OPTIMAL BATTERY ENERGY STORAGE SCHEDULE FOR A RESIDENTIAL SYSTEM IN A DAY-AHEAD MARKET

A Project Report

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by

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CERTIFICATE

This is to certify that the thesis entitled **"Optimal Battery Energy Storage Schedule for a Residential System in a Day-Ahead Market"** submitted by **Shainam Kharumnuid, (EE12B106)** to the **Indian Institute of Technology Madras** in partial fulfilment of the requirements for the award of the degree in **Bachelor of Technology and Master of Technology** in **Electrical Engineering** is a bona-fide record of the project work done by him under my supervision.

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Shainam Kharumnuid

ABSTRACT

There is an increase in the use of dynamic pricing of electricity by most of the developed countries. In this project a study is done on the day-ahead Nordic pool market to observe whether the use of a battery energy storage system will benefit a consumer household. An algorithm is formulated which takes advantage of the dynamic pricing of electricity and the use of a battery energy storage system to buy power when the price is low and sell power when the price is high. The algorithm also ensures that the consumption demand of the consumer is met. It is observed that there is indeed a reduction in the cost-per-day of electricity by using this algorithm. An approximate optimal battery capacity is then estimated for a specific case of battery efficiency and power capacity by using the algorithm on increasing values of battery capacity and plotting a cost-per-day vs. battery capacity graph. It is observed that beyond a specific battery capacity, the cost-per-day no longer reduces making it the approximate optimal battery capacity. Finally, the payback period of the investment is calculated and it is observed that the payback period is greater than the warranty period of the battery making the investment infeasible. However, with an increase in research on battery energy storage systems, the initial cost will decrease and will one day make this a viable investment.

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NOTATIONS

B_{max}	Maximum Capacity of the BESS
BE (t)	Energy contained in the BESS at the time instant "t"
BESS	Battery Energy Storage System
B_G (i)	Energy transferred from the Battery to the Grid in the interval "i"
B_H (i)	Energy transferred from the Battery to the Household in the interval "i"
C (i)	Energy consumption by the Household in the interval "i"
G_H (i)	Energy transferred from the Grid to the Household in the interval "i"
G_B (i)	Energy transferred from the Grid to the Battery in the interval "i"
η	Efficiency of the BESS
P_{max}	Maximum Power of the BESS
SP (i)	Spot Market Price of the interval "i"

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION AND LITERATURE REVIEW

The global demand for electricity is increasing day-by-day due to the exponential increase in population and the constant advancement in technology. Due to this increase in demand there is a requirement for a similar increase in supply. However, the upgrading of power stations and power networks happen at a slower pace due to the funding required and the economic risk involved in setting up new power plants. Hence, sometimes it is not possible to satisfy peak demands either due to unexpected outages or faults at the generators.

One way to reduce peak demand would be for the consumers to use a Battery Energy Storage System (BESS) thereby storing energy during non-peak times and using the energy from the BESS during peak times. This would cause a reduction in peak demand thereby reducing the number of instances where supply does not meet demand. This however, will not work in a system which has a constant price for electricity.

Dynamic pricing has been enabled by recent smart-grid technologies such as smart meters. There are two main types of dynamic pricing methodologies adopted.

The first method is called “Time-Of-Use” pricing where the price is divided into two or three constant levels (‘off-peak’, ‘mid-peak’ and ‘on-peak’) depending on the time of the day.These levels will have a correlation with the average demand during that segment of the day. These price levels are determined well in advance and are usually not changed more than twice a year. Studies have been done to examine the optimal operation of the BESS in a "Time-Of-Use" system using Dynamic Programming [3], Non-linear Programming [4] and Multipass Iteration Particle Swarm Optimization [5] approaches to optimize the system with respect to charge and discharge scheduling of the battery in order to maximize the benefits of the difference in prices.

The second method of dynamic pricing is called "Real-Time Pricing" where the price changes either hourly or half-hourly to reflect the price on the wholesale energy market. Studies have been done in a "Real-Time Pricing" environment as well to show that the use of a BESS will help to cut down the cost of electricity [1]-[2]. In [2], they argued that the cost-optimizing storage policy is threshold-based and analytically showed the existence of an optimal threshold policy. However, in [2], they did not consider the possibility of selling power back to the grid. Studies have been done in the day-ahead market as well [1] where the hourly electricity prices are available one day in advance. Here they, also try to find the payback period of using a battery energy storage system but the cost optimization formulation does not take the demand pattern into consideration.

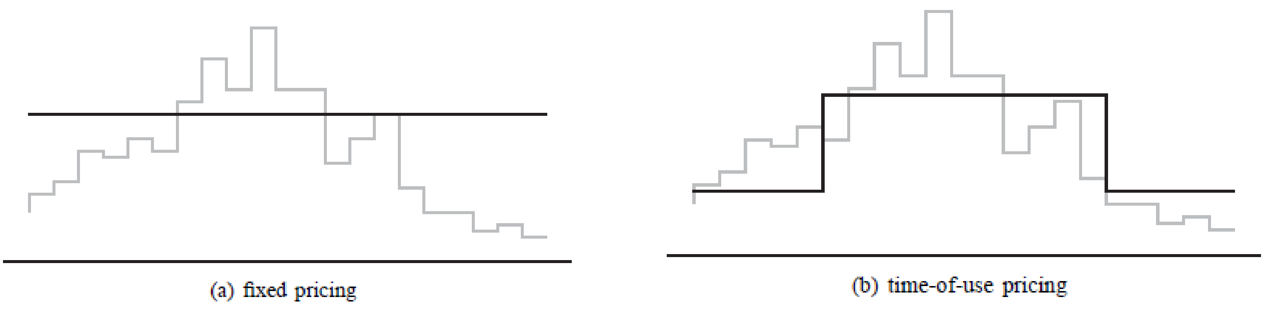

Fig. 1.1 Different types of pricing methods

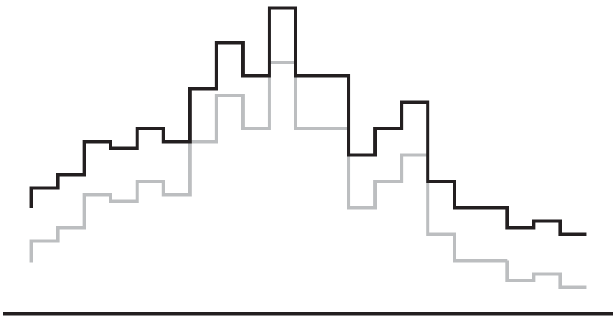

Fig. 1.1.(**contd.**)

The use of a BESS will thus help a user take advantage of the dynamic pricing by buying power when the price is low and selling it back to the grid when the price is high. This allows users to benefit from the varying electricity price without changing their electricity consumption pattern accordingly. The economic viability of such a setup has always been a drawback in the past but recent developments and reductions in cost of home-batteries has made this setup more viable.

In this project we will try to formulate and test an algorithm which will help a consumer household use a battery energy storage system to take advantage of the dynamic pricing of electricity. Hence, the algorithm should help schedule the transfer of energy between the grid, battery and the household every day at the same time minimizing the cost of electricity per day of the household.

1.2 OVERVIEW AND STRUCTURE OF THE THESIS

In the 2ndchapter of this thesis, we will formulate a model where a consumer household uses a battery energy storage system in a dynamic pricing environment and the model will try to schedule the transfer of energy between the three entities (Grid, BESS and household) and try to minimize the household's cost-per-day of electricity and at the same time meet the consumption demands of the household for that day.

In Chapter 4, we will test the model on real-life data and observe if there is any cost optimization for the household by comparing with the cost when a battery energy storage system is not used and also with the case when we can buy from the grid but not sell it back.

In Chapter 5, we will use the model formulated in Chapter 5 and test it on a few case studies. First, the model will be tested for the case of stacking N batteries and observing if there is any minimization in cost-per-day with an increase in N. The next simulation will be to find the battery capacity at which the cost saturates. Finally, the payback period of the investment will be calculated to conclude whether the investment is viable or not.

A flow chart is given which will help to understand the structure of the thesis better.

1.2.1 Flow Chart

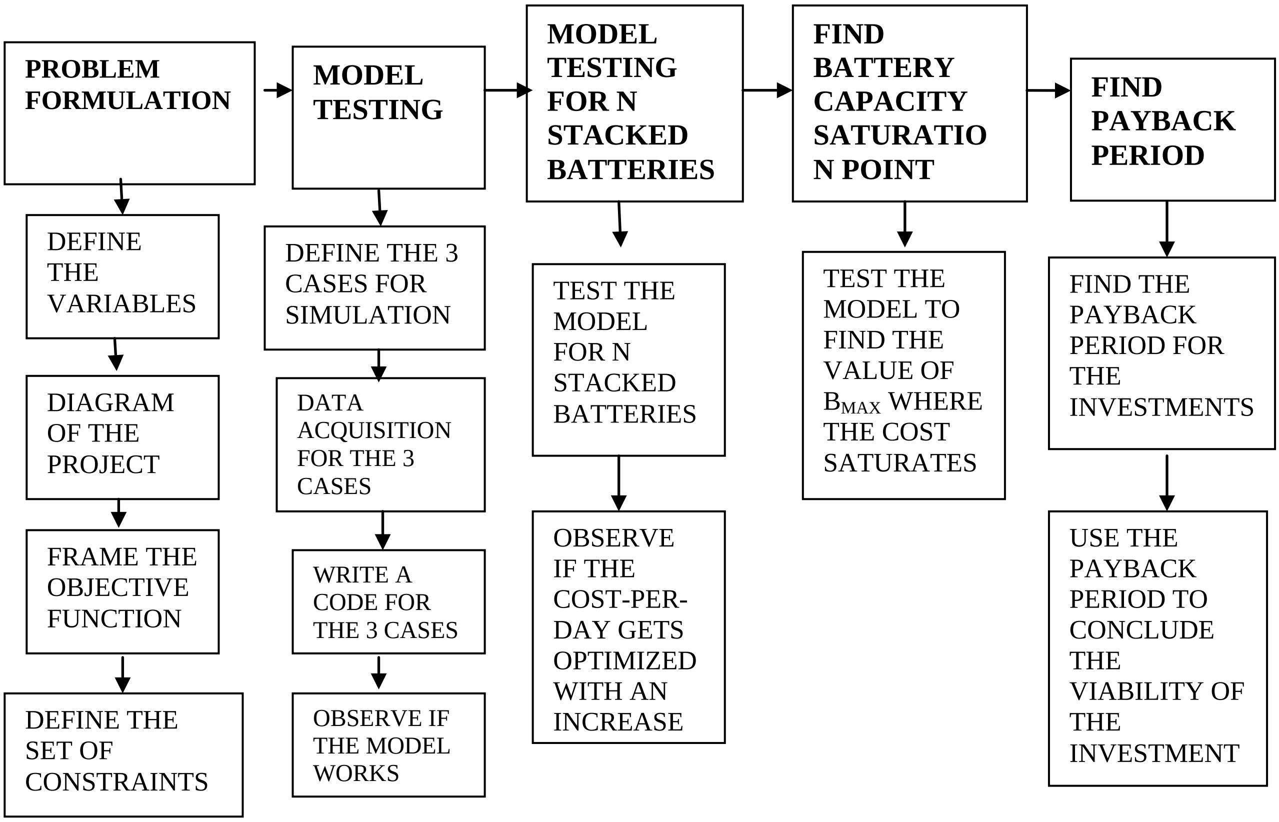

Fig 1.2 Flow Chart of the Structure of the Thesis

CHAPTER 2

FORMULATION AND METHODOLOGY

2.1 MODEL FORMULATION

The main purpose of this chapter is to formulate a model which will help a consumer household take advantage of the dynamic pricing of electricity by using a battery energy storage system (BESS). The model should take the daily price and the consumption demand from the households as inputs and produce an energy transfer schedule between the grid, the battery and the household which will minimize the cost-per-day of the household but at the same time meet the demands.

We start offby defining the variables and the assumptions that are necessary for the model. Then we formulate the objective function along with the specific set of constraints necessary.

We then present the methodology that will be used to solve the model.

2.1.1 Variables And Notations Used

We first start the formulation by defining the variables that will be used in the simulation.

- Let us divide the day into 24 equal hourly intervals and define each interval as i={1,2,3,4,5,.......22,23,24} such that:
    - i=m, is the time interval from the (m-1)th hour to the mth hour
- We define a variable to represent the time instant at the beginning and end of every time interval as t={1,2,3,4,.....,25} such that:
    - t=n, represents the time instant at the nth hour of the day

- Here, we start from 1 instead of 0 for simplification while writing the code

- Let the energy flow in each time interval be defined as:

  - G_H(i) : the total amount of energy transferred from the grid to the household during the time interval i

  - G_B(i): the total amount of energy transferred from the grid to the battery energy storage system (BESS) during the time interval i

  - B_G(i): the total amount of energy transferred from the battery energy storage system (BESS) to the grid during the time interval i

  - B_H(i): the total amount of energy transferred from the battery energy storage system (BESS) to the household during the time interval i

- We also define the following variables with respect to the time interval i:

  - C(i): The energy consumption by the household during the time interval i

  - SP(i): The spot market price for the time interval i

- We define the energy stored in the battery energy storage system (BESS) at every hourly time instant as:

  - BE(t): the Battery Energy contained in the BESS at the $(t-1)^{th}$ hour

- We also define the following constants which will be provided prior to the simulation:

  - η: the efficiency of the BESS(which includes any inverters/converters that might be used with the battery)

  - B_{max}: the maximum capacity of the BESS

  - P_{max}: the maximum power of the BESS

2.1.2 Diagram

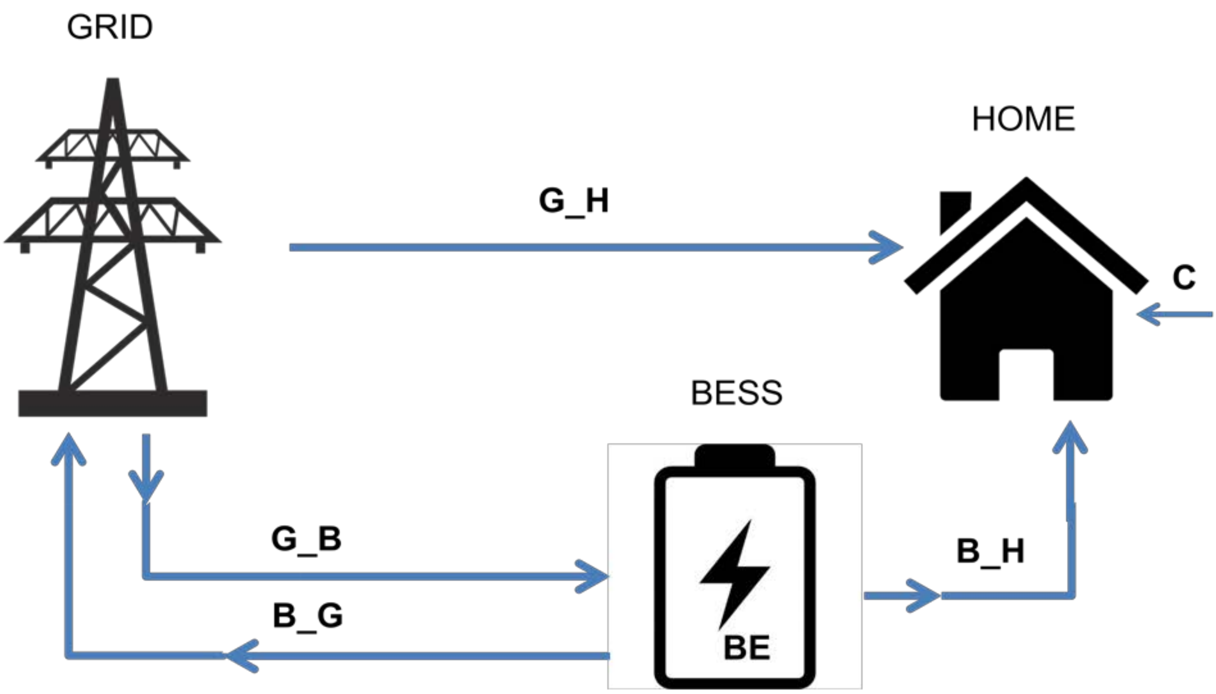

Fig 2.1 Model Diagram

2.1.3 Assumptions

Before we proceed with any further formulation, we first make the following assumptions:

1. Since the spot market price is available one day ahead, it is assumed that all the energy stored in the battery energy storage system (BESS) is discharged in the same day. Hence, we assume that the energy stored in the battery energy storage system at 0:00 hour is zero, or BE(1) = BE(25) = 0.

2. We assume that the spot market prices are not changed by the operation of the battery energy storage system.

3. The η used for the simulation includes the efficiency of the battery as well as any inverters or converters used along with the battery and we simply state this whole setup as the Battery Energy Storage System (BESS)

4. We also assume that the Battery Efficiency (η) remains constant with time.

2.1.4 Objective Function

Our main objective is to use a battery energy storage system (BESS) to take advantage of the varying electricity price by buying electricity when the price is low and selling it back to the grid when the price is high. We want to reduce the amount of money being used by the consumer on electricity hence we want to minimize the cost of using electricity with the help of the battery energy storage system (BESS). We also want to ensure that the electricity consumption demand of the consumer household is met.

Hence the objective function will be:

$$\text{Cost} = \sum_{i=1}^{24} [G\_H(i) + G\_B(i) - (\eta * B\_G(i))] * SP(i) \; ; \qquad (2.1)$$

where,

- [G_H(i) + G_B(i)]: Total amount of energy drawn from the grid during the time interval “i”
- η*B_G(i): Total amount of energy transferred back to the grid during the time interval “i”
- SP(i): Spot market price of the time interval “i”.

Here, we want to minimize the above objective function under a defined set of constraints.

2.1.5 Constraints

For every optimization problem, there exists an objective function and a set of constraints which have to be met while optimizing (maximizing or minimizing) the objective function. For the above objective function, the following are the set of constraints:

- **Non-negativity constraints**

The energy transfer variables represent a one-way transfer of energy and hence they cannot be negative. We therefore impose the following constraints on the variables:

$$G\_H(i) >= 0; \text{ for all } i \in [1, 24] \quad (2.2)$$

$$G\_B(i) >= 0; \text{ for all } i \in [1, 24] \quad (2.3)$$

$$B\_G(i) >= 0; \text{ for all } i \in [1, 24] \quad (2.4)$$

$$B\_H(i) >= 0; \text{ for all } i \in [1, 24] \quad (2.5)$$

The energy present in the battery can also never be negative; hence we impose the following constraint on the battery energy variable:

$$BE(t) >= 0; \text{ for all } t \in [1,25] \quad (2.6)$$

- **Consumption constraint**

The energy that is being transferred to the household at a particular time interval "i" should be equal to the consumption demand [C(i)] of that time interval. Hence, we get the following equation:

$$G\_H(i) + \{\eta * B\_H(i)\} = C(i), \text{ for all } i \in [1,24] \quad (2.7)$$

where,

- [G_H(i) + {η*B_H(i)}] is the total amount of energy that arrives at the household during the time interval "i".

- **Battery energy equation**

At every time interval "i", there will be an energy transfer between the grid and the battery (G_B(i) and B_G(i)) as well as between the grid and the household (B_H(i)). Hence there will be a change in the energy present in the battery (BE(t)) between the time instant "t" and "t+1". The time interval between the time instants "t" and "t+1" is "i". We therefore define the change in battery energy with the following equation:

$$BE(t+1) = BE(t) + [\eta * G\_B(i)] - [B\_G(i) + B\_H(i)], \text{ for all } \mathbf{i=t} \in [1,24] \quad (2.8)$$

where,

> -[η*G_B(i)] is the amount of energy that arrives at the battery energy storage system (BESS) during the time interval "i" which is the time period between the instants t and (t+1)
>
> -[B_G(i) + B_H(i)] is the amount of energy that leaves the battery energy storage system (BESS) during the time interval "i" which is the time period between the instants t and (t+1)

- **Battery constraints**

The battery energy storage system that we use will have it's own functional limitations like the capacity and power constraints. Hence we add them below:

1. Capacity constraint

$$BE(t) <= B_{max} \text{ , for all } t \in [1,25] \quad (2.9)$$

2. Power constraint

$$G\_B(i) <= P_{max}; \text{ for all } i \in [1,24] \quad (2.10)$$

$$B\_G(i) <= P_{max}; \text{ for all } i \in [1,24] \quad (2.11)$$

$$B\_H(i) <= P_{max}; \text{ for all } i \in [1,24] \quad (2.12)$$

We earlier made the assumption that the energy stored in the battery on a particular day is completely used up in that day itself, which means that the battery should be completely discharge at the beginning and at the ending of the day. We apply this constraint by using the following equation:

3. BE(1) = BE(25) = 0; (2.13)

Now, it is not optimal for energy transfer to take place from the grid to the battery and from the battery to the consumer in the same time interval. It is also not optimal for the battery to draw power from the grid and transfer power to the grid in the same interval. Hence we impose the following constraints:

- [G_B(i)]*[B_H(i)] = 0; for all i ϵ [1, 24] (2.14)
- [G_B(i)]*[B_G(i)] = 0; for all i ϵ [1, 24] (2.15)

Hence, this now becomes a Quadratic Programming (QP) Problem.

Now that the model has been defined properly, we need to test the model on real-life practical cases and observe if the model performs well. We want to observe if the model takes advantage of the price differences throughout the day to buy when the price is low and sell when the price is high and at the same time meeting the required consumption needs of the consumer household.

2.2 METHODOLOGY

A mathematical optimization technique formulates the problem in a mathematical representation; provided the objective function and/or the constraints are nonlinear, the resulting problem is designated as Non Linear optimization Problem (NLP). A special case of NLP is quadratic programming in which the objective function is a quadratic function of x. If both the objective functions and the constraints are linear functions of x, the problem is designated as a Linear Programming (LP) problem. Other categories may also be identified based on the nature of the variables. For instance, if x is of integer type, the problem is denoted by Integer Programming (IP). Mixed types such as MILP (Mixed Integer Linear Programming) may also exist in which even though the variables may be both real and integer, the problem is also of LP type.

The above problem is solved using the LINGO programming language. LINGO includes a set of built-in solvers to tackle a wide variety of problems. Unlike many modelling packages, all of the LINGO solvers are directly linked to the modelling environment. This integration allows LINGO to pass the problem to the appropriate solver directly in memory rather than through more sluggish intermediate files. This direct link also minimizes any compatibility problems between the modelling language component and solver components.

The optional Barrier solver of LINGO provides an alternative means of solving linear models. The Barrier option utilizes a barrier or interior point method to solve linear models. Unlike the Simplex solvers that move along the exterior of the feasible region, the Barrier solver moves through the interior space to find the optimum. Depending upon the size and structure of a particular model, the Barrier solver may be significantly faster than the Simplex solvers and can provide exceptional speed on large linear models -- particularly on sparse models with more than 5,000 constraints or highly degenerate models.

For nonlinear programming models, the primary underlying technique used by LINGO's optional nonlinear solver is based upon a Generalized Reduced Gradient (GRG) algorithm which is a generalization of the reduced gradient method. However, to help get to a good feasible solution quickly; LINGO also incorporates Successive Linear Programming (SLP). The nonlinear solver takes advantage of sparsity for improved speed and more efficient memory usage.

Local search solvers are generally designed to search only until they have identified a local optimum. If the model is non-convex, other local optima may exist that yield significantly better solutions. Rather than stopping after the first local optimum is found, the Global solver will search until the global optimum is confirmed. The Global solver converts the original non-convex, nonlinear problem into several convex, linear sub problems. Then, it uses the branch-and-bound technique to exhaustively search over these sub problems for the global solution.

In addition to solving linear and mixed integer models, with the Barrier option LINGO can automatically detect and solve models in which the objective function and/or some constraints include quadratic terms. By taking advantage of the quadratic structure, LINGO can solve these models much more quickly than using the general nonlinear solver. LINGO can even handle quadratic models with binary and general integer restrictions.

CHAPTER 3

DAY-AHEAD ELECTRICITY MARKET AND BATTERY ENERGY STORAGE SYSTEMS

3.1 DAY – AHEAD ELECTRICITY MARKET

The Day-Ahead Market that we use in our project is the Nordic Pool Market.

3.1.1The Nordic Pool Market

Power is a vital component of our everyday lives that supports our modern basic necessities. As power production and transmission capacity has been extended over the years, transmission of power between countries has become more common. This has resulted in the evolution of a dynamic market where power can be bought or sold across areas and countries more easily.

Supply and demand set the price

The balance between supply and demand determines the power price. The weather conditions and the production levels of the power plants are other factors that can impact power prices.

Integrating Nordic and Baltic markets

The Nordic countries deregulated their power markets in the early 1990s and brought their individual markets together in a common Nordic market. Estonia, Latvia and Lithuania deregulated their power markets and joined the Nord Pool market in 2010-2013.

The meaning of the term ‘deregulation’ is that the state is no longer running the power market and instead, free competition is introduced. The efficiency of the market for the exchange of power between countries and increased security of supply was the main motivation for deregulation. Available power capacity can be used more efficiently in a large region as compared to a small one, and integrated markets enhance productivity and improve efficiency.

An emerging European market

Now that transmission capacity and coupling is in place between the Nordic countries, the European continent and the Baltics, the power market covers large parts of Europe. This means that power from many different sources – hydro, thermal, nuclear, wind and solar – enters the grid. This ensures a more ‘liquid’ market, where large volumes are traded daily, and a more secure power supply.

3.1.2 Day-Ahead Market

The day-ahead market is the main arena for trading power. Here, contracts are made between seller and buyer for the delivery of power the following day, the price is set and the trade is agreed.

Driven by planning

Daily trading is driven by a member’s planning. A buyer, typically a utility, needs to assess how much energy (volume) it will need to meet the demand the following day, and how much it is willing to pay for this volume, hour by hour. The seller, for example the owner of a hydroelectric power plant, needs to decide how much he can deliver and at what price, hour by hour. These needs are reflected through orders entered by buyers and sellers into the Nord Pool day-ahead trading system.

Setting the price and closing the deal

12:00 CET is the deadline for submitting bids for power which will be delivered the following day. The trading system feeds the information into a specialist computer system which calculates the price, based on advanced algorithm. Put simply, the price is set where the curves for sell price and buy price meet.

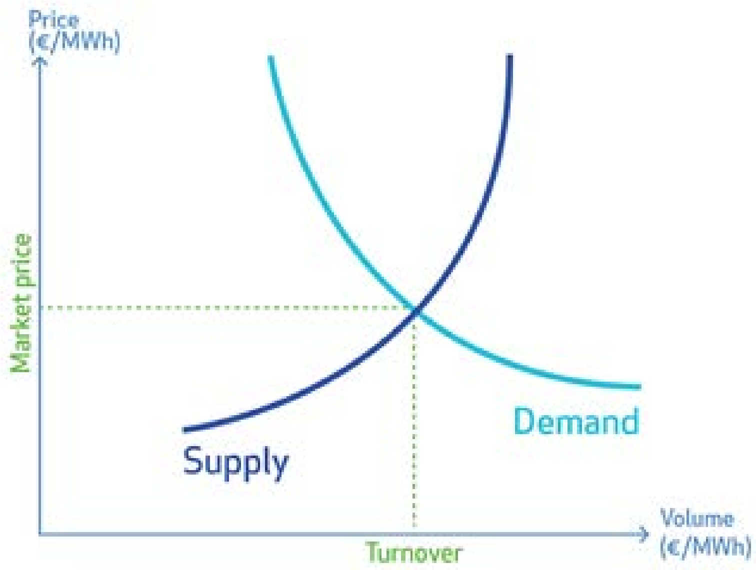

Fig. 3.1 Supply-Demand curve

Hourly prices are typically announced to the market at 12:42 CET or later. Once the market prices have been calculated, trades are settled. From 00:00 CET the next day, power contracts are physically delivered (meaning that the power is provided to the buyer) hour for hour according to the contracts agreed.

The cost of transmission constraints

While supply and demand are the key factors determining the hourly market prices, transmission capacity also plays a role. Bottlenecks can occur where power connections are linked to each other, if large volumes need to be transmitted to meet demand. To relieve this congestion, different area prices are introduced. In other words, when transmission capacity gets constrained, the price is raised to reduce demand in the areas affected.

3.1.3 Price Formation

The primary role of a market price is to establish equilibrium between supply and demand. The day-ahead market is at Nord Pool is an auction based exchange for the trading of prompt physically delivered electricity.

The day-ahead market carries out the key task of balancing supply and demand in the power market with a certain scope for forward planning. In addition to this, there is a final balancing process for fine adjustments in a real-time balancing market.

The 'Invisible Hand' which creates equilibrium in most other markets is replaced in the power markets by a concrete visible hand. This is the day-ahead market which receives bids and offers from producers and consumers alike and calculates and hourly price which balances these opposing sides. Nord Pool publishes a price for each hour of the coming day in order to synthetically balance supply and demand.

Every morning, members post their orders for the coming day. Each order specifies the volume in MWh/h that a member is willing to buy or sell at specific price levels (EUR/MWh) for each individual hour in the following day.

Electricity produced at the lowest cost every hour of the day

A properly functioning and competitive power market produces electricity at the lowest possible price for every hour of the day. The balance price represents both:

i. The cost of producing one kWh of power from the most expensive source needed to be employed in order to balance the system – either from a domestic installation or from external imports, and

ii. The price that the consumer group is willing to pay for the final kWh required to satisfy demand.

The price formation process is therefore economically effective for society.

Nord Pool establishes prices in the same way as other energy markets

This type of price formation is usually labelled as marginal price setting and gives a false impression that the establishment of prices in the electricity market is different from the price formation process in other commodity markets. The only difference lies in the significantly higher requirements for the secure delivery of electricity because it must be delivered at the precise moment it is needed by the consumer. Market price formation is therefore a more accurate term than marginal price setting.

There is, however, a great difference between electricity and the other energy (and commodity) markets in that the variable costs of production vary so greatly between different types of installations – wind and hydropower with a virtual nil cost at one extreme and gas turbines at the other end of the scale.

In order to satisfy fluctuating consumer demand at the lowest cost, a broad variety of generating techniques are required. Some installations are capital intensive but can be run year round and are relatively fuel efficient (hydro, nuclear, coal-fired). Other units such as CHP (combined heating and power) are used less frequently to cover winter heating demand at times of higher prices, while energy intensive units such as gas fired turbines are used for brief periods of very high price and demand.

3.1.4 Intraday Market

Nord Pool offers an intraday market covering the Nordic, Baltic, UK and German markets. The intraday market supplements the day-ahead market and helps secure the necessary balance between supply and demand in the power market for Northern Europe.

A majority of the volume handled by Nord Pool is traded on the day-ahead market. For the most part, the balance between supply and demand is secured here. However, there may be unpredictable incidents that take place between the closing of the day-ahead market at noon CET and delivery the next day. These unpredictable incidents may vary from the shutting down of operations of a Nuclear power plant in Sweden, to the presence of stronger winds in Germany which leads to a higher than anticipated power generation. At the intraday market, buyers and sellers can trade volumes close to real time to bring the market back in balance.

Trading close to real time

At 14:00 CET, capacities available for Nord Pool's intraday trading are published. This is a continuous market and trading takes place everyday around the clock until one hour before delivery. Prices are set based on a first-come, first-serve principle, where best prices come first – highest buy price and lowest sell price.

Increasingly Important

As the generation of power due to wind increases, the unpredictability of power generation also increases making the intraday market even more important. Wind power is unpredictable by nature, and imbalances between day-ahead contracts and produced volume often need to be offset. The market plays a key role in the development of intraday power trading in Europe. Future prospects indicate exponential growth, reaching 1.9 GW installed wind capacity worldwide in 2020 (Source: World Wind Energy Association). This type of market will help to increase the share of renewable energy in the energy mix.

3.2 BATTERY ENERGY STORAGE SYSTEMS

The increase in funding for research in energy storage systems has led to the development of more advanced batteries which have a longer lifetime, which are cheaper, more portable and efficient. This has led to the increase in the use of a battery energy storage system in households. Some of the more renowned Battery Energy Storage Systems are as follows:

3.2.1 Powervault

The Powervault is a home electricity product which helps households use energy more efficiently by storing and supplying solar energy or cheap electricity, and provide emergency power during black outs. Its properties are given below:

Lithium Ion Version (G200 –Li 2kWh)

Nominal Capacity:	2.2 kWh
Usable Capacity:	2 kWh
Weight:	85 kg
Batteries :	1 x 75 Ah (90% Depth of Discharge)

Input (AC)

Max. Continuous Power:	800 VA
Nominal Voltage:	230 V
Full Power Voltage Range:	217 to 253
Maximum Current:	Fused to 7A
Peak Power:	1.6 kW (1 second)

Output (AC)

Maximum Continuous Power:	1200 VA
Nominal Voltage:	230 V
Nominal Current:	5.2 A
Frequency:	50 Hz
PF:	0.99

3.2.2 SonnenBatterie Eco

Engineered in the energy village Wildpoldsried in Germany and made in the U.S.A., the sonnenBatterie is one of the world's most accepted lithium based energy storage system. It has its own integrated smart electronics which helps to manage energy use throughout the day, detecting when there is excess power and storing it for use at night. It's properties are given below:

Power Unit

Continuous Output(AC):	3000 W – 8000 W
Usable Capacity:	4 kWh – 16 kWh (in 2kWh steps)
Dimensions W/H/D (4 – 8 kWh):	26 inches / 51 inches / 14 inches
Dimensions W/H/D (10 – 16 kWh):	26 inches / 71 inches / 14 inches
Backup Power Capability	

General

Maximum Efficiency of Inverter:	93%
Ambient Temperatures:	5^{o} C to 45^{o} C / 41^{o}F to 113^{o}F
AC Specs:	240 VAC/ Split Phase/60Hz
Lifetime:	1000les or 10 years

3.2.3 Tesla Powerwall 2

The Tesla Powerwall 2 is a home for small businesses that can store solar energy as well as energy from the grid to deliver power as and when the user wants. It is compact and easy to install. It is touch-safe for the entire family with no live wires or bulky vents. Wall mounted or floor mounted, up to ten Powerwall units can be stacked to power homes of any size. It has a water resistant and dust proof enclosure for installation inside or outdoors. The powerwall has an internal inverter to convert DC solar energy from the Solar Roof to the AC energy required at home, thus lowering cost and complexity in the case of solar energy. It also has a liquid thermal control system which regulates the Powerwall's internal temperature to maximize battery performance in any climate. It is also the most affordable home battery in terms of cost per kWh. The technical specs of the Tesla Powerwall are given below:

Usable Capacity:	13.5 kWh
Depth of Discharge:	100%
Efficiency:	>90% round-trip
Power :	7kW peak / 5kW continuous
Scalable:	Up to 10 Powerwalls
Operating Temperature:	-4^{o}F to 122^{o}F / -20^{o}C to 50^{o}C
Dimensions: L x W x D :	45 inches x 30 inches x 6 inches
Weight:	276 lb / 125 kg
Warranty:	10 years
Installation:	Floor or Wall mounted and Indoors or Outdoors

The Tesla Powerwall 2 is the battery used for the simulations in the project.

CHAPTER 4

MODELING AND SIMULATION

We want to test the model formulated in Chapter 2 using LINGO programming language for three special cases and observe if there is any advantage to the cost of using electricity.

Case 1

We find the cost per day when no battery energy storage system (BESS) is used.

Case 2

We take the case when a battery energy storage system (BESS) is used but the option of selling back to the grid is not available.

Case 3

This is the main objective where we optimize for the case when a battery energy storage system (BESS) is used and both buying from the grid and selling to the grid is possible.

4.1. DATA USED FOR SIMULATION

For the day-ahead spot market price, we take the data from the Nordic Pool [7] for 2nd March 2015 in Great Britain. As for the consumption data, we get it from [8].

For the battery energy storage system (BESS) capacity and efficiency data, we take the values of the Tesla Powerwall 2.

– $B_{max} = 13.5kWh$ (4.1)

– $P_{max} = 7kW$ (4.2)

– $\eta = 0.9$ (4.3)

The hourly spot market price and consumption data for 2nd March 2015 is given in Table 4.1

Table 4.1 Energy and Consumption Data for 2nd March 2015

Index	Time	Energy Consumption in Wh (02-03-2015)	Spot Market Price EUR/Wh (02-03-2015)
1	12am -1 am	2759	0.00004819
2	1- 2am	1300	0.00005082
3	2- 3am	227	0.0000483
4	3- 4am	178	0.00004131
5	4- 5am	279	0.00003854
6	5- 6am	183	0.00004805
7	6- 7am	256	0.00006383
8	7- 8am	204	0.00006332
9	8- 9am	190	0.00007109
10	9- 10am	270	0.00006671
11	10- 11am	171	0.0000633
12	11- 12am	285	0.00005435
13	12- 1pm	172	0.00005229
14	1- 2pm	184	0.00005454
15	2- 3pm	276	0.00004953
16	3- 4pm	173	0.00005093
17	4- 5pm	1058	0.00005941
18	5- 6pm	2248	0.00006141
19	6- 7pm	1792	0.00012812
20	7- 8pm	1105	0.0000867
21	8- 9pm	1375	0.00005719
22	9- 10pm	4964	0.00005622
23	10- 11pm	3382	0.00004976
24	11- 12am	2366	0.0000506

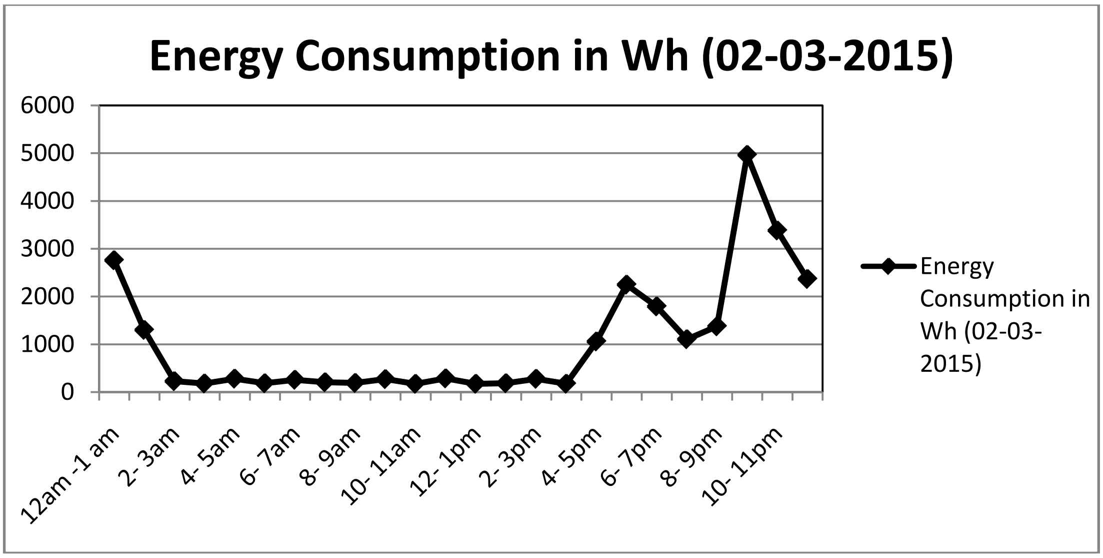

Fig 4.1 Energy Consumption Trend

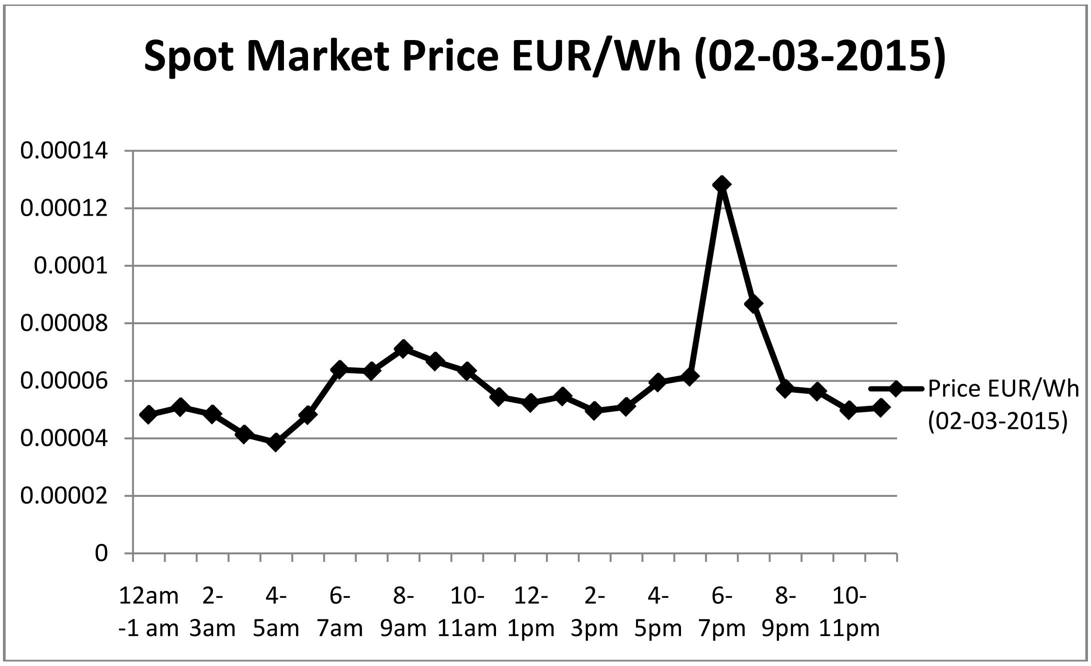

Fig 4.2 Spot Market Price Trend

Notice the **price peaks** for the intervals (8am – 9am) and (6pm- 7pm), **price depression** for the interval (4am-5am) and also the consumption peaks for the intervals (5pm-6pm) and (9pm-10pm) for future reference.

4.2. MODEL TESTING

4.2.1 Case 1: When No Battery Is Used

This is the normal case where the household does not use a battery energy storage system and energy gets transferred from the grid directly to the household. The cost-per-day for this case is simply the sum of the product of the consumption per interval with the price per interval, or,

$$\text{Cost} = \sum_{i=1}^{24} [C(i)*SP(i)]; \tag{4.4}$$

where,

- C(i): Consumption during the time interval "i";
- SP(i): Spot market price for the time interval "i";

The cost for this case comes to:

$$\textbf{CASE 1 COST = € 1.538 per day} \tag{4.5}$$

4.2.2 Case 2: When A Battery Is Used But The Option Of Selling Back To The Grid Is Not Available

In this case, the household uses a battery energy storage system but does not sell back any power to the grid, i.e., all the energy from the battery gets transferred only to the household. This implies that there will be no transfer of energy from the battery energy storage system to the grid, that is,

$$\mathbf{B\_G(i) = 0}; \text{ for all } i \in [1,24] \tag{4.6}$$

Hence, the original optimization model needs to be adjusted to match this scenario. The adjusted model is as follows:

Objective Function

$$\text{Cost} = \sum_{i=1}^{24} [G\_H(i) + G\_B(i)]*SP(i); \quad (4.7)$$

Constraints

1. Non-negativity constraints

- $G\_H(i) >= 0$; for all $i \in [1,24]$ (4.8)
- $G\_B(i) >= 0$; for all $i \in [1,24]$ (4.9)
- $B\_H(i) >= 0$; for all $i \in [1,24]$ (4.10)
- $BE(t) >= 0$; for all $t \in [1,25]$ (4.11)

2. Consumption constraint

- $G\_H(i) + [\eta*B\_H(i)] = C(i)$; for all $i \in [1,24]$ (4.12)

where,

- $\{G\_H(i) + [\eta*B\_H(i)]\}$ is the total amount of energy transferred to the household during the time interval "i".

3. Battery Energy constraint

- $BE(t+1) = BE(t) + [\eta*G\_B(i)] – B\_H(i)$, for all **i=t** $\in [1,24]$ (4.13)

where,

-[η*G_B(i)] is the amount of energy that arrives at the battery energy storage system (BESS) during the time interval "i" which is the time period between the instants t and (t+1)

- B_H(i) is the amount of energy that leaves the battery energy storage system (BESS) during the time interval "i" which is the time period between the instants t and (t+1)

4. Battery constraint

- $BE(t) <= B_{max}$, for all t ϵ [1, 25] ………. *Capacity constraint* (4.14)
- BE(1) = BE(25) = 0; ……………………*due to initial assumption* (4.15)
- $G\_B(i) <= P_{max}$, for all i ϵ [1, 24] ………*Power constraint* (4.16)
- $B\_H(i) <= P_{max}$, for all i ϵ [1, 24] ……...*Power constraint* (4.17)

Results

After running the code in Appendix 1 on the data from (4.1), we get the following results:

Table 4.2 Energy Transfer pattern for Case 2

Index	Time	G_H(Wh)	G_B(Wh)	B_G(Wh)	B_H(Wh)
1	12am -1 am	2759	0	0	0
2	1- 2am	1300	0	0	0
3	2- 3am	227	0	0	0
4	3- 4am	178	6999	0	0
5	4- 5am	279	6999	0	0
6	5- 6am	183	0	0	0
7	6- 7am	0	0	0	284.4444
8	7- 8am	0	0	0	226.6667
9	8- 9am	0	0	0	211.1111
10	9- 10am	0	0	0	300
11	10- 11am	0	0	0	190
12	11- 12am	285	0	0	0
13	12- 1pm	172	0	0	0
14	1- 2pm	184	0	0	0
15	2- 3pm	276	0	0	0
16	3- 4pm	173	0	0	0
17	4- 5pm	0	0	0	1175.556
18	5- 6pm	0	0	0	2497.778
19	6- 7pm	0	0	0	1991.111
20	7- 8pm	0	0	0	1227.778
21	8- 9pm	0	0	0	1527.778
22	9- 10pm	2294.62	0	0	2965.978
23	10- 11pm	3382	0	0	0
24	11- 12am	2366	0	0	0

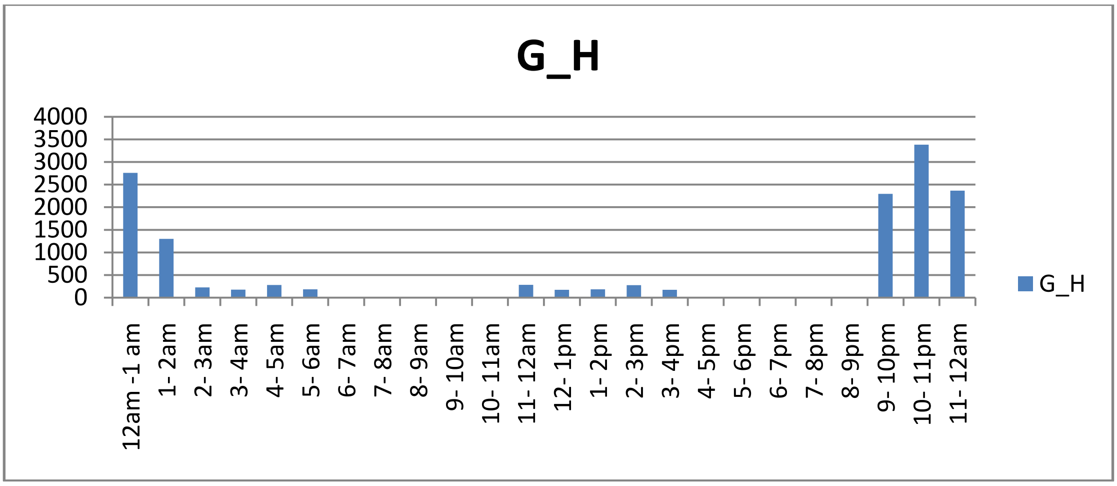

Fig 4.3 Hourly energy transfer pattern from the grid to the household

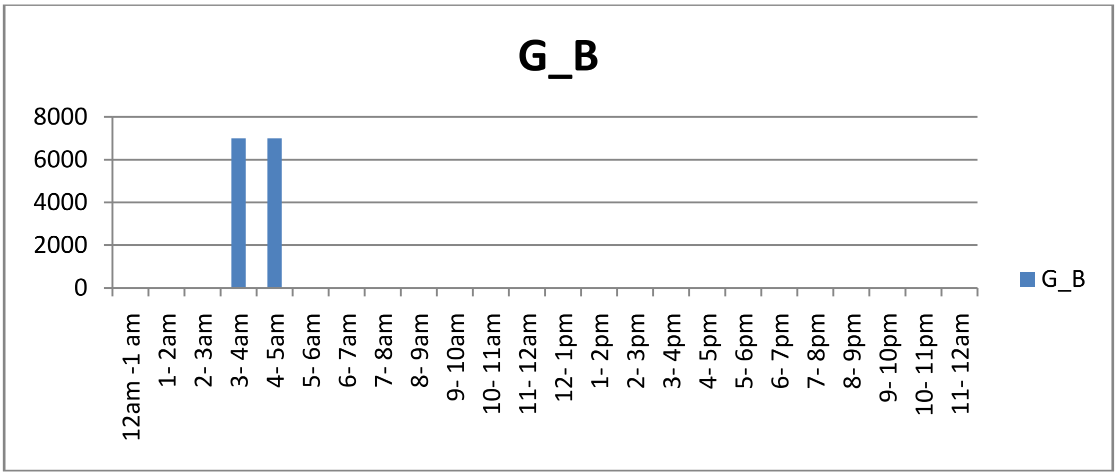

Fig 4.4 Hourly energy transfer pattern from the grid to the battery

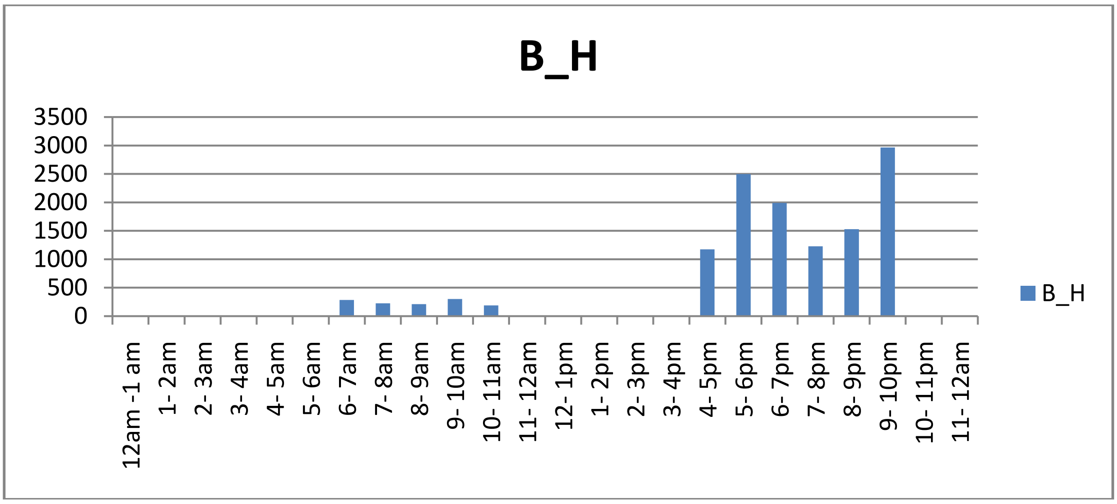

Fig 4.5 Hourly energy transfer pattern from the battery to the household

As we can see, the scheduling takes into account the dynamic pricing of electricity and adjusts accordingly such that more energy is drawn from the grid when the price of electricity is low. It can be seen that during the peak price interval of (6pm – 7pm), there is no energy transferred from the grid and all the energy required by the household is taken from the battery energy storage system. This means that the scheduling was done in such a way that the battery was charged up in the earlier intervals and that energy was then used during the price peak interval.

Table 4.3 Hourly Battery Energy pattern for Case 2

Index	Time	BE(Wh)		Index	Time	BE(Wh)
1	12am	0		**14**	1pm	11385.97778
2	1am	0		**15**	2pm	11385.97778
3	2am	0		**16**	3pm	11385.97778
4	3am	0		**17**	4pm	11385.97778
5	4am	6299.1		**18**	5pm	10210.42222
6	5am	12598.2		**19**	6pm	7712.644444
7	6am	12598.2		**20**	7pm	5721.533333
8	7am	12313.75556		**21**	8pm	4493.755556
9	8am	12087.08889		**22**	9pm	2965.977778
10	9am	11875.97778		**23**	10pm	0
11	10am	11575.97778		**24**	11pm	0
12	11am	11385.97778		**25**	12am	0
13	12pm	11385.97778				

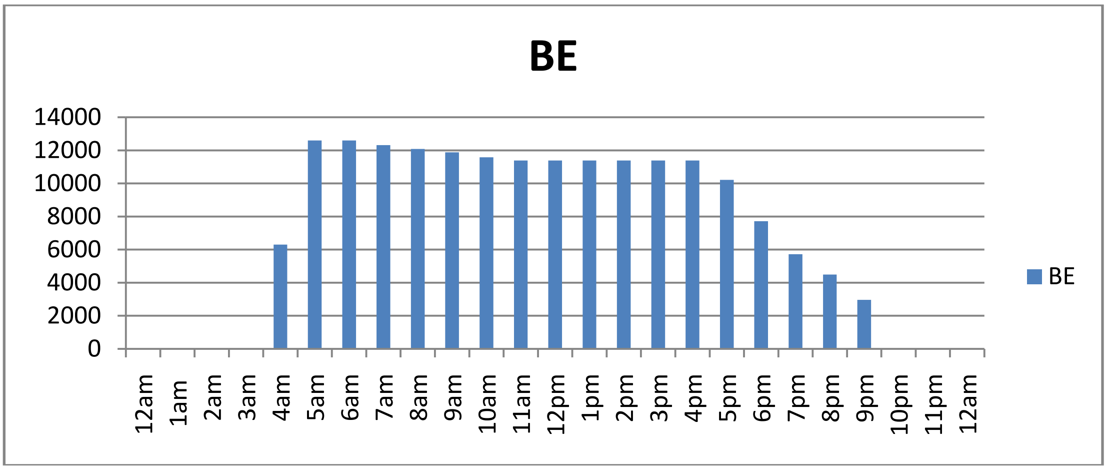

Fig 4.6 Hourly battery energy pattern for Case 2

As we can see, the model takes advantage of the presence of the battery energy storage system (BESS) to buy more power when the price is low with the intention of using it during instances when the price is high.

Naturally, a minimization of the cost is achieved as compared to Case 1. The cost comes down to € 1.27 per day.

$$\textbf{CASE 2 COST = € 1.27 per day} \tag{4.18}$$

4.2.3 Case 3: When A Battery Is Used And Both Selling And Buying Of Power Is Considered

Here, we take the original optimization model stated in Chapter 2 which takes advantage of the fact that power can be sold to the grid in the day-ahead market. Hence, the formulation remains the same as that stated in Chapter 2.

Results

When we run the code in Appendix 2 for the data provided in (4.1), we get the following results:

Table 4.4 Hourly Energy Transfer pattern for Case 3

Index	**TIME**	**G_H (Wh)**	**G_B (Wh)**	**B_G (Wh)**	**B_H (Wh)**
1	12am -1 am	2759	0	0	0
2	1- 2am	1300	0	0	0
3	2- 3am	227	0	0	0
4	3- 4am	178	6999	0	0
5	4- 5am	279	6999	0	0
6	5- 6am	183	1002	0	0
7	6- 7am	256	0	0	0
8	7- 8am	204	0	0	0
9	8- 9am	0	0	6999	211.1111111
10	9- 10am	0	0	5989.888889	300

Table 4.4 (**contd.**)					
11	10- 11am	171	0	0	0
12	11- 12am	285	0	0	0
13	12- 1pm	172	1002	0	0
14	1- 2pm	184	0	0	0
15	2- 3pm	276	6999	0	0
16	3- 4pm	173	6999	0	0
17	4- 5pm	1058	0	0	0
18	5- 6pm	2248	0	0	0
19	6- 7pm	0	0	6999	1991.111111
20	7- 8pm	1105	0	4509.888889	0
21	8- 9pm	1375	0	0	0
22	9- 10pm	4964	0	0	0
23	10- 11pm	3382	0	0	0
24	11- 12am	2366	0	0	0

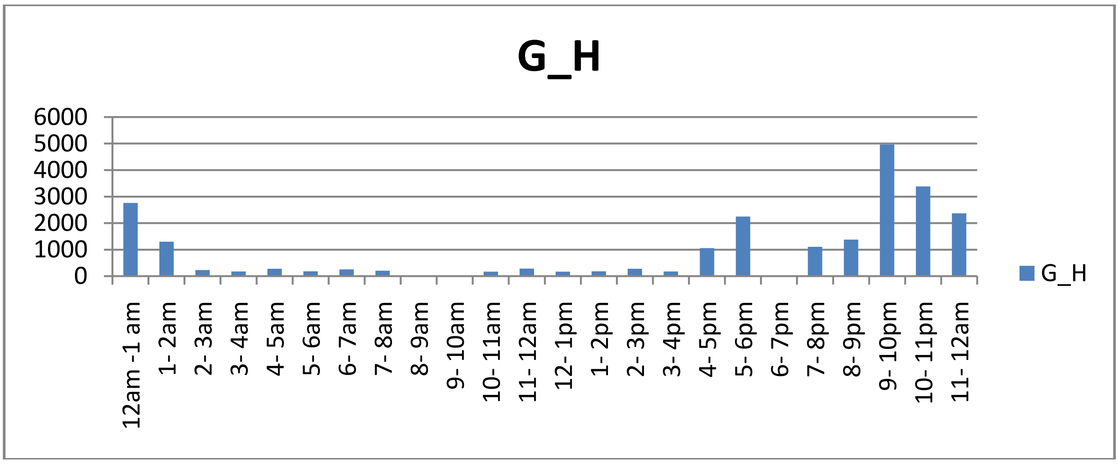

Fig 4.7 Hourly energy transfer pattern from the grid to the household

From the above figure, we can observe that maximum energy is transferred from the grid to the household only during times of low prices which is in the early hour of the day and in the later part of the day.

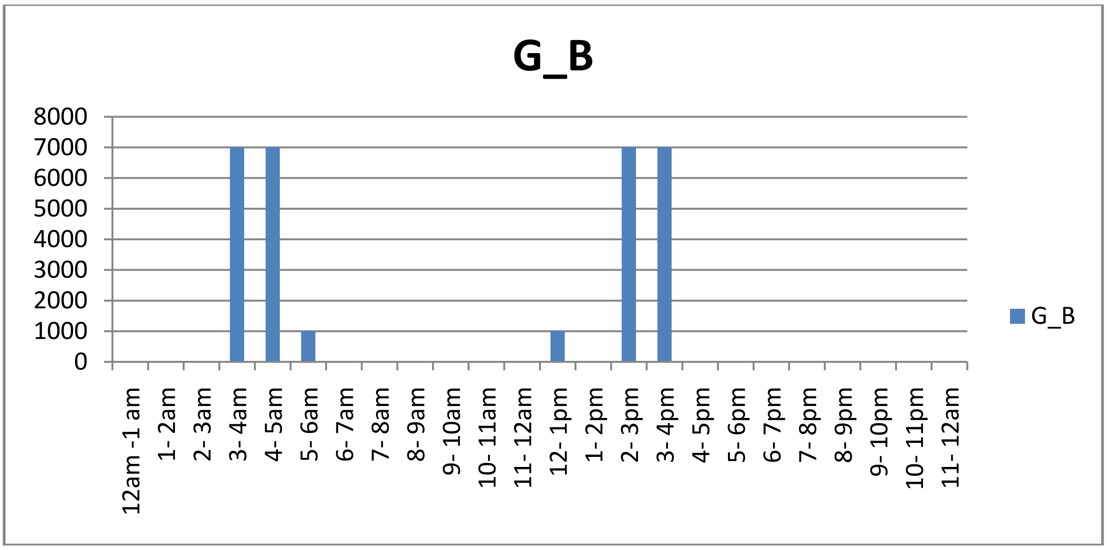

Fig 4.8 Hourly energy transfer pattern from the grid to the battery

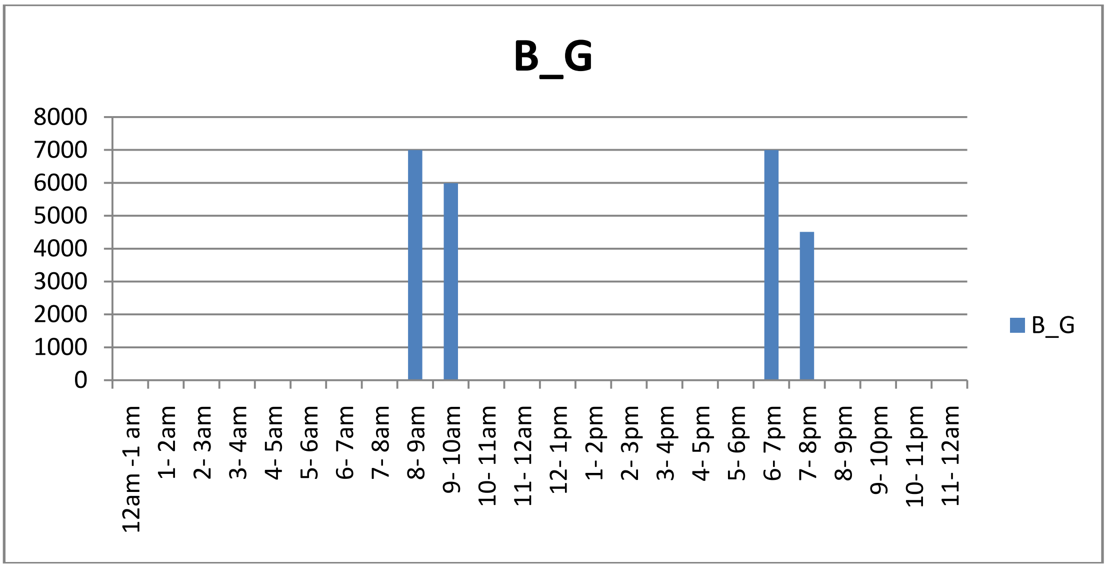

Fig. 4.9 Hourly energy transfer pattern from the battery to the grid

As we had seen earlier from figure 4.2., the peak price time intervals were at 8am-9am and at 6pm-7pm. From the above figure, we can observe that the model takes advantage of these peak price intervals to sell power back to the grid. This further validates the working of the model.

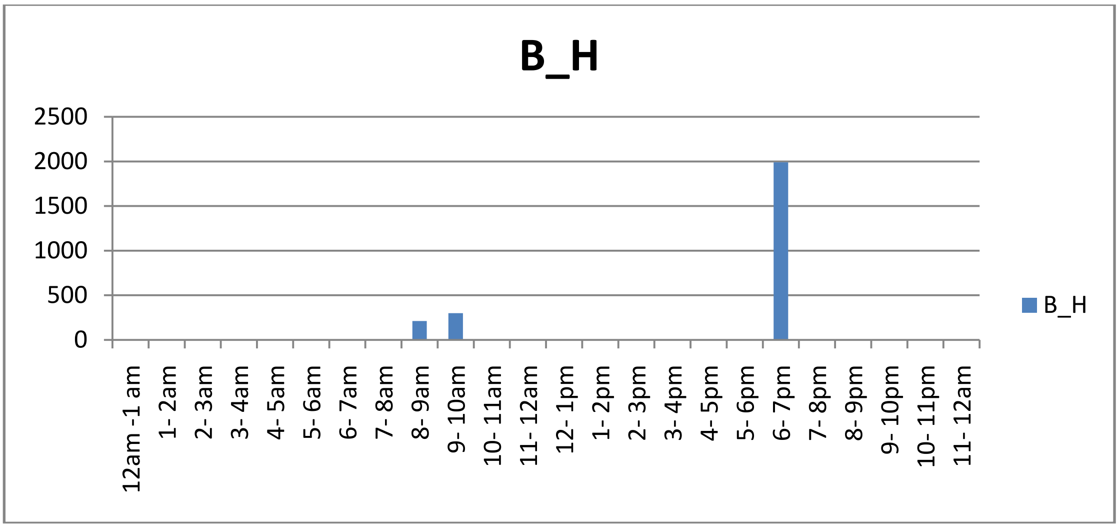

Fig. 4.10 Hourly energy transfer pattern from the battery to the household

From the pattern in figure 4.10.above, we observe that power is being transferred from the battery to the household during the time intervals of peak pricing. This indicates that the model selects to use the energy from the battery instead of buying from the grid when the price is high.

Table 4.5 Hourly Battery Energy Pattern for Case 3

Index	**Time**	**BE (Wh)**		**Index**	**Time**	**BE (Wh)**
1	12am	0		**14**	1pm	901.8
2	1am	0		**15**	2pm	901.8
3	2am	0		**16**	3pm	7200.9
4	3am	0		**17**	4pm	13500
5	4am	6299.1		**18**	5pm	13500
6	5am	12598.2		**19**	6pm	13500
7	6am	13500		**20**	7pm	4509.889
8	7am	13500		**21**	8pm	0
9	8am	13500		**22**	9pm	0
10	9am	6289.889		**23**	10pm	0
11	10am	0		**24**	11pm	0
12	11am	0		**25**	12am	0
13	12pm	0				

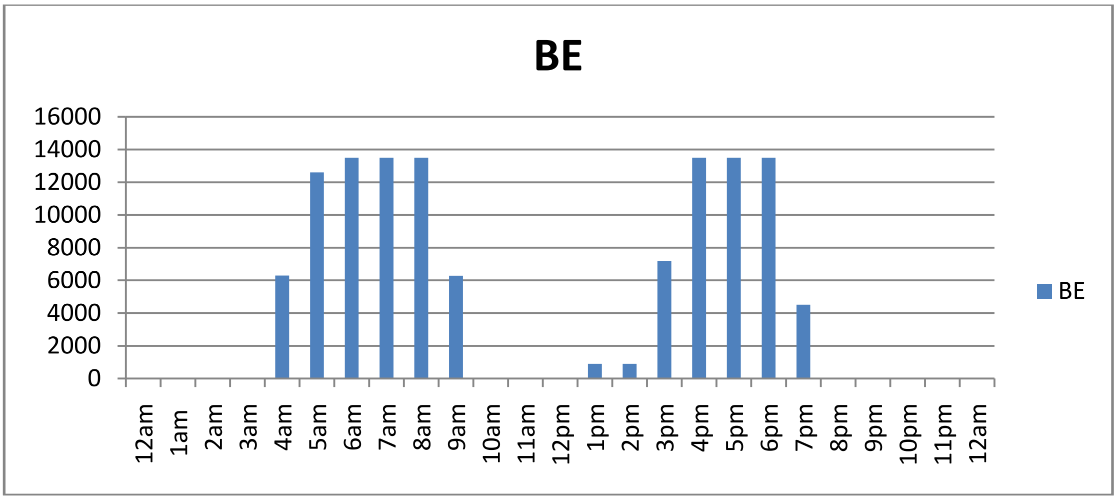

Fig. 4.11. Hourly battery energy pattern for Case 3

As we can observe, this model also takes into account the option of selling back power to the grid when the spot market price is high, thereby giving a more different battery energy pattern as compared to Case 2. A large amount of energy stored in the battery is sold back to the grid instead of it being transferred to the household for consumption, thereby minimizing cost even further than in Case 2.

The cost in Case 3 comes down even further to € 0.673 per day.

CASE 3 COST = € 0.673 per day (4.19)

4.2.4 Observation

As we can see, there is a definite advantage in using a Battery Energy Storage System in a consumer household. When we use a Tesla Powerwall 2 with η=0.9, B_{max}= 13.5 kWh and P_{max} = 7kW for the three cases, we make the following observations:

Table 4.6 Comparison of the results between the three cases

CASE 1	**CASE 2**	**CASE 3**
BESS is not used	BESS is used but **SELLING IS NOT INVOLVED**	BESS is used and **SELLING IS INVOLVED**
G_B(i) = 0, B_G(i) = 0, B_H(i) = 0; for all i϶[1,24] BE(t)=0; for all t϶[1,25]	B_G(i)=0; For all i϶[1,24]	
COST PER DAY **€1.538**	COST PER DAY **€1.27** **17.43% reduction** from CASE 1	COST PER DAY **€0.673** **56.24% reduction** from CASE 1

We therefore end this chapter by concluding that using a battery energy storage system in the presence of dynamic pricing for a consumer household helps in reducing the daily cost of electricity by up to **56.24%** which was the main objective of the model. In the next chapter, we will apply the model on a few real life cases and make some observations.

CHAPTER 5

CASE STUDIES

In this chapter, we will apply the algorithm which was modelled, formulated and tested in Chapters 2 and 4 on a few cases. In the first case, we will test the model when the Tesla batteries are stacked up to “N” batteries where Nϵ[1,10] and observe whether there is any advantage in increasing the number of stacked batteries. In the second case, we try to find a saturation point for the battery capacity beyond which there is no decrease in the daily cost of electricity. Finally, we try to find a payback period to conclude the investment viability of using a battery energy storage system with the same specifications and cost as a Tesla Powerwall 2.

5.1 TESTING THE MODEL FOR N STACKED BATTERIES

One of the advantages of the Tesla Powerwall 2 is that it is possible to stack up to 10 units for an individual household without any extra requirements. Hence, we obviously want to find out if there is any advantage in stacking more batteries considering that there will be an increase in the initial investment but will also lead to an increase in the battery capacity.

Now, let the number of units be defined by N where Nϵ[1,10].

We now simulate the model defined and formulatedin Chapters 2 and 4 for all cases of N and we get the following results.

5.1.1 Results

The cost per day for "N" number (Nϵ[1,10]) of Tesla Powerwalls is given in the table below:

Table 5.1 Battery Capacity and Cost per day for "N" stacked Batteries

"N" number of PowerWalls	**Capacity (B_{max}) in kWh**	**Cost per day in €**
1	13.5	0.673
2	27	0.53981
3	40.5	0.52167
4	54	0.52167
5	67.5	0.52167
6	81	0.52167
7	94.5	0.52167
8	108	0.52167
9	121.5	0.52167
10	135	0.52167

As we can observe, the cost decreases only from N=1 till N=3 but it remains the same for N=3 to N=10. This means that the cost has saturated and adding beyond 3 stacks of batteries does not have any economic advantage.

Table 5.2 Hourly Energy transfer pattern from the Grid to the household and battery

			G_H				**G_B**		
Index	**TIME**		**N=1**	**N=2**	**N ϵ [3, 10]**		**N=1**	**N=2**	**N ϵ [3, 10]**
1	12am -1 am		2759	2759	2759		0	6999	6999
2	1- 2am		1300	1300	1300		0	0	6999
3	2- 3am		227	227	227		0	2004	6999
4	3- 4am		178	178	178		6999	6999	6999
5	4- 5am		279	279	279		6999	6999	6999
6	5- 6am		183	183	183		1002	6999	6999

Table 5.2 (**contd.**)

7	6- 7am		256	0	0		0	0	0
8	7- 8am		204	0	0		0	0	0
9	8- 9am		0	0	0		0	0	0
10	9- 10am		0	0	0		0	0	0
11	10- 11am		171	171	0		0	0	0
12	11- 12am		285	285	285		0	0	0
13	12- 1pm		172	172	172		1002	0	0
14	1- 2pm		184	184	184		0	0	0
15	2- 3pm		276	276	276		6999	6999	6999
16	3- 4pm		173	173	173		6999	6999	6999
17	4- 5pm		1058	1058	1058		0	0	0
18	5- 6pm		2248	2248	2248		0	0	0
19	6- 7pm		0	0	0		0	0	0
20	7- 8pm		1105	0	0		0	0	0
21	8- 9pm		1375	1375	1375		0	0	0
22	9- 10pm		4964	4964	4964		0	0	0
23	10- 11pm		3382	3382	3382		0	0	0
24	11- 12am		2366	2366	2366		0	0	0

Table 5.3 Hourly energy transfer pattern from the battery to the grid and household

			B_G				**B_H**		
Index	**02-Mar-14**		**N=1**	**N=2**	**N ϵ [3, 10]**		**N=1**	**N=2**	**N ϵ [3, 10]**
1	12am -1 am		0	0	0		0	0	0
2	1- 2am		0	0	0		0	0	0
3	2- 3am		0	0	0		0	0	0
4	3- 4am		0	0	0		0	0	0
5	4- 5am		0	0	0		0	0	0
6	5- 6am		0	0	0		0	0	0
7	6- 7am		0	6999	6999		0	284.44	284.44
8	7- 8am		0	362.0889	6999		0	226.67	226.67
9	8- 9am		6999	6999	6999		211.11	211.11	211.11
10	9- 10am		5989.889	6999	6999		300	300	300
11	10- 11am		0	0	3967.689		0	0	190
12	11- 12am		0	0	0		0	0	0
13	12- 1pm		0	0	0		0	0	0
14	1- 2pm		0	0	0		0	0	0
15	2- 3pm		0	0	0		0	0	0
16	3- 4pm		0	0	0		0	0	0
17	4- 5pm		0	0	0		0	0	0
18	5- 6pm		0	0	0		0	0	0
19	6- 7pm		6999	6999	6999		1991.11	1991.1	1991.11
20	7- 8pm		4509.889	6999	6999		0	1227.8	1227.78
21	8- 9pm		0	0	0		0	0	0

Table 5.3 (**contd.**)									
22	9- 10pm		0	0	0		0	0	0
23	10- 11pm		0	0	0		0	0	0
24	11- 12am		0	0	0		0	0	0

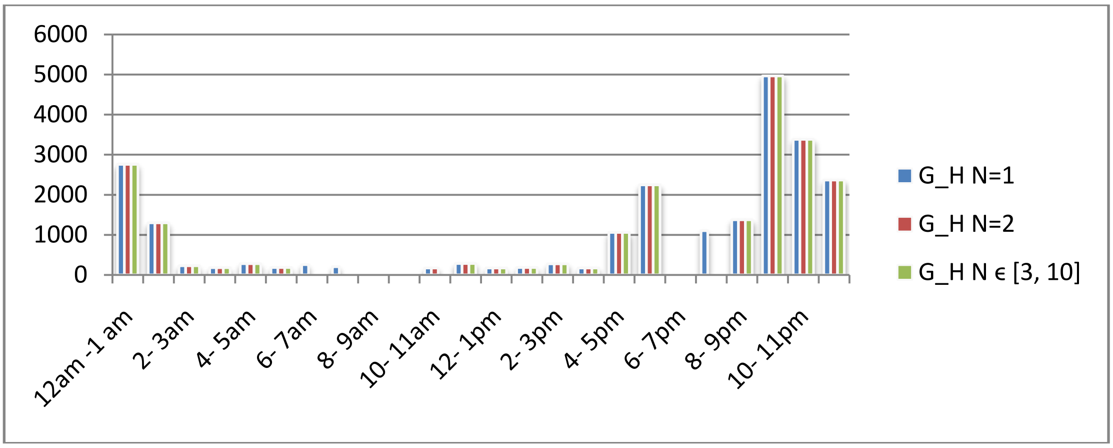

Fig. 5.1 Hourly energy transfer pattern from the grid to the household

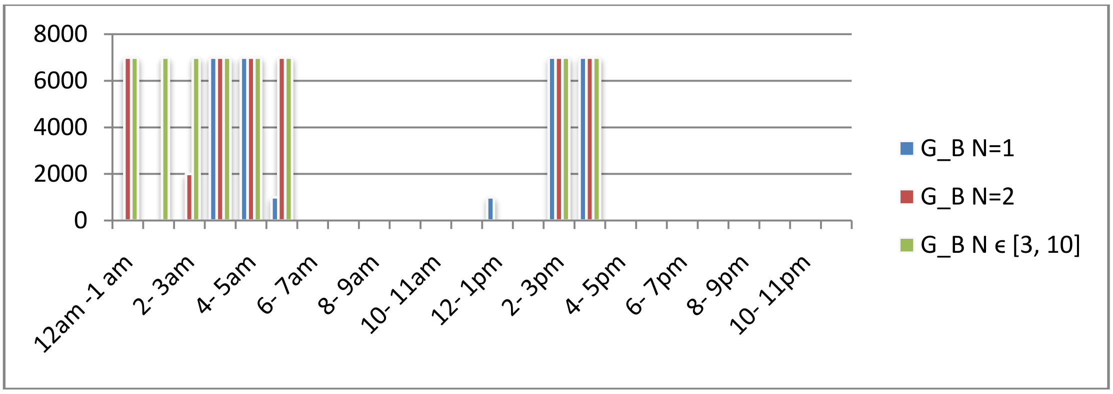

Fig. 5.2 Hourly energy transfer pattern from the grid to the battery

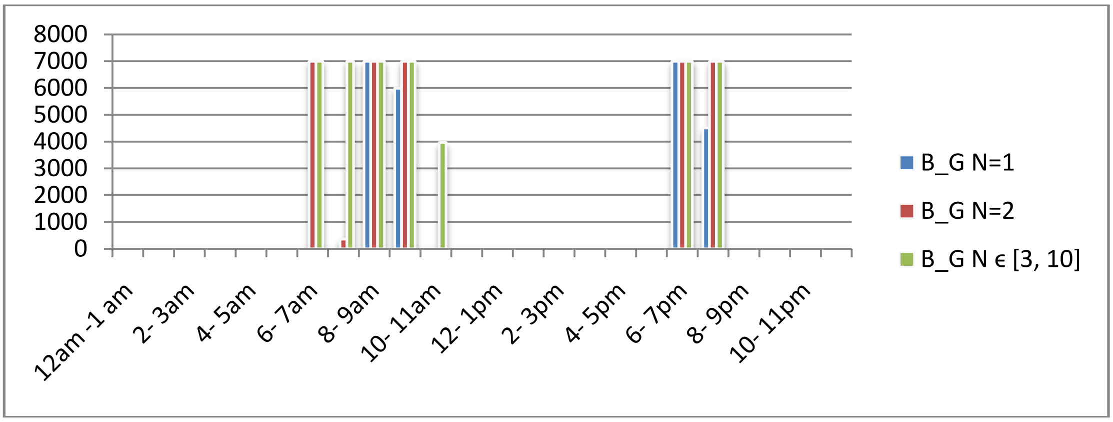

Fig. 5.3 Hourly energy transfer pattern from the battery to the grid

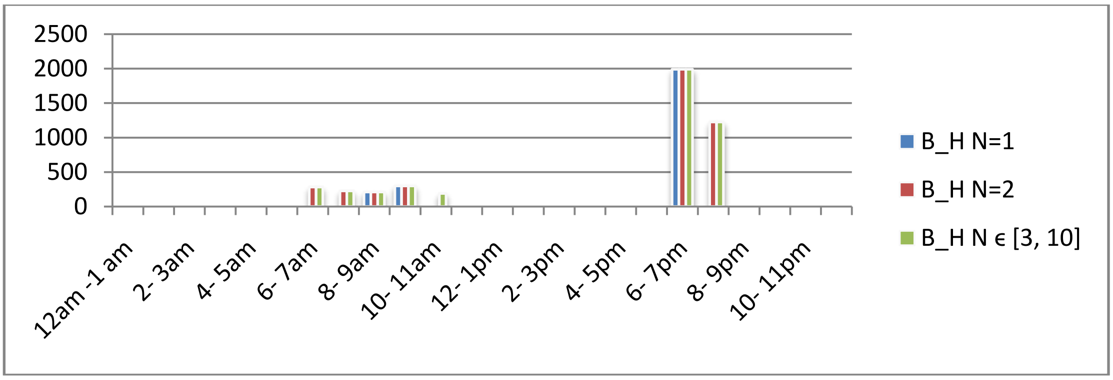

Fig. 5.4. Hourly energy transfer pattern from the battery to the household

From the above results, we can observe that as N increases from 1 to 3, the hourly energy transfer patterns also changes but it remains the same from N=3 onwards. This shows that increasing the number of batteries from 1 to 3 causes a change in the optimal strategy for energy transfers but increasing the number of batteries from 3 to 10 does not cause any change.

Table 5.4 Hourly battery energy pattern

		BATTERY ENERGY		
Index	**Time**	**N=1**	**N=2**	**N ϵ [3, 10]**
1	12am	0	0	0
2	1am	0	6299.1	6299.1
3	2am	0	6299.1	12598.2
4	3am	0	8102.7	18897.3
5	4am	6299.1	14401.8	25196.4
6	5am	12598.2	20700.9	31495.5
7	6am	13500	27000	37794.6
8	7am	13500	19716.56	30511.15556
9	8am	13500	19127.8	23285.48889
10	9am	6289.889	11917.69	16075.37778
11	10am	0	4618.689	8776.377778
12	11am	0	4618.689	4618.688889
13	12pm	0	4618.689	4618.688889
14	1pm	901.8	4618.689	4618.688889
15	2pm	901.8	4618.689	4618.688889
16	3pm	7200.9	10917.79	10917.78889

Table 5.4 (**contd.**)				
17	4pm	13500	17216.89	17216.88889
18	5pm	13500	17216.89	17216.88889
19	6pm	13500	17216.89	17216.88889
20	7pm	4509.889	8226.778	8226.777778
21	8pm	0	0	0
22	9pm	0	0	0
23	10pm	0	0	0
24	11pm	0	0	0
25	12am	0	0	0

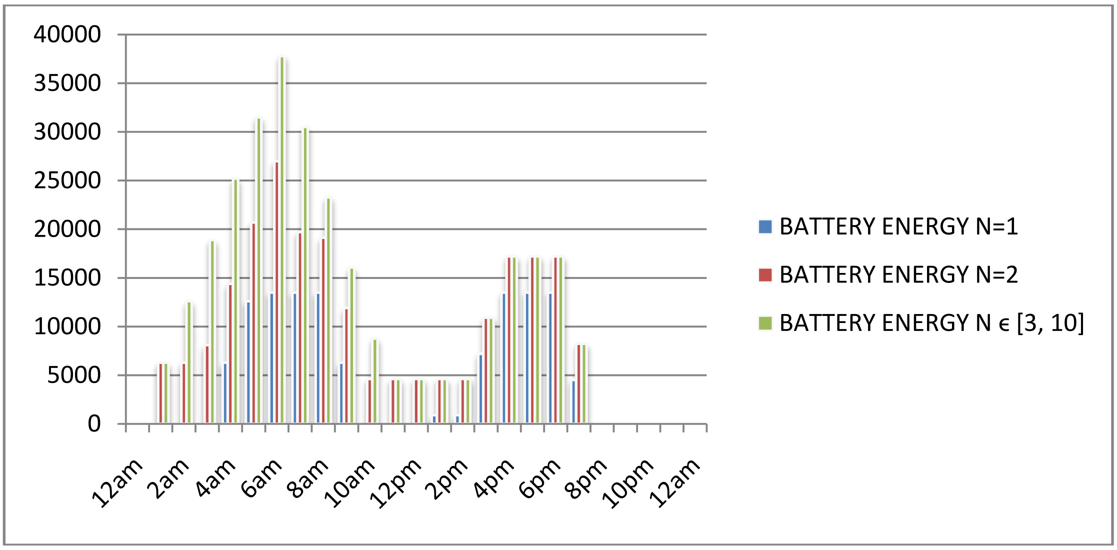

Fig. 5.5 Hourly battery energy pattern

5.1.2 Observation

As we can see, there is a decrease in cost as we go from N=1 to N=3 but there is no change in cost as we move from N=3 to N=10.

We now take a look at the hourly patterns for G_H, G_B, B_G, B_H and Battery Energy. We can similarly observe that the patterns change from N=1 to N=3 but remains constant from N=3 to N=10. This indicates a change in the optimal strategy for energy transfers as well as battery energy from N=1 to N=3 but not from N=3 to N=10.

Hence what we can conclude from this observation is that there is obviously a **Saturation Point** somewhere between N=2 to N=3 for this specific case of η=0.9 and P_{max}=7kW, beyond which there is no change in the optimal strategy for the energy transfer patterns and the battery energy patterns.

In the next section, we will try to find the saturation point for the battery capacity beyond which there is no change in the cost or optimal patterns for energy transfers and battery energy. This means that the saturation point will be the optimal battery capacity for this model.

5.2 BATTERY CAPACITY SATURATION POINT FOR A SPECIFIC CASE OF η AND P_{MAX}

Now, let us take the case of η=0.9 and P_{max}=7kW. As we increase B_{max} from 0, the cost keeps decreasing but saturates after a certain point. Hence we run the simulation for increasing values of B_{max} and try to find the saturation point of B_{max}.

5.2.1 Results

After running the simulation 84 times, starting from B_{max} = 0 and increasing B_{max} in steps of 0.5kWh, we get the following results:

Table 5.5 Cost per day in Euros as Battery Capacity increases

Sl. No.	B_{max}(kWh)	Cost (€)		Sl. No.	B_{max}(kWh)	Cost (€)
1	0 (No Battery)	1.53751		43	21	0.56273
2	0.5	1.49679		44	21.5	0.56078
3	1	1.45607		45	22	0.55883
4	1.5	1.41536		46	22.5	0.55688
5	2	1.37464		47	23	0.55493

Table 5.5 (**contd.**)						
6	2.5	1.33392		48	23.5	0.55298
7	3	1.29321		49	24	0.55102
8	3.5	1.25249		50	24.5	0.54907
9	4	1.21177		51	25	0.54712
10	4.5	1.17106		52	25.5	0.54521
11	5	1.13034		53	26	0.54332
12	5.5	1.08962		54	26.5	0.54147
13	6	1.04891		55	27	0.53981
14	6.5	1.00912		56	27.5	0.53815
15	7	0.97072		57	28	0.53649
16	7.5	0.933463		58	28.5	0.53483
17	8	0.897034		59	29	0.53317
18	8.5	0.860605		60	29.5	0.5315
19	9	0.824544		61	30	0.52984
20	9.5	0.806754		62	30.5	0.52818
21	10	0.788964		63	31	0.52652
22	10.5	0.771174		64	31.5	0.52487
23	11	0.753384		65	32	0.52461
24	11.5	0.735594		66	32.5	0.52435
25	12	0.717804		67	33	0.52409
26	12.5	0.700014		68	33.5	0.52383
27	13	0.68584		69	34	0.52358
28	13.5	0.67255		70	34.5	0.52333
29	14	0.65926		71	35	0.52307
30	14.5	0.64597		72	35.5	0.52282
31	15	0.633631		73	36	0.52257
32	15.5	0.621311		74	36.5	0.52232
33	16	0.60899		75	37	0.52207
34	16.5	0.59667		**76**	**37.5**	**0.52182**
35	17	0.58435		**77**	**38**	**0.52167**
36	17.5	0.57767		78	38.5	0.52167
37	18	0.57532		79	39	0.52167
38	18.5	0.57296		80	39.5	0.52167
39	19	0.57062		81	40	0.52167
40	19.5	0.56859		82	40.5	0.52167
41	20	0.56663		83	41	0.52167
42	20.5	0.56468		84	41.5	0.52167

5.2.2 Observation

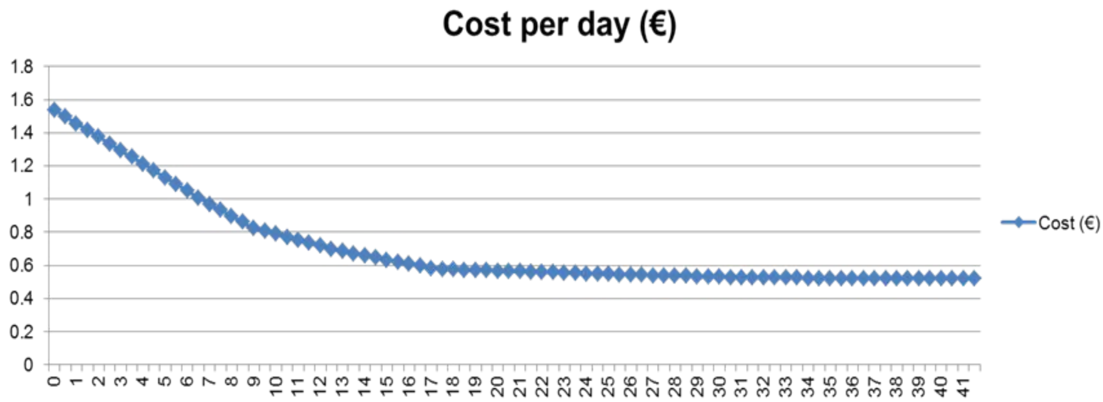

Fig. 5.6 Cost per day Vs. Battery Capacity

As we had seen earlier, there is a decrease in the cost-per-day as the Battery Capacity increases. However, we also find that the slope of the graph slowly reduces indicating that the rate of decrease of cost-per-day starts reducing and eventually the cost-per-day saturates.

From the above results, we can see that the saturation point lies somewhere between B_{max}=37.5 kWh and B_{max}=38 kWh.

Hence, we perform the simulation between these values to try and close-in on the approximate value of the Saturation Point for B_{max} when η=0.9 and P_{max}=7kW.

Table 5.6 Cost vs. B_{max} to find Saturation Point

Sl. No.	B_{max}(kWh)	Cost (€)
1	37.5	0.521815
2	37.6	0.521765
3	37.7	0.521715
4	37.71	0.52171
5	37.72	0.521705
6	37.73	0.5217

Table 5.6 (**contd.**)		
7	37.74	0.521695
8	37.75	0.52169
9	37.76	0.521684
10	37.77	0.521679
11	37.78	0.521674
12	37.79	0.521669
13	37.791	0.521669
14	37.792	0.521668
15	**37.793**	**0.521668**
16	**37.794**	**0.521667**

After the simulations are done, we can see that when η=0.9 and P_{max}=7kW, the **Saturation Point** of B_{max} is at:

$$\mathbf{B_{max}\ (sat.) = 37.794\ kWh} \tag{5.1}$$

where,

$$\mathbf{Cost/day = €\ 0.521667} \tag{5.2}$$

5.3 PAYBACK PERIOD

The main factor that will decide whether a battery energy storage system is a viable investment for a household would be the Payback Period.

Here, we define the Payback Period as the time taken for the Cost Savings to add up to the initial investment in the Battery Energy Storage System which can be equated as:

$$\text{Initial Investment} = \sum_{i=1}^{Payback\ \ Period} \left(\frac{Cost\ Saving\ per\ year}{(1+r)i}\right); \tag{5.3}$$

where,

r is the Risk-free rate; (5.4)

Cost Saving = Cost without a BESS – Cost with a BESS; (5.5)

Here, we will only try to find an approximate payback period. To do this, first we have to make the following assumption:

1. We assume that the cost-per-day remains the same for the whole year. This will obviously not be true but it is a good enough assumption for a strong approximation of the approximate payback period.

For the calculation, we will take the 10-year US Treasury rate as the risk-free rate.

Therefore, risk-free rate (r) = 2.6% (5.6)

Now, we calculate the Payback Periods for the case of N=1 to N=3 and we get the following results:

Table 5.7 Payback Period for N=1 to N=3

N	Initial Investment (€)	Cost Savings per year (€)	Payback Period (Years) [approx.]
1	6351.69	315.725	29
2	12703.38	364.339	>29
3	19055.07	370.96	>29

Here, we can see that the payback period will not be less than 29 years, and with the 10 year warranty period, this will not be a viable investment if the battery is used for storing only power from the Grid (it might be close to viable if solar panels are used as well).

However, with further research leading to cost reductions and with the use of other sources of energy (solar, wind) along with the conventional sources, this has the potential to become a viable investment if the Payback Period goes below the 10 year mark.

To bring the Payback Period to within the 10 year mark, the initial investment should come down below a certain value which we shall define as the “Required Initial Investment”. Hence, the criteria will be as follows:

$$\text{Required Initial Investment } < \sum_{i=1}^{10} \left(\frac{Cost\ Saving\ per\ year}{(1+r)i}\right); \tag{5.7}$$

Or, for the case of N = 1,

$$\text{Required Initial Investment } < \sum_{i=1}^{10} \left(\frac{315.725}{(1+0.026)i}\right);$$

$$\text{Required Initial Investment } < € \, 2749.0213 \text{ (approximately)}; \tag{5.8}$$

Hence, only after the required initial investment of a battery energy storage system (BESS) with η=0.9, P_{max}=7kW and B_{max} = 13.5 kWh come down to approximately € 2749.0213, will it be a viable investment plan for a consumer household.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1. CONCLUSION

The motivation behind the project was the increased use of dynamic pricing of electricity. Due to the difference in prices of electricity, a battery energy storage system could be used to take advantage of this volatility to buy power when the price is low and sell it when the price is high. Hence an algorithm was formulated which would try to minimize the cost of electricity per day to a household consumer by taking advantage of the dynamic pricing of electricity. The model was then tested and it was observed that the use of a battery energy storage system (BESS) reduces the cost-per-day of electricity by **56.24%** from the case when a battery energy storage system (BESS) is not used. This shows that the algorithm proposed works.

Next, three case studies were done to better understand the working of the algorithm and to come to a conclusion about the economic feasibility of using a battery energy storage system (BESS).

1. The first case study was to test the model on “N” stacked batteriesfrom N=1 to N=10 for the case of the Tesla Powerwall 2 (η=0.9, P_{max}=7kW and B_{max} per N=13.5kWh). It was observed that there is a change in strategy and a reduction in the cost-per-day as we move from N=1 to N=3, but no change occurs from N=3 to N=10.

2. The second case study aimed to find the Battery Capacity Saturation Point which is the battery capacity above which no reduction in cost is observed. This is done for a battery energy storage system(BESS) with η=0.9andP_{max}=7kW. It was observed that for a battery energy storage system (BESS) with these specifications, the Battery Capacity Saturation Point is **B_{max}=37.794kWh** where the cost-per-day comes to **€ 0.521667**.

3. The purpose of the third case study was to find the Payback Period for the investment. This is basically the amount of time taken for the savings in cost-per-day to add up to the initial investment of the battery energy storage system (BESS). This measures the viability of the investment. The payback period is observed to be **not less than 29 years** which is beyond the 10 year warranty period for a Tesla Powerwall 2 making this investment infeasible. The Required Initial Investment was also calculated which is the initial investment needed to bring the payback period to within the 10 year mark. The Required Initial Investment comes out to be approximately **€ 2749.0213**.

Hence, it can be concluded that the algorithm does help in reducing the cost-per-day of electricity for a consumer household. However, the payback period is too long for it to be viable right now. With increased research and the use of other renewable sources of energy however, the cost of using a battery energy storage system could be further decreased such that the payback period will be reasonable enough to make it a viable investment.

6.2. FUTURE SCOPE

This algorithm can be further improved and then implemented in smart meters for households in a day-ahead market. It can also be incorporated by the distributor itself which will help in demand side management. This model might indirectly cause a reduction in peak loads and ease the demand during peak hours.

This model can also be extended to a community whereby a stack of batteries can be used in a neighbourhood and the initial cost can be split amongst the households in the neighbourhood. This will help reduce the payback period for the investment and thereby increase the viability of the investment.

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APPENDIX 1

LINGO Code for Case 2. [Page 29]

```
!Declaring the variables as Sets(Vectors);
SETS:
      SET_ENERGY /1..24/ : G_H , G_B, B_H, CONSUMPTION, PRICE ;
      SET_BATTERY /1..25/ : BE ;
ENDSETS

!Exchanging Data between the variables and desired Excel spreadsheet;
DATA:
      PRICE = @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx');
      CONSUMPTION = @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx');

      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx') = G_H ;
      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx') = G_B ;
      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx') = B_H ;

      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 4 - No selling\Simulation4Excel.xlsx') = BE ;

END DATA

!Objective Function;
MIN = @SUM ( SET_ENERGY (I) : ((G_H(I) + G_B(I))*PRICE(I)));

!Constraints;
@FOR ( SET_ENERGY (I) : G_H(I) + (0.9*B_H(I)) = CONSUMPTION (I));
@FOR ( SET_ENERGY (I) : (G_B(I))*(B_H(I)) = 0 );

@FOR ( SET_ENERGY (I): G_B(I) <= 6999);
@FOR ( SET_ENERGY (I): B_H(I) <= 6999);

@FOR ( SET_BATTERY (J): BE(J) <= 13500);

BE (1) = 0;
BE (25) = 0;

@FOR ( SET_ENERGY(I) :
      @FOR ( SET_BATTERY(J)| I #EQ# J : BE(J+1)= BE(J)+(0.9*G_B(I))- B_H(I) ));
```

APPENDIX 2

LINGO Code for Case 3. [Page 32]

```
!Declaring the variables as Sets(Vectors);
SETS:
      SET_ENERGY /1..24/ : G_H , G_B, B_G, B_H, CONSUMPTION, PRICE ;
      SET_BATTERY /1..25/ : BE ;
ENDSETS

!Adding Data to the variables from desired Excel spreadsheet;
DATA:
      PRICE = @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx');
      CONSUMPTION = @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx');

      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx') = G_H ;
      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx') = G_B ;
      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx') = B_G ;
      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx') = B_H ;

      @OLE ('E:\ACADS\Sem 10\DDP\Simulations\Simulation 2 - 2 March 2015\Simulation2Excel.xlsx') = BE ;

END DATA



!Objective Function;
MIN = @SUM ( SET_ENERGY (I) : ((G_H(I) + G_B(I) - (0.9*B_G(I)))*PRICE(I)));

!Constraints;
@FOR ( SET_ENERGY (I) : G_H(I) + (0.9*B_H(I)) = CONSUMPTION (I));
@FOR ( SET_ENERGY (I) : (G_B(I))*(B_H(I)) = 0 );
@FOR ( SET_ENERGY (I) : (G_B(I))*(B_G(I)) = 0 );

@FOR ( SET_ENERGY (I): G_B(I) <= 6999);
@FOR ( SET_ENERGY (I): B_G(I) <= 6999);
@FOR ( SET_ENERGY (I): B_H(I) <= 6999);

@FOR ( SET_BATTERY (J): BE(J) <= 13500);

BE (1) = 0;
BE (25) = 0;
B_G(1)= 0;
B_H(1)=0;

@FOR ( SET_ENERGY(I) :
      @FOR ( SET_BATTERY(J)| I #EQ# J : BE(J+1)=BE(J)+(0.9*G_B(I))- B_G(I) - B_H(I) ));
```