P. J. Culligan, "Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback", *Energy and Buildings*, vol. 66, pp. 119-127, 2013.

[18] S. Saini, "Conservation vs. generation: the significance of demand side management

(DSM), its tools and techniques" *Refocus*, 2005.

[19] L. Suganthi, A. A. Samuel, "Energy models for demand forecasting-A review" *Renewable and Sustainable Energy Reviews*, vol. 6, pp. 1223-1240, 2012.

[20] R. Madlener, H. Myles, "Modelling socio-economic aspects of bioenergy systems: a survery prepared for IEA bioenergy task 29", in *IEA Bioenergy Task 29 Workshop*, Brighton/UK, July 2000.

[21] P. Palensky, D. Dietrich, "Demand side management, demand response, intelligent systems and smart loads", *IEEE Transaction on Industrial Informatics*, vol. 7, pp. 381-388, 2011.

[22] HomeFlex, Eskom time of use tariff 2012 [online], Available at http://www.eskom.co.za/content/Eskom% 20Booklet.pdf.

[23] S. Boccaletti, V. Latora, Y. Moreno, M. Chevez, D. -U. Hwang, "Complex networks: structure and dynamics", *Physical Reports*, vol. 424, pp. 175-308, 2006.

[24] R. Albert, A. -L. Barabasi, "Statistical mechanics of complex networks", *Reviews of Modern Physics*, vol. 74, pp. 47-108, 2002.

[25] M. E. J. Newman, "Scientific collaboration networks I. network construction and fundamental results", *Physical review E*, vol. 64, 016131, 2001.

[26] A. Barrat, M. Barthelemy, P. Pastor-Satorras, A. Vesplgnani, "The architecture of complex weighted network", *PNAS*, vol. 101, pp. 3747-3753, 2004.

[27] J. R. Banavar, A. Maritan, A. Rinaldo, "Size and form in efficient transportation networks", *Nature*, vol. 399, pp. 130-132, 1999.

[28] D. J. Watts, S. H. Strogatz, "Collective dynamics of ‘small - world’ network", *Nature*, vol. 393, pp. 440-442, 1998.

[29] L. Backstorm, P. Boldi, M. Rosa, J. Ugander, S. Vigna, "Four degrees of separation [online], Available http://avxiv.org/pdf/1111.4570.pdf.

[30] M. Ruth, "Information, order and knowledge in economic and ecological systems: implications for material and energy use", *Ecological Economics*, vol. 13, pp. 99-114, 1995.

[31] D. J. Watts, "Network, dynamics and small world phenomenon", *American Journal of Sociology*, vol. 105, pp. 493-527, 1999.

[32] P. V. Marsden, "Homogeneity in confiding relations", *Social Networks*, vol. 10, pp. 57-76, 1988.

[33] J. Travese, S. Milgram, "An experimental study of the small world problem", *Sociometry*, vol. 32, pp. 425-443, 1969.

[34] S. Milgram, "The small world problem", *Psychology Today*, vol. 1, pp. 61-67, 1967.

[35] A. Rapport, W. J. Horroth, "A study of a large sociogram", *Behavioural Sciences*, vol. 9, pp. 279-291, 1961.

[36] M. E. J. Newman, D. J. Watts, S. H. Strogatz "Random graphs model of social networks", *PNAS*, vol. 99, pp. 2566-2572, 2002.

[37] C. Castellano, R. Pastor-Satorras, "Thresholds of epidemic spreading in networks", *Physical Reviews*, vol. 105, 218701, 2010.

[38] H. T. Buckner, "A theory of rumour transmission", *The Public Opinion Quaterly*, vol. 29, pp. 54-70, 1965.

[39] D. H. Zanette, "Dynamics of rumour propagation on small world networks", *Physical Review E*, vol. 65, 041908, 2002.

[40] Y. Moreno, M. Nekovee, A. F. Pacheco, "Dynamics of rumour spreading in complex

networks", *Physical Review E*, vol. 69, 066130, 2004.

[41] L. M. A Bettencourt, A. Cintron-Aries, D. I. Kaiser, "The power of the spread of ideas from epidemiological models", *Physica A*, vol. 364, pp. 513-536, 2006.

[42] D. J. Watts, P. S. Dodds, "Influential networks and public opinion formation", *Journal of Consumer Research*, vol. 34, pp. 441-458, 2007.

[43] B. Latane, "The psychology of social impact", *American Psychologist*, vol. 36, pp. 343-356, 1981.

[44] S. Aral, "Identifying social influence: A comment on opinion leadership and social contagion in new product diffusion", *Marketing Science*, pp. 1-7, 2010.

[45] H. Louch, "Personal network integration: transitivity and homophily in strong-tie relations", *Social Networks*, vol. 22, pp. 45-64, 2000.

[46] M. Mcpherson, L. Smith-Lovin, J. M. Cook, "Birds of a feather: homophily in social networks", *Annual Review of Sociology*, vol. 27, pp. 414-444, 2001.

[47] R. S. Burt, "Kinds of Relationships in American Discussion Networks", in *Structure of power and constraint*, Cambridge University Press, pp. 411-451, 1990.

[48] W. Kuckshinrichs, T. Kronenberg, P. Hansen, "The social return on investment in the energy efficiency of buildings in Germany", *Energy Policy*, vol. 38, pp. 4317-4329, 2010.

[49] C. E. Shannon, "A mathematical theory of communication",*The Bell Technical Journal*, vol. 27, pp. 376-423, 623-656, 1948.

[50] W. K. Ang, P. W. Jowitt, "Path entropy method for multiple source water distribution networks" *Engineering Optimization*, vol. 37, pp. 705-715, 2005.

[51] A. Yassin-Kassab, A. B. Temleman, T. T.Tankyimboh, "Calculating maximum entropy flows in multi-source, multi-demand networks", *Engineering Optimization*, vol. 31, pp.

695-729, 1999.

[52] R. E. Ulanowicz, "Information theory in ecology", *Computers and Chemistry*, vol. 25, pp. 393-399, 2001.

[53] C. Balocco, G. Grazzini, "Sustainability and information in urban system analysis", *Energy Policy*, vol. 34, pp. 2905-2914, 2006.

[54] G. Peschiera, J. E. Taylor, "The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems", *Energy and Buildings*, vol. 49, pp. 584-590, 2012.

[55] X. Xu, J.E. Taylor, A.L. Pisello, P.J. Culligan, "The impact of place-based affiliation network on energy conservation: an holistic model that integrates the influence of buildings, residents and the neighborhood context", *Energy and Buildings*, vol. 55, pp. 637-646, 2012.

[56] J. Chen , J. E. Taylor , H. Wei "Modeling building occupant network energy consumption decision making: the interplay between network structure and conservation", *Energy and Building*, vol. 47, pp. 515-524, 2012.

[57] S. Wassaerman, K. Faust, *Social network analysis in the social and behavioural sciences*, Social Network Analysis: Methods and Applications, Cambridge University Press, Cambridge, 1994.

[58] U. E. Ekpenyong, J. Zhang, X. Xia, "Mathematical modelling for social impact to energy efficiency savings", *Energy and Buildings*, vol. 47, pp. 515-524, 2014.

[59] U. E. Ekpenyong, J. Zhang, X. Xia, "Social impact of energy efficiency savings based on time of use tariff", in *Proceedings of International Conference on Applied Energy*, Pretoria, South Africa, 2013.

[60] U. E. Ekpenyong, J. Zhang, X. Xia, "How Information Propagation in Social Networks Can Improve Energy Savings Based on Time of Use Tariff", *Sustainable Cities and*

Society, vol. 19, pp. 26-33, 2015.

[61] International Performance Measurement and Verification Protocol, EVO 10000-1. Energy Valuation Organisation, 2007.

[62] X. Xia, J. Zhang, "Modelling and control of heavy-haul trains", *IEEE Control Systems Magazine*, vol. 31, pp. 18-24, 2011.

[63] C. Li, G. Chen, "Synchronization in general complex dynamical network with coupling delays", *Physica A*, vol. 343, pp. 263-278, 2004.

[64] F. Sorrentino, M. Bernardo, F. Garofalo, G. Chen, "Controllability of complex network via pinning", *Physical Review E*, vol. 75, 046103, 2007.

[65] W. Yu, G. Chen, "On pinning synchronization of complex dynamic networks", *Automatica*, vol. 45, pp. 429-435, 2009.

[66] R. Weinstein, R. Scott, C. Jones, "Measurement of 'free-riders' in energy conservation programs", *Evaluation and Program Planning*, vol. 12, pp. 121-130, 1989.

[67] M. Croucher, "Potential problems and limitations of energy conservation and energy efficiency" *Energy Policy*, vol. 39, pp. 5795-5799, 2011.

[68] Solar water heating program [Internet], Eskom Holdings SOC Limited [cited 2013 June 28], Available from: www.eskom.co.za/c/56/eskom-solar-water-heating-programme.

[69] HomeFlex Eskom Tariff [Internet], HomeFlex time of use tariff [cited 2015 June 3], Available from: www.eskom.co.za/content/Eskom% 20Booklet.pdf

[70] M.E.J. Newman, D.J. Watts, S.H. Strogatz, "Random graphs model for social networks", in *Proceedings of the National Academy of Sciences*, vol. 99, pp. 2566-2572, 2002.

[71] S. P. King, "Search with free riders", *Journal of Economic, Behaviour and Organiza-*

tion, vol. 26, pp. 253-271, 1989.

[72] *Tariffs & Charges Booklet* 2011/2012 (2011), Eskom.

[73] A. Aravindakshan, P. K. Naik, "How does awareness evolve when advertising stops?", *Marketing Letters*, vol. 22, pp. 315-326, 2011.

[74] P. A. Naik, "Estimating the half life of advertisement", *Marketing Letters*, vol. 10, pp. 351-362, 1999.

[75] M. West, B. Harrison, *Bayesian forecasting and dynamic models*. New York: Springer-Verlag, 1989.

[76] *Trimming 10% is easier than you think* [Internet] (2011). Eskom Integrated Demand Management, [cited 2015 January 10]. Available from: http://www.eskom.co.za/sites/IDM/Documents.

[77] H. Lund, “Renewable energy strategies for sustainable development", *Energy*, vol. 32, pp. 912-919, 2007.

[78] U. E. Ekpenyong, J. Zhang, X. Xia, "Social Influence and Energy Efficiency Savings", in *Proceedings of IEEE AFRICON Conference*, Mauritius, 9-12 September, 2013.

[79] N. Lior, "Energy resources and use: the present situation and possible paths to the future", *Energy*, vol. 33, pp. 842-857, 2008.

[80] B. Yu, J. Zhang, A. Fujiwara, "Analysis of the residential location choice and household energy consumption behaviour by incorporating multiple self-selected effects", *Energy Policy*, vol. 46, pp. 319-334, 2012.

[81] S. P. Borgatti, M. G. Everett, L. C. Freeman, *UCINET for Windows: Software for Social Network Analysis*, Harvard, MA: Analytic Technologies, 2002.

[82] K. Gillingham, M. J. Kotchen, D. S. Rapson, G. Wagner, "Energy policy: The rebound

effect is overplayed", *Nature*, vol. 493, pp. 475-476, 2013.

[83] B. Thomas, I. Azevedo, "Estimating direct and indirect rebound effects for U.S. households with input-output analysis Part 1: Theoretical framework", *Ecological Economics*, vol. 86, pp. 199-210, 2013.

[84] B. Thomas, I. Azevedo, "Estimating direct and indirect rebound effects for U.S. households with input-output analysis. Part 2: Simulation", *Ecological Economics*, vol. 86, pp. 188-198, 2013.