Institutionen för systemteknik
Department of Electrical Engineering

Examensarbete

Design, Management and Optimization of a Distributed Energy Storage System with the presence of micro generation in a smart house

Examensarbete utfört i Elektroteknik
vid Tekniska högskolan vid Linköpings universitet
av

Hannes Eliasstam

LiTH-ISY-EX--12/4647--SE

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Titel
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Design, Management and Optimization of a Distributed Energy Storage System with the presence of micro generation in a smart house

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Sammanfattning
Abstract

The owners of a house in today's society do not know in real-time how much electricity they use. It could be beneficial for any residential consumer to have more control and overview in real-time over the electricity consumption. This could be done possible with a system that monitors the consumptions, micro renewables and the electricity prices from the grid and then makes a decision to either use or sell electricity to reduce the monthly electricity cost for the household and living a "Greener" life to reduce carbon emissions. In this thesis, estimations are made based on artificial neural network (ANN). The predictions are made for air temperature, solar insolation and wind speed in order to know how much energy will be produced in the next 24 hours from the solar panel and from the wind turbine. The predictions are made for electricity consumption in order to know how much energy the house will consume. These predictions are then used as an input to the system. The system has 3 controls, one to control the amount of sell or buy the energy, one to control the amount of energy to charge or discharge the fixed battery and one to control the amount of energy to charge or discharge the electric vehicle (EV). The output from the system will be the decision for the next 10 minutes for each of the 3 controls.

To study the reliability of the ANN estimations, the ANN estimations (S_{ANN}) are compared with the real data (S_{real}) and other estimation based on the mean values (S_{mean}) of the previous week. The simulation during a day in January gave that the expenses are 0.6285 € if using S_{ANN}, 0.7788 € if using S_{mean} and 0.5974 € if using S_{real}. Further, 3 different cases are considered to calculate the savings based on the ANN estimations. The first case is to have the system connected with fixed storage device and EV ($S_{con,batt}$). The second and third cases are to have the system disconnected (without fixed battery) using micro generation ($S_{discon,micro}$) and not using micro generation (S_{discon}) along with the EV. The savings are calculated as a difference between $S_{con,batt}$ and S_{discon}, also between $S_{discon,micro}$ and S_{discon}. The saving are 788.68 € during a year if $S_{con,batt}$ is used and 593.90 € during a year if $S_{discon,micro}$ is used. With the calculated savings and the cost for the equipment, the pay-back period is 15.3 years for $S_{con,batt}$ and 4.5 years for $S_{discon,micro}$. It is profitable to only use micro generation, but then the owner of the household loses the opportunity to be part of helping the society to become "Greener".

Nyckelord
Keywords

Forecasting, ANN, Modelling, Optimization, Control, Energy, Micro renewables, Storage devices, Electric Vehicle

Abstract

The owners of a house in today's society do not know in real-time how much electricity they use. It could be beneficial for any residential consumer to have more control and overview in real-time over the electricity consumption. This could be done possible with a system that monitors the consumptions, micro renewables and the electricity prices from the grid and then makes a decision to either use or sell electricity to reduce the monthly electricity cost for the household and living a "Greener" life to reduce carbon emissions. In this thesis, estimations are made based on artificial neural network (ANN). The predictions are made for air temperature, solar insolation and wind speed in order to know how much energy will be produced in the next 24 hours from the solar panel and from the wind turbine. The predictions are made for electricity consumption in order to know how much energy the house will consume. These predictions are then used as an input to the system. The system has 3 controls, one to control the amount of sell or buy the energy, one to control the amount of energy to charge or discharge the fixed battery and one to control the amount of energy to charge or discharge the electric vehicle (EV). The output from the system will be the decision for the next 10 minutes for each of the 3 controls.

To study the reliability of the ANN estimations, the ANN estimations (S_{ANN}) are compared with the real data (S_{real}) and other estimation based on the mean values (S_{mean}) of the previous week. The simulation during a day in January gave that the expenses are 0.6285 € if using S_{ANN}, 0.7788 € if using S_{mean} and 0.5974 € if using S_{real}. Further, 3 different cases are considered to calculate the savings based on the ANN estimations. The first case is to have the system connected with fixed storage device and EV ($S_{con,batt}$). The second and third cases are to have the system disconnected (without fixed battery) using micro generation ($S_{discon,micro}$) and not using micro generation (S_{discon}) along with the EV. The savings are calculated as a difference between $S_{con,batt}$ and S_{discon}, also between $S_{discon,micro}$ and S_{discon}. The saving are 788.68 € during a year if $S_{con,batt}$ is used and 593.90 € during a year if $S_{discon,micro}$ is used. With the calculated savings and the cost for the equipment, the pay-back period is 15.3 years for $S_{con,batt}$ and 4.5 years for $S_{discon,micro}$. It is profitable to only use micro generation, but then the owner of the household loses the opportunity to be part of helping the society to become "Greener".

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Linköping, December 2012
Hannes Eliasstam

Contents

Notation

Simulations

Notation	Meaning
S_{ANN}	Simulation for one day in January based on the ANN predations.
S_{mean}	Simulation for one day in January based on the mean values.
S_{real}	Simulation for one day in January based on the real values.
$S_{con,batt}$	Simulation for one week with system connected, usage of micro generation, fixed battery and EV.
$S_{discon,micro}$	Simulation for one week with system disconnected, usage of micro generation and EV (no usage of fixed battery).
S_{discon}	Simulation for one week with system disconnected, usage of only EV (no usage of micro generation nor fixed battery).

Abbreviations

Abbreviation	Meaning
EV	Electric Vehicle
CAGR	Compound Annual Growth Rate
REE	RED ELÉCTRICA DE ESPAÑA
PV	PhotoVoltaic
NiCd	Nickel-Cadmium
NiMH	Nickel-Metal Hydride
Li-ion	Lithium-ion
SOC	State Of Charge
EVSE	Electric Vehicle Supply Equipment
ANN	Artificial Neural Network
NPV	Net Present Value

1

Introduction

The owners of a house in today's society do not know in real-time how much electricity they use. It usually takes about three months before the owners receive the bills and realize how much electricity they have used. It could be beneficial for any residential consumer to have more control and overview in real-time over the electricity consumption. This could be done possible with a system that monitors the consumptions, micro generations (wind and solar) and the electricity prices from the grid and then makes a decision to either use or sell electricity every 10 minutes to reduce the monthly electricity cost for the household.

Such a system would manage different storage devices i.e. a fixed battery in the basement and/or an electric vehicle (EV) when it is plugged in for charging. An initial prerequisite would be for the EV's battery to be enough charged before the owner heads to work. The system then would manage and optimize the energy usage to make a profit for the owner, i.e. by minimizing the costs or maximizing the income. It may be a problem during the peak hours that there is a higher demand than the demand pre-calculated by the electricity suppliers. To meet these demands the electricity companies need to start new generators which usually are expensive and time consuming. Instead the mini suppliers can meet these extra demands from their storage devices. This would result in less cost to the electricity company and a profit for the individual household, thus a win-win situation. The idea is to apply this kind of system to multiple houses in a certain area. This group of houses can work as a mini supplier of electricity to the grid through an aggregator. The task of the aggregator is to control the amount of energy that enters the grid to avoid overflow and blackouts. Figure 1.1 below shows the "smart house" concept.

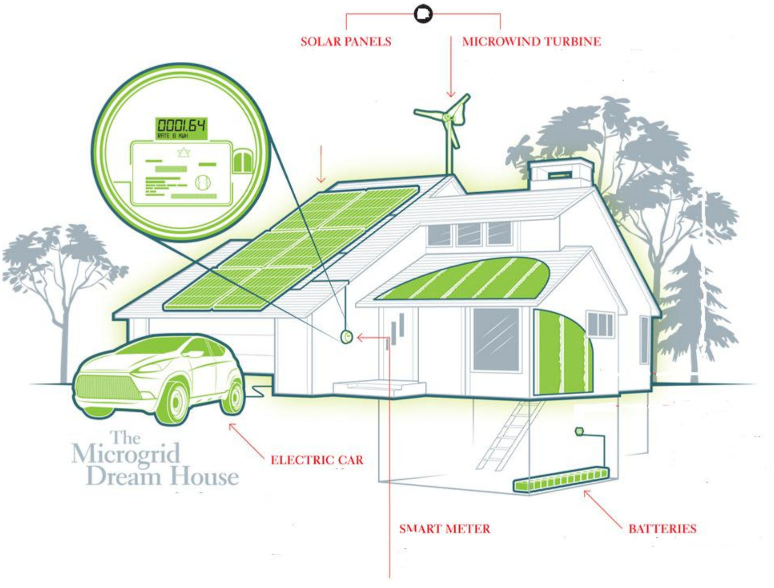


Figure 1.1: *The "smart house" concept.*

Instead of only talking about smart houses, one should mention the concept of smart buildings in general like parking lots, shopping centers etc. The design, construction and operation of smart buildings is occurring as a result of major financial, technical and environmental changes [Smart-Buildings, 2012-12-20]. The advantage of these systems is to reduce capital and operating costs major importance to control energy usage and costs within the building which is a way of living a "Greener" life to reduce carbon emissions. However, owners, designers and managers of buildings want integrated building systems to produce high performance buildings that add value, control costs and meet sustainability and energy requirements. The need for energy conservation is increasing worldwide [Global-Market, 2011-04-01]. The market for energy management is expected to grow with a compound annual growth rate (CAGR) of 23.7 % from 2010 to 2015. The North American smart homes market is the largest today. North America is followed by Europe and developing nations across the Asia Pacific region are expected to grow in the next five years. Japanese housing companies are constantly investing in energy saving housing projects [Japan-House, 2011-02-10]. According to the Japanese media, major home builders in the country are launching experimental technology projects related to the development of energy efficient homes. Several projects are focusing on the efficient use of electricity in homes via residential energy platforms and control systems. The ultimate goal is to build a "smart house" in Japan that emphasizes reduced carbon emissions, increased energy efficiency, and the utilization of renewable energy sources. Most of the smart house projects found in Japan are integrated systems with at least two energy generation or storage technologies.

In this thesis, an attempt will be made to estimate the micro production and the electricity consumption to use them as an input to the system that will be constructed to optimize and make a decision to either use or sell electricity every 10 minutes based on the electricity prices to reduce the monthly electricity cost for the household. Different estimations will be tested with the system and different case studies will be considered to calculate the costs for the equipment and the savings for the household. In the last few years a lot of companies and research facilities have started to research and develop the smart house concept, coming up with optimization models of residential energy hubs with automated decision making technologies in smart grids [Bozchalui M. C., 2012], the same as in this thesis. Some of the recent research is trying to give increased intelligence and flexibility in the control and optimization to avoid serious disturbances in the grid [Bevrani H., 2012] caused in modern power systems that includes smart houses like the one in this thesis. Other research is trying to come up with a way to provide flexible charging optimization for electric vehicles [Sundstrom O., 2012], therefore the EV is considered in this thesis.

Energy demand management for residential users is a promising research area within the smart grid revolution. The whole energy generation and distribution system performance can indeed be improved by optimizing the house energy management that efficiently balance out production and consumption while still meeting the energy needs of customers [Barbato A., 2011] (both cooperative and non-cooperative), the same way as in this thesis. Adding to the list, cellular network combined with the new generation wireless network communication technology to achieve controlling and monitoring the home applications. This design has reflected the characteristic of low cost, low power dissipation and great practical detail for the household owner [Gao Mingming, 2010]. In this thesis, fixed (non-mobile) monitoring of the household's micro production, electricity consumptions and the electricity prices are obtained.

As mentioned before, there is a global interest to include this system in the society, mainly to reduce the energy costs but also to reduce carbon emissions and live a "Greener" life. Is it possible to create a control structure that manages and optimizes the energy either use or sell to make a profit for the owner and how much can a household save with this system? Another interesting thing is what impact do the estimations have on the system's decision making?

2 Background

The concept is to have a system in a house with the presence of micro generation (micro renewables) and a storage device (fixed and EV). The micro generation consists of a small-scale energy producer near the consumption points. Micro generation technologies include small scale solar panels, wind turbines, or fuel cells. Micro generation fits into a decentralized or distributed power generation system, it allows consumers to become energy producers and the advantages are lower costs, greater efficiency and more sustainability. To do so, the system needs to know in advance how much energy will be produced, electricity consumption and the electricity prices in the next couple of hours so that make a decision.

2.1 Data Collecting

The need of some data that will be used in this work is important for the project. The air temperature and solar insolation are needed for the solar panel. The wind speed is needed for the wind turbine. The electricity consumptions are needed to know how much electricity the household consumes and the electricity prices are needed to know how much the electricity costs. The data of air temperature, solar insolation and the wind speed, which is converted from $\left[\frac{km}{h}\right]$ to $\left[\frac{m}{s}\right]$, has been collected through a local weather station [Euskalmet, 2011-10-13]. The data is downloaded as excel files and then fetched to the software tool MATLAB. The outliers have to be corrected and an interpolation is done, since some of the data was missing.

The electricity consumptions are presented as a profile with coefficients multiplied by the annual average consumptions. This is done by the unit of energy (DeustoTech) at the University of Deusto in Bilbao, Spain. There are different prices for selling and buying the energy. The electricity prices in the Spanish market are regulated by RED ELÉCTRICA DE ESPAÑA (REE). The sell prices are downloaded [REE, 2011-11-06] from REE as excel file and then fetched to MATLAB as $\left[\frac{€}{W10min}\right]$. The buy prices depend on what electricity supplier is chosen. For more details about which supplier is chosen and what are the prices, see at the chapter related with electricity consumption and prices.

2.2 Modeling

In this part, the models of a solar panel and a wind turbine are presented.

2.2.1 Solar panel

Photovoltaic (PV) generation is a method for generating electric power by using solar cells to convert energy from the sun into a flow of electrons. The photovoltaic effect refers to photons of light exciting electrons into a higher state of energy, allowing them to act as charge carriers for an electric current. The generated energy depends on various things like the angle of the solar insolation, the geographic location on earth and the season due to the temperature changes during different seasons and the intensity of the solar insolation. Some of the parameters are specific for different panels. The Sunpower A300 panel[1] is proposed and used in this thesis.

The simplified circuit model [Huan-Liang Tsai, 2008] of a solar cell is shown in figure 2.1 below.

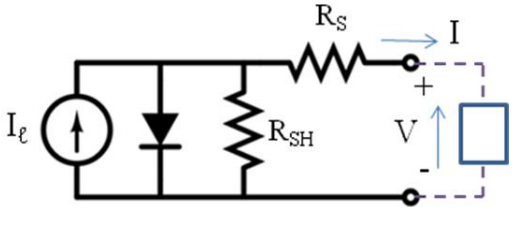


Figure 2.1: *Circuit diagram of the PV single diode.*

The net current of the cell is the difference of the photo current I_L and the diode saturation current I_0 (see figure 2.1)

$$I = I_L - I_0 * (e^{\frac{V+I*R_s}{N*V_{t-cell}}} - 1) - I_{02} * (e^{\frac{V+I*R_s}{N_2*V_{t-cell}}} - 1) - \frac{V + I * R_s}{R_{sh}}$$

[1] Sunpower A300 Cell and Panel Datasheet, See Appendix

A simplification of the model can be done by using a single diode model and assuming that R_{sh} (in an ideal cell) would be infinite and will not provide an alternate path for the current to flow. This means that the third and fourth term in the equation can be ignored [Gonzalez-Longatt, 2005].

$$I = I_L - I_0 * (e^{\frac{V+I*R_s}{N*V_{t-cell}}} - 1), \text{ where} \tag{2.1}$$

$$V_{t_{cell}} \; [V], \text{ is the thermal voltage, } \frac{k * T_{cell}}{q}, \text{ where} \tag{2.2}$$

$k = 1.3806503 * 10^{-23} \left[\frac{J}{K}\right]$, the Boltzmann constant.

$q = 1.60217646 * 10^{-19}$ $[C = A * s]$, the elementary charge of an electron.

T_{cell} $[K]$, the cell temperature.

$N = 1.2$, the quality factor (diode emission coefficient).
V, the voltage across the solar cell electrical ports.

The model includes temperature dependence of the photo current I_L and the saturation current of the diode I_0.

$$I_L = I_L(T_{norm}) + K_0 * (T_{cell} - T_{norm}), \text{ where} \tag{2.3}$$

$$I_L(T_{norm}) = I_{SC}(T_{norm}) * \frac{I_r}{I_{r0}} \tag{2.4}$$

$$K_0 = \frac{I(T_2) - I_{SC}(T_{norm})}{T_2 - T_{norm}} = 3.5 * 10^{-3} \left[\frac{A}{k}\right], \text{ given by the manufacturer.} \tag{2.5}$$

$I_r \left[\frac{W}{m^2}\right]$, the irradiance (light intensity)falling on the cell (estimated in chapter 3).
$I_{SC}(T_{norm}) = 5.75$ $[A]$, the short-circuit current at T_{norm} $[A]$, given by the manufacturer.
$I_{r0} = 1000 \left[\frac{W}{m^2}\right]$, the normalized irradiation.
$T_{norm} = 25 + 273.14$ $[K]$, normalized temperature.
T_2 $[K]$, another model specific temperature chosen by the manufacturer.

$$I_0 = I_0(T_{norm}) * (\frac{T_{cell}}{T_{norm}})^{\frac{3}{N}} * e^{\frac{-q*V_g(T_{norm})}{N*k*(\frac{1}{T_{cell}} - \frac{1}{T_{norm}})}}, \text{ where} \tag{2.6}$$

$$I_0(T_{norm}) = \frac{I_{SC}(T_{norm})}{e^{\frac{V_{OC}(T_{norm})}{N*V_{t-norm}}} - 1}, \text{ where} \tag{2.7}$$

$V_g(T_{norm}) = 1.12\ [eV]$, the voltage of the crystalline silicon.
$V_{t-norm} = 0.0257\ [V]$, calculated the same way as V_{t-cell} but with T_{norm} (see equation 2.2).
$V_{OC}(T_{norm}) = 0.665\ [V]$, the open-current voltage at T_{norm}. given by the manufacturer.

The solar cell/panel loses some efficiency when the cell temperature increases. Every solar panel has a temperature coefficient, for example a Suntech 190 $[W]$ (mono crystalline) solar panel has a temperature coefficient of -0.48 %. This means that for each degree the temperature of $25°C$ increases, the maximum power of the panel [Solar-Facts, 2012-12-20] is reduced by 0.48 %. The relation between the ambient temperature and the cell temperature can be written as [NOCT, 2012-12-20]:

$$T_{cell} = T_{amb} + \frac{T_{NOCT} - 20}{800} * I_r, \text{ where} \tag{2.8}$$

$T_{amb}\ [K]$, the ambient temperature (estimated in chapter 3).
$T_{NOCT} = 45 + 273.14\ [K]$, the nominal operating cell temperature, given by the manufacturer.

R_s, the resistance inside each cell in the connection between the cells. R_s can be written as

$$R_s = \frac{-dV}{dI_{V_{OC}}} - \frac{1}{X_V} \tag{2.9}$$

$$X_V = \frac{I_0(T_{norm})}{N * V_{t-norm}} * e^{\frac{V_{OC}(T_{norm})}{N*V_{t-norm}}}, \text{ where} \tag{2.10}$$

$\frac{dV}{dI_{V_{OC}}} = -0.00985 \left[\frac{A}{V}\right]$, the coefficient $\frac{dV}{dI}$ at V_{OC} , given by the manufacturer.

To be able to calculate the cell current I, one has to measure V. V is the voltage across the solar cell electrical ports, but there is not an actual physical cell in this project that can be measured. So in this case one can consider that the cell is operated as open circuit i.e. $I = 0$ the voltage across the output terminal is defined as the open-circuit voltage (See equation 2.1).

$$V = V_{OC} = N * V_{t-cell} * ln(\frac{I_L}{I_0} + 1) \tag{2.11}$$

In the morning when the sun rises, the voltage for each solar cell in the Sunpower A300 panel starts to rise from zero till it reaches 0.56. To adapt the voltage in the model to the Sunpower A300, the calculated V needs to be corrected so that it reaches 0.56 volts during the peak.

$$V_{max} = 0.56 = m_V * max(V), \text{ where} \tag{2.12}$$

$m_V = \frac{0.56}{max(V)}$, calculated for each day to adapt the model to the Sunpower A300.

Now the induced current I can be calculated with Newton's method

$$I_{n+1} = I_n - \frac{f(I_n)}{f'(I_n)}, \text{ where} \tag{2.13}$$

$$f(I_n) = 0 = -I_n + I_L - I_0 * (e^{\frac{V+I_n*R_s}{N*V_{t-cell}}} - 1) \tag{2.14}$$

$$f'(I_n) = -1 - I_0 * (e^{\frac{V+I_n*R_s}{N*V_{t-cell}}}) * \frac{R_s}{N * V_{t-cell}} \tag{2.15}$$

Each solar cell in the Sunpower A300 panel provides 5.35 Ampere at maximum power. To adapt the current in the model to the Sunpower A300, the calculated current needs to be corrected so that it reaches 5.35 Ampere at some point during a year. To do so, the data measured from the previous year i.e. the year 2010 is used.

$$I_{max} = 5.35 = m_I * max(I), \text{ where} \tag{2.16}$$

$m_I = \frac{5.35}{max(I)}$, calculated to adapt the model to the Sunpower A300 panel and then used for the data of the year 2011. This gives m_I=1.4357

The electric power of one solar cell can be calculated according to the formula below:

$$P_{cell} = U * I, \text{ where} \tag{2.17}$$

U, the electric voltage of one cell.
I, the electric current of one cell.

A Sunpower A300 Solar Cell has a rated power of 3.0 $[W]$. With the calculated m_V , m_I and the measured data of the year 2010 it follows that the maximum power of one cell is $P_{cell-max} = 2.8484$ $[W]$, about 95 % of the rated power.

The solar cells can be connected to each other either as a series circuit, or as a parallel circuit. The series circuit increases the electric voltage and the parallel circuit increases the current, but the electric power would be the same. Many solar cells connected to each other make a solar module/panel and solar modules connected to each other make a solar array. The solar panel effect is the effect from a single cell multiplied by the amount cells in a single panel or array.

$$P_{panel} = N_{cell} * P_{cell}, \text{ where} \tag{2.18}$$

$N_{cell} = 96$, the amount of cells in the Sunpower A300 panel, given by the manufacturer.

$$P_{module} = N_{panel} * P_{panel}, \text{ where} \tag{2.19}$$

$N_{panel} = 12$, the amount of panels used in this thesis.

2.2.2 Wind turbine

The wind turbine converts kinetic energy in the wind into rotational energy and then into electrical energy. The definition of a kinetic energy of an object with mass m and speed v is given by the formula:

$$E = \frac{m * v^2}{2} \tag{2.20}$$

The power produced by the wind is given by the energy flow rate:

$$P_{wind} = \frac{dE}{dt} = \frac{v^2}{2} * \frac{dm}{dt}, \text{ as the mass flow rate is given by} \tag{2.21}$$

$$\frac{dm}{dt} = \rho * A * \frac{dx}{dt} = \rho * A * v \tag{2.22}$$

Inserting equation (2.22) into equation (2.21), gives

$$P_{wind} = \frac{v^2}{2} * \rho * A * v = \frac{\rho * A}{2} * v^3 \tag{2.23}$$

Every wind turbine has a specific power curve due to different manufacturing. This indicates that a wind turbine can not extract all the energy from the wind and a power coefficient has to be included in the above mentioned equation.

$$P_{wind} = \frac{\rho * A}{2} * C_p * v^3, \text{ where} \tag{2.24}$$

$\rho = 1.225 \left[\frac{kg}{m^3}\right]$, the air density
$A = \pi * r^2 \left[m^2\right]$, the swept area of the turbine, r is the radius.
$v \left[\frac{m}{s}\right]$, the wind speed (estimated in chapter 3).
C_p, the power coefficient.

However there is a theoretical maximum value of the power coefficient [Stiebler, 2008] $C_p = \frac{16}{27} \approx 0.59$, which has been calculated by a German physicist Albert Betz in 1919. In reality the wind turbines achieves peak values for C_p in the range of 0.40 to 0.50 (about 68% to 85% of the theoretically possible maximum) due to profile loss, tip loss and loss due to wake rotation. Also, in high wind speed where the turbine is operating at its rated power the turbine rotates (pitches) its blades to lower C_p to protect itself from damage and in order to determine the mechanical power available for the load machine (electrical generator, pump).

The wind turbine model Anern 1000L [Anern, 2012-12-20] is considered in the modeling. This model has a radius of 1.9 $[m]$, cut-in speed of 3 $\left[\frac{m}{s}\right]$ (at this wind speed the turbine start to generate energy) and cut-out speed of 18 $\left[\frac{m}{s}\right]$ (at this wind speed a braking system is employed on the turbine to not damage the rotor). Figure 2.2 below demonstrates the power curve [Anern, 2012-12-20].

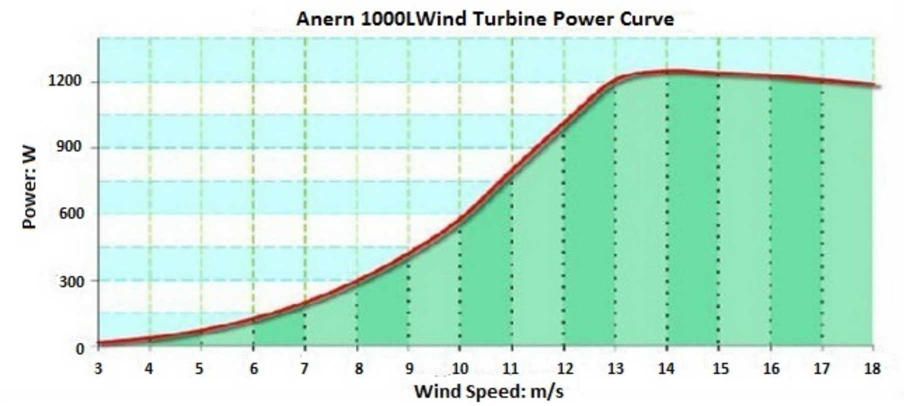


Figure 2.2: *The power curve of Anern 1000L Wind Turbine.*

Since there is a limit of mechanical and electric generation the power curve has the shape shown in figure 2.2. Different C_p values calculated for different wind speeds backward according to the formula below:

$$C_p = \frac{P_{anern}}{0.5 * \rho * A * v_{anern}^3} \tag{2.25}$$

This is done through a lookup table that has values of the power curve for every 0.5 $\left[\frac{m}{s}\right]$. The actual wind speed v between 3 and 18 $\left[\frac{m}{s}\right]$ is rounded to the closest 0.5 value (the rounded velocity becomes v_{anern}) and for every 0.5 value there is a corresponding power value (P_{anern}). P_{anern} is set to zero for the wind speed less than 3 and more than 18 $\left[\frac{m}{s}\right]$. Now the output power of Anern 1000L can be calculated according to equation (2.24).

$$P_{anern,tot} = N_{anern} * P_{anern}, \text{ where} \tag{2.26}$$

$N_{anern} = 2$, the amount of turbines used in this thesis.

2.3 Storage device

The storage device is a battery that includes battery cells. The most commonly used batteries are lead-acid, nickel-cadmium (NiCd), nickel-metal hydride (NiMH) and lithium-ion (Li-ion). However, Lithium-ion batteries presently are preferably used for electric vehicles due to their high specific energy whereas nickel-metal batteries are used for residential purposes due to their long lifetime.

A study of charging and discharging cycle [Mirone, 2012] is made of a lithium iron phosphate cell battery that has typical capacity of 10 $[Ah]$, up to 2000 cycles, discharge current of $1c$ (c is the rate of charging/discharging per hour [Buchmann, 2012-12-20], multiplied with the total battery capacity $[A]$) and charge current of $0.3c$ (standard) or $1c$ (rapid). This means that the discharge current limit is about 10 $[A]$ and charge current limit is about 3 $[A]$ (standard) or 10 $[A]$ (rapid). The study was made with 10.5 $[A]$ to charge and discharge the one cell battery, from 0% to 100% SOC (State Of Charge) and 100% to 0% SOC respectively. The result is illustrated in figure 2.3 below.

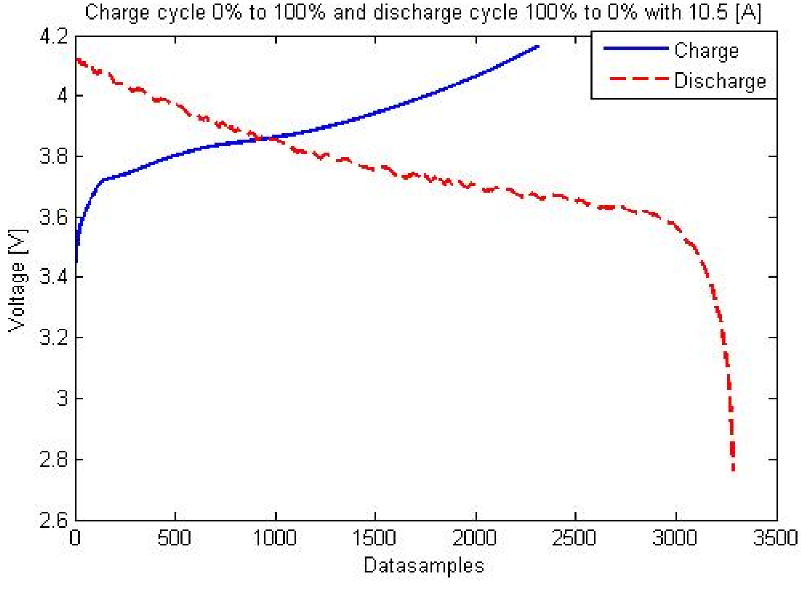


Figure 2.3: *Charge and discharge cycle of one cell battery with current 10.5* $[A]$.

In figure 2.3 above, the charge cycle is sampled with 1.2 seconds interval and the discharge cycle is sampled with 1 second interval. As seen, the voltage increases rapidly when charging the first 10-20% SOC and drops rapidly when discharging the last 10-20% SOC. The system will keep the SOC between 15% and 85%, due to the voltage rapid changing at the first/last SOC when charging/discharging and the long time to deliver the last SOC when charging [Simpson, 2012-12-20].

The battery chosen as a fixed storage device for the smart house case is a nickel-metal type[2] and has a total capacity of 12 $[kWh]$ with a charging/discharging rate per hour of $0.2c$ for the first 85% SOC (2.04 $[kWh]$). This means that the battery can charge/discharge 0.34 $[kWh]$ (2040 $[W10min]$) every 10 minutes.

[2]Nickel-Iron Batteries Info, see Appendix

2.3.1 Electric Vehicle (EV)

The EV chosen for this project is a Nissan Leaf that has a high response 80 $[kW]$ AC synchronous electric motor and a range of 100 $[miles]$, about 161 $[km]$ per charge based upon US EPA LA4 city cycle [Nissan-Info, 2012-12-20]. This EV has a top speed of 90 $[mph]$, about 145 $\left[\frac{km}{h}\right]$ and a 24 $[kWh]$ lithium-ion battery pack. The battery pack has 48 modules and each module includes a total of four cells (total 192 cells) [Battery-Pack, 2012-12-20]. The battery has a charging per hour rate of $0.3c$ for the first 85% SOC (6.12 $[kWh]$) and a discharging per hour rate of $1c$ for the first 85% SOC (20.4 $[kWh]$). This means that the battery can charge 1.02 $[kWh]$ (6120 $[W10min]$) every 10 minutes and discharge 3.4 $[kWh]$ (20400 $[W10min]$) every 10 minutes.

The Nissan Leaf consumes $\frac{24}{161}\left[\frac{kWh}{km}\right]$ of energy, about 0.15 $\left[\frac{kWh}{km}\right]$. A round trip, a standard driving pattern is about 40 $[km]$. This gives a consumption of 6 $[kWh]$, which is about 25% of the total capacity. The EV is considered to leave home at 8 am and return back to home at 7 pm, after this time the EV is plugged in. It takes about 22 hours to charge the Nissan Leaf from 0% to 100% SOC on a Level 1 charging: electric vehicle supply equipment (EVSE) on 110/120 $[V]$ and it takes about 8 hours to fully charge the Nissan Leaf on a Level 2 charging: EVSE on 240 $[V]$ 40 $[A]$ circuit. These are the standard households charging options. However, there is a fast charging option that can charge the Nissan Leaf up to 80% SOC, Level 3 DC fast charging that takes about 30 minutes.

2.4 Electricity consumption and prices

The house consumption varies throughout the day and during different seasons. Since the study is done in Bilbao, Spain, the consumptions are considered for a single household in Spain of four people or otherwise a couple with two children. According to the consumption profile for the year 2010, the household consumption is approximately 17.7 $[kWh]$ during a day. For this project the consumption profile for the year 2011 is used (estimated in chapter 3).

It is important for this project to know the electricity prices for buying and selling the energy. The prices are determined through a contract with the supplier and the prices are listed in $\left[\frac{€}{kWh}\right]$. According to the consumption profile for the year 2010, the yearly consumptions of the household are about 6470 $\left[\frac{kWh}{year}\right]$. It is normal that the supplier gives different prices for $[kWh]$ depending on how much energy each household uses. According to Europe's Energy Portal [Energy-Portal, 2011-12-20], the energy cost in Spain is 0.2013 $\left[\frac{€}{kWh}\right]$ for households that use up to 3500 $\left[\frac{kWh}{year}\right]$ compared to 0.1839 $\left[\frac{€}{kWh}\right]$ for households that use up to 7500 $\left[\frac{kWh}{year}\right]$. The electricity supplier usually offers different contract that include variable or fixed prices while some suppliers offer a mix of both variable and fixed prices.

As mentioned before, the electricity prices in the Spanish market are regulated by RED ELÉCTRICA DE ESPAÑA (REE). REE calculates the sell prices for the 24 hours ahead bidding market which are set for every hour. In figure 2.4 below one can see the prices for one week of 24 hours ahead bidding market.

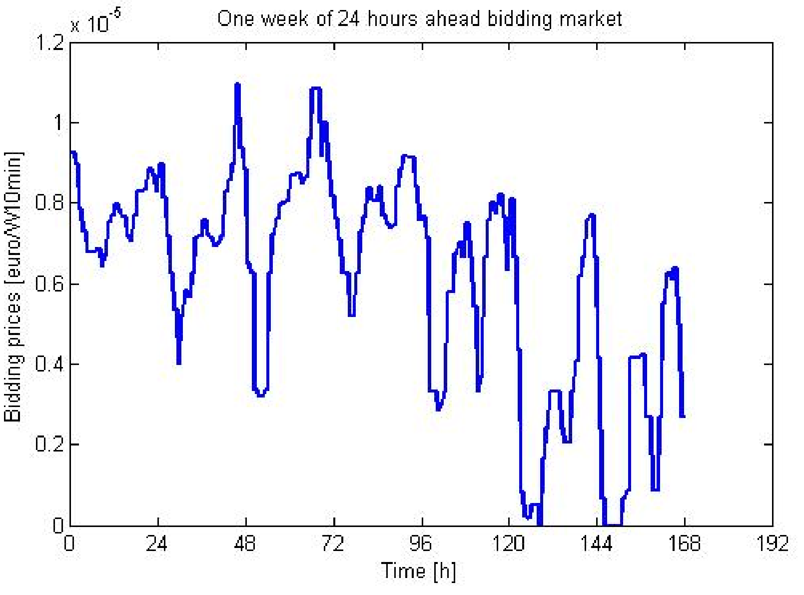


Figure 2.4: *One week of 24 hours ahead bidding market.*

These prices are based on the demand in the market and some of the prices are set to zero. This means that there is no demand at all i.e. the market is saturated with energy and there is no bidding. Since the prices that REE offers are the prices of the next 24 hours, there is no need to estimate them. The sell prices in $\left[\frac{€}{W10min}\right]$ for the year 2011 are used in this project. The electric utility company Iberdrola is considered as the electricity supplier in this project. Iberdrola offers peak and valley prices as well winter and summer time table [Iberdrola, 2011-11-10]. The peak prices correspond to 10 hours a day, from 12 h to 22 h winter time and from 13 h to 23 h summer time. The electricity prices [Tarifas-Eléctricas, 2011-11-22] are updated twice a year. For the first 6 months of the year 2011, the prices are 0.168743 $\left[\frac{€}{kWh}\right]$ for peak and 0.06089 $\left[\frac{€}{kWh}\right]$ for valley. For the last 6 months of the year 2011, the prices are 0.17282 $\left[\frac{€}{kWh}\right]$ for peak and 0.064047 $\left[\frac{€}{kWh}\right]$ for valley. This data is inserted in MATLAB as $\left[\frac{€}{W10min}\right]$.

2.5 Artificial Neural Network (ANN)

An ANN [Mark Hudson Beale, 2011] is a mathematical model that is inspired by the structure and functional aspects of biological neural networks, like the human brain. A neural network consists of an interconnected group of artificial neurons. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the training phase. Advanced neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. Even though artificial neurons are simplified, they can show a variety of input-output relations, depending on the transfer functions they apply. The different choice or combination of transfer functions gives different behavior and fits different types of problems.

The ANN consists of layers, the first layer has input neurons, which send data via synapses to the second layer of neurons (one hidden layer is standard in MATLAB, more than one hidden layers can be used) and then via more synapses to the third layer, which includes the output neurons. More complex systems have more hidden layers with increased number of input and output neurons. The synapses store parameters called weights that manipulate the data in the calculations.

An ANN is defined by the below types of parameters

1. The interconnection pattern between different layers of neurons.
2. The learning process for updating the weights of the interconnections.
3. The activation function that converts a neuron's weighted input to its output activation.

Figure 2.5 illustrate the different layers.

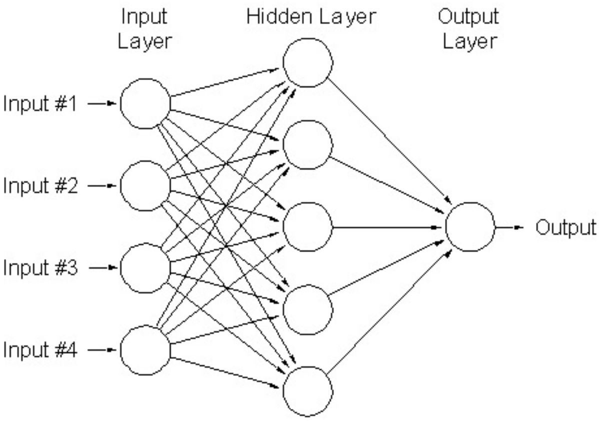


Figure 2.5: *Artificial Neural Network (ANN).*

3 Estimation

To be able to construct a control system that makes decisions for the future, an estimation of the future data is needed. The estimation for the next 24 hours requires 144 values (6*24), since the data is collected every 10 minutes. The prediction of the next 24 hours is based on the last 24 hours i.e. the last 144 values (24 hours) are used to predict the next 144 data (24 hours). The predictions of air temperature, solar insolation and wind speed are needed in order to know how much energy will be produced in the next 24 hours from the solar panel and from the wind turbine. The predictions of electricity consumption and electricity prices are needed in order to know how much energy the house will consume and what will the prices be in the grid.

All predictions are made with an Artificial Neural Network (ANN) in MATLAB which is trained with the measured meteorological data from the year 2010. Depending on the application, one may choose among the fitting tool, pattern recognition tool, clustering tool or time series tool. It depends on what is appropriate for the problem. Here, the Neural Network fitting tool (input-output and curve fitting) is used and since the prediction is for the next 24 hours, the data is divided (day 1 to day 364) as input and (day 2 to day 365) as target. Then the data is divided as 70% training data, 15% validation data and 15% testing data. Neural Network consists of layers. In this case the network will be trained with the function Levenberg-Marquardt backpropagation algorithm, unless there is not enough memory then the scaled conjugate gradient backpropagation algorithm will be used. These are chosen by MATLAB as standard when choosing fitting tools.

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance. The default performance function for feedforward networks is mean square error. In this network one hidden layer and one output layer is used as seen in figure 3.1 below.

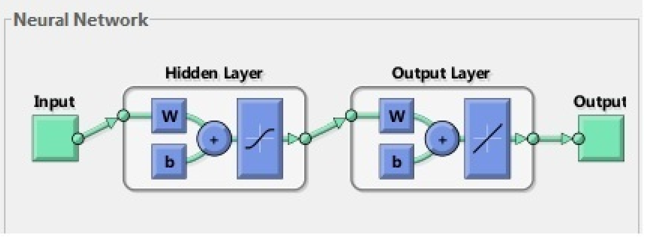


Figure 3.1: *Neural Network layers fitting tool.*

The hidden layer has 10 neurons with Tan-Sigmoid transfer function and the output layer has 1 neuron with Linear transfer function, (see figure 3.2 below). These functions are chosen by MATLAB as standard when choosing fitting tool.

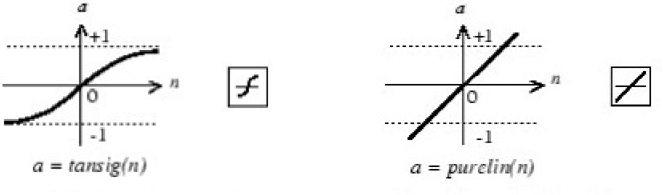


Figure 3.2: *Transfer function Tan Sigmoid (left) and Linear (right).*

As mentioned before, the solar insolation and the air temperature are needed to calculate the output energy of the solar panel. The estimation is done by a network trained with the data from the year 2010 and the functions mentioned above. Estimation along with actual data of one week during the year 2011 is illustrated in figure 3.3 for the solar insolation $\left[\frac{W}{m^2}\right]$, each peak corresponds to a day of solar insolation. Estimation along with actual data of one week during the year 2011 is illustrated in figure 3.4 for the air temperature $[°C]$. The input data is for instance from day 1 and the output data would be the estimation for day 2.

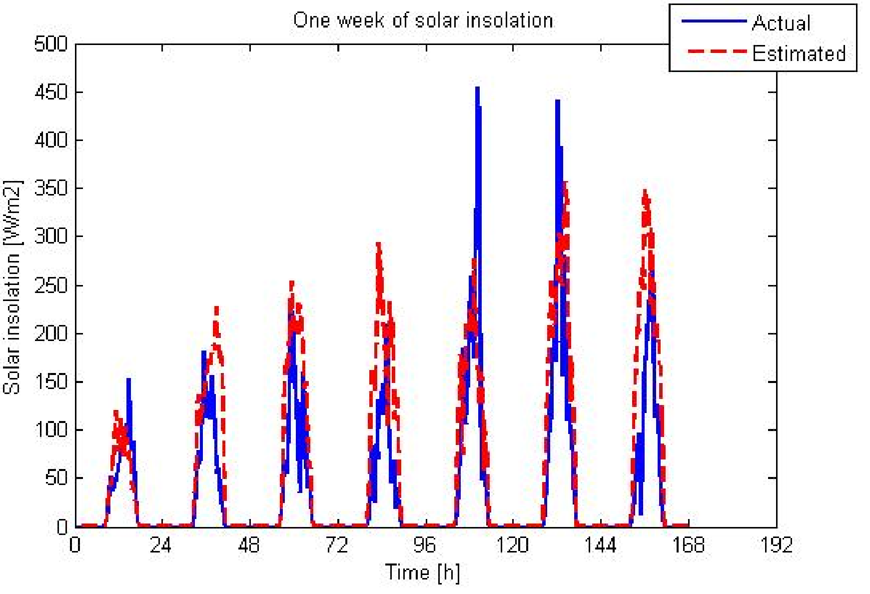


Figure 3.3: *One week of solar insolation, estimated and actual data.*

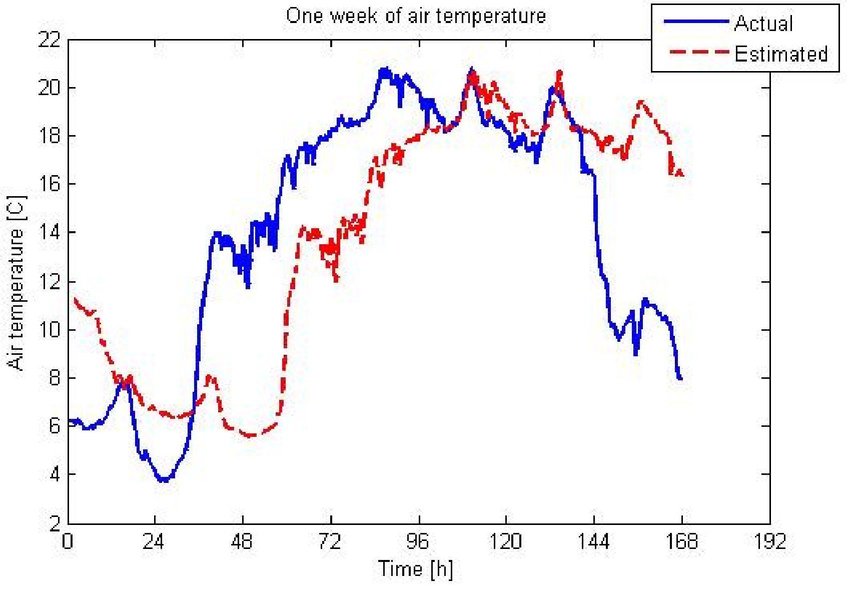


Figure 3.4: *One week of air temperature, estimated and actual data.*

The wind speed is needed to calculate the output energy of the wind turbine. The estimation is obtained from by a network trained with the data from the year 2010 and the functions mentioned above. One day instead of one week of estimation is made. Estimation along with actual data of one day during the year 2011 is illustrated in figure 3.5 for the wind speed $\left[\frac{m}{s}\right]$. The wind speed is very variable and the estimation errors are expected to be higher compared to the previous cases.

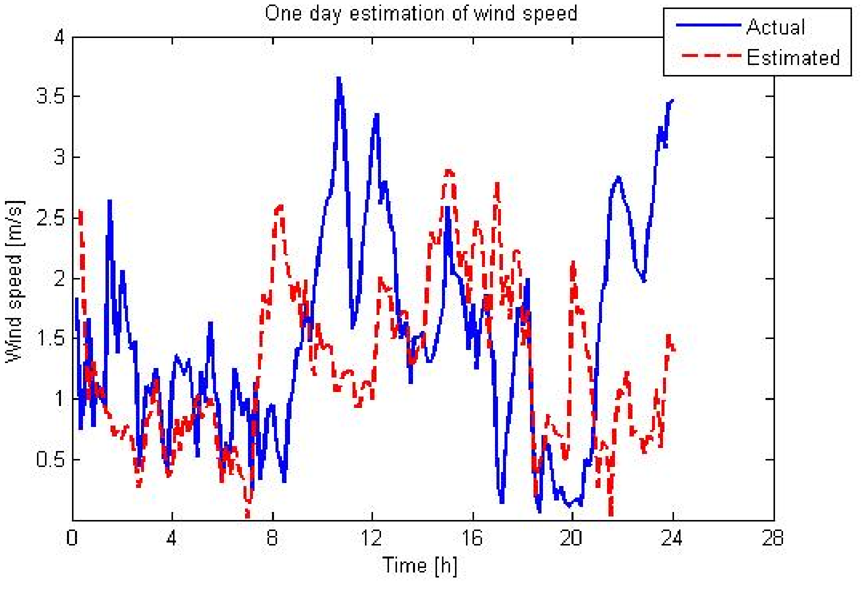


Figure 3.5: *One day of wind speed, estimated and actual data.*

As mentioned before, it is important for the system to know how much electricity the house consumes. The estimation is made by a network trained with the data from the year 2010 and the functions mentioned above. Estimation along with actual data of one week during the year 2011 is illustrated in figure 3.6 for the electricity consumption $[W10min]$. The electricity consumption has probably the smallest error, since the consumptions do not change so much from day to day.

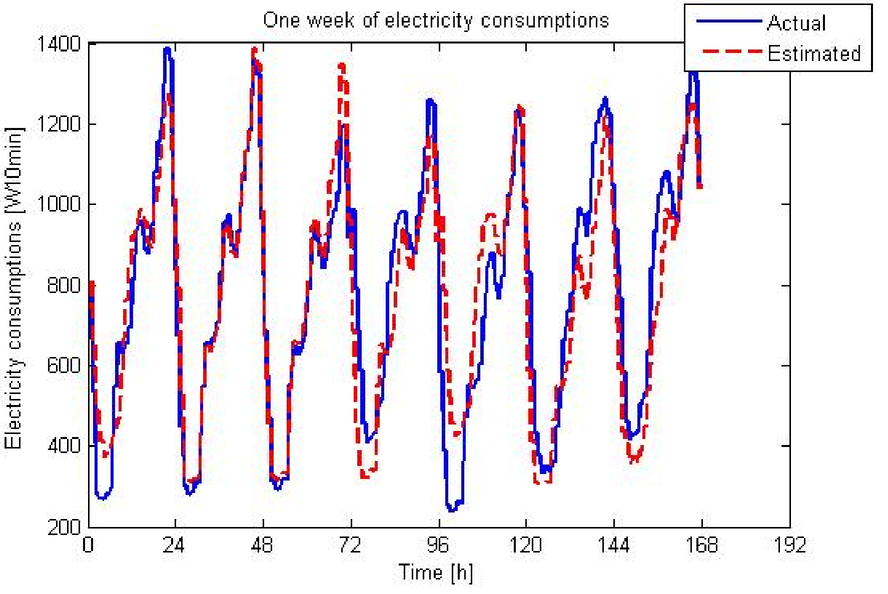


Figure 3.6: *One week of electricity consumptions, estimated and actual data.*

4

Control system

To be able to solve an optimization problem the problem need to be modeled. The system includes three controls, a control (P_{market}) to either sell or buy energy, a control to charge or discharge the fixed battery (P_{batt}) and a control to charge or discharge the EV (P_{EV}). The system interprets selling energy as a negative flow and buying energy as a positive flow. Charging the fixed battery or EV is set as a positive flow of energy while discharging the fixed battery or EV is set as a negative flow of energy, in turn the negative flow of energy from the battery or EV is a supplement to the system i.e. positive flow of energy to the system. The positive flow of energy to the system including (P_{prod}) should be equal to the negative flow of energy from the system i.e. the house consumptions (P_{demand}). This is shown in the equation below.

$$P_{market} - P_{batt} - P_{EV} + P_{prod} = P_{demand}, \text{ which can be written as} \tag{4.1}$$

$$P_{market} - P_{batt} - P_{EV} = P_{demand} - P_{prod} \tag{4.2}$$

The EV is not plugged in between 8 am and 7 pm, this gives

$$P_{market} - P_{batt} - P_{EV} * c_{plug} = P_{demand} - P_{prod}, \text{ where} \tag{4.3}$$

$c_{plug} = 0$ when unplugged and 1 when plugged, the EV presence vector.

As mentioned before, the estimation is made for every 10 min for the next 24 hours (144 time steps). This can be written as.

$$\begin{bmatrix} 1 & -1 & -c_{plug} & 0 & 0 & 0 & & \cdots & & 0 & 0 & 0 \\ 0 & 0 & 0 & & \ddots & & & \cdots & & & \vdots & \\ & \vdots & & & & \cdots & & & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & & & \cdots & 0 & 0 & 0 & 1 & -1 & -c_{plug} \end{bmatrix} * \begin{bmatrix} P_{market} \\ P_{batt} \\ P_{EV} \end{bmatrix} = \begin{bmatrix} P_{demand1} - P_{prod1} \\ P_{demand2} - P_{prod2} \\ \vdots \\ P_{demand144} - P_{prod144} \end{bmatrix}$$

The variables P_{market}, P_{batt} and P_{EV} have a lower and upper bound according to the inequalities below

$-inf \leq P_{market} \leq inf$, negative selling energy and positive buying energy
$-2040 \leq P_{batt} \leq 2040$, negative discharging and positive charging
$-20400 * c_{plug} \leq P_{EV} \leq 6120 * c_{plug}$, if EV is not present this is set to zero

To solve this optimization problem, the solver function "fmincon" is used with an objective function that includes a cost function according to the equation below. The objective function will return the sum over all 144 time steps.

$$f = P_{market}(\leq 0) * Price_{sell} + P_{market}(\geq 0) * Price_{buy}, \text{ where} \tag{4.4}$$

$P_{market}(\leq 0)$, includes only negative values of P_{market}
$Price_{sell}$, the prices to sell energy
$P_{market}(\geq 0)$, includes only positive values of P_{market}
$Price_{buy}$, the prices to buy energy

To keep track of the SOC for the battery and EV, a simple model is used according to the following equation.

$$SOC_{batt}(n+1) = SOC_{batt}(n) + \frac{P_{batt}(n) * \eta^{sign(P_{batt}(n))}}{Capacity_{batt}} * dt, \text{ where} \tag{4.5}$$

$SOC_{batt}(n)$, the current State Of Charge.
$P_{batt}(n)$, the amount of power to charge or discharge.
$\eta = 0.98$, the battery efficiency rate.
$sign(P_{batt}(n)) = 1$ when P_{batt} is positive, 0 when P_{batt} is zero and -1 when P_{batt} is negative.
$Capacity_{batt} = 12000\ [Wh]$, the total capacity of the battery.
$dt = \frac{1}{6}$, time step ($\frac{10min}{60min} = \frac{1}{6}$).

As mentioned before, the EV consumes about 25% of the battery. The SOC of the EV is calculated the same way as the battery ($Capacity_{EV} = 24000\ [Wh]$) but with a subtraction of 0.25 when the value of c_{plug} changes from 0 to 1. This means that the EV is plugged in when returning home and consumed 25% of the battery. As mentioned before, the system should keep the SOC between 15% and 85% (lower and upper bound). The level of the current time step plus the previous time steps and the initial level should not exceed the upper and lower bounds. However, the function $sign(P_{batt}(n))$ in equation 4.5 can only be used when the simulation is done, since the vector $P_{batt}(n)$ can not be reached externally during the simulation. As seen, η is used when charging ($P_{batt}(n)$ is positive) and η^{-1} is used when discharging ($P_{batt}(n)$ is negative). The only way that can risk exceeding the upper bound adjacent to 0.85 is if the system chooses to charge the battery, therefore η is used in equation 4.6. The only way that can risk exceeding the lower bound adjacent to 0.15 is if the system chooses to discharge the battery, therefore η^{-1} is used in equation 4.7. The same conditions are also applied to the EV.

$$sum(P_{batt}(n) * \eta) * \frac{dt}{Capacity_{batt}} + SOC_{initial} \ \leq \ 0.85, \text{ can be written as} \tag{4.6}$$

$$sum(P_{batt}(n)) \ \leq \ (0.85 - SOC_{initial}) * \frac{Capacity_{batt}}{dt * \eta}$$

$$sum(P_{batt}(n) * \eta^{-1}) * \frac{dt}{Capacity_{batt}} + SOC_{initial} \ \geq \ 0.15, \text{ can be written as} \tag{4.7}$$

$$-sum(P_{batt}(n)) \ \leq \ -(0.15 - SOC_{initial}) * \frac{Capacity_{batt} * \eta}{dt}, \ where$$

$SOC_{initial} = 0.8$, the initial State Of Charge.
The bounds for the EV are the same as the fixed battery but extra few things need to be included. The presence vector c_{plug} and the 25 % drop after returning home should be included all the way through all time steps, see the equation 4.8 below.

$$sum(P_{EV}(n) * c_{plug}(n) * \eta) * \frac{dt}{Capacity_{EV}} + SOC_{initial} - \tag{4.8}$$

$$-0.25 * 1(c_{plug}\ 0\ to\ 1, .., end) \ \leq \ 0.85, \text{ can be written as}$$

$$sum(P_{EV}(n) * c_{plug}(n)) \ \leq \ (0.85 - SOC_{initial} + 0.25 * 1(c_{plug}\ 0\ to\ 1, .., end)) * \frac{Capacity_{EV}}{dt * \eta}$$

The EV should be fully charged (85 %) at 8 am. To ease the problem solving, the lower bound is increased gradually starting from 11 pm (the valley for buy prices) according to the formula below. Notice that the system will operate freely, since the EV will probably not return home with 15 % SOC. The system can charge the EV at any time and if it chooses to charge the EV too late then it will only be forced to charge the EV with maximum power the last 3 or 4 hours.

$0.15 + n_{EV} * c_{EV} * \frac{P_{EV,max}}{Capacity_{EV}} * dt, where$

$n_{EV} = 1, .., 54$, the steps from 11 pm to 8 am.
$c_{EV} = 0.3050$, the step size to reach SOC 85%
$P_{EV,max} = 6120$ $[W]$, the maximum charging power during 10 min.
$Capacity_{EV} = 24000$ $[Wh]$, the total capacity of the battery.
$dt = \frac{1}{6}$, time step ($\frac{10min}{60min} = \frac{1}{6}$)

$$sum(P_{EV}(n)*c_{plug}(n)*\eta^{-1})*\frac{dt}{Capacity_{EV}}+SOC_{initial}-0.25*1(c_{plug}\ 0\ to\ 1,..,end)\ \geq \tag{4.9}$$

$$\geq\ 0.15+n_{EV}(1,..,54 \text{ steps from 11 pm to 8 am})*c_{EV}*\frac{P_{EV,max}}{Capacity_{EV}}*dt,\ \text{can be written as}$$

$$-sum(P_{EV}(n)*c_{plug}(n))\ \leq\ -(0.15+n_{EV}(1,..,54\ steps\ from\ 11\ pm\ to\ 8\ am)*$$

$$*c_{EV}*\frac{P_{EV,max}}{Capacity_{EV}}*dt-SOC_{initial}+0.25*1(c_{plug}\ 0\ to\ 1,..,end))*\frac{Capacity_{EV}*\eta}{dt}$$

The first start points for the simulation are chosen as follows:

$$x_0 = \begin{bmatrix} P_{market1} \\ P_{batt1} \\ P_{EV1} \\ \\ \vdots \\ \\ P_{market144} \\ P_{batt144} \\ P_{EV144} \end{bmatrix} = \begin{bmatrix} P_{demand1} - P_{prod1} \\ 0 \\ 0 \\ \\ \vdots \\ \\ P_{demand144} - P_{prod144} \\ 0 \\ 0 \end{bmatrix}$$

When the simulation is done, "fmincon" will return 144 values for each of P_{market}, P_{batt} and P_{EV} and the first value of each one will be the decision for what to do the next 10 min. Since the simulation is done based on the estimated values of P_{demand} and P_{prod}, P_{market} needs to be corrected according to the following equation.

$$P_{market,actual} = P_{demand,actual} - P_{prod,actual} + P_{batt,sim} + P_{EV,sim} \tag{4.10}$$

To run a couple of simulations consecutively, different vectors are updated. The $SOC_{initial}$ and the starting points (P_{batt}, P_{EV}) for the next simulation are the decisions from the last simulation.

5

Resultat and Analysis

To test the system, 288 simulations that correspond to 2 days were made. In figures 5.1, 5.2 and 5.3 below the control variables in equation 4.2 (P_{market}, P_{batt} and P_{EV}) can be seen. These are the decisions for what to do for each time instance. In figure 5.4 below the left and the right side of equation 4.2 can be seen.

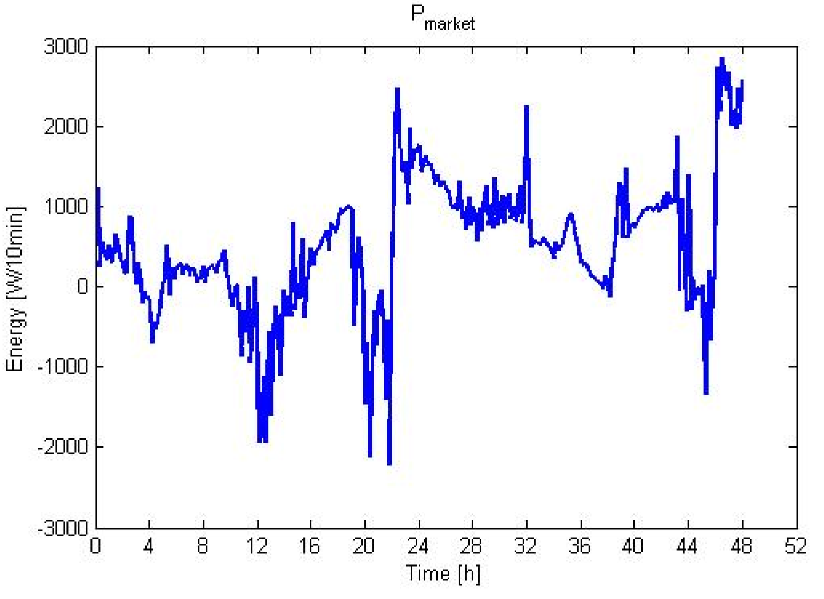


Figure 5.1: *The decisions (P_{market}) for two days period.*

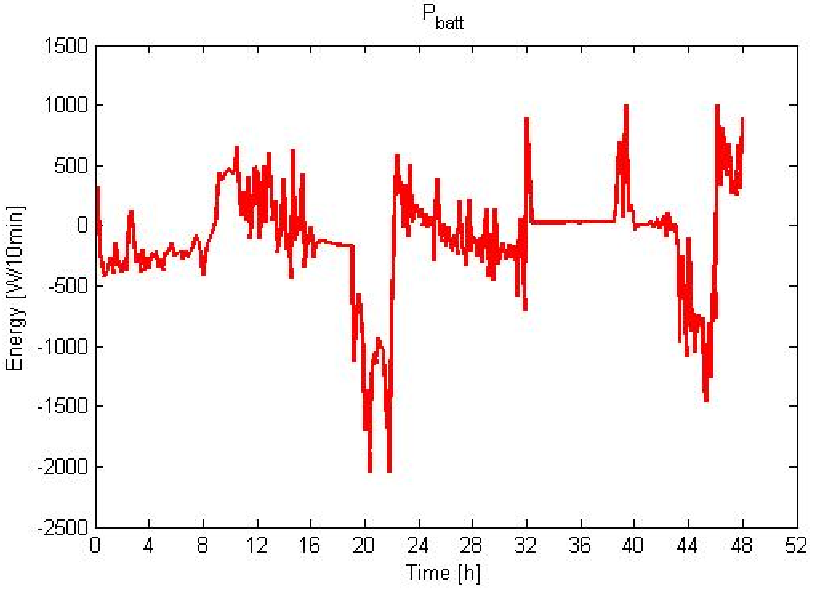


Figure 5.2: *The decisions (P_{batt}) for two days period.*

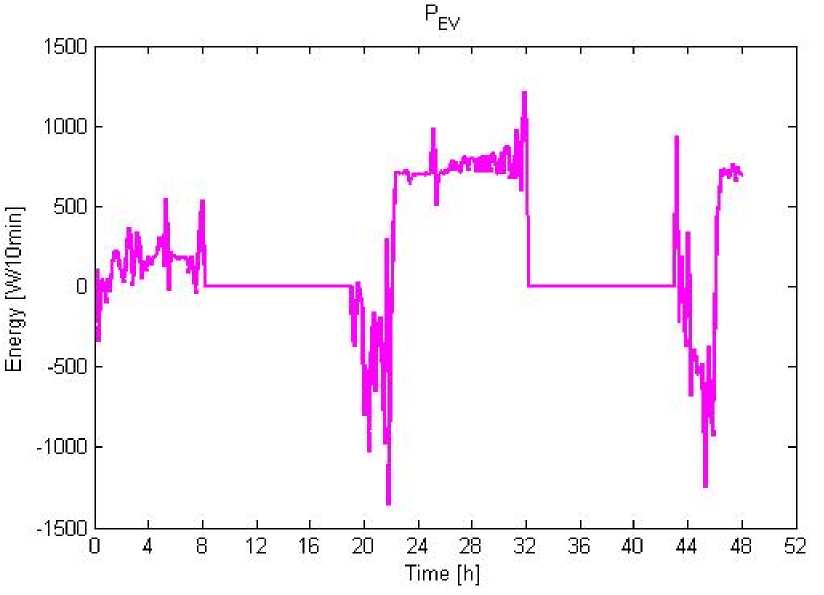


Figure 5.3: *The decisions (P_{EV}) for two days period.*

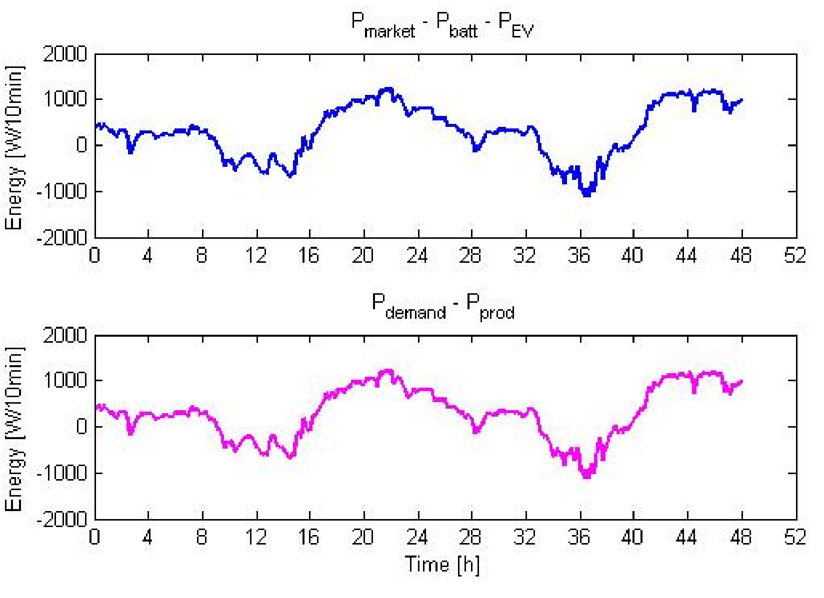


Figure 5.4: *The left and the right side of equation 4.2.*

To examine if the system is working properly, the system error and the state of charge (SOC) can be checked. In this case, the error is defined as the difference between the left and the right side of equation 4.2. Figure 5.5 below shows the system error and figure 5.6 below shows the SOC.

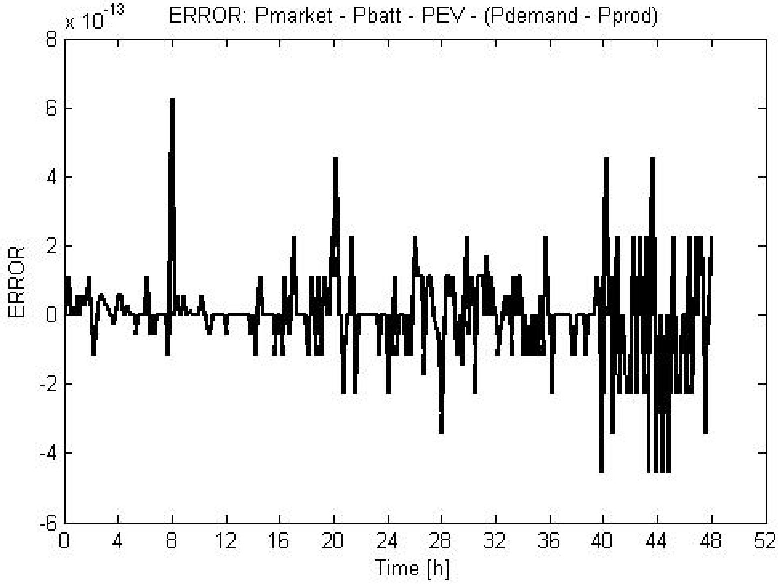


Figure 5.5: *The system error.*

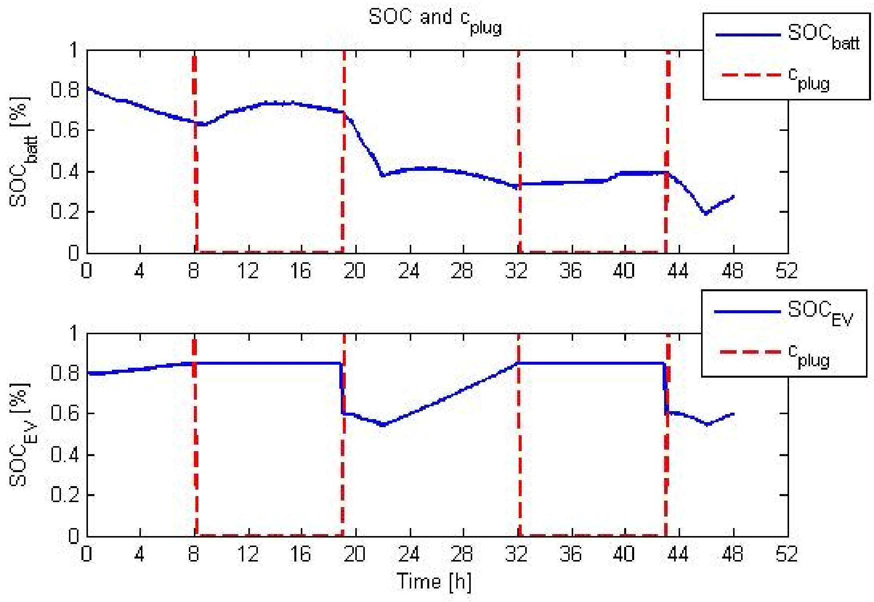


Figure 5.6: *The state of charge of the EV during two days.*

The results are promising and the output of the system is as expected. Figure 5.5 shows the system error i.e. the left side minus the right side of equation 4.2 before executing equation 4.10. The values in the figure are multiplied with 10^{-13} (almost zero). This means that P_{market}, P_{batt} and P_{EV} are chosen in a way that the equation 4.2 is satisfied. As shown in figure 5.3 that P_{EV} is zero from 8 am to 7 pm, the EV is away during that time and the system does not charge the EV. As expected in figure 5.6, the EV is fully charged (85 %) at 8 am and drops 25% at 7 pm when the EV is plugged back. To understand the solver's performance, a closer look is inevitable. Figure 5.7 below shows P_{market}, P_{batt} and figure 5.8 below shows P_{EV}, $Price_{sell}$ from 8 to 24 h.

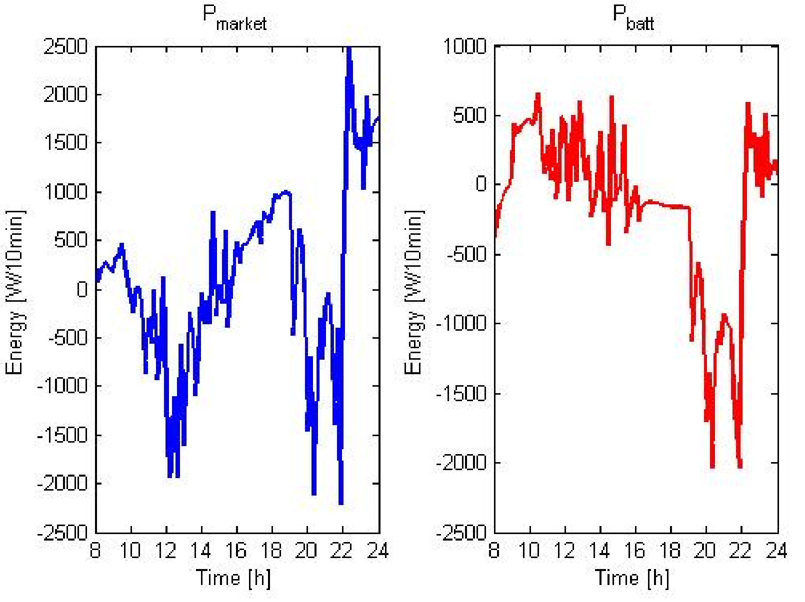


Figure 5.7: *P_{market} and P_{batt} from 8 to 24 h.*

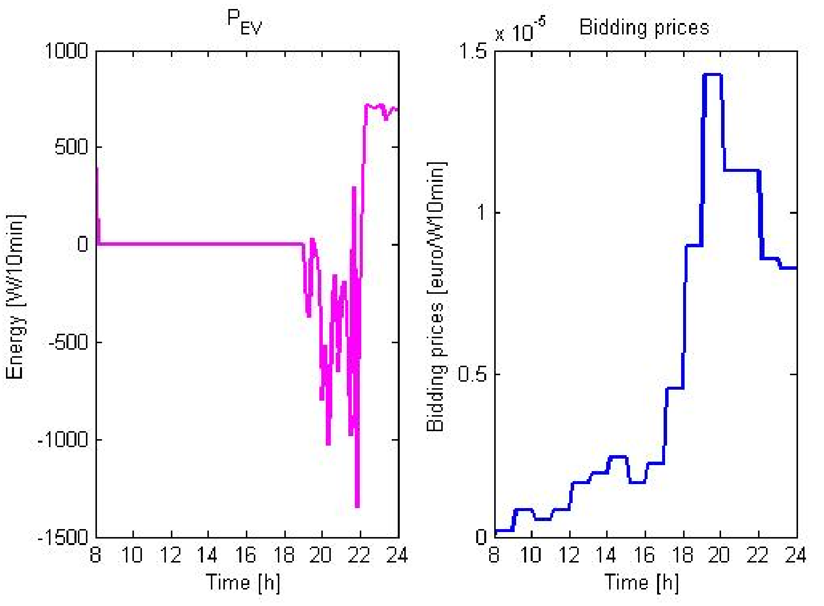


Figure 5.8: *P_{EV} and $Price_{sell}$ from 8 to 24 h.*

As seen in figures 5.7 and 5.8 above that the system triggers on the bidding prices in the market. Starting from 8 h where the system chooses to buy energy and charge the fixed battery when the bidding prices are low. Later during the day, after 12 h the system charge the fixed battery and sells a big amount of the produced energy when the bidding prices gets higher. At 15 h the system buys energy to store some of it and use the rest. Later during the evening, after 19 h the system discharge the EV and the fixed battery in order to sell the energy when the bidding prices are relatively high. After 22 h when the bidding prices gets lower and the buy prices are low, the system starts to charge both the EV and the fixed battery. Notice that there is some noise, since the simulations were made based on the estimated values from ANN of the produced energy and the electricity consumptions.

To study the reliability of the ANN estimations, two other types of simulations are made for one day in January. The first type of simulation is based on the mean value of each time instance from the previous week i.e. the sum of day 1 to day 7 divided by 7. The mean values are considered as estimation for day 8. This is done for solar insolation, air temperature, wind speed and electricity consumptions. Figure 5.9 below shows estimation (mean values) and actual data for the wind speed. The second type of simulation is based on the real values of the produced energy and the electricity consumptions. The definitions of the simulations are listed below and the results are shown in table 5.1 below.

* S_{ANN}, simulation for one day in January based on the ANN predations.

* S_{mean}, simulation for one day in January based on the mean values.

* S_{real}, simulation for one day in January based on the real values.

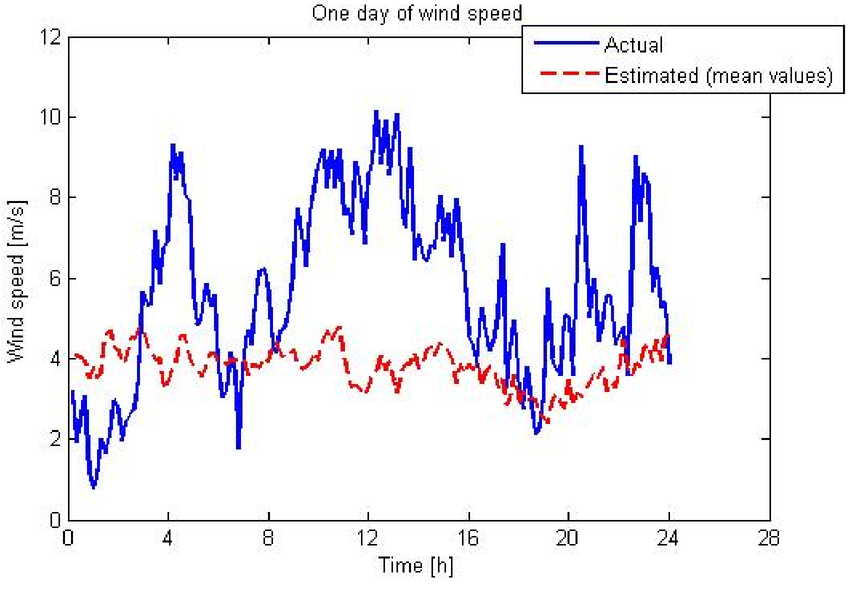


Figure 5.9: *One day of wind speed, estimated (mean values) and actual data.*

	S_{ANN}	S_{mean}	S_{real}
Bought energy $[W10min]$	$5.0690 * 10^4$	$5.7379 * 10^4$	$4.9893 * 10^4$
Bought energy $[kWh]$	8.4484	9.5631	8.3155
Sold energy $[W10min]$	$3.4540 * 10^4$	$3.9717 * 10^4$	$3.3332 * 10^4$
Sold energy $[kWh]$	5.7567	6.6195	5.5554
Spending	0.8017 €	0.9281 €	0.7560 €
Income	0.1732 €	0.1493 €	0.1586 €
Expenses	0.6285 €	0.7788 €	0.5974 €

Table 5.1: *One day comparison between different estimations.*

As seen in table 5.1 above, the simulation S_{real} resulted in buying less energy and selling less energy than the simulations S_{ANN} and S_{mean}. This resulted in 0.5974 € of expenses for that day. The simulation S_{ANN} resulted in buying and selling less energy than the simulation S_{mean}. S_{ANN} gave 0.0311 € and S_{mean} gave 0.1814 € more expenses than what it would be if the real values could be estimated during that day. It seems that it is more important to know the amount of energy is needed to be bought and at what time, the system avoids extra and unnecessary expenses to make savings for the household. Notice that the results from the S_{ANN} are closer to the real values and will be used further on in this thesis.

To check how much savings the system makes based on the ANN estimations, the expenses are calculated when the system is connected and not connected. Two considerations are made when the system is not connected, one with micro generation and the other without micro generation. When the system is not connected, the EV heads to work and is recharged with maximum power when it gets back. Energy is bought to satisfy the need for the house and EV. To make a comparison between winter and summer time, the simulation is made for one week in January and one week in July. The definitions of the simulations are listed below and the results are presented in table 5.2, 5.3 and 5.4 below.

* $S_{con,batt}$, simulation for one week with system connected, usage of micro generation, fixed battery and EV.

* $S_{discon,micro}$, simulation for one week with system disconnected, usage of micro generation and EV (no usage of fixed battery).

* S_{discon}, simulation for one week with system disconnected, usage of only EV (no usage of micro generation nor fixed battery).

	$S_{con,batt}$	
	January	**July**
Bought energy $[W10min]$	$7.6034 * 10^5$	$5.7516 * 10^5$
Bought energy $[kWh]$	126.7229	95.8592
Sold energy $[W10min]$	$1.3663 * 10^5$	$3.8033 * 10^5$
Sold energy $[kWh]$	22.7721	63.3880
Spending	10.4661 €	7.5854 €
Income	1.0537 €	3.2604 €
Expenses	9.4125 €	4.3250 €

Table 5.2: *Results of one week in January and July, system connected.*

	$S_{discon,micro}$	
	January	**July**
Bought energy $[W10min]$	$6.6913 * 10^5$	$2.0074 * 10^5$
Bought energy $[kWh]$	111.5211	33.4564
Sold energy $[W10min]$	0	0
Sold energy $[kWh]$	0	0
Spending	15.1924 €	6.0369 €
Income	0 €	0 €
Expenses	15.1924 €	6.0369 €

Table 5.3: *Results of one week in January and July, system disconnected with usage of micro production.*

	S_{discon}	
	January	**July**
Bought energy $[W10min]$	$1.0677 * 10^6$	$9.3690 * 10^5$
Bought energy $[kWh]$	177.9495	156.1492
Sold energy $[W10min]$	0	0
Sold energy $[kWh]$	0	0
Spending	23.2653 €	20.8062 €
Income	0 €	0 €
Expenses	23.2653 €	20.8062 €

Table 5.4: *Results of one week in January and July, system disconnected.*

The simulation $S_{con,batt}$ gave that the expenses of a week are 9.4125 € in January and 4.3250 € in July. The simulation $S_{discon,micro}$ gave that the expenses of a week are 15.1924 € in January and 6.0369 € in July. Normal case without fixed battery and micro production (S_{discon}), the expenses of a week are 23.2653 € in January and 20.8062 € in July. The savings are calculated as a difference between the last case and the first 2 cases. The savings obtained with $S_{con,batt}$ are 13.8528 € in January and 16.4812 € in July. The savings obtained with $S_{discon,micro}$ are 8.0729 € in January and 14.7693 € in July. Let us assume that the savings are the same as the week in January for the first 6 months (26 weeks) and the same as the week in July for the last 6 months (26 weeks). Then the average savings for the entire year with the system connected or disconnected with usage of micro generation would be 360.1728 € + 428.5112 € ≈ 788.68 € and 209.8954 € + 384.0018 € ≈ 593.90 € respectively.

The costs[1] in € [Exchange-Rate, 2012-10-31] for micro production depend on the ordered quantity, however the average cost is considered in this thesis. The costs for micro production are shown in table 5.5 below.

[1] 1 € = 1.29645 US$, 2012 – 10 – 31

	Cost in €	Cost in US $
Solar panel	0.478228 $\left[\frac{€}{watt}\right]$	0.55 – 0.68 $\left[\frac{\$}{watt}\right]$, [Panel, 2012-12-20]
Anern wind turbine	401.134 $\left[\frac{€}{set}\right]$	460 – 580 $\left[\frac{\$}{set}\right]$, [Anern, 2012-12-20]

Table 5.5: *The costs for micro production.*

In this thesis, 12 panels of Sunpower A300 with 300 $[W]$ each[2] and 2 Anern turbines are used, that gives the cost of 1721.62 € for the solar energy and 802.27 € for wind energy. Both the panel and the turbine have a lifetime of 25 years and work with 24 $[V]$ system. The 24 $[V]$ nickel-metal fixed storage device for the smart house with the capacity of 12000 $[Wh]$ ($\frac{12000}{24}\left[\frac{Wh}{V}\right] = 500\ [Ah]$) costs 7780.59 € (10080 $) and has a lifetime[3] up to 40 years. An assumption was made in the simulations that the battery and EV has an initial SOC, which must be included in the cost. The cost for charging 80 % of the EV's total capacity can be neglected, since the 3 cases had the EV with 80 % SOC as a common denominator. The cost for charging 80 % of the fixed battery is $9.6 * 0.168743 = 1.6199$ € in the first 6 months and $9.6 * 0.17282 = 1.6591$ € in the last 6 months. The average cost is about 1.64 € to charge the fixed battery up to 80 % SOC. The total costs for the 2 comparisons are shown in table 5.6 below.

	$S_{con,batt}$	$S_{discon,micro}$
Solar energy	1721.62 €	1721.62 €
Wind energy	802.27 €	802.27 €
Fixed battery	7780.59 €	0 €
Initial SOC (80 %)	1.64 €	0 €
Total cost	10306.12 €	2523.89 €

Table 5.6: *The total costs for the 2 comparisons, system connected and disconnected with usage of micro production.*

The costs can be considered as an investment that the owner of the household is ready to make. The cost of capital should be taken into account in every investment, such as return requirement on equity, inflation, loss of purchasing power and risks. In this thesis the risk is that the equipment breaks or extra costs may occur as maintenance. The chosen cost of capital is 2 % to calculate the net present value (NPV) [Andersson, 2008]. The payback period is when the investment is equal to the sum of the yearly return value according to equation 5.1 below.

[2]Sunpower A300 Panel Datasheet, see Appendix
[3]Nickel-Iron Batteries Info and Prices, see Appendix

$$\sum_{n=0}^{T} \frac{a_n}{(1+p)^n} = G, \text{ where} \tag{5.1}$$

a, the return value.
$p = 0.02$, the cost of capital (2 %).
G, the initial investment.

The return value is fixed, since the savings are considered to be the same every year. The payback period is:

$$T = -\frac{ln\left(1 - \frac{G}{a} * p\right)}{ln\,(1+p)} \tag{5.2}$$

With the costs and savings obtained when using the system, the payback period is:

$$T = -\frac{ln\left(1 - \frac{10306.12}{788.68} * 0.02\right)}{ln\,(1+0.02)} \approx 15.3 \ years$$

With the costs and savings obtained when using only micro generation, the payback period is:

$$T = -\frac{ln\left(1 - \frac{2523.89}{593.90} * 0.02\right)}{ln\,(1+0.02)} \approx 4.5 \ years$$

As seen that the payback period that it is almost 3.5 greater when the system is connected compare to the system is disconnected with usage of micro generation. The user would still have about 9.7 years of lifetime for the panels and the turbines and 24.7 years of lifetime for the fixed storage when choosing the system. When choosing only micro production, the user would have about 20.5 years of lifetime for the panels and the turbines.

6

Conclusion and Discussion

As shown in this thesis, it is possible to construct a system that both monitors the electricity costs and makes savings for the household. Thanks to the system, the contracted company can observe how much electricity the household can sell and at what time for the next 24 hours. These values are updated every 10 min and the company can have a clearer view as the time passes. The electricity company can contract an area of houses and potentially offer them a discount for using an energy management system such as the proposed one in this thesis. The electricity company will benefit from houses with this kind of system, given that generating electricity during peak hours is much more costly in both economic and environmental terms. The company does not have to use, for example, coal to generate electricity fast to meet the demand in the market.

As seen in the previous chapter, the system fulfills the requirement that the EV should be fully charged (85 %) before heading to work and recharged when it gets connected again to the house. In order not to buy expensive and unnecessary energy mainly during the peak hours where the electricity prices are high, the system calculates the amount of energy needed and at what time it should be bought. To reduce the daily expenses, the system sells energy when the sell prices are high to get some income. The main equation to model the optimization problem (equation 4.2) is satisfied with an error of 10^{-13}, can be considered negligible. This means that the function "fmincon" in Matlab can be efficiently employed to solve this optimization problem.

The estimation quality varies from day to day, especially for the wind speed. An estimation closer to the real data results in better performance which means further reduction of expenses could be realized if the estimation is made by a more accurate model, such as the one used by a meteorological station. A complex model needs more computation power with more variables included like clouds movement, wind speed, wind direction, air pressure, air temperature, precipitation and maybe a satellite image etc. It would be a good idea if the area of the smart houses can be connected together to a weather station that offers this kind of utilities to get estimation closer to the real values of the needed variables. This thesis showed that the use of ANN and the corresponding estimations gave more savings than the use of the mean values. The ANN estimations resulted in 0.0311 € and the mean values resulted in 0.1814 € more expenses than what it would be if the real values could be estimated during the simulated day. The difference is quite big between the two estimations that were made for a typical day during January and it could be bigger for another day, since the solar panels and wind turbines provide more output power during a day with more solar insolation and wind speed. In that case, estimations that are not close to the real data will result in more expenses.

As presented in the previous chapter, the house made savings about 788.68 € a year using the system including micro generation, fixed storage and EV. The house made savings about 593.90 € without using the system, with only micro generation and EV. The entire system costs 10306.12 €, which makes the payback period to 15.3 years. Using only micro generation costs 2523.89 €, this resulted in a payback period of 4.5 years. These values were obtained as a comparison of the household expenses between using the system or only micro generation and not using anything at all. When not using the system, the electricity is bought to satisfy the needs for the house and EV. The EV gets recharged with maximum power when it gets back. When using the system, the electricity is bought or sold as a result of solving an optimizing problem based on the estimated values of the electricity production, electricity prices and electricity consumptions.

The most profitable is to only use micro generation (both cheaper and shorter payback period), but then the owner of the household loses the opportunity to be part of helping the society to become "Greener". The payback period may be reduced, since the calculations were made without the considerations of the discount that can be offered by the electricity company or the government.

7 Future work

This project presented a system that is designed to manage and optimize a distributed energy storage system with the presence of micro generation in a standalone smart house. A future project can continue where this project leaves off i.e. design and manage a system that monitors and optimizes an area with multiple houses. The system could be connected through an aggregator, which in turn is connected to the grid. The electricity companies will be able to communicate with this system i.e. with multiple houses at once instead of a single house. The company will know how much electricity the area can provide and the single house can monitor the costs in real time.

A
Appendix

This is an appendix chapter, where needed data and information for the thesis are presented.

A.1 Sunpower A300

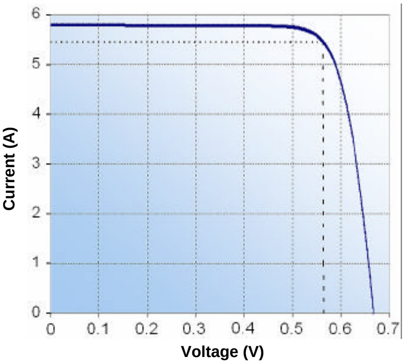
A.1.1 Cell Datasheet

SUNPOWER

A-300 Solar Cell

Mono Crystalline Silicon

A-300 Cell Performance— Typical I-V Curve



Construction:	All-back contact
Dimensions:	125 mm x 125 mm - nominal
Thickness:	250 μm ± 30 μm

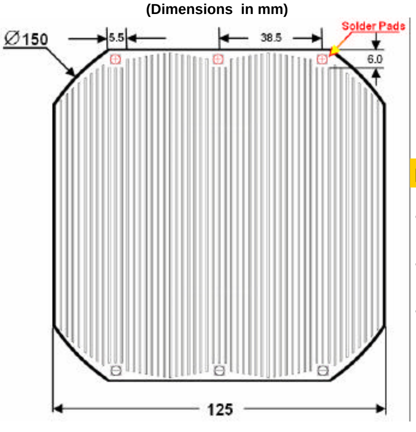
Typical Electrical Performance

Open Circuit Voltage:	0.665 V
Short Circuit Current:	5.75 A
Maximum Power Voltage:	0.560 V
Maximum Power Current:	5.35 A
Rated Power:	3.0 W
Efficiency:	20.0% minimum

Temperature Coefficients

Voltage:	-1.9 mV / ºC
Power:	-0.38 % / ºC

Cell Backside View
(Dimensions in mm)



Attributes

- High efficiency reduces module assembly and system installation costs
- Uniform front appearance—no contact grid
- Back contact design simplifies circuit assembly
- Lower temperature coefficient improves energy delivery

Packaging

- Cells are packed in boxes of 250 each grouped in shrink-wrapped stacks of 50 with interleaving
- Ten boxes are packed in a water-resistant “Master Carton” containing 2,500 cells suitable for air transportation
- Master Cartons are permanently labeled with cell tracking information and date of manufacture

Document Number 70-0006 Rev 02.
Specifications may change without notice.

SunPower Corporation®
1.877.786.0123 Email: sales@sunpowercorp.com www.sunpowercorp.com

A.1.2 Panel Datasheet

SUNPOWER

PANNEAU SOLAIRE 300

PERFORMANCE ET RENDEMENT EXCEPTIONNELS

Caractéristiques électriques

Mesurées dans des conditions de test standard : ensoleillement de 1000W/m², AM 1,5 et température de cellule de 25°C

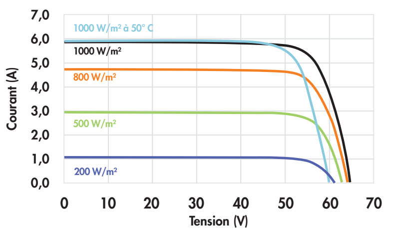
Puissance nominale (+5%/-3%)	P_{nom}	300 W
Tension à puissance maximale	V_{pm}	54,7 V
Courant à puissance maximale	I_{pm}	5,49 A
Tension en circuit ouvert	V_{co}	64,0 V
Courant de court-circuit	I_{cc}	5,87 A
Tension maximale du système	IEC	1000 V
Coefficients de température		
	Puissance	-0,38% / K
	Tension (V_{co})	-176,6mV / K
	Courant (I_{cc})	3,5mA / K
NOCT		45° C +/-2° C
Valeur nominale des fusibles de série		15 A
Limite de courant de retournement (3 strings/rangées)	I_R	14,7 A

Caractéristiques électriques

Valeurs à température nominale d'opération de la cellule (NOCT): ensoleillement de 800W/m², AM 1,5

Puissance nominale	P_{nom}	220 W
Tension à puissance maximale	V_{pm}	50,1 V
Courant à puissance maximale	I_{pm}	4,40 A
Tension en circuit ouvert	V_{co}	59,9 V
Courant de court-circuit	I_{cc}	4,75 A

Courbe courant/tension



Caractéristiques courant/tension en fonction de l'ensoleillement et de la température du module.

Conditions de fonctionnement testées

Température	-40° C à +85° C
Charge maximale	245 kg/m² (2400 Pa) à l'avant et à l'arrière - par ex. pour le vent
Résistance à l'impact	Grêle: 25 mm avec une vitesse de 23 m/s

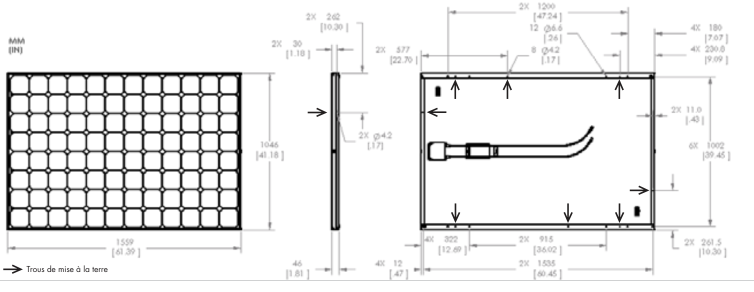
Garanties et certifications

Garanties	Performance: 25 ans
	Produit: 10 ans
Certifications	IEC 61215 Ed. 2, IEC 61730 (SCII)

Caractéristiques mécaniques

Cellules photovoltaïques	96 cellules monocristallines SunPower à contact arrière
Vitre avant	Verre trempé pour une haute transmission
Boîtier de connexion	Classé IP-65 avec 3 diodes de dérivation 32 x 155 x 128 (mm)
Câbles de sortie	Longueur de 1000 mm/connecteurs MultiContact (MC4)
Cadre	Alliage d'aluminium anodisé de type 6063 (noir)
Poids	18,6 kg

Dimensions



ATTENTION : VEUILLEZ LIRE LES CONSIGNES DE SÉCURITÉ ET LES INSTRUCTIONS D'INSTALLATION AVANT D'UTILISER LE PRODUIT.

Pour plus d'informations, www.sunpowercorp.fr

www.sunpowercorp.fr

Document #001-45625 Rev*A / A4_FR

A.2 Nickel-Iron Batteries

A.2.1 Info

Nickel-Iron Batteries From BeUtilityFree!

Thomas A. Edison invented the nickel-iron battery at the turn of the century while searching for a rugged, long-lived storage battery for electric vehicles. Actual performance records have proven his design with thousands of batteries still in service to day. Nickel-iron battery technology has withstood the test of time. BeUtilityFree™ considers this battery to be the "ultimate" battery for longevity, durability, ruggedness, and ease of maintenance with its translucent battery case. It can offer a lifetime of reliable service for home power systems, railroads, telecommunications, boats, island home power systems, or any other application where "you only want or need to buy just ONE battery and be done with it."

The nickel-iron batteries we offer have been manufactured for over 28 years by a Chinese manufacturing company which has won 36 prizes in their country. The advanced battery manufacturing assembly line was imported from VARTA AG Germany, so the manfacturing equipment they use is very high quality.

These batteries have many advantages listed below. Review them and compare. Once you use a nickel iron battery, you'll never return to lead acid batteries again! Our company is the exclusive importer for North America and South America and we have been importing then into the US from 1995. We have batteries that are over 15 years old and still producing 100% of their rated capacity! These are facts, not myths or half-truths.

Battery Features	Nickel-Iron	Lead-Acid
Up to 40-year life	Yes	No
Frequent hydrometer readings	No	Yes
Use on DC to AC inverters (1)	Yes	Yes
Add to system anytime (2)	Yes	No
Bad cell easily removed (3)	Yes	No
Wide operating temperature	Yes	No
Safely fully charge in 5-7 hours	Yes	No
Equalization charge required (4)	Yes	Yes
Has memory effect (5)	No	Yes
Over/undercharging damage	No	Yes
Safely left in any state of charge	Yes	No
Plate sulfation	No	Yes
Toxic substances	No	Yes
Corrosive fumes (6)	No	Yes
HydroCaps™ available	Yes	Yes

1. Most inverters on the market are designed for lead-acid batteries, but NiFe batteries can be used on most inverters today. Buy only inverters that have high and low voltage adjustment or have high and low set points if you can't adjust the voltage. We recommend Exeltech MSX, OutBack, Samplex and Scheidier Electric sine wave inverters. Battery voltage settings should be about 10-16 or higher for 12V battery, 21-34 V for 24V system and 40V-66V for a 48V system.
2. While a lead-acid battery's internal resistance (IR) increases at a steady rate, an alkaline battery's IR stabilizes. Don't mix batteries with different IR's. Lead acid cells you cannot add to a bank after a year. NiFe cells can be added at any tiem in the future. There is no time limit.
3. NiFe cells are lighter then lead-acid cells and also have lower voltage per cell.
4. Once a year for alkaline batteries recommended and once a month for lead-acid batteries.
5. Some lead-acid batteries have a memory effect. A pocket plate nickel-iron battery doesn't.
6. Nickel-iron batteries produce only hydrogen and oxygen past 80% state of charge. Gases still should be vented to meet electrical code if cells are in an encloser.

WARRANTY

We have the best 10-year warranty in the home power industry.

In the first 6 years it offers free cell replacement in case of defect, then 4 years of prorated warranty that expects the battery to be used, not just floated. In other words these batteries like to be worked! Contact us for a copy of the warranty.

FINANCING

We offer battery financing for those who need it. Not being able to afford these batteries has been a deterrent for many people... until now! There should never be a reason NOT to consider this battery for your next battery bank because of cost. We can finance up to 40% of the cost of this battery. You can take the money you would have paid for a top quality lead-acid battery and get a true lifetime battery instead! No other company selling batteries offers battery financing. We consider the battery the heart of your renewable energy system, so why not purchase your battery just once like other component parts of your system? Contact us for our battery financing flyer.

www.beutilityfree.com 1.888.320.9211
8:30-5:30 MST, Mon-Fri

A.2.2 Prices

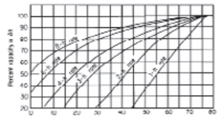
BATTERY OPERATING CHARACTERISTICS

WHY CAN A NICKEL-IRON BATTERY LAST 40 YEARS?

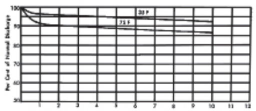
In a lead-acid battery the acidic electrolyte interacts with the plates during every charge and discharge cycle, causing lead to shed off the plates and reducing the battery capacity. From the day you start charging a lead-acid battery you are losing capacity with each use, ending in plate disintegration.

With a nickel-iron battery there is NO chemical interaction between the plates and the electrolyte. In fact the electrolyte used in a nickel-iron battery (potassium hydroxide, i.e. KOH) is a metal preserver.

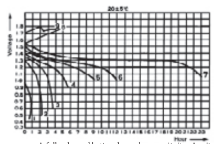
Exposure to air causes the electrolyte to form potassium carbonate and lose its ability to conduct electricity. One to two electrolyte replacements may be needed to replenish the battery capacity in its lifetime. The need to replace electrolyte depends on many factors, but is relatively easy with proper equipment. This is why we have nickel-iron batteries in the field that are producing 100% of their rated capacity after over 50 years of use!



How cold weather effects performance on the nickel-iron battery.



Period of Rest Between Charge and Discharge in Days



A fully-charged battery loses charge as it sits. A suitable trickle charge will offset this loss.

1. 1-hr discharge rate
2. 2-hr discharge rate
3. 3-hr discharge rate
4. 4-hr discharge rate
5. 8-hr discharge rate
6. 10-hr discharge rate
7. 20-hr discharge rate
8. Normal charge
9. Rapid charge

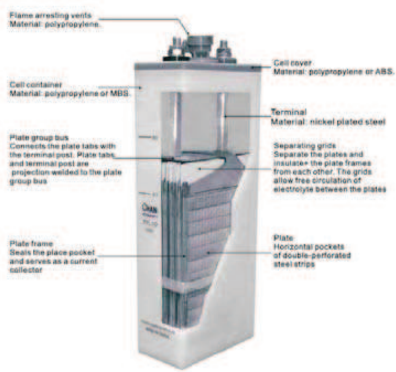
BATTERY PRICING AND SPECIFICATIONS

Part #	Ah* Capacity	Dimensions (inches) W x L x H	Dimensions (mm) W x L x H	Weight (lb)	Weight** (kg)	Price Per Cell	12V System	24V System	48V System
7008	122/100	6 x 3 x 15	141 x 80 x 370	15	7	$101	$1010	$2020	$4040
7009	183/150	7 x 4.2 x 14	164 x 106 x 345	21	10	$151	$1510	$3020	$6040
7010	244/200	7 x 4.2 x 14	164 x 106 x 345	24	11	$202	$2020	$4040	$8080
7011	305/250	11 x 6 x 17	276 x 138 x 425	45	20	$252	$2520	$5040	$10,080
7012	366/300	11 x 6 x 19	276 x 138 x 490	56	25	$302	$3020	$6040	$12,080
7013	488/400	11 x 6 x 18	276 x 138 x 450	51	23	$403	$4030	$8060	$16,120
7015	610/500	11 x 6 x 19	276 x 138 x 490	58	26	$504	$5040	$10,080	$20,160
7016	732/600	12 x 7 x 20	291 x 176 x 510	84	38	$605	$6050	$12,100	$24,200
7017	854/700	12 x 7 x 20	291 x 176 x 510	86	39	$706	$7060	$14,120	$28,240
7018	976/800	16 x 8 x 22	398 x 186 x 570	133	60	$806	$8060	$16,120	$32,240
7019	1080/900	16 x 8 x 22	398 x 186 x 570	137	62	$909	$9,090	$18,180	$36,360
7020	1220/1000	16 x 8 x 22	398 x 186 x 570	142	64	$1008	$10,080	$20,160	$40,320

Cells 300 Ah to 600 Ah get a 10% discount. Cells larger than 600 Ah get a 15% discount! Specifications subject to change withour notice.

*Ah for 100 and 5 hr **discharge/charge** rate. Manufacturer **charge** rate is C/5. Batteries are sold by the cell to get end battery voltage. Includes interconnect bars between cells, manual, flip-top battery caps and dry electrolyte chemicals (buyer must by distilled water and add chemicals). For BeUtilityFree to fill and cycle cells, add $175 per 10 cells. Buyer pays freight FOB Los Angeles, CA to final destination. Typical cell numbers: 12V: 10 cells, 24V: 18-21 cells, 48V: 36-41 cells. Battery specifications @ 25° C (77° F).
Table updated: November 18, 2010
**filled cell

What's Inside The Nickel-Iron Battery?




NiFe batteries shown in their shipping crates, with orange battery post covers to meet NEC requierments.


A smaller Ni-Fe battery with it's flip-top cap, max and min fill lines and BeUtilityFree logo.

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