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Evaluation tool for dimensioning off-grid solar power systems

Investigating electric boats and households powered by solar

Master's thesis in Electric Power Engineering

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Master's Thesis 2021
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Cover: One of the electric powered fishing boats on the way into the harbour in the mangrove in Bali, Indonesia.

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Abstract

The need to reduce carbon emissions is clear. In this thesis a software model was created to assist in the planning phase of building systems that help decarbonize transportation and electricity production by deploying solar power stations with battery storage. These off-grid solar power stations are meant to power household loads and charge electric vehicles. The model and results can be helpful in many locations and with different electric vehicle types. This work is centered around tropical coastal communities using electric boats built by Azura Indonesia.

Two data logging power devices were built to measure household loads and boat chargers. The measurements were used to build a computer model to simulate a wide range of scenarios. The outputs from the model are: required installed solar power, storage battery capacity, C-rate and a rough estimate of economic payback time.

The influences of different input variations were tested such as: number of households, number of boats, varying system availability and varying household energy. Two storage battery types were also simulated, flooded lead acid and li-ion.

When testing the different scenarios the li-ion battery storage system was the winner in terms of installed capacity, maintenance, longevity and economic payback time. Furthermore most of the economic savings are due to avoided gasoline rather than avoided electricity from the grid. This implies that replacing combustion engine should be a priority. Even when including household loads the economic payback-time is reasonable when using li-ion storage batteries. Some design modifications are possible such as lower availability and power limitations in order to make the system even more economically feasible. The results, especially the ones related to cost, are based on assumptions and measurements from a few cases. Thus the results are to be taken as an indication and further work is needed for a more accurate model.

Keywords: Solar Energy, Energy Storage, Li-ion Storage, FLA Storage, Electric Boat, EV, off-grid energy, Battery Charging, Household Energy Measurements

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Nomenclature

AC Alternating Current
ADC Analog to Digital Converter
BMS Battery Management System
CoV Coefficient of Variance
CSV Comma Separated Value File
CT Current Transformer
DC Direct Current
DoD Depth of Discharge
EVCS Electric Vehicle Charging Station
EV Electric Vehicle
FLA Flooded Lead Acid
ICE Internal Combustion Engine
IDR Indonesian Rupiah (currency of Indonesia)
Li-ion Lithium Ion
PBT Payback Time (economic)
PV Photo Voltaic
RTC Real Time Clock
SD Secure Digital
SoC State of Charge
SoH State of Health

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1
Introduction

Climate change is arguably one of the biggest and most challenging problems currently facing humankind. A big part of the change is due to increased global warming caused by green house gases. Emissions of green house gases can be attributed to most human activities such as farming, energy production, manufacturing and transportation. One of the major green house gases is carbon dioxide which is added to the atmosphere when burning fossil fuels [4]. Within the transport sector this can be limited by using power trains driven by bio fuels or by using electrified vehicles. This is true for any type of vehicle, however in this project the focus is electrified boats. When using electricity it is important to consider how the energy is produced as a fossil dominated energy mix still generates carbon dioxide and will, at worst, only move the emissions to another location. With combustion engines comes more downsides connected to the combustion of any type of fuel such as noise, high fuel cost, local emissions and a high maintenance need. Further problems of higher concern in aquatic environments are oil and gas leaks from the engine.

1.1 Azura Indonesia

This project is done in collaboration with Azura Indonesia with the aim to tackle all the stated problems above. They are developing electric boats and solar based charging stations to provide sustainable, low emission and cost effective marine transportation. Azura has several products and in this project the focus is the Manta electric outboard motor.

1.2 Electric Boats and Solar Charging Station

This project was done in Kelan village, Bali, Indonesia. In this village a solar charging station built by Azura Indonesia already powers a number of electric boats used by fishermen for coastal small scale fishing. The electric motors have long shaft propellers and can be mounted on any existing boat with a corresponding combustion engine configuration. The motor is a 2.5 kW brushless DC motor powered by a 1.5 kWh, 48 V, li-ion battery pack. Currently, three such motors are deployed in the village. In one of the households there is also a solar power system with an installed PV capacity of 1.8 kW. The panels are connected to a small storage battery pack consisting of four FLA batteries with a total capacity of 150 Ah at 48 V. The solar power is currently used for household loads and boat charging but the installed capacity in not enough to cover all the loads at the time. This is however the end goal for such systems built by Azura in the future. These boats and the households in the village was used in the data collection part of this study.

1.3 Background

Indonesia has the worlds fourth largest population and as of 2017 was the home to 261 million people [5]. This means that Indonesia can have a big global impact in regards to emissions of fossil fuels depending on how the nation acts. Today a large amount of the electric grid is powered by fossil fuels. In many parts of the country the population is suffering from instability and a weak grid. Furthermore most locations in Indonesia has a great potential for PV when looking at weather and solar irradiance. These factors indicates the huge potential for solar power with off grid capabilities [6]. By using solar generated energy the carbon dioxide emissions related to electricity production can be reduced. Furthermore this maximizes the positive impact of electrified vehicles as the electricity used for charging them is renewable. This effort will help create sustainable and affordable energy according to the UN sustainable development goal 7 [7]. As mentioned, this thesis focuses on electric boats but the principle is the same and the purpose of this thesis is to build a model that could be easily modified for investigating any type of EV. This would help in the creation of a cleaner transportation infrastructure according to climate goal 9. There are problems related to the oceans such as anthropogenic noise pollution found to be harmful to marine environments [8]. This can be reduced by an electric motor as it will operate more quietly. Finally small oil spills and gasoline leaks are eliminated when using an electric motor. The two latter points will move towards solving goal 14.

A similar type of system was investigated by researchers at the university of Sebelas Maret, Surakarta for charging electric cars in Indonesia with solar generated electricity stored in battery packs with promising results [9]. Furthermore another project investigated a micro grid powering electrified boats and industrial loads in Lake Victoria, Uganda [10].

The tool developed in this thesis will not provide system layouts or specific designs. It is built to give the user a good insight in what sort of impacts general choices such as battery storage type and installed capacity will have on the system cost and functionality. It can also help evaluate where cost savings can be done with as small an impact as possible on performance. If the user is to develop a solar energy system, this tool should be used early in the process to determine a rough estimate on the requirements by trying different options. Then, when the most promising results are found, the user will proceed with other tools to create a specific design based on the results from the model developed in this thesis.

1.4 Aim

The aim of this project is to build an evaluation tool to make design choices easier when developing an off grid solar power station. In this project the type of loads powered by the system are categorized as either household loads or electric vehicle charging. Furthermore the project aims to use the evaluation tool to give general design recommendations and insights for building off grid solar power systems. The aspects covered are installed PV power, installed battery capacity, current capabilities and battery storage type as well as economic payback time.

1.5 Problem Statement

To create a reliable implementation of the tool mentioned in section 1.4, a model had to be built based on measurement data. This model was then used to test a number of scenarios around the same number of users as the solar station currently operated by Azura Marine. The output data from these scenarios was then compared and analysed in order to give general design recommendations. This challenge can be broken down into a number of sub problems as follows.

The first sub-problem is to represent boat charging events in the software. The model should be based on real measured data to represent reality as good as possible. These loads has to be simulated so that the model can dimension a solar power system accordingly.

Secondly, similar to the first sub-problem, the household loads must be represented. Some variation of the load pattern is necessary for a realistic representation. The user has to be able to decide the 24 hour total energy in order to make the model useful for any type of household. These loads has to be simulated so that the model can dimension a solar power system accordingly.

When the data is collected a model has to be built. The model has to efficiently be able to simulate a large number of scenarios according to user inputs. Furthermore the results of these simulations has to be presented in an clear manner that makes comparison between scenarios easy.

Finally, a variety of scenarios has to be defined to determine factors that has an impact on system size and economic feasibility. This should make possible a list of recommendations and insights for future system construction and design.

1.6 Scope

The model will not include a life cycle analysis of the components used in the system. This would be interesting data to have but with limited time it was not feasible. The main focus of the model was to give storage energy and PV power requirements while payback times are more of a rough bonus estimation. Thus the economic calculations are done in a basic way and ignores potential debt associated with the investment as well as inflation. Grid buy back possibilities and tax cuts are ignored. As this thesis is done in cooperation with Azura Indonesia, the model is built for Indonesian circumstances and other locations are not considered. Furthermore it is focused on the boats currently in use and no other vehicles. This would however be easy to change by modifying the model slightly to fit other places and vehicles.

2
Batteries

The ability to store energy is crucial for an off grid system, especially so if it's depending only on solar energy. There are many promising storage technologies such as pumped storage, flywheels and hydrogen. This project is focusing on readily available components for small scale systems and thus batteries are the only storage medium investigated. This chapter gives a brief insight in the battery parameters relevant to the constructed model.

2.1 Cell chemistry

The cell chemistry describes what electrochemical reaction is behind the stored energy in a battery. There is a large variety of types on the market. In this project two types of batteries will be compared. The first type is a flooded lead acid (FLA) battery and the second is a lithium ion (li-ion) battery.

2.1.1 Flooded Lead Acid

Lead acid batteries was the first type of batteries to be invented [11]. The positive electrode is made up of lead dioxide and the negative electrode is sponge lead. Both electrodes are surrounded by sulfuric acid and in the current generating reaction the electrodes will transform the acid to ions. Thus the sulfuric acid concentration drops as the battery discharges. When charging takes place, the reaction is reversed. Some maintenance is usually required in the form of acid refilling. The FLA type is sensitive to high operating temperatures [11].

2.1.2 Li-ion Batteries

Lithium ion batteries is a more recent innovation and creates current when li-ions travel in an electrolyte from the negative to the positive electrode. The positive electrode can be made of a lithium compound and the negative a material such as graphite. Li-ion batteries are maintenance free and has a comparatively high energy density. They also perform better in warm environments. A downside is the risk of fire in the event of high C-rate or puncture of the cell [11][12].

2.2 C-rate

The C-rate describes the amount of current that can safely flow through a battery cell. A high C-rate means a high current. It can be expressed as follows,

$$C = \frac{I_{cell}}{Q_{cell}} \ [h^{-1}] \, , \tag{2.1}$$

where Q_{cell} is the capacity in ampere hours and I_{cell} the current flowing through the cell. For a battery pack consisting of many cells it follows that putting more cells in series will keep the C-rate constant, but increase the voltage. Whereas putting more cells in parallel will increase the C-rate while keeping the voltage constant. Typically the C-rate for FLA batteries is lower than for li-ion, as seen in table 4.5 the C-rate is 10 times lower for the FLA batteries for the cells compared in this project.

2.3 Cell Efficiency

All batteries has some internal resistance that will create losses in terms of heat when charged or discharged. The cell efficiency describes how good a battery is at delivering power without heating up. The cell efficiency is lower for FLA batteries compared to li-ion batteries.

2.4 Cycle life

Each time a battery is used it ages as the cathodes degrades. This happens every time a battery is put through a cycle, that is, every time a discharge followed by a charge takes place. The cycle life describes how many times this can happen before the battery state of health (SoH), and thus performance, is significantly reduced. The cycle life for the li-ion cells used in this project is twice as long as for the FLA cells.

2.5 Depth of Discharge

The depth of discharge (DoD) describes the amount of energy used compared to the total energy stored at full charge, as described by

$$DoD = 100 \cdot \frac{I \cdot t}{Q_{tot}} \, . \tag{2.2}$$

DoD is usually given in percent and is the complement of State of Charge (SoC). Thus a fully charged battery has $DoD = 0\,\%$ and $SoC = 100\,\%$. For most battery types the allowed DoD in each cycle has a significant impact on cycle life. The higher the DoD the lower the cycle life. This means that the cycle life is defined for a chosen depth of discharge. With the cycle life in table 4.5 the allowed depth of discharge is larger for the li-ion cells.

2.6 Price

The price is a very important factor when choosing a battery type. In order to properly determine which type is most economical the price needs to be related to one or more of the properties stated above. A cheaper cell chemistry can for example have a low price per kWh but a low cycle life which for a system with a long lifetime increases the price per kWh as the cells need replacing. The price is therefore not only the purchase price but the user scenario and the life cycle has to be considered as well. The purchase price per kWh is significantly lower for FLA batteries.

3

Method

This chapter explains the methodology behind solving the sub problems presented in section 1.5. It also gives an explanation to the different test scenarios and why each scenario was simulated.

3.1 Building a Model

The first part of this project was focused on building the model. The model was based on measured values. These values were collected using measurement systems custom built for this project. When the necessary data was collected it was integrated into the software built in Matlab.

3.1.1 Modeling Charging of the Boats

Data was collected on the boat charger using a custom build data logger. This data was used to create a simplified computer model of a boat charge event. Fishermen were asked regarding how and when they use their boats in order understand when charging events can be expected. All this was done to be able to represent charging events in a realistic way.

3.1.2 Household Load Modeling

To be able to include realistic household loads a household energy logger was built using a modified design of the one used for the charger. This unit was deployed at four different households and the measured data was used in the model. In one of the households the reading on the already installed energy meter recorded as a reference to the other measurements in order to ensure that the logger gave reasonable results.

3.1.3 Building a Model as a Simulation Tool

A model was built in Matlab using the simulated load patterns designed from measurements. It was created so that a number of inputs are chosen according to the desired scenario. The model used normalized household load patterns in order to have user defined household energy. The charger events were simplified to make the simulation run more efficiently. Before a simulation is initiated the user defines the scenario to be evaluated The model is built around 24 hour periods of system use and one run will consist of a large number of 24 hour semi-randomly generated use patterns represented by a load curve. It will in other words run several iterations resulting in different daily load curves. Each 24 hour period is hereby referred to as one iteration. For each iteration the model will output a range of requirements based on all the iterations. The model was built in this way to simulate a large variety of user patterns for each scenario.

3.2 Running Simulations in the Model

After a model was built it was used to compare system requirements and costs of different costumer demands. The different scenarios were chosen based on the current solar charging system in use. Some scenarios were also simulated in order to attempt to reduce shortcomings of some designs, such as a power limit to reduce C-rate needs. The results were then analyzed and insights and recommendations were presented. Some scenarios are run with a varying number of users to see what impact it has on the system. FLA and li-ion batteries are also compared. FLA batteries are included since the existing system uses them as storage batteries. Li-ion batteries are included due to their high performance. All results are presented as average values with coefficient of variance for all iterations for each set of input parameters. Averages were chosen to make the results repeatable and easily comparable.

3.2.1 Base Case

In order to compare results from different simulation runs a base case was specified. The base case aims to represent a nominal system specification and deviations from this scenario are considered modifications to the standard system requirements. The base case will supply energy to five fishermen with one boat each. Each boat is charged once per day and there are five chargers available for simultaneous charging. In addition to the five boats the system also supplies five households with a daily energy consumption. All households uses the same amount of daily energy which is the average of conducted measurements. The daily energy used in the base case is based on measurements on the households. The storage battery type for the base case is li-ion.

3.2.2 One Boat per Household with Li-ion Storage Batteries

The first simulation simulates the base case explained above and some values around the base case. The simulation is run with 1, 2, 5 and 10 number of households and boats.

3.2.3 One Boat per Household with FLA Storage Batteries

It is possible that FLA batteries, with a lower initial investment cost per kWh, can be a good substitute to li-ion batteries. This was investigated by running the same simulation as in "One Boat per Household with Li-ion Storage Batteries" but with FLA batteries as energy storage units. This type of storage batteries are currently used in the existing solar charging station. The simulation is run with 1, 2, 5 and 10 number of households and boats.

3.2.4 Only Boats with Li-ion Storage Batteries

The primary purpose of the solar energy system is to supply energy for electric boats. Is is therefore of interest to test the system without household loads. In this simulation the number of boats were 1, 2, 5 and 10 with the same number of chargers and charges per day.

3.2.5 Only Boats with FLA Storage Batteries

Again, in order to investigate potential benefits of using FLA batteries the same simulation as in section 3.2.4 were run with the only difference being the type of energy storage batteries.

3.2.6 Varying Daily Household Energy with Li-ion Storage Batteries

Since the average of the measured daily energy consumption that is used in the base case is not representative for all households the need for investigating a range of household energy uses was clear. The complete set of values are as follows: 5, 10.5, 25 and 50 kWh. The lowest value of 5 kWh was the lowest daily energy consumption measured for the four measured households. 10.5 kWh is the average value of all four households. 25 and 50 kWh represents costumers with significantly larger consumption. Values this high were not measured in this project but they were included to see what effect a larger energy consumption has on the system.

3.2.7 Varying Number of Boats per Household with Li-ion Storage Batteries

This case tests the system economy when the number of boats per household varies. The number of households is five for all simulations and the number of boats are 1, 2, 5 and 10. This is similar to the case in section 3.2.6, with varying household, load since the ratio of household energy and boat energy is changed in both cases.

3.2.8 Varying Power with FLA Storage Batteries

The low C-rate capabilities is a big drawback for FLA batteries. This simulation scenario tests what impact a power limit will have on installed battery capacity. The simulation is run with the base case for FLA batteries but varying power limits. The power limit is put on the household loads and are as follows: 1, 2, 3 and 4 kW. These power limits will also decrease energy use.

3.2.9 Varying System Availability with Li-ion Storage Batteries

Since the highest cost of the system is the energy storage batteries it is of interest to limit the installed capacity. This comes at the cost of limiting the user in some way and thus the availability. In this project the availability is defined as all the days where the system can provide all the energy and power that the user demands. If, for example, a specific user requires 7 kWh during a period of one hour and the storage batteries only has 6 kWh of capacity the requirements are not met and that hour is considered as downtime. When analyzing the results of varying the availability it is worth considering the tiers of availability defined in The Energy Sector Management Assistance Programs report on energy in developing countries. The different tier levels defines how many hours per day energy is available as well as during what time of the day. Tier 3 is 8 out of 24 hours availability with at least 3 hours during the evening, Tier 4 is 16 out of 24 hours and tier 5 is 23 out of 24 hours [13]. Both tier 4 and 5 requires 4 hours availability during the evening. In this project only the amount of hours per day are considered for simplicity. These simplified definitions of tiers are used when analysing the results. Full availability is the base case and was also included in this scenario. This corresponds to the following percentages of availability: 33 %, 67 %, 98 % and 100 %.

4
Model Construction

The following chapter gives insight into the process and working principles of the tool that was built. It also describes the underlying assumptions and necessary measurements made in order to create it. The basic idea was to create a model that could simulate different scenarios and give estimations on required system parameters such as PV power and battery capacity as well as C-rate battery capacity and peak power draw. The economic payback time is also calculated as well as the number of battery replacements during the PBT. These parameters are explained in more detail later in this chapter. The model was built in Matlab and contains one main script with a number of sub-scripts, functions and data files. For each iteration the output information is saved. When all iterations are done the model will output a file with results from all iterations. This file can then be used to design an appropriate system. A block diagram of the process for each iteration is shown in figure 4.1. In the sections below, the functionality and process behind the creation of these individual blocks are explained in more detail.

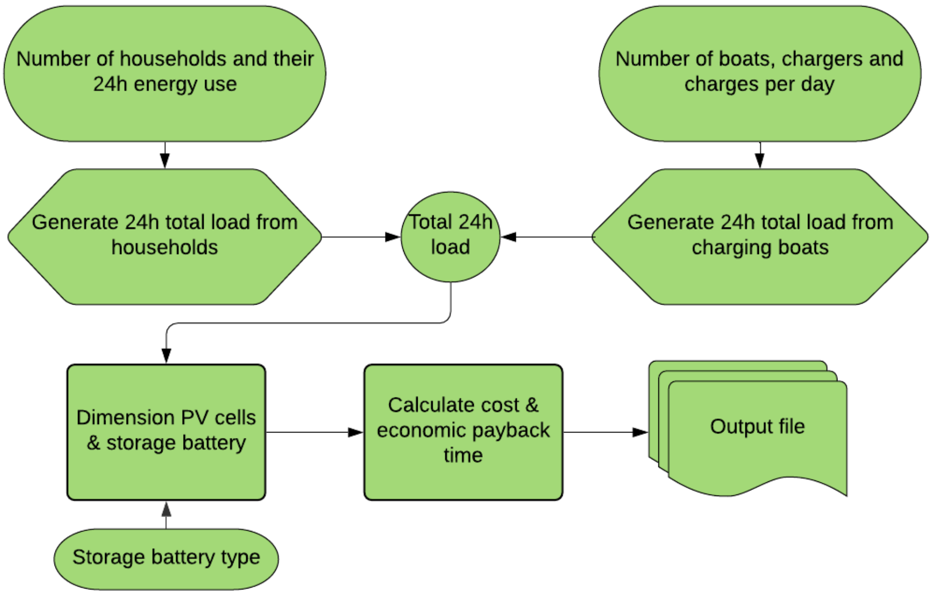

Figure 4.1: A block diagram of the model information flow and sub-functions.

4.1 Measurement Hardware

To make an accurate model of a system it is desirable to base it on measurements when possible. In this project the loads were measured. The end goal was to make an estimation of system parameters and hence measurements with lower accuracy was tolerable. Instead the focus was to get a measurement over a long period of time with short intervals. A low cost and portable system that could measure power in the low kilo-watt range over long time could not be locally sourced and instead two devices with logging capabilities were built using low cost components.

4.1.1 Micro controller and data storage

The readily available and cost effective Arduino UNO was the choice of micro controller. However using only the Arduino and external sensors poses two problems. Firstly the internal memory is only 1024 bytes. This is not enough to store the data generated by a frequent and long lasting measurement setup. The second issue is keeping time. The Arduino starts an internal timer when it's powered on and this timer counts as long as the power is not lost. With frequent power outages and risk of the device being unplugged it would be impossible to know when in time the charge events would happen after loosing power the first time.

The two issues presented above are solved by a separate module that easily connects to the Arduino. The shield features an SD card reader/writer and a real time clock. The SD card installed is 4 GB and gives space for more than two years of measurements with a one second interval. The RTC, once set one time, keeps the time even when no external power is available with it's own back up battery. When the logger is restarted the new measurements will be saved with a correct time stamp.

The code will create a CSV file on the SD card for each power on and start logging voltage and power. To reduce noise the system will make 15 measurements with the analog inputs every second. These 15 values are then averaged and only the average values are saved one time per second.

4.1.2 DC Power Measurement for the Battery Charger

For measuring charger currents up to 10 A the ACS712 chip was used [14]. This uses a hall effect sensor and no current shunt resistor is needed. The high voltages around 50 V can not be fed straight into the analog inputs of the micro controller but a 240 $k\Omega$ voltage divider with a reduction ratio of 12 was used. The total power draw of the divider is 15 mW. The circuit can be seen in figure 4.3. It was build in a watertight plastic container and powered from the same source as the boat charger. When the charger is plugged in, the device will start logging voltage and current, even if no battery is charging. A photo of the container without lid is seen in figure 4.2.

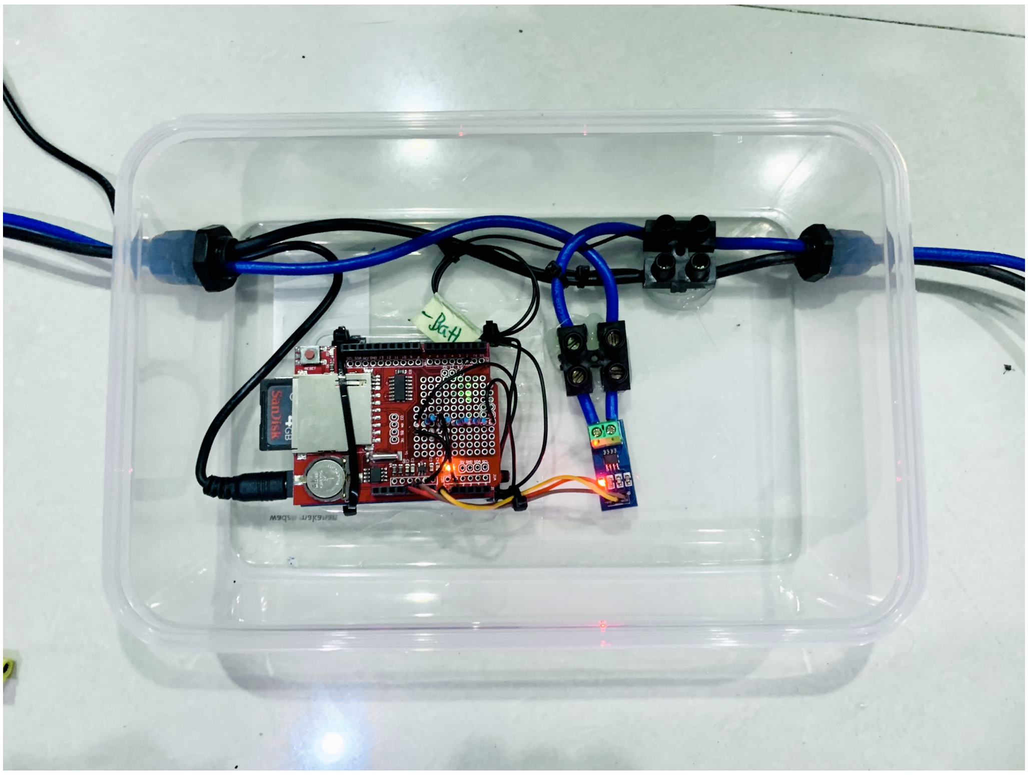

Figure 4.2: A closeup of the DC measurement system.

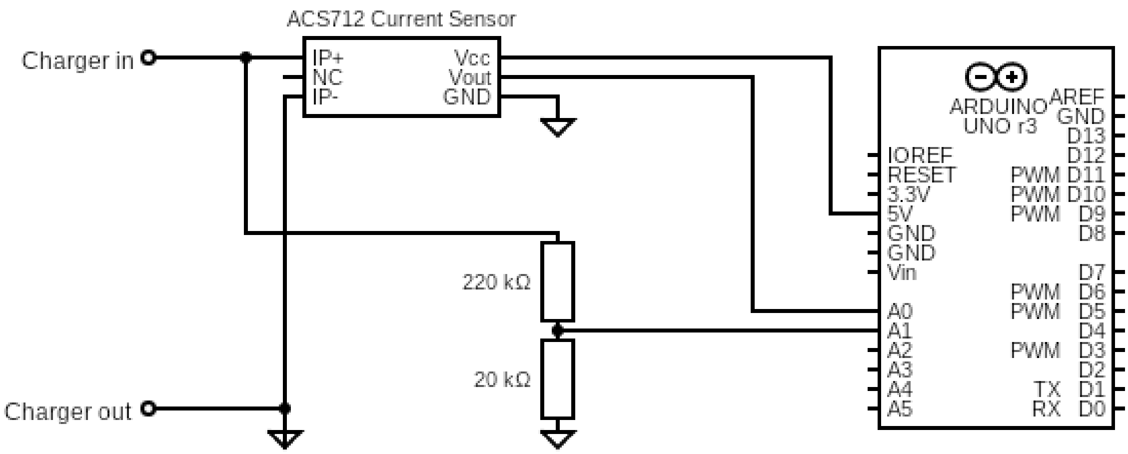

Figure 4.3: A circuit diagram of the DC measurement system, data logging shield not included.

4.1.3 DC logger accuracy

In this project the focus was not to make measurements with high accuracy. Even if high accuracy was possible there are many introduced errors elsewhere such as the approximation in the modeling of the charge event. With this in mind a brief look into the measurements are presented as follows. The voltage sensing circuit measures zero when the voltage is zero. At 52 V, according to a multimeter, the voltage sensor reads 51 V. The current differed around 0.1-0.4 A for the different values in the charger operating range of 0-10 A. This gives four points of error according to table 4.1.

Table 4.1: Measurement errors calcutaled for different operating points.

Multimeter Reading	Sensor Reading	Error
0 [V]	0 [V]	0 %
52 [V]	51 [V]	2 %
1.1 [A]	1 [A]	9 %
10.4 [A]	10 [A]	4 %

4.1.4 AC Power Measurement for Household Loads

Due to the hazardous nature of 220 VAC and the inconvenience caused by shutting of the mains for installment it was desirable to use a non-invasive sensor. The SCT-013 split core current transformer (CT) was used with an internal burden resistor. A CT, as with any type of transformer, can only be used with alternating currents. For a CT sensor the primary winding is one of the mains conductors, either neutral or live, and the secondary is the sensor output. The core is a ferrite ring split in half so that the device can be clamped onto a conductor. When the CT is installed the varying current in the mains conductor (primary winding) will cause a fluctuating magnetic field in the core and in turn induce a current in the secondary winding circuit. Since the turns ratio is known, the current in the secondary winding can be calculated.

The ADC on the micro controller is a voltage sensing input and hence this secondary current has to be converted into a voltage using a burden resistor. The circuit can be seen in figure 4.4. As the current on the output is also AC, the reference ground has to be lifted to half of the micro controllers maximum analog input voltage $V_{Aref}/2$. This is done with a voltage divider. Now the desired burden resistance can be calculated as

$$R_{burden} = 0.5 \cdot V_{Aref}/I_{sec,peak} \,. \tag{4.1}$$

The sensor used in the logger can be seen in figure 4.5. The blue CT has a built in burden resistor and has a conversion ratio of 5A:1V. For the DC logger, power to the system was easily taken from the charger. For the AC logger it was not as convenient and in order to not have to run extension cords the system was run on a 20 Ah, 5 V li-ion power bank.

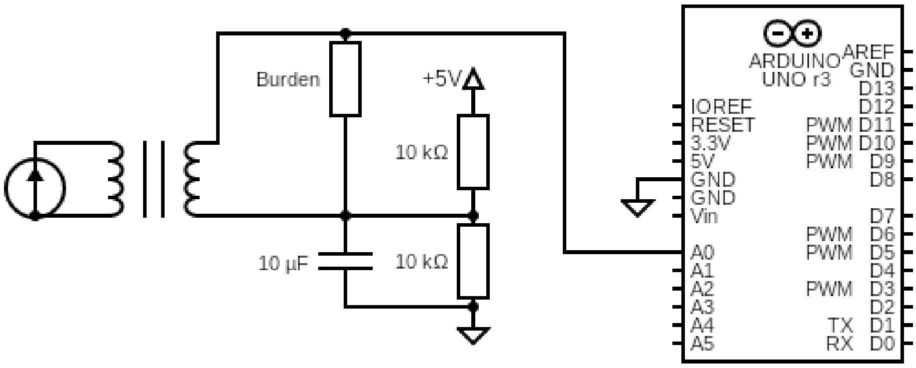

Figure 4.4: A circuit diagram of the AC measurement system, data logging shield not included.

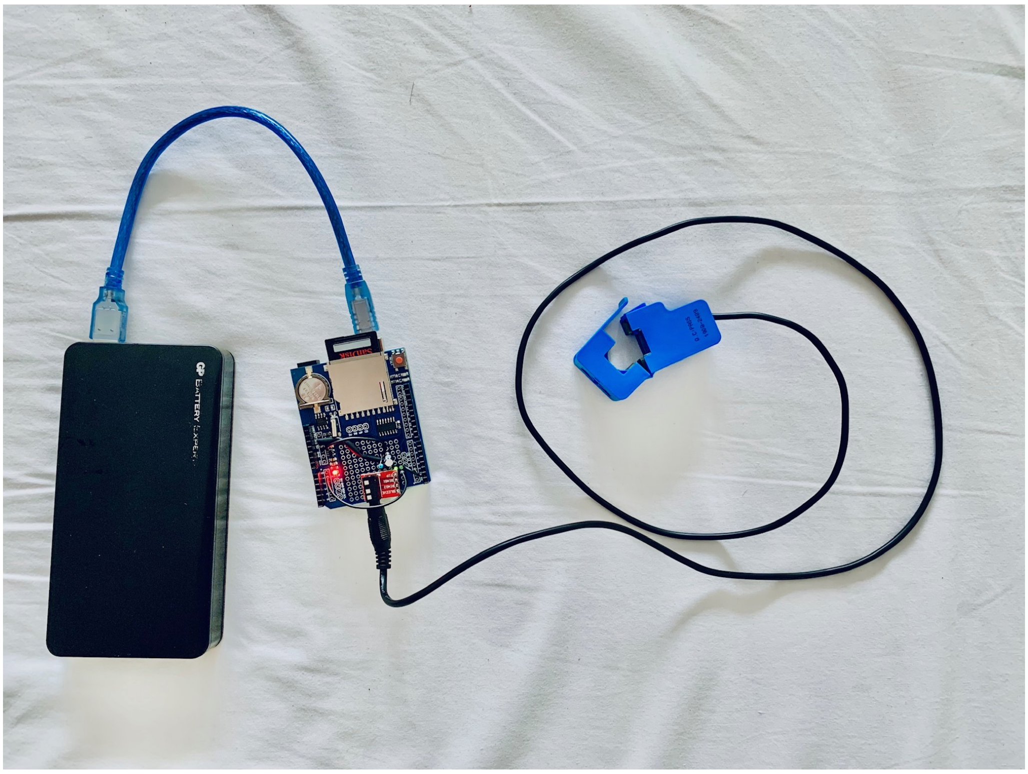

Figure 4.5: The AC logger built, without protective case.

The AC power is calculated from the currents measured by the CT. When doing these calculations two assumptions are made. The first is that the grid voltage is stable at 220 VAC. The second is that there is only active power flowing to the load and thus all current sensed by the CT probe gives a contribution to the active power curve. In figure 4.6 one of the measurements done on one of the households is seen, where the power has been calculated using measured current and the assumptions above.

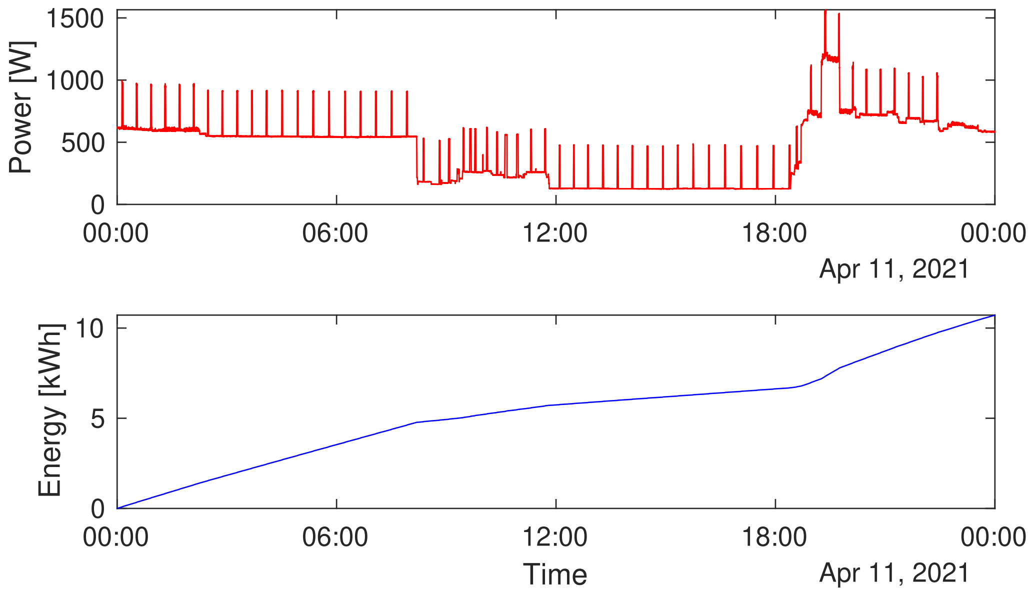

Figure 4.6: A 24 hour measurement on one of the households.

4.1.5 AC Energy Measurement

In addition to the power logger above, the energy meter on the building was also measured manually on the dial at regular intervals. In figure 4.7 the power meter is seen and above it is the AC power logger enclosed in a protective case and running on a power bank.

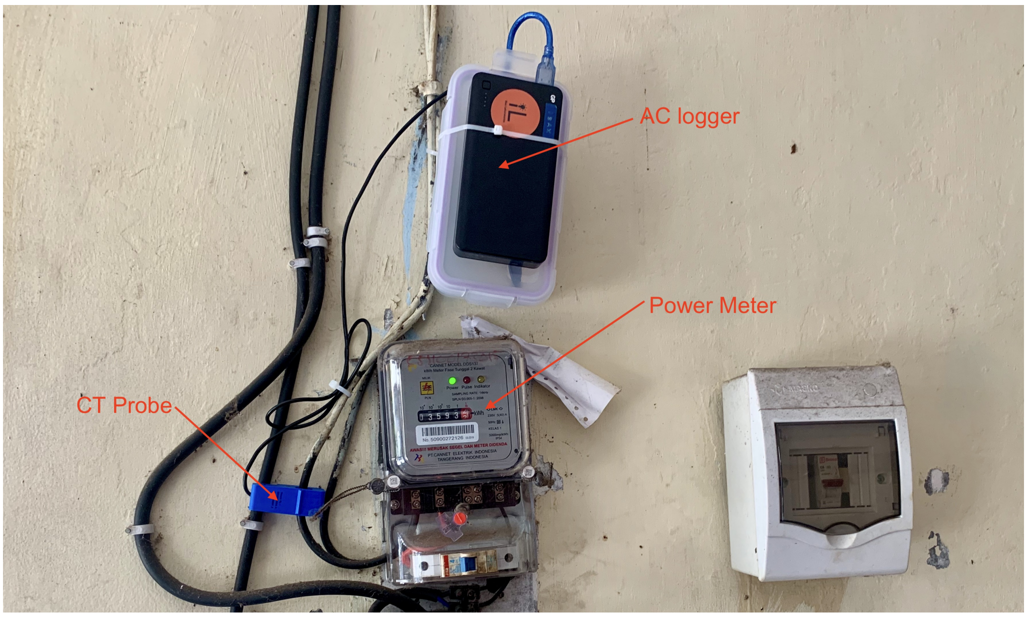

Figure 4.7: The AC logger used next to the installed power meter.

The energy measurement was used as a reference and gave insights into the accuracy of the power logger. Several visits to the village were made over a period and the results are seen in table 4.2.

Table 4.2: Measured energy usage from one of the households and calculated averages.

Date **Time**		10/3 11:30	18/3 9:30	25/3 14:00	30/3 12:00	5/4 16:30
Energy on Meter	[kWh]	3478.1	3523	3564	3593.2	3628
Consumed Energy	[kWh]	-	190	172.5	118	148.5
Avg. 24 h Energy Use	[kWh]	-	5.67	5.7	5.94	5.62
Average Power	[W]	-	236	238	247	234

4.1.6 AC logger accuracy

When comparing the grid energy meter provided by the network supplier with the power meter built, the error in energy over time was around 2 % for a 6 day period. The network power meter was consistently giving a lower reading than the self made sensor. This is probably since the CT probe in the self made meter measures apparent power and the loads are not purely restive as assumed. If the measured power is consistently higher than in real life that means that the model will overestimate the load. This makes the approximate energy consumption conservative.

4.2 Modeling Boat Charging

The following section explains the process and the estimations behind the part of the model that simulates boat charging. This part is seen in diagram box "Generate 24 hour total load from charging boats" in figure 4.1.

4.2.1 Model a Charge Event

In order to simulate one charge of a boat battery pack, the DC power logger was used to sample charge data from real charge events. One such charge event is seen in figure 4.8 with the charger operating in two modes. When the SoC is low the battery is charged at a constant current. During this time the voltage rises around 10 %. This rise in voltage is due to the rising cell voltage when the SoC increases. At a certain point, around 90 % SoC, the current is instead decreased until it reaches 0 A when the battery is full.

In the model a charge event was assumed to have two phases. The first being a constant power mode with the measured peak power as the constant operating point. This is followed by a linearly decreasing power for the last part of the charge. Both these approximations gives a slightly larger energy demand than in reality. The duration of the charge and the peak power is however maintained. The approximation and the accumulated energy error can be seen in figure 4.8. Note that the total energy transferred to the battery in this charge was 1.2 kWh making the over estimation around 10% or approximately 0.12 kWh. This implies a conservative approach to energy and power need in the system as a whole.

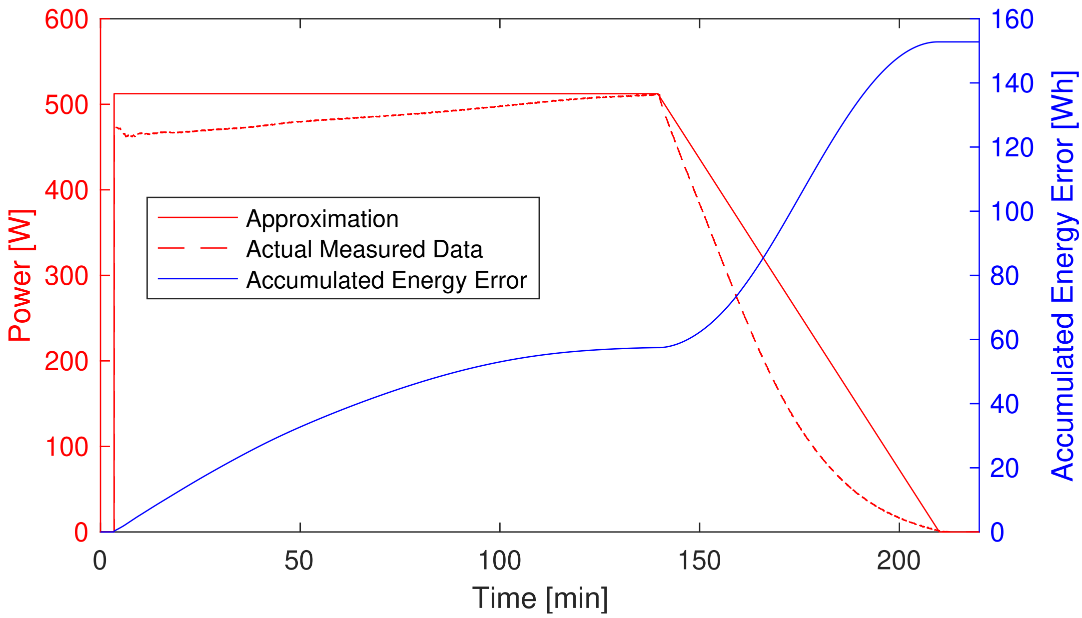

Figure 4.8: The charge event used in the model to represent all charge events, including measured and approximated charge power as well as accumulated energy error.

4.2.2 Generate 24 hour Charge Events

When the model is asked to generate one charge event, the internal sub-function takes SoC as one input and outputs a power curve. The power curve will have the same shape and peak as the approximation seen in figure 4.8 but the duration will vary depending on the SoC. The SoC has to be within the specified limits: $10\,\% < SoC < 90\,\%$. The lower limit is the cutout limit for the battery packs internal BMS. The upper limit is put there since it is unlikely to initiate a charge of an almost full battery pack, and such very short charges would not have significant impact on they system anyway with low power and low energy.

Unless the simulation has only one charge per day there is a need to generate more than one charge event and add the power required together. When the model is asked to generate one whole 24 hours of charge events a sub-function takes number of chargers and number of charges per day as input. When adding another charge event to the day the model will randomly generate a start time for the charge event and then call the sub-function described above to get the power curve according to a random SoC. When this is done the first thing to consider is if there are enough chargers available. If there is then the suggested charge starting time is accepted and the charge event is added to the daily power curve. If not, the loop restarts with a new start time until there are available chargers. If the loops restarts more than 500 times without finding a free spot, the simulation stops and gives an error message saying "not enough chargers". A block diagram of the process is seen in figure 4.9.

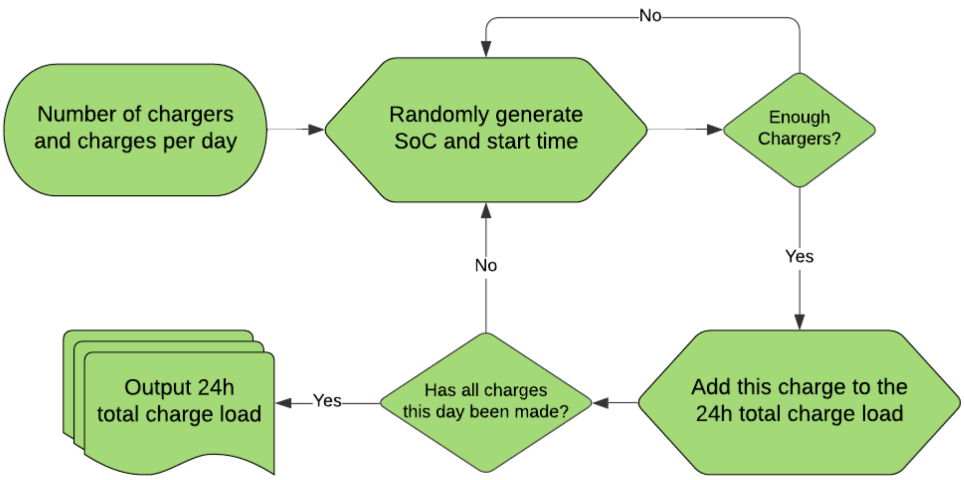

Figure 4.9: A block diagram of the process behind creating one full day of charging.

In figure 4.10 is the total power curve for all charge events in one iteration of the base case is seen. Note that at no point are there more than two batteries charging a the same time. The varying duration of the events correspond to varying initial SoC. The last charge event is continuing after midnight and will then be folded to run in the morning instead. This curve will be added with the household power demand described below and those two curves will form the total power demand.

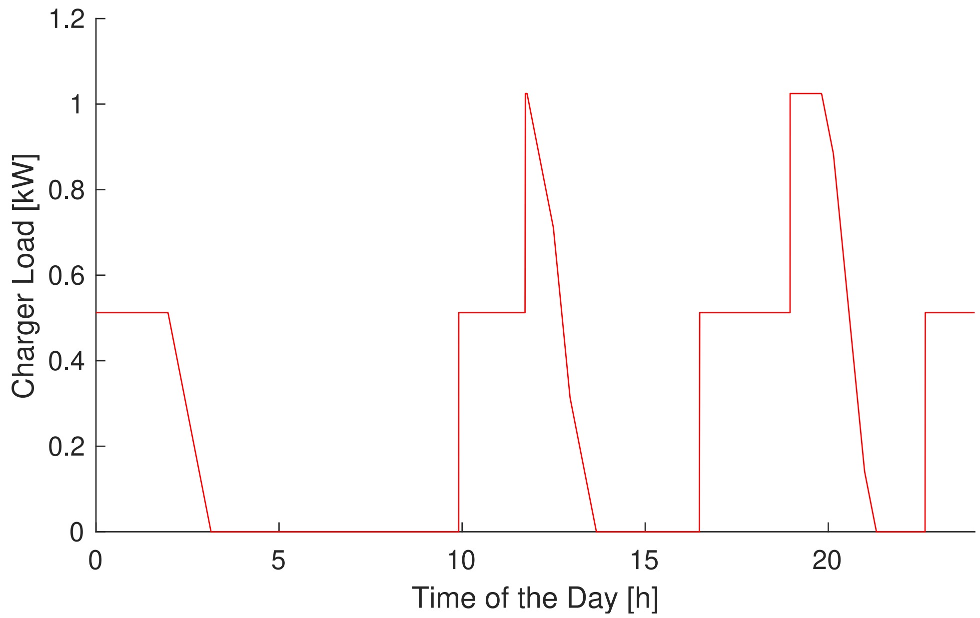

Figure 4.10: Total charger power curve for the base case with five charges per day.

4.3 Modeling Household Loads

When estimating the household loads the power logger was used for energy and power measurements. This section describes the system block "Generate 24 hour total load from households" from figure 4.1.

4.3.1 Household Energy Demand

Measurements on four different households were conducted using the data logger described above. Household A was shared by three grownups and three children. Household B had three grownups. Household C was a family home with two grown ups and two children. Household D was a hotel room with two grown ups. This data was used to calculate the average 24 hour energy use for each individual household, as well as the total average, as seen in table 4.3. The total average of 10.5 kWh is used in all simulation scenarios unless otherwise stated. It is assumed to be constant all year around. Unlike in regions with large differences between temperatures in different seasons the temperature in Indonesia is fairly constant. This gives less error to an estimated constant daily energy consumption all year, although some seasonal differences might still exist due to other factors.

Table 4.3: Measured household energy usage for all households and calculated averages.

Household	A	B	C	D	Total Avg.
Average Consumption [kWh/24h]	5.7	18.0	12.2	6.1	10.5

4.3.2 Household Power Demand

In addition to the energy need there is also a need to dimension the power capabilities to ensure the battery pack has a high enough C-rate tolerance to handle the currents needed. To implement this in the model the measured household power curves were used. The measurement data was collected and divided into 24 hour intervals, as seen in the top graph in 4.6. Then each 24 hour interval was normalized and stored in the model file. The file contains a number of different such normalized curves from different days and different households. By using this data in the model the simulation will have power curves proportional to the real measured system. A load curve will always have the same shape as the original measurement but the magnitude depends on the desired energy use.

4.3.3 Generate 24 hour Household Loads

When the system block "Generate 24 hour total load from households" seen in figure 4.1 is called it will generate a total household load curve with the number of households and their energy according to the input. For each household the daily energy need is multiplied with a randomly chosen normalized power curve previously stored in the model file. All the separate households are then added together to form the total 24 hour load for that iteration.

4.4 Total 24 hour Load

When the full load curves from the chargers and the households are generated they are added together. In figure 4.11 the total 24 hour load is seen for one iteration of the base case. The charge events from figure 4.10 was added together with five household loads generated by the function described above.

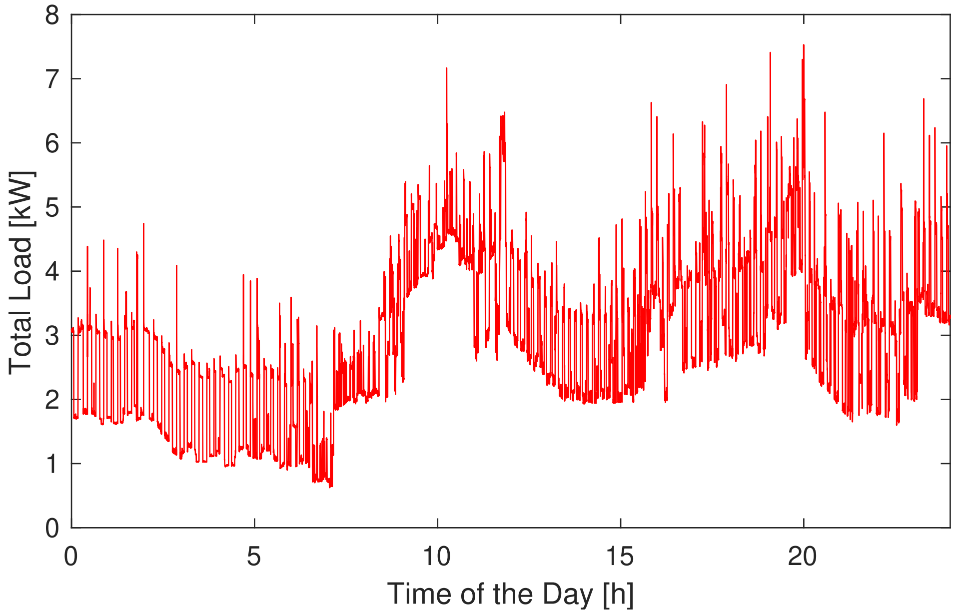

Figure 4.11: Total power curve for the base case with five charges per day and five household loads, each using 10.5 kWh per day.

4.5 Dimensioning the Solar Power System

When a total power curve, like the one in figure 4.11, is created it is sent as an input to the system block "Dimension PV cells & storage battery". This block will use the load curve to determine the power capacity and energy need.

4.5.1 Installed PV Power

For the model to work, the user has to define a number of hardware related constants such as panel rated power, cell efficiency and voltage. The output will be given in installed PV power as multiples of the a single panels power rating. Then the direct solar normal irradiation is defined. In this model the irradiation is assumed to be constant during daytime and zero during night. At sunrise and sunset the irradiation level will rise and fall with a step. This is not a perfect representation of reality since even if the length of the days close to the equator varies very little the irradiation is not the same in rain season as in dry season. The step representation of daily values gives an accurate average daily irradiation value. It is, however, not accurate for instantaneous values as a real day will have a rising slope, a peak and a falling slope. To mitigate these shortcomings the daily solar irradiation used in this model for all days is taken from the lowest monthly average value for Bali in February at 85 kWh/m^2 [15]. The yearly average is around 60 % lager than the monthly average for February and that makes the model conservative in this regard. The model ignores shading effects and angling of the panels. The conservative irradiation can account for some of this but it should be remembered when using the model.

When calculating the installed PV power the model will consider all the energy needed during 24 hours, including losses. It will then calculate how many panels are needed to generate that energy with the given irradiation during the given daytime interval. The answer is given in watts and will always be a multiple of the closest number of individual panels needed rounded upwards.

The parameters for the cell were taken from a similar type as the one currently installed in the village [1] and are seen in table 4.4.

Table 4.4: PV panel specifications from a panel similar to the one installed in the current solar charging station [1]. These parameters were used in the model.

Parameter	Unit	Value
Short Circuit Current	[A]	9.72
Open Circuit Voltage	[V]	21.6
Max Power Current	[A]	8.72
Max Power Voltage	[V]	17.2
Installed Power Per Panel	[W]	150

4.5.2 Installed Battery Capacity

The hardware specific parameters defined for the battery are those mentioned in chapter 2. The individual cell capacity is also defined as well as number of cells in series. When the model calculates battery capacity the first step is to calculate the needed capacity for storage only, disregarding C-rate capabilities. This is done by sorting out the part of the total 24 hour load curve that is needed during the user defined night time. All the energy that is to be supplied during night has to be stored in the battery pack. The energy lost in the internal resistance of the battery also has to be stored. The initial C-rate capacity ($C_{initial}$) calculated in this first step assumes that the cells will be able to handle any C-rate. This is however not always the case and therefore the next step is to check if the C-rate capability of the pack is enough for the given load pattern. The initial C-rate capability of the pack is calculated as

$$C_{initial} = N_{parallel\,cells} \cdot C_{cell}\,, \tag{4.2}$$

where C_{cell} is the C-rate capability of one cell and $N_{parallel\,cells}$ is the number of parallel strings of batteries in the initial battery pack. The next step is to check how large the C-rate capability has to be to handle the load curve. This is done using

$$C_{needed} = \frac{P_{peak}}{E_{batt\,initial}}\,, \tag{4.3}$$

where P_{peak} is the maximum power during the iteration and $E_{batt\,initial}$ is the total battery capacity before C-rate considerations. Now the model will check if $C_{initial}$ is lower than the required C-rate, C_{needed}. If it is, a series string of batteries will be added to the pack until the condition is no longer met and the C-rate capability can handle the load. It should be noted that short intervals of high C-rate might be acceptable in a real system. This model is conservative as it will trigger the C-rate warning even if the peak is only one second.

In the model two type of cells were used. The first one is the very same type of FLA battery currently installed in the solar charging station [2]. The second is a li-ion battery made for energy storage [3]. The parameters were taken from two data sheets for the two different cells. All used battery parameters are seen in table 4.5.

Table 4.5: Battery specifications from the two types of cells used in this model. The FLA cell is the same model currently used [2] and the li-ion is a typical storage cell [3].

	DoD	**Cycle Life**	**Cell Efficiency**	**Price** [€/kWh]	**C-rate** [h^{-1}]
FLA	50%	1500	70%	85	0.05
Li-ion	70%	3000	92%	150	0.5

4.6 Cost and Payback Time

The economic payback calculation done in this thesis is meant to be an indication only and a more thorough cost calculation has to be done to get accurate results. The numbers influencing the price is broken down according to costs and avoided costs related to grid electricity, gasoline, solar power station hardware and boat propulsion systems.

4.6.1 Solar Power Station Costs

The power station consists of batteries, PV panels, converters and various hardware such as wires and switches. The single most expensive part of the system is the storage battery. The acquisition cost for a generic li-ion battery in Indonesia is seen in table 4.6 and the FLA battery cost is estimated to be around 65 % lower [16]. Some of the costs are expressed relative to the PV system cost. This model ignores cost for maintenance and operation. It also ignores gained funds from salvaging and omits high volume purchasing discounts. Replacements are only considered for storage batteries and thus the PBT becomes increasingly inaccurate as PBT increases. This is due to the likelihood of other components needing replacements being higher the longer the system operates. Furthermore potential interest rates and inflation is also disregarded. The avoided costs that make up for these expenses in the long run is avoided grid electricity and gasoline for the boats.

Table 4.6: Costs and avoided costs related to the installment and usage of a solar charging station.

Absolute Costs	Estimated Cost	Unit	Reference
Li-ion Battery	8500	kIDR/kWh	[9]
FLA Battery	5525	kIDR/kWh	[16]
PV Panels	14	kIDR/W	[9]
Relative Costs	Percentage of PV Cost		
Power Electronics	20%		[17]
Wiring and Misc.	20%		[18]
Installation	10%		[17]
Avoided Costs	Estimated Savings	Unit	
Grid Electricity Price	14	kIDR/kW	[19]

4.6.2 Boat Related Costs

When calculating the boat related costs it is assumed that the user buys a new electric motor and battery system from Azura Indonesia. The cost saved is only that of not buying gasoline. Other costs related to an ICE such as oil and replacement parts are ignored.

Table 4.7: Costs and avoided costs related to the purchasing and usage of a Azura Indonesia longtail electrified boat system.

Electric Boat Costs	Estimated Cost	Unit	Reference
Electric Motor	15000	kIDR/piece	[20]
Boat Battery	28000	kIDR/piece	[20]
Avoided Costs	Estimated Savings	Unit	
ICE Propulsion System	5000	kIDR/piece	[20]
Gasoline	9.5	kIDR/L	[21]

4.6.3 PBT Calculation

When the PBT is to be given the model will first calculate the initial investment. Thereafter it will give the number of days required for the avoided costs to pay for the initial investment. If the number of days are longer than the cycle life of the storage battery a new battery will be added to the investment cost and the calculation will be made again until the cycle life is lower than the PBT.

4.7 Evaluated Parameters

For each iteration, representing one day, the results are saved in the Matlab workspace memory. Then, for each scenario, consisting of several iterations or equivalently several simulated days, the results are presented. In the results there are six output specifications to consider:

- **Installed PV Power:** The installed PV capacity needed to run the system.
- **Total Installed Battery Capacity:** The required storage battery capacity, including extra capacity installed only for C-rate.
- **Battery Replacements:** The number of times the whole pack has to be replaced before the payback time is reached due to cycle life limit. Can be zero.
- **Extra Battery Capacity for C-rate:** The extra capacity installed only to handle high power. Can be zero.
- **Peak Power:** The maximum power used. This number is used when calculating C-rate.
- **Payback Time:** The number of years until the system has payed for itself.

The simulations done was run with 350 iterations per scenario. The model will in this case, for each scenario, use the 350 iterations and calculate average values and coefficient of variance (CoV) for all scenarios. This means that for each scenario the 350 iterations are represented by one average value and one CoV for each of the six output specifications in the list above. The average value was chosen to make comparison between scenarios easy. It should however be remembered that the actual specification for the system might be significantly higher than the average for satisfactory user experience. The CoV was included in the results to show how much the answers differ from the average value and gives an insight in how predictable the outcome is.

5

Simulating Scenarios in the Model

This chapter presents results from the different simulation scenarios explained in section 3.2. These results are then analysed and reflections relevant each simulation scenario is presented. A discussion between the different simulations can be found in the next chapter. For the first simulation there are graphs showing the results from installed PV power, total installed battery capacity, peak power and PBT together with the table. These are included to show how how the results in each 24 hour iteration can vary. In the simulations following the first the results are presented with tables, however, all simulation runs will have data in similar distributions as seen in the first example.

5.1 One Boat per Household with Li-ion Storage Batteries

In the following simulation there were one boat per household and the tested numbers were: 1, 2, 5 and 10 boats and households. The case with five boats and households is the base case. The batteries for solar energy storage were li-ion batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are first presented in table 5.1 followed by four figures.

Table 5.1: Simulation results for one boat per household with li-ion storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The number of households and boats varied as follows: 1, 2, 5 and 10.

Number of Boats and Households	1	2	5	10
Installed PV power, (avg) [kW]	4.2	8.5	22	43
Installed PV power, Relative	0.2	0.4	1	2
Installed PV power, CoV	5%	4%	2%	2%
Total installed batt. cap. (avg) [kWh]	14	22	51	98
Total installed batt. cap, Relative	0.27	0.44	1	1.9
Total installed batt. cap, CoV	26%	22%	15%	11%
Battery replacements , (avg) [number of]	1.4	1.3	1.1	1.1
Battery replacements , Relative	1.3	1.2	1	1
Battery replacements , CoV	38 %	35 %	30 %	25 %
Extra Batt. cap for C-rate, avg [kWh]	0	0	0	0
Extra Batt. cap for C-rate, Relative	-	-	-	-
Extra Batt. cap for C-rate, CoV	-	-	-	-
Peak Power, (avg) [kW]	2.0	3.2	6.3	11
Peak Power, Relative	0.32	0.5	1	1.8
Peak Power, CoV	34 %	26 %	16 %	15 %
Payback time, (avg) [years]	8.9	8.1	7.4	7.3
Payback time, Relative	1.2	1.1	1	0.99
Payback time, CoV	43 %	30 %	21%	16%

The installed solar capacity is seen in table 5.1 and figure 5.1. In the figure it can be seen that installed PV power increases with the number of users, since more power is needed. It varies with discrete steps, these occur due to the fixed power of the solar panels, adding a new panel will add one string of two 150 W panels to the system and it is therefore almost always slightly oversized. This is done to guarantee that the energy need is always covered and gives some extra margin. The average values seen in the table correspond roughly to the peak of the histogram bins in figure 5.1 since the bins are evenly distributed on each side of the peak. The relative values of installed PV follows exactly the number of users, when increasing from 5 to 10, the power is doubled, and when decreasing from 5 to 1 the PV power is 19 %.

The cases with higher levels of installed PV, as seen in the figure, can be caused by one or a combination of the following reasons. Firstly a large number of the charge events could have taken place at night and thus the power must first be stored in the batteries and the losses in the storage batteries must be provided for. Secondly the state of charge for the charges done that day could have been low and more energy is then needed for the boat batteries. Finally the household load curve for that day could have been more or less demanding during night. Even if the same energy is always used by the household during 24 hours, there are some curves with more night time use and some with more day time use. For the lower values of installed power the conditions have been the opposite with high SoC and/or mostly daytime energy use.

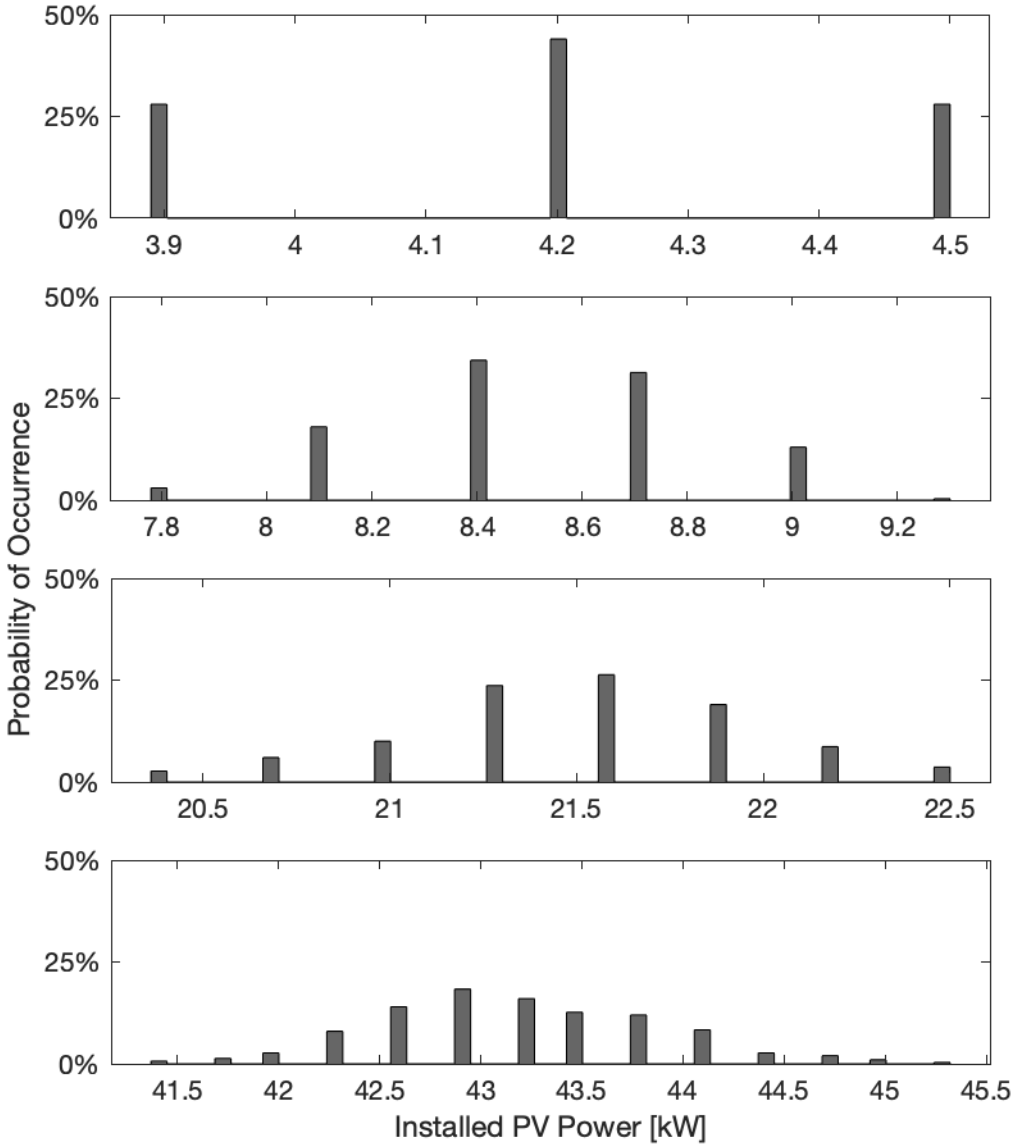

Figure 5.1: Simulation results for probability of occurrence of installed PV power from 350 iterations. From top to bottom the number of households and boats were: 1, 2, 5, 10. The storage battery type was li-ion.

The installed battery capacity varies in a similar pattern as installed PV power, as seen in figure 5.2. In the figure it is seen that for one boat and household, the lowest capacity that can occur is 8 kWh, whereas the highest is 23 kWh. This gives a ratio between the highest and lowest needed battery capacity of around 2.9. If the same comparison is done for PV power in figure 5.2, where the lowest installed PV power for one user is 3.9 kW and the highest is 4.5 kW, the ratio is only 1.15.

This is also seen in the larger CoV for battery capacity in table 5.1. The variation is caused by the same factors as described for the installed PV power. A load pattern with heavy night load will have to store that energy and thus a higher battery capacity is required for storage, whereas a load pattern with mainly daytime energy use will not require as much storage. The larger variance in battery capacity makes the needed battery capacity less predictable when designing the system. The effect wears off when the number of users increase as the ratio between the highest and lowers capacity needed in the 10 user case is closer to 2 and the CoV has decreased from 26 % to 11 %. This indicates that more users are desirable if a system is to be designed for all cases.

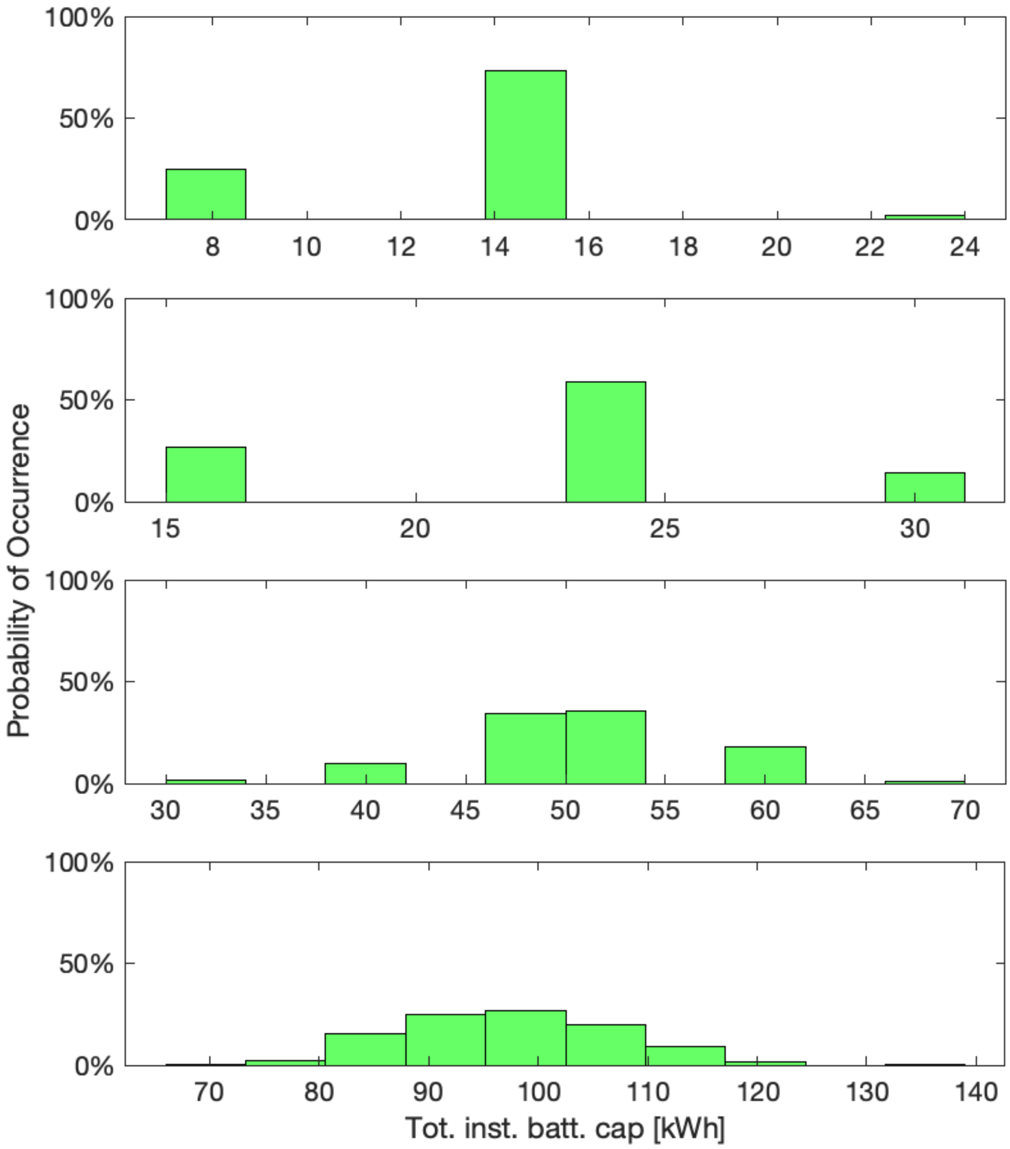

Figure 5.2: Simulation results for probability of occurrence of installed storage battery capacity from 350 iterations. From top to bottom the number of households and boats were: 1, 2, 5, 10. The storage battery type was li-ion.

In figure 5.3, the highest power draws of the total load for each of the iterations are shown. As seen, some peaks are significantly higher than the surrounding ones, the largest at 1.5 kW with a probability of 14 %. This peak is there because the highest power draw of two of the fourteen normalized household loads are 1.5 kW. This means that given a large number of iterations these two curves will together have been randomly selected 14 % of the iterations. The second largest peak at 2.5

kW has close to 7 % chance of happening and correspond to another peak from one of the power curves. This higher peak is only present in one of the 14 curves and thus after a large number of iterations it will show up 7 % of the times. These types of peaks originates from the measured load patterns from the actual households and reflects the highest loads experienced there. It could be an electric stove or heater. With increasing number of boats and households the histogram is smoothed out and the peak bars in the histograms are less prominent. This is because even if the same peaks as before occur in the individual households, there are a lot of other loads at the same time, and the peak will vary as all loads adds up. In the bottom one for 10 users most of the peaks are spread around the mean value of 11 kW.

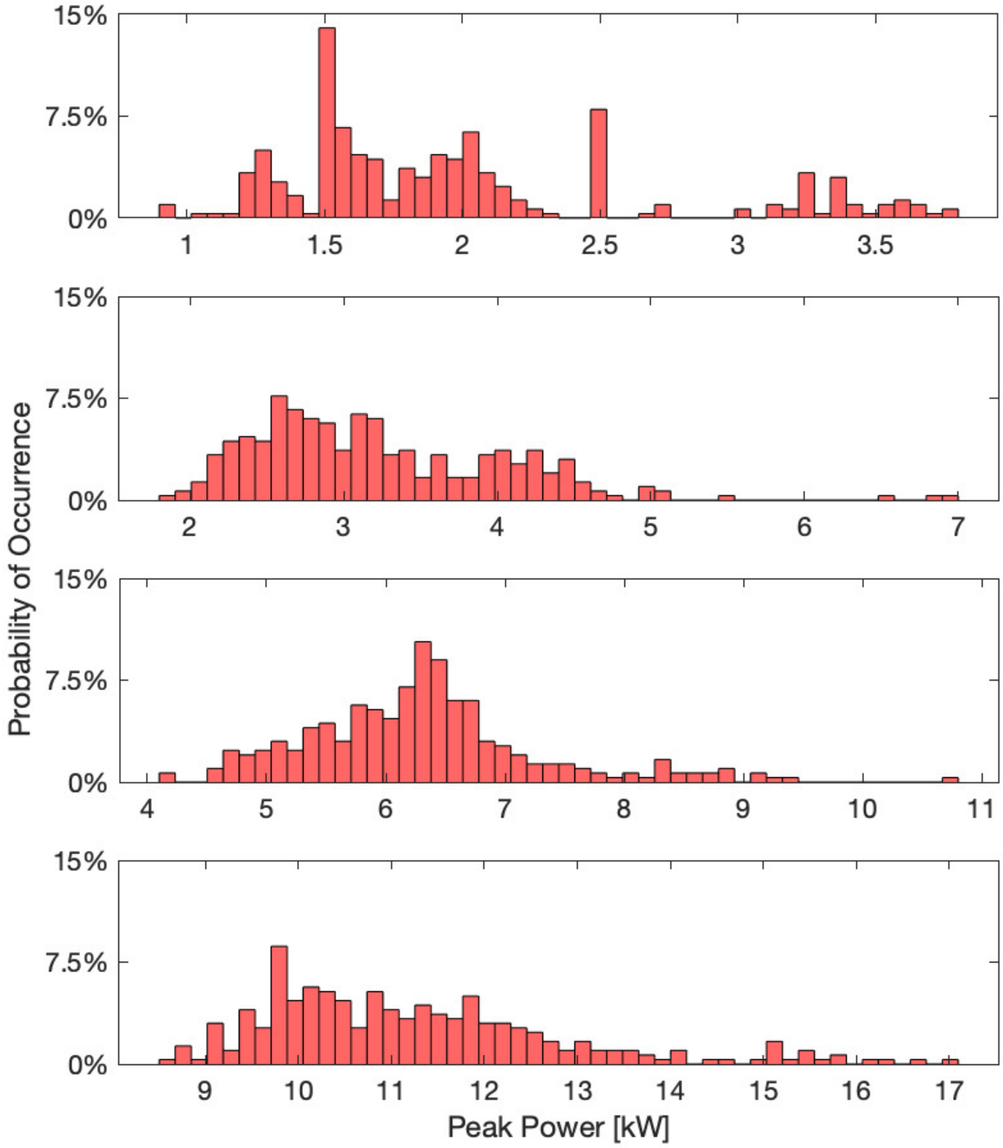

Figure 5.3: Simulation results for probability of occurrence of peak power output for the entire system from 350 iterations. From top to bottom the number of households and boats were: 1, 2, 5, 10. The storage battery type was li-ion.

In figure 5.4 the economic payback time is seen. All number of boats and costumers have local maximums around at least two different years on the timeline, for the first case there are three local maximums at around 6, 12 and 22 years respectively. The number of maximums and the average PBT decreases as the number of users increase. The reason for the local maximums and minimums is the need for storage battery pack replacements. If, for example, a set of system requirements causes a first iteration payback time of eight years in the system block "cost calculation" in figure 4.1 but the storage batteries has reached maximum lifetime cycles already after 7.5 years the function will add another complete pack of storage batteries to the system cost. This will then substantially prolong the new payback time making it impossible to have a payback time of 8 years for this iteration. Instead the added battery cost must be regained by avoided costs over time and there is some years before a new PBT is possible. The fact that the average and maximum possible PBT decreases with the number of users correlates with the decreasing number of battery replacements. For these parameters the average value of PBT and the CoV decreases together.

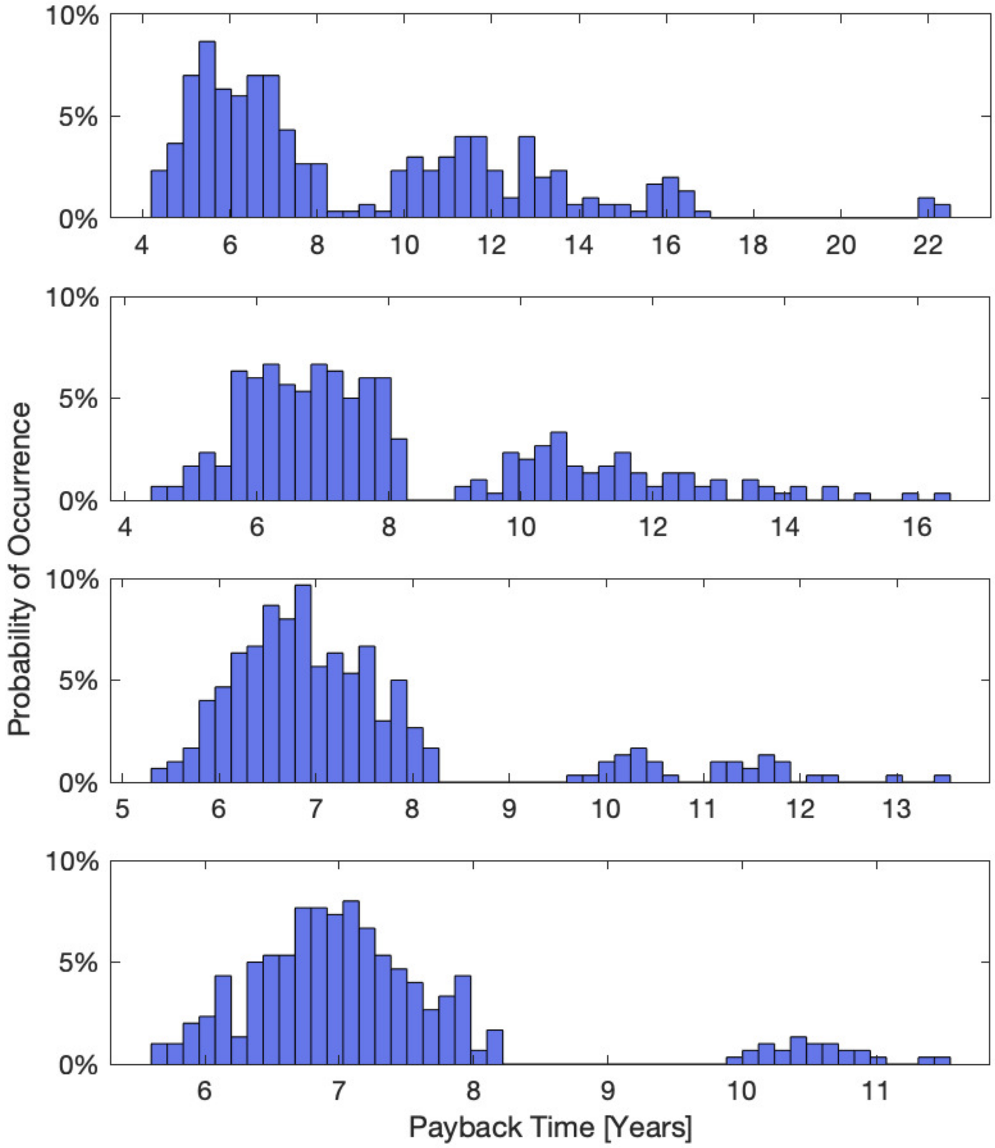

Figure 5.4: Simulation results for probability of occurrence of payback time for the entire system for the entire system from 350 iterations. From top to bottom the number of households and boats were: 1, 2, 5, 10. The storage battery type was li-ion.

5.2 One Boat per Household with FLA Storage Batteries

In the following simulation there were one boat per household and the tested numbers were: 1, 2, 5 and 10 boats and households. The case with five boats and households is the base case. The batteries for solar energy storage were FLA batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are presented in table 5.2.

Table 5.2: Simulation results for one boat per household with FLA storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The number of households and boats varied as follows: 1, 2, 5 and 10.

Number of Boats and Households	1	2	5	10
Installed PV power, (avg) [kW]	4.9	9.8	25	50
Installed PV power, Relative	0.2	0.4	1	2
Installed PV power, CoV	8 %	5 %	3 %	2 %
Total installed batt. cap. (avg) [kWh]	44	70	140	240
Total installed batt. cap, Relative	0.32	0.51	1	1.8
Total installed batt. cap, CoV	29 %	20 %	15 %	11 %
Battery replacements , (avg) [number of]	3.5	3.1	2.8	2.7
Battery replacements , Relative	1.3	1.1	1	0.96
Battery replacements , CoV	35 %	23 %	17 %	17 %
Extra Batt. cap for C-rate, avg [kWh]	9.5	10	9.8	7.4
Extra Batt. cap for C-rate, Relative	0.97	1.02	1	0.76
Extra Batt. cap for C-rate, CoV	76 %	83 %	120 %	180 %
Peak Power, (avg) [kW]	2	3.2	6.4	11
Peak Power, Relative	0.31	0.5	1	1.8
Peak Power, CoV	32 %	24 %	19 %	14 %
Payback time, (avg) [years]	25	19	14	13
Payback time, Relative	1.7	1.3	1	0.94
Payback time, CoV	72 %	42%	23%	19 %

With FLA batteries there is a need for extra batteries installed for C-rate reasons only. If a day has several charge events taking place at the same time, or a high peak in the household curve, a large maximum power is needed and therefore also a high C-rate capability. This can cause the need for extra batteries in parallel to supply enough current. The effect is larger in smaller battery packs since C-rate is proportional to the number of parallel batteries. The relative capacity need for C-rate is fairly constant around 1 for the first three scenarios and decreases more for the 10 user case. When comparing the C-rate capacity with the total capacity it is seen that even if the C-rate capacity is fairly constant the total capacity increases a lot. For the 1 user case the average C-rate capacity is 22 % of the total and for the 10 user case it is only 3 %. This is because a larger battery pack will also have a larger C-rate by default and makes the larger pack less sensitive to high power peaks. As the average C-rate capacity decreases there is an increasing variance in the needed C-rate. This is due to some rare cases with many users where a lot of charge events takes place at once. Even if the variance for C-rate capacity increases the variance for total installed battery decreases.

In the best case scenario there is no need for extra C-rate capacity as the capacity is not used for energy purposes. This implies that a larger number of users is desirable since one battery capacity fits most cases as the CoV decreases and less of the capacity is installed due to C-rate reasons. However it is important to remember that the input to the simulation is completely randomized charge events and even if the fishermen all have different schedules and operated all day and night there might be patterns or habits that causes charging to be done in a lot less randomized manner. This can impact the need for night time storage as well as C-rate capacity need.

5.3 Only Boats with Li-ion Storage Batteries

In the following simulation there were no households, the only type of loads were boat charging events. The tested numbers were: 1, 2, 5 and 10 boats. The batteries for solar energy storage were li-ion batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are presented in table 5.3.

Table 5.3: Simulation results for only boats with li-ion storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The number of boats varied as follows: 1, 2, 5 and 10.

Number of Boats	1	2	5	10
Installed PV power, (avg) [kW]	0.6	0.9	2.2	4.6
Installed PV power, Relative	0.27	0.41	1	2.1
Installed PV power, CoV	27%	31%	19%	14%
Total installed batt. cap. (avg) [kWh]	7.7	7.7	9.2	14.8
Total installed batt. cap, Relative	0.84	0.84	1	1.6
Total installed batt. cap, CoV	0%	0%	33%	29%
Battery replacements , (avg)[number of]	1.2	1	1	1
Battery replacements , Relative	1.2	1	1	1
Battery replacements , CoV	32%	14%	0%	0%
Extra Batt. cap for C-rate, avg [kWh]	1.4	0.5	0	0
Extra Batt. cap for C-rate, Relative	-	-	-	-
Extra Batt. cap for C-rate, CoV	140%	270%	-	-
Peak Power, (avg)[kW]	0.5	0.6	1.1	1.7
Peak Power, Relative	0.5	0.5	1.1	1.5
Peak Power, CoV	0%	32%	25%	18%
Payback time, (avg) [years]	5.3	3.9	3.0	2.9
Payback time, Relative	1.8	1.3	1	0.97
Payback time, CoV	52%	37%	15%	10%

An interesting effect is seen on the total installed battery capacity, where the needed average is the same for one and two boats. The reason for this is the high C-rate capability needed for lower number of boats. Even with the high C-rate capability provided by li-ion batteries the power when charging is high in relation to the total energy needed. This means that if a system is designed for one boat it might very well be designed for two boats by default. If the system is designed and used with only one boat it will be more expensive per user due to the extra C-rate capacity needed. For five and ten boats there is no need for extra C-rate capacity and here the ratio of required peak power in relation to energy capacity is different. The payback time and number of replacements decreases with lower variance as the number of boats increases.

5.4 Only Boats with FLA Storage Batteries

In the following simulation there were no households, the only type of loads were boat charging events. The tested numbers were: 1, 2, 5 and 10 boats. The batteries for solar energy storage were FLA batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are presented in table 5.4.

Table 5.4: Simulation results for only boats with FLA storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The number of boats varied as follows: 1, 2, 5 and 10.

Number of Boats	1	2	5	10
Installed PV power, (avg) [kW]	0.6	1.0	2.7	5.4
Installed PV , Relative	0.22	0.37	1	2
Installed PV power, CoV	48%	32%	22%	15%
Total installed batt. cap, (avg) [kWh]	15	17	26	41
Total installed batt. cap, Relative	0.59	0.65	1	1.5
Total installed batt. cap, CoV	0%	18%	25%	17%
Battery replacements , (avg) [number of]	1.9	1.4	1.1	1
Battery replacements , Relative	1.7	1.3	1	0.9
Battery replacements , CoV	50%	38%	27%	15%
Extra Batt. cap for C-rate, avg [kWh]	5.3	4.2	4.6	5.5
Extra Batt. cap for C-rate, Relative	1.2	0.91	1	1.2
Extra Batt. cap for C-rate, CoV	49%	75%	98%	97%
Peak Power, (avg) [kW]	0.5	0.6	1.1	1.7
Peak Power, Relative	0.45	0.55	1	1.5
Peak Power, CoV	0%	32%	25%	21%
Payback time, (avg) [years]	7.8	4.7	3.5	3.3
Payback time, Relative	2.2	1.3	1	0.94
Payback time, CoV	76%	41%	22%	12%

With only boat charging as a load and FLA batteries used for storage, the average extra capacity needed for C-rate can be more than 35 % of the total energy storage need. This is a big downside and "wasting" this much capacity for only C-rate should be avoided. The average C-rate capacity stays fairly constant around 5 kWh. However the percentage of total battery capacity being installed for C-rate reasons decreases from 35 % to 13 %. Keeping in mind that this is average values, it is important to look at variance as well. The variance increases with more users. This is due to the possibility of up to 10 chargers running simultaneously in the worst case scenario with 10 boats. Many charging events taking place at the same time will cause a very high C-rate demand and this explains the large CoV. Even with the increasing variance of C-rate battery capacity, the variance for total installed battery capacity seems to decrease for 10 boats. The total battery capacity CoV will however first increase before decreasing again. The average peak power increases with number of boats. Even if the potential peak power for 10 boats per day is more than 5 kW the average is 1.7 kW. The average number of simultaneous charge events is therefore between three and four. The payback time is decreasing significantly with more charges per day. The CoV is also decreasing significantly.

5.5 Varying Daily Household Energy with Li-ion Storage Batteries

In the following simulation there were five boats and households in all iterations. The daily energy need for the households varied as 5, 10.5, 25 and 50 kWh. The batteries for solar energy storage were li-ion batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are presented in table 5.5.

Table 5.5: Simulation results for varying daily household energy with li-ion storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The daily household energy varied as follows: 5, 10.5, 25 and 50 kWh.

Household energy use [kWh]	5	10.5	25	50
Installed PV power, (avg) [kW]	7.7	22	48	94
Installed PV power, Relative	0.36	1	2.2	4.4
Installed PV power, CoV	6%	2%	1%	1%
Total installed batt. cap, (avg) [kWh]	21	51	110	210
Total installed batt. cap, Relative	0.41	1	2.1	4.1
Total installed batt. cap, CoV	18%	14%	14%	14%
Battery replacements , (avg) [number of]	1	1.2	2	2
Battery replacements , Relative	0.83	1	1.7	1.7
Battery replacements , CoV	0%	30%	6%	6%
Extra Batt. cap for C-rate, avg [kWh]	0	0	0	0
Extra Batt. cap for C-rate, Relative	-	-	-	-
Extra Batt. cap for C-rate, CoV	-	-	-	-
Peak Power, (avg) [kW]	2.4	6.4	14	29
Peak Power, Relative	0.38	1	2.2	4.5
Peak Power, CoV	15%	18%	18%	18%
Payback time, (avg) [years]	4.5	7.5	13.1	17.1
Payback time, Relative [years]	0.6	1	1.7	2.3
Payback time, CoV	18%	22%	13%	12%

The PV power increases, as expected, with energy demand. The CoV on the other hand decreases. The same is true for battery capacity and PBT. This can be explained by the household loads being a larger and larger portion of the total load. Even if the load patterns from the households has peaks and varies over time the total household load will vary less from day to day than the total load from the chargers. In other words, as the household loads has a smaller variance than charger loads, the increased household load corresponds to lower over all CoV for PV power, PBT and battery capacity.

The number of battery replacements increases with energy. For 10.5 kWh the average is 1.2 replacements, with a substantially larger variance than the other cases. When the average is either 1 or 2, the variance is lower. The CoV is higher when the simulation inputs causes an average of battery replacements that is not a whole number. In reality the number can only be 1 or 2 (or any positive integer) as the pack either needs replacing or not. When the average is 1.2, the actual numbers will vary between 1 and 2 (and possibly 3) and cause a large CoV. Since a replacement will prolong the payback time significantly the highest variance of the payback time is where the highest variance for battery replacements is.

5.6 Varying Number of Boats per Household with Li-ion Storage Batteries

In the following simulation there were a varying number of boats distributed over five households. The number of boats per five households were 1, 2, 5 and 10. The daily energy need for the households were 10.5 kWh. The batteries for solar energy storage were li-ion batteries. Each boat were charged once per day and there were enough chargers so they could be charged simultaneously. The results are presented in table 5.6.

Table 5.6: Simulation results for varying number of boats per household with li-ion storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The number of boats per five households varied as follows: 1, 2, 5 and 10.

Boats per 5 Households [kWh]	1	2	5	10
Installed PV power, (avg) [kW]	20	20	22	24
Installed PV power, Relative	0.91	0.93	1	1.1
Installed PV power, CoV	1%	2%	2%	3%
Total installed batt. cap, (avg) [kWh]	47	47	51	57
Total installed batt. cap, Relative	0.91	0.92	1	1.1
Total installed batt. cap, CoV	16%	13%	14%	14%
Battery replacements , (avg) [number of]	2.2	2	1.1	1
Battery replacements , Relative	2	1.8	1	0.91
Battery replacements , CoV	19%	11%	31%	6%
Extra Batt. cap for C-rate, avg [kWh]	0	0	0	0
Extra Batt. cap for C-rate, Relative	-	-	-	-
Extra Batt. cap for C-rate, CoV	-	-	-	-
Peak Power, (avg) [kW]	6	6.1	6.3	6.7
Peak Power, Relative	0.95	0.97	1	1.1
Peak Power, CoV	19%	19%	19%	18%
Payback time, (avg) [years]	18	13	7.4	5.3
Payback time, Relative [years]	2.5	1.8	1	0.72
Payback time, CoV	27%	20%	20%	12%

When looking at the table it is seen that neither installed PV power, peak power or installed battery capacity varies more than 10 %, as compared to the base case for each parameter. This is due to the relatively small energy needed by boat charging when comparing to households. The need for C-rate capacity is zero for all cases. The payback time is however substantially changed with more than a factor of three between 1 and 10 boats per 5 households. It decreases as the number of boats go up. The cost saved by avoided gas is higher than the cost saved from avoided grid power and this effect is apparent. The decreasing payback time correlates to the decreasing number of battery replacements. Furthermore the CoV for payback time is decreased as the number of boats increases, this gives a more predictable system. The results indicates that more boats per households are better from an economic PBT perspective.

5.7 Varying Power with FLA Storage Batteries

In the following simulation there was a power limit on the household loads. The scenario was the base case with FLA storage batteries. The power limit started as infinite (no limit) and then decreased to 3, 2 and 1 kW. The results are presented in table 5.7.

Table 5.7: Simulation results for varying power limit with one boat per household using FLA storage batteries. For all outputs the answers are given as absolute and relative average values from 350 iterations as well as the coefficient of variance. The power limit varied as follows: ∞, 3, 2 and 1 kW.

Household Power Limit [kW]	∞	3	2	1
Relative 24h Energy	1	0.95	0.82	0.51
Installed PV power, (avg) [kW]	25	24	21	13
Installed PV power, Relative	1	0.96	0.83	0.51
Installed PV power, CoV	3%	6%	7%	6%
Total installed batt. cap, (avg) [kWh]	130	110	100	64
Total installed batt. cap, Relative	1	0.84	0.74	0.48
Total installed batt. cap, CoV	15%	14%	12%	11%
Battery replacements , (avg) [number of]	2.8	2.6	2.4	2
Battery replacements , Relative	1	0.93	0.86	0.71
Battery replacements , CoV	17%	20%	20%	10%
Extra Batt. cap for C-rate, avg [kWh]	9.5	0.2	0	0.1
Extra Batt. cap for C-rate, Relative	1	0.021	-	0.011
Extra Batt. cap for C-rate, CoV	120 %	600%	-	890%
Peak Power, (avg) [kW]	6.3	4	3.1	2.1
Peak Power, Relative	1	1.1	0.5	0.33
Peak Power, CoV	18%	7%	9%	14%
Payback time, (avg) [years]	14	13	11	8
Payback time, Relative [years]	1	0.89	0.77	0.56
Payback time, CoV	24%	25%	25%	20%

The implementation of a power limit was done by simply forcing all power above the limit down to the limit. This happened without redistributing that energy to some other time. As seen in the added row in the top of 5.7 the total energy decreases as the power limit decreases. The goal with the power limit was to make the FLA system more feasible by not having to install C-rate capacity. When comparing the no-limit case with a 3 kW limit case the desired effect of lower C-rate capacity need is found. The average C-rate is only 2 % of the total capacity in the 3 kW limit case even if the energy is only down to 95 % relative to the base case. The "blocked" remaining 5% energy that was used at total load power levels above the limit could in a real life scenario simply be redistributed without causing a higher C-rate capacity need. For example don't charge the boat batteries while using heavy appliances. This is of course a slight inconvenience and even if the C-rate capacity is decreased a lot the payback time is only decreased by one year. Even lower power limits will not effect the C-rate significantly as it is already close to zero. It will have a larger impact on the user however and thus a lower power limit is not beneficial. It should be noted that the very large CoV for C-rate in the scenarios with low C-rate are not accurate. The CoV will approach infinity as the mean value approaches zero and this causes the high values, they can thus be ignored in this case.

5.8 Varying System Availability with Li-ion Storage Batteries

In figure 5.5 we see availability for the same scenario as run in section 5.1. In the first case the curve is fairly steep. The average payback times are marked by a star for each number of users. If all the cases up until the PBT average value are included an availability of just under 60 % is achieved for the 1 user case. For the other three scenarios the availability increases to around tier 4. In order to have 100 % availability the actual payback time is almost three times larger than the mean value. In the last few percent there is a very steep increase in payback time when the curve at around 16 years PBT gives tier 5 and reaches 100 % at 23 years, the last two percent increases the PBT with ca 40 %. This steep increase is also seen in figure 5.4 in the top most histogram to the right in the timeline where a few of the blue histogram bars are scattered around 23 years PBT. The steep increases occurs when a new storage battery pack is needed and thus prolongs the PBT significantly. This characteristic is a big downside as it creates a dilemma for the designer. The desire is to make the system 100 % available but the price is very high for the last few percent. Furthermore a system that is build like this will have a lot of it's capacity unused most of the time. This wastes not only money for the user but also resources and energy when producing the system. The alternative is to save a lot of cost by settling for tier 5 and allowing for a few percent downtime but avoiding the high increase in payback time. This will have a negative impact on the end user but might play an important role in making the investment economically feasible. Keeping in mind that there will still be energy available during these 2 % of the days, but not for all loads, the sacrifice of 2 % downtime is well worth considering due to the significantly reduced cost. In reality this could, for example, force the user to postpone a battery charge or shut off a household load. Perhaps the negative impact on user experience is acceptable, although this is a decision to be taken case by case. The ratio between PBT for the mean value with around Tier 5 availability and 100 % is around 2.5.

As the number of boats and households goes up, the average value of availability is above Tier 3 for case 2, 5 and 10. The ratio between the mean value and the full availability also decreases. The curves are flatter for more users and thus the system is more predictable. In the case with 2 users a lot can still be saved by sacrificing the last few percent but the number of years saved is around three times less as compared to the one user case. For even more users the benefit of lowering the availability diminishes.

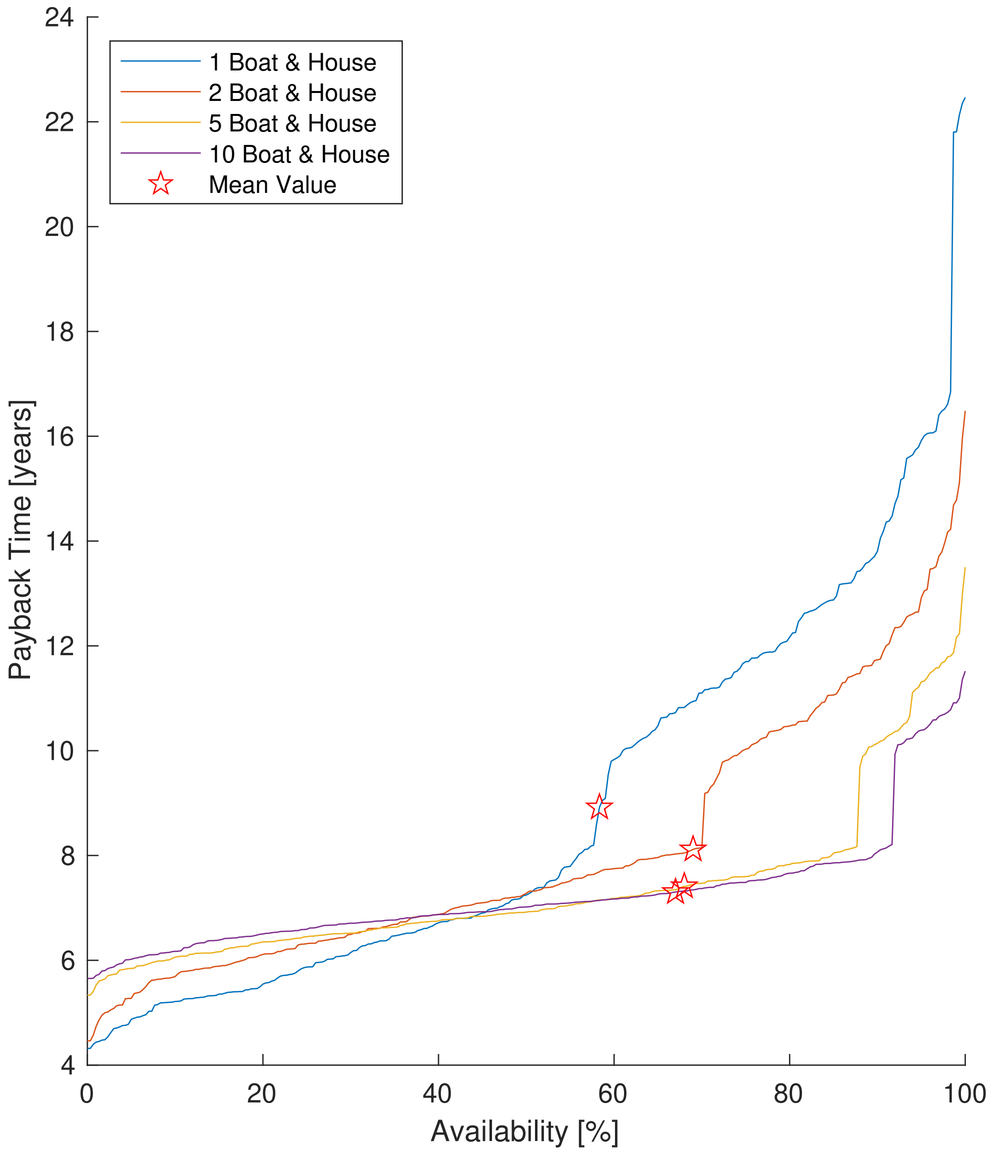

Figure 5.5: Payback times and corresponding availability for one boat per household using li-ion storage batteries. The stars are the average values. The number of households and boats varied as follows: 1, 2, 5 and 10.

6
Discussion

This chapter aims to give insights in what can be found when comparing the different scenarios simulated.

6.1 Installed PV Capacity

When comparing the first two cases (one boat per household) with the following two cases (only boats) it becomes clear that the majority of the PV capacity is installed to cover the household loads. This is not surprising as each household draws 10.5 kWh per day while one charge is in the 1 kWh range. There is a larger capacity need in the FLA systems due to higher battery losses. This is an obvious disadvantage inherent to the FLA batteries.

If the only difference is the storage battery type the extra PV power needed is around 15 % more for FLA than when li-ion is used. This will increase cost and the surface needed for the panels. Increasing losses will also decrease the environmental benefit as a less efficient system will waste more energy during it's lifetime. The same is true for materials, if more solar panels are needed, there will be more resources required to manufacture those panels. This will increase the use of natural resources and energy in the supply chain and should be avoided if possible. From a community point of view the area needed for panels is a potential problem. This is probably more of an issue if the needed area is significantly larger than the roofs available, as valuable land then has to be sacrificed for panels. When looking at the area needed to supply the base case with power using FLA storage batteries it is around 200 m^2 square meters. This gives each house a required area of 40 m^2. While most roofs in the area are larger it is possible that this is not true in all cases and the 15 % saved space using li-ion might be worth it accounting for. Since shading and angling of the panels are not accounted for, there is a need to further investigate these properties. If they were accounted for a larger PV capacity might be needed. On the other hand the solar irradiation data for the worst month was used and this will cause a over estimation of the needed capacity.

6.2 Storage Battery

The following section discusses the three parameters related to the storage battery: installed capacity, C-rate capacity and number of pack replacements. As with PV power, the installed capacity is larger in the FLA scenarios than in the li-ion scenarios. The battery capacity in the FLA system needs more than twice the installed capacity in the corresponding li-ion system. Thus the battery capacity requirements of an FLA system has a much more severe disadvantage compared to PV capacity. There are several reasons for this. Firstly the allowed DoD for the FLA systems is lower which causes a higher need for more installed capacity. Secondly, the higher losses in the FLA system also has to be stored in the battery. Finally more capacity is needed for C-rate reasons in some scenarios.

In general the average installed capacity for C-rate reasons is higher with fewer users. A part of the explanation for this is that with fewer users the daily load curve is much more varying. The most extreme case in terms of C-rate capacity is where there are only boats and FLA storage batteries. In this case the energy need is low compared to the maximum power and the C-rate demand is high. This could be avoided by limiting the amount of chargers and thus very efficiently limiting the peak power. This is of course done at the expense of the end users and might not be an acceptable solution in all cases. When households are added, the total power curve is smoothed out by the households and the ratio of peak power and energy is lower. However, even in this scenario the average C-rate need is large for few users. It gets lower as the number of users increase but the CoV increases. As already mentioned this is caused by many chargers running simultaneously in some rare cases. The scenario with the power limit was created to try to solve this problem and look into using FLA batteries together with a power limit to decrease battery capacity need for C-rate reasons. The average C-rate capacity need was reduced to almost zero, even with a high power limit, and having a power limit is helpful to reduce battery capacity. If a system is built for only boats using FLA batteries the effect is however not large enough to make FLA batteries better overall. The only scenarios where C-rate has to be considered for the li-ion systems are when only boats are used for few users.

The downside of the shorter cycle life of FLA batteries is apparent when looking at the number of pack replacements. In the comparable scenarios the average number of replacements during the PBT will always be larger for the FLA storage system. Some of the downsides of a replacement are not apparent in the results. One issue is the labour cost related to a pack replacement. The model only considers the hardware cost of the new pack. Especially if the location is remote the manual work will not only consist of installation but also transport. Batteries are heavy and not locally manufactured and transporting them to the final location can be a demanding job for the workers involved. This also leads into the other part of the problems with more replacements. The environmental strain caused by more transport, manufacturing and generated waste is much larger in the FLA case due to more pack replacements and larger installed capacity for each pack.

Based on the results it seems that li-ion batteries are favourable. Lower losses, higher cycle life, higher allowed DoD and higher C-rate are all parameters contributing to a lower capacity needed if li-ion batteries are used. A lower capacity will benefit the user since less space is needed for the battery pack and fewer replacements will minimize replacement operations. Both these factors improves the experience for the families in the households.

6.3 Peak Power

Having a high peak power is in itself not a bad thing if the system is build for it, this is however not always the case. Considering this it is desirable to have a peak power as close as possible to the average power. This will decrease the need for C-rate capacity and can be implemented with a power limit as already described. It could also be achieved with a control system that could decide when to turn on and off certain loads. This approach is called demand side management. This adds complexity if it is done automatically and manual load management is probably the better solution. This means simply that the user knows not to run heavy loads when charging. The use of li-ion batteries will increase the tolerable power and in most scenarios the use of li-ion batteries was enough to allow desired peak powers. Again, power limits should be implemented. It is also generally good for the health of a battery to keep the C-rate as low as possible and by limiting the power, the cycle life is expected to increase. This effect is not considered in this model as the cycle life is assumed to be fixed.

6.4 Payback Time

The payback time increases as the household load increases. This is first seen when comparing the PBT for the first two scenarios with one boat per household with the following two simulating only boats. For both FLA and li-ion storage the PBT is higher when including households. Secondly, in the scenario with varying household loads the payback time increases as the household energy goes up. What is also seen is that even if the FLA batteries are less expensive to buy the PBT is generally higher when using FLA batteries. From a PBT perspective the ideal case is a li-ion setup with only boats. These cases gives payback times in the rage of a few years. Similar findings were seen in the study previously mentioned in Lake Victoria where the investment in a li-ion based electric boat is regained after 3 years [10]. If the model built in this project was used with electric cars the PBT might be different. The study conducted in Indonesia on charging electric cars suggests that the idea is feasible for cars as well with a conclusion as follows: "PV-standalone power plant system for EVCS is the most recommended choice with its cost- effectiveness and expected to spread across the country of Indonesia in near future" [9]. This study did however not include households. As stated already the reason for household loads having a longer PBT is that the cost savings related to replacing grid electricity with solar are lower than replacing gasoline with solar. Even if the PBT is longer for household loads it is still a viable option as we see in figure 5.5. In cases with more users the system can be built with 100 % availability with reasonable PBT and in cases with fewer users a lower availability might be something to consider. From an environmental point of view this slightly higher PBT when covering the household loads is worth it. Especially in Indonesia where most of the grid power is from fossil fuels [6].

6.5 Future Work

In this section some interesting paths to continue continue are presented.

6.5.1 Second Life for li-ion batteries

The batteries used in the electric boats are not covered in great detail in this report. It would be interesting to investigate the possibility to reuse the boat batteries as storage batteries. This would create a beneficial ecosystem since the deployer of boats and charging stations, in this thesis Azura Indonesia, could keep the first step of recycling within the organization and thus saving cost. It would also decrease emissions by eliminating some of the need for transport as the boat batteries already are at the location of the solar charging station.

6.5.2 Grid Connected System

In areas where a grid is available, the model could be expanded to allow for grid connectivity. This is interesting for two main reasons. Firstly there is a possibility to sell power to the grid when there is a local high supply from the PV plant, and the batteries are full or chose to charge slower and sell some power. There is even the possibility to sell energy stored in the battery to the grid if the price for electricity is high. Secondly a system with lower availability could be designed that would use grid power in the worst case scenarios, for example high night time loads. This could all help decrease PBT and make the initial investment lower. Having grid support can also enable a modular construction where the first priority is to build a system capable of charging boats and then adding more capacity in stages while decreasing grid power use.

6.5.3 Different Energy Storage

Batteries are the single most expensive part of the system and the use of other storage technologies could potentially decrease system cost.

7
Design Recommendations

This chapter aims to give general design recommendations for building an off-grid solar power system. It gives insights into where costs can be saved and what necessary sacrifices are made to do so.

7.1 Number of Users

In all scenarios the benefit of having more users is clear. It helps spreading out the power curve and makes the PBT more predictable. The system should have some power limit to eliminate the most demanding scenarios that can happen with many users. An example of a way to limit power is a fuse or a limited number of chargers.

7.2 Household Loads

The main cost saving is done by avoiding gasoline and this should be the focus. Adding household loads will increase the PBT. The PBT is however still reasonable when adding household loads and as long as the PBT can be accepted the system makes sense economically in the long run. If necessary, a system with limited availability can be a good option to reduce PBT. Having an off grid system gives other benefits as well such as reliable power independent of grid downtime and sustainable power production.

7.3 Boat Usage Patterns

Since avoided gasoline is the biggest economical benefit a high usage of the boats is desirable. In the simulated scenarios each boat was charged once per day. If a system could be implemented where the boats were used twice per day the PBT could be even shorter as the same initial hardware cost of the boats would be covered much quicker.

7.4 Battery Storage Type

The li-ion battery as energy storage is the best choice in all scenarios tested and in all aspects. It gives shorter payback times, takes up less space and will last longer. The only scenario where the FLA batteries would be preferred due to their lower price is if the planned lifetime of the system was shorter than the lifetime of the FLA batteries (and therefore also the li-ion batteries). In the off grid solar power systems covered in this project the aim is to have as long a lasting system as possible and this makes li-ion batteries the best option in all cases. If the initial investment is a big concern it appears to be better to start with a lower battery capacity using li-ion and then add to it later instead of being tempted by the cheaper FLA batteries as they will end up costing more in the long run. Since these systems are modular in terms of panels and battery cells this makes a step by step approach feasible. On the other hand there are aspects that could lessen the apparent benefit of the li-ion batteries in a real scenario when initial investment is an issue. The main drawback of this study is in the economic calculations where interest rates from loans are ignored which means the cost of a large initial investment can be high if it is obtained through a mortgage. It's also important to know that while the panels and battery cells are completely modular, the power electronics and other components are not. If a modular approach is taken it is therefore important to consider sizing of power electronics from the start. Either start with an oversized system or add smaller chargers and inverters as the system grows. The later option will cost more per watt but the initial investment will be lower.

7.5 System Availability

In the ideal case the system is of course designed to work at all times as all other options will make the quality of life lower for the user. There can however be cost benefits if the availability is lower than 100%. The highest benefit is seen when the number of users are low. With higher users however the difference in PBT is probably not worth the sacrificed availability.

8
Conclusion

In this report a model was built to provide a tool for dimensioning solar power systems meant to power household loads and electric vehicles. The study was based in a coastal fishing village in Bali, Indonesia and the EVs in this study was electric boats. Measurements on household loads showed that the average energy need was 10.5 kWh per 24 hours and this was used in the model.

The model as a whole was build using measurements on household loads and boat chargers. Furthermore a basic cost analysis was included in the model based on data from Azura Indonesia and other papers on the subject.

When the model was complete a number of scenarios were tested in order to evaluate the impact of varying inputs. One factor tested was which storage battery type was most beneficial, FLA or li-ion. In all scenarios the li-ion was the winner in terms of installed capacity, maintenance, longevity and economic payback time. The different scenarios also show that most of the avoided cost from using a solar powered system to power household loads and boats comes from avoided gasoline. This implies that replacing the gasoline engines should be a priority. There are also savings from not buying electricity from the gird. Furthermore, some modifications are possible such as lower availability and power limitations in order to make the system more economically feasible. In all scenarios using li-ion batteries for storage, the payback times are reasonable and the system makes sense for the types of load configurations tried in this thesis.

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