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SMILE

Smart Island Energy Systems

Deliverable D3.8
Demand response evaluation for the system
Final Version

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1 Introduction

The overall scope of SMILE project is to demonstrate, in real-life operational conditions, a set of both technological and non-technological solutions adapted to local circumstances targeting distribution grids to enable demand response schemes, smart grid functionalities, storage and energy system integration with the final objective of paving the way for the introduction of the tested innovative solutions in the market in the near future. To this end, three large-scale demonstrators are under implementation in three European islands with similar topographic characteristics but different policies, regulations, and energy markets: Orkneys (UK), Samsø (DK), and Madeira (PT).

The purpose of this deliverable is to evaluate the appropriate demand response (DR) programs applicable to the Samsø demonstrator. The report will describe the outcome of the trials and the demonstration of the demand response methods set up in the SMILE work-package 5 (WP5) in the real application. It will moreover include an assessment of the control methods based on market price signals developed with input from SMILE work-package 8 (WP8) dealing with the analysis of the energy system impacts, energy strategies and energy market design.

This report is made as an extension of the preliminary version named D3.6. In particular, the section 7 "DR evaluation and market perspectives in Marina" has been added to the initial version D3.6, to demonstrate the applicability of proposed demand response and evaluating the market signals for the real energy system of Ballen's Marina.

The report is structured as follows. Regarding the demand response (DR) solutions for Ballen Marina, first in section 2, the initial academic solution for the control of the marina is described. However, during the evolution of the project, it has been realized that some of the original presented ideas here for the supervision and control, has proven not efficient or realistic to be implemented by considering also the services that the Marina is currently envisaging to provide to its customers. For this reason, alternative solutions are proposed in the next sections. In section 3, forecast methods are set up by Route Monkey, they have been tested as discussed in section 7. Section 4 describes the scheduler set up by Lithium Balance. Section 5 describes the physical set up in Ballen Marina. In section 6 simulations are performed by AAU to justify some of the set up algorithms before the final implementation. Section 7 describes the final implemented system at Ballen Marina. Section 8 and 9 include the conclusion and references, respectively.

1.1 Inputs from other deliverables

In connection with this deliverable, the inputs are considered from the public deliverable D5.1[1] (OVO) about appropriate Demand Respond (DR) services, as well as from the confidential deliverables D5.2 (Route Monkey) about the predictive algorithms for DR services, D5.3 (Route Monkey) about the smart integration of electric vehicles (EVs) and D5.5 (RINA Consulting) about improved control and automation of the distribution network including renewable sources and demand side management. For the final section 7 also input from the deliverable D3.7 (AAU/ET) about overall energy system control at the Samsø pilot, as well as input from D5.7 on algorithms for smart integration of storages has been used as background information when writing the final evaluation.

[1] https://cordis.europa.eu/project/id/731249/results

1.2 Contribution from partners

The following SMILE partners contributed in various sections in this document.
1 Appropriate DR to the Samsø demonstrator is defined by OVO partners as a part of WP5 and is included in section 2. The content is taken from D5.1.
2 Route Monkey described their forecasting algorithms and its accuracy in section 3.
3 Lithium Balance provided the working of BESS scheduling in section 4.
4 In section 5, relevant contribution from Samsø Energy Academy (SE) is added.
5 Aalborg University (AAU/ET) are the leader for this deliverable, they have coordinated in writing the report and formulated section 6.
6 AAU/ET has collected material from SE, Lithium Balance and used content from D3.7 and D5.7 for setting up the final evaluation of the set up system at Samsø pilot in section 7.
7 Finally, the conclusions from this deliverable are listed in the section 8 followed by references that are used in the document in section 9.

2 Samsø's objective

With its highest share of renewable energy sources (RES) in its total power production, Samsø is working on maximizing the local penetration of renewable generation by implementing appropriate DR programs for power consumers in the Marina. Thereby, minimizing the dependency on grid and cost of electricity.

2.1 Marina behaviour and proposed DR: Initial academic solution

The marina witnesses more tourist sailors especially during summer and other holidays, leading to an increase in load. The peak load caused by these boats are to be managed by both the photo-voltaic (PV) and battery storage system (BESS) along with support from the grid whenever it is necessary. Both the PV and BESS systems have been already installed at the Marina during the first 24 months of the SMILE project. The Solar-PV system is rated at 60 kWp, BESS system of 240 kWh energy capacity with inverter of 50 kW power rating. Accordingly, for peak load management, Time of Use (TOU) DR was found to be appropriate according to the theoretical studies, for the Marina users including boats and other controllable loads. Furthermore, the users could for example, receive lower fees, if their consumption was adjusted not only in accordance with the peak load, but also to match with the PV generation.

To elaborate the functioning, whenever boat owners' charges during midday where there is more PV generation, then they would be given more points counting to more discount for adjusting their demand in accordance with not only peak hours but also to match the PV system generation. It should be remarked, that the intention was not to fully interrupt the loads, merely to adjust their consumption to a maximum level, ensuring that they have access to a certain level of kW all day. The overall envisaged control architecture is shown in Figure 2.1.

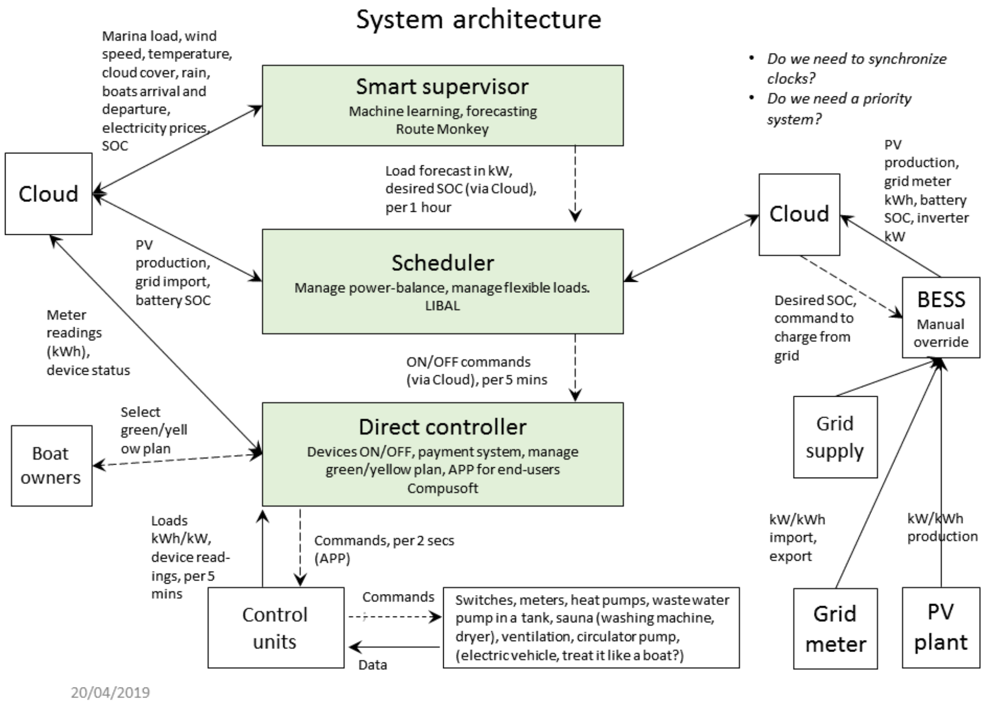

Figure 2.1 Overall control architecture for Ballen-Marina demonstration

The smart supervisor proposed by Route Monkey was expected to be responsible for forecasting the Solar-PV production and Marina load through machine learning techniques. This information could further be used to find the desired state of charge (SOC) for the BESS and passed onto scheduler that is derived by Lithium Balance. The scheduler then would send ON/OFF commands to the controller, which further executes this operation directly on flexible loads. The direct controller represents a device from Compusoft, which in turn should process the ON/OFF commands and would send green/yellow signals to boat owners through a mobile app. It was the wish that boat owners respond to these signals. Nevertheless, the consumers responding to these signals were expected to be granted attractive discounts for their shifted consumption. However, as it will be discussed in section 7 about the real implementation, anthropological studies showed, that this activation of the both owners would not be attractive for them, why this solution was not implemented in the final demonstration.

3 Route Monkey: Forecasting algorithms

Route Monkey (RM) have produced two key streams of forecasts to support the Samsø demonstrator; these are the *demand forecast*, which estimates future load at the harbour, and the *PV forecast*, which directly estimates the future power available from the harbour's PV installation. In both cases, the forecast provides 24 future data points, one for each hour from T+1 to T+24, where T is the 'current' time, or the time that the forecast is made. Each forecast is made available via an API, which enables upstream use of the forecast by planning algorithms and controllers, such as the Libal scheduler. In the remainder of this section, we outline how the forecasts are produced, provide estimates on their accuracy, and also provide details of the APIs.

3.1 Harbour Load Forecasting

Load data for the harbour at Samsø is provided by Compusoft, who have made a secure API available to RM. This API provides a meter reading (whose timestamp can be assumed to be the time it was called), which is taken to be accumulated consumption at the harbour. RM polls this Compusoft API regularly, and infers point demand values in kW at hourly intervals. Figure 3.1 illustrates this, showing the kW demand values inferred at the harbour for the 30 days to April 27th.

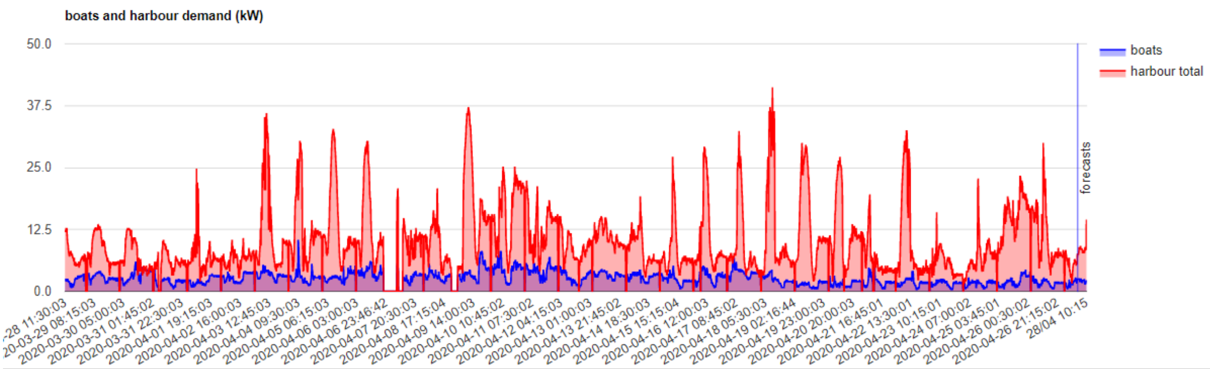

Figure 3.1– Harbour load (in red) inferred from meter readings provided by Compusoft API.

Note that figure 3.1 also shows demand from boats alone, which is also indicated on a separate meter by the Compusoft API, however this is not used since there are currently discussions concerning its accuracy.

RM operates hourly machine learning, to produce 24 separate forecast models for harbour load, respectively predicting load at 1, 2, …, 24 hours ahead. These forecasts are shown on the dashboard available to SMILE participants, as indicated in Figure 3.2, and are provided via the API described in section 3.3. The general algorithm machinery behind the machine learning and forecasting was detailed in deliverable D5.2 "Predictive Algorithms for DR Services". In the current report, we will summarise the details by indicating general characteristics of the setup for the harbour at Samsø and providing an indication of the accuracy levels.

Each of the forecasts is based on a model which maps a historical window of load values to the forecast value. The historical window always contains the current load value (at time T) along with a number of recent values (typically T−24, and then T−6, T−5, T−4, …., T−1). The machine learning algorithm used is gradient boosting (an ensemble decision tree method) as implemented in the python scikit-learn toolkit. The model is built using 21 days of training data (70% for training, 30% for validation).

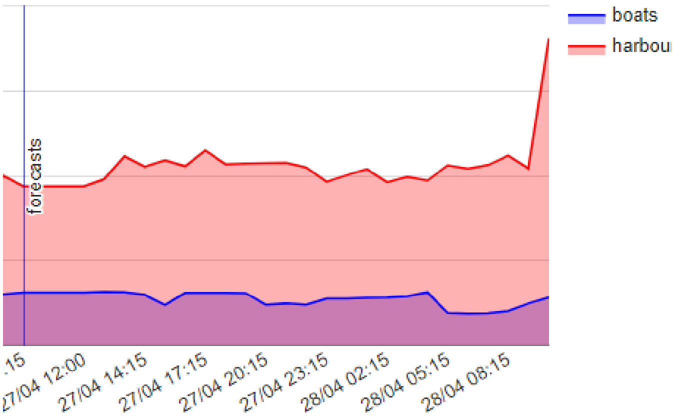

Figure 3.2– Forecasts of Harbour load (in red) produced by RM machine learning.

Figure 3.3 shows the current typical forecast accuracy profile for harbour forecasts from 1hrs ahead to 24hrs ahead, where the vertical axis is the mean absolute error in kW. This corresponds to errors in respect to 10% to 20%, which reflects partly the general volatility of demand in a relatively small community, but also reflects the changes in demand currently happening as a result of the Covid-19 pandemic.

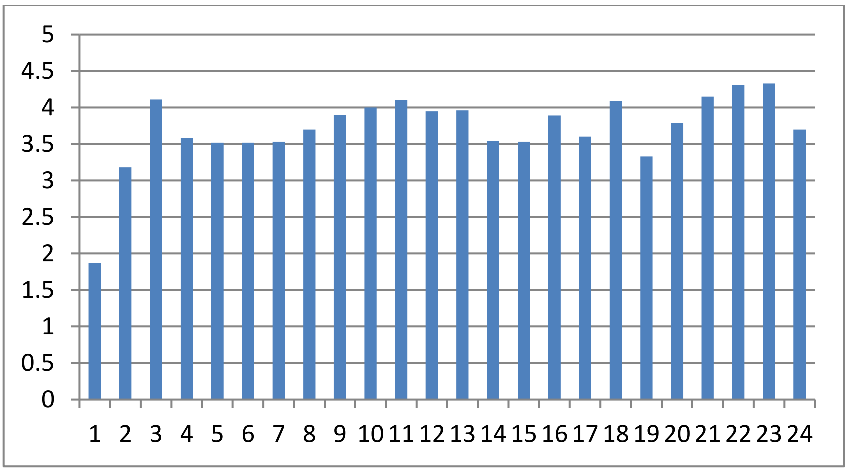

Figure 3.3– Illustrating Accuracy of Harbour load forecasting towards end of April 2020

3.2 Harbour PV Forecasting

PV data for the harbour at Samsø is provided by Lithium Balance, who have given RM access to APIs that query their IoT platform for the appropriate variables. This API provides a direct PV reading which RM accesses every 5 minutes. The red line in Figure 3.4 shows these measurements over a recent four-day period.

As mentioned in the harbour load forecasting section, RM again operates hourly machine learning, to produce 24 separate forecast models, respectively predicting it at 1, 2, …, 24 hours ahead. These forecasts are provided via the API outlined in section 3.3 and arise from the predictive analytics platform that was detailed in deliverable D5.2 "Predictive Algorithms for DR Services". In the current report, we will summarise the details by indicating general characteristics of the current setup and briefly discuss accuracy.

To forecast PV, the key factor is to forecast cloud cover; PV values can then be forecast by using the cloud cover forecast in conjunction with a mapping between the 'clear sky' irradiation level (which can be calculated exactly for any given location and time) and the power characteristics of the PV installation in question. In our case, the inputs to the machine learning model at time T, for a forecast A hours ahead, are: the forecast cloud cover at T+A, the 'clear sky' irradiation at T+A, the cloud cover at T, clear-sky irradiation at T, and the PV power at T. The latter three features enable the machine learning algorithm to build a model of the characteristics of the particular PV installation. The machine learning algorithm used is gradient boosting (again, shown to be generally the best performing approach in preliminary tests), and we use a window of 21 days of training data (70% for training, 30% for validation)

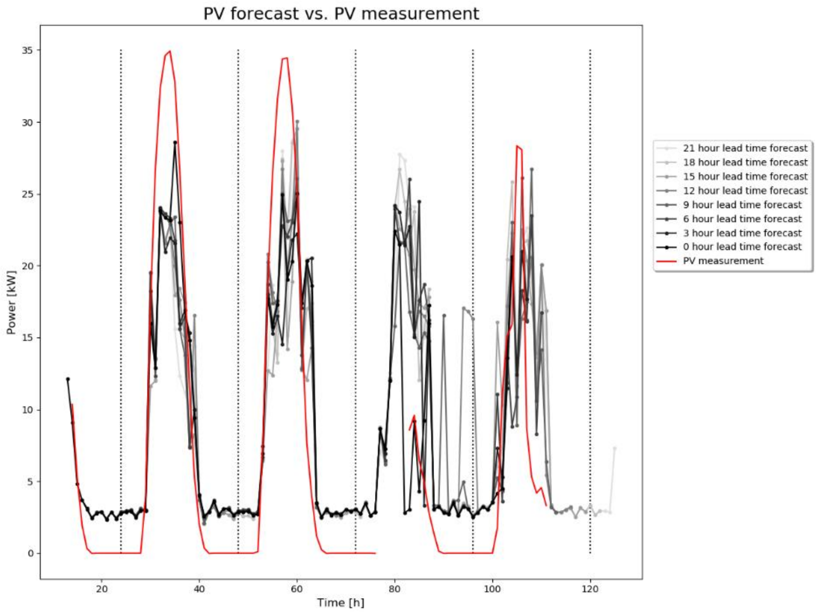

Figure 3.4– PV measurements compared with forecasts (figure provided by Libal/Xolta)

Figure 3.4 shows a recent evaluation of the PV forecasting, done by Lithium Balance using the API described in section 3.3. This revealed a broad correspondence between actual and forecast power, although showed up issues at night-time (where small levels of power were wrongly forecast), and a general underestimate of available power at later hours. These issues have been addressed along with ongoing refinements to the forecasting models. Route Monkey provides harbour load and PV forecasts via a password-protected RESTful API

4 Scheduler

4.1 Input data

To set up the scheduler there are three types of input data for the optimization model: forecast, telemetry, and configuration data. In this section, the three types of data are introduced.

4.1.1 Forecast data

The data that needs to be forecasted are Marina load, Solar-PV production profile and the electricity price.

4.1.1.1 Load forecast

User demand has strong connection with season, weather, user behavior and so on [1]. In order to have accurate forecast, historical data of user demand and third-party weather forecast should be used to produce load forecast. In this project, load forecast of Samsø harbor is produced by partner Route Monkey. The data is hourly based with a horizon of 24 hours. A new update comes every hour to correct the prediction from the previous hour.

4.1.1.2 PV production forecast

PV production data is very sensitive. It is firmly tied to the weather, location, and the mounting angle of solar panels and so on [2]. In order to increase the forecast accuracy, besides historical PV production data, a third-party weather forecast which contains information such as solar irradiance, wind speed, cloudiness and temperature is recommended to include in the PV forecast algorithm. The PV forecast data received within the project is delivered by Route Monkey. Similar to the load forecast, it is hourly based data with 24 hours horizon and a new update is sent every hour.

4.1.1.3 Electricity price forecast

Electricity price forecast is normally based on spot market price or pre-determined pricing scheme. Spot market price is an equilibrium of demand (willing to buy) and supply (willing to sell). It varies from time to time, which can illustrate the grid congestion situation from another angle. However, from user's point of view spot market price still has some distance to the real electricity price, which is missing VAT, transportation, and other service fee. In this project, Samsø site is currently using a flat price scheme, this diminishes the impact from price variation to the final optimization result. Nevertheless, the optimization model is made to take variable price situation that may happen in the further into account. The variable price can either come from a third-party spot market price API or produced as forecast from partners within the project.

4.1.1.4 Feed-in tariff

Electricity selling price in this project means the solar feed-in tariff – that is the price of excess renewable energy which are to be sold to the grid. There are different prices and policies in different countries regarding feed-in tariff. Due to the increase of solar energy penetration, policies are also changing from time to time. In general, the feed-in tariff can be split into 2 scenarios: zero tariff and non-zero tariff. When the tariff is zero, the optimization model will help the user to avoid injecting excess solar energy to the grid in order to maximize their renewable consumption and consume less electricity from the grid. When the tariff is not zero, depending on the difference between electricity price and the tariff, the optimization model will find the correct time to inject power to the grid to make some profit. During the SMILE project, the feed-in tariff was constant, but it will switch to the spot market price in the near future according to the current policy in Denmark.

4.1.2 Telemetry data

Telemetry data are BESS related data provided by the Xolta system (BESS from Lithium Balance). One of the most important data from BESS is the battery state of charge. Optimization needs to have the knowledge of battery current status in order to decide how much energy it can take or give. It is both for better utilization of the BESS and for safety of the system operation. The Xolta system in Samsø updates telemetry reading every 10 seconds and the optimization model will always take the latest update into its calculation.

4.1.3 Configuration data

Configuration data contains site information such as location, grid configuration, renewable installation and BESS dimension. These data are normally obtained during the BESS commissioning period and are later carefully stored in the Xolta cloud database. Any physical changes on site regarding the electricity network needs to be updated to the Xolta cloud database to ensure the system safety operation.

4.2 Output data

With the above input, the optimization model will produce a charge/discharge schedule accordingly. Depending on the forecast input resolution and horizon, the output will keep the shape. In the SMILE project, the forecast inputs are hourly based 24 hours long data, this returns an output of a charge/discharge instruction with 24 set points as shown in Figure 4.1

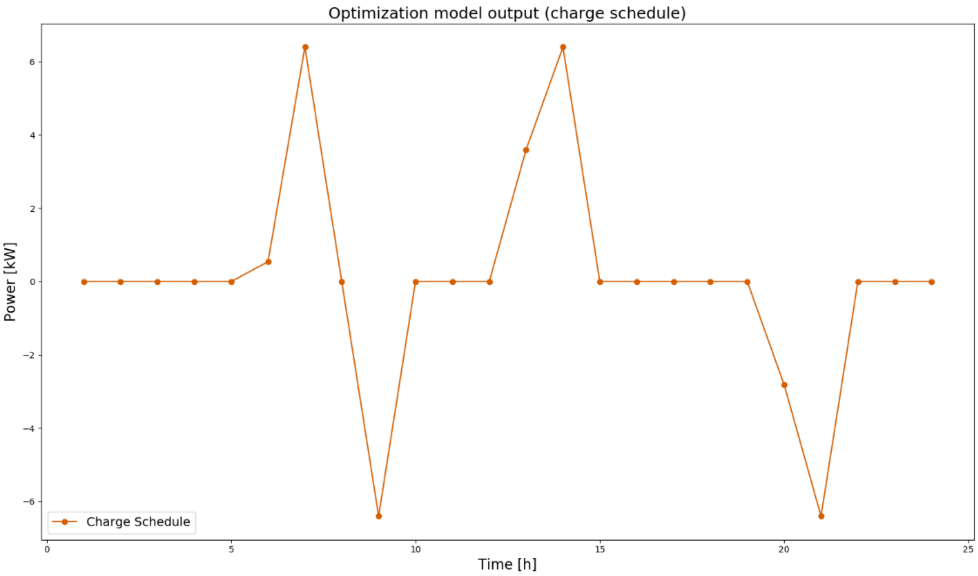

Figure 4.1- Optimization model output illustration

This charge schedule is expected to be packed into a specific format and send to the site controller which is the local control unit in the Xolta system. Once the site controller receives a new charge schedule, it will check the timestamp and act upon. Currently the optimization model is running every 15 mins, so that it can rematch the battery state of charge in case the forecast deviate too much from the reality. However, this 4 times per hour run brings another challenge to the optimization model. The mismatch updating rate and resolution of the forecast data cannot always cover the need of input data horizon for the optimization algorithm. There will often be a 15-45 mins forecast data lacking for each run. This aspect was then negotiated with Route Monkey to have a 24h horizon forecast in the future to solve the problem.

4.3 Optimization algorithm

The objective of the optimization of the BESS usage is to minimize the overall cost of energy consumed, which includes maximize the profit from selling excess solar energy and maximize the renewable self-consumption. This is done by operating the ESS (charging and discharging the energy storage) in the most optimal way, based on the available information introduced in section 4.1 . The optimization will be based on forecasted information that may be not precise. Therefore, the operation of the BESS may not turn out to be optimal under the actual conditions (actual consumption and production).

The optimization model algorithm is formulated as a mixed integer linear programming (MILP) problem and consists of an objective function and a set of constraints. The objective function aims at minimizing energy bill for the user. The constraints are formed by different technical and economical limitations of the energy storage system, which includes energy balancing, energy storage operation constraints, grid-side constraints and so on. Besides the main objective, the overall performance of the optimization model should also give impact to:

- maximize renewable self-consumption
- relieve power congestion in the grid
- charge BESS when electricity market price is low
- consider battery cycles and be aware of battery operational lifetime

A test result of the optimization model can be seen in Figure 4.2. The battery model used in this test has a capacity of 9.6 kWh and power of 6.4 kW

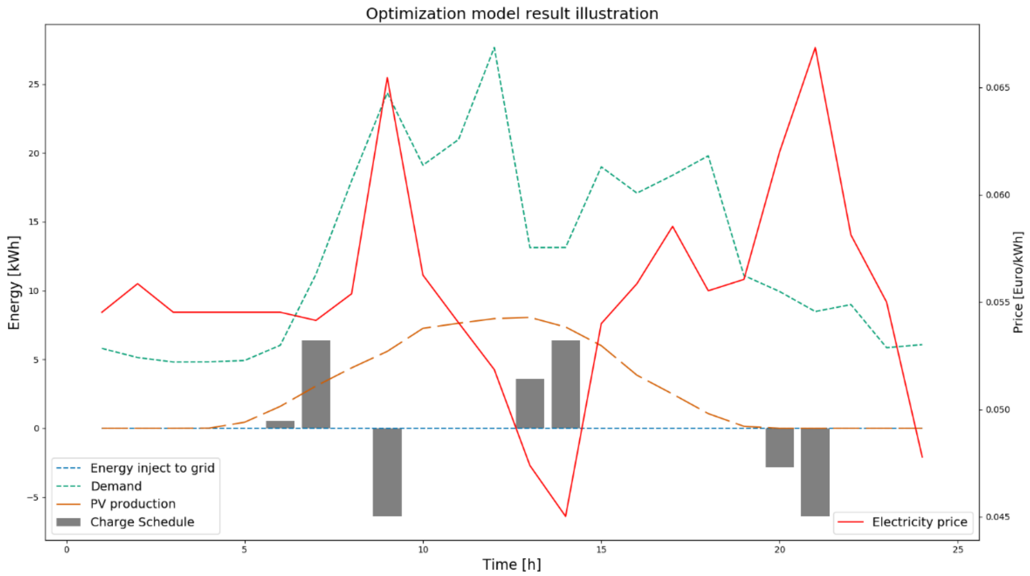

Figure 4.2- Optimization model test result illustration

The test above simulates the optimization model result of a low solar production day. When the solar production is much lower than the demand, user will have to purchase power from the grid. As electricity price varies during the day, battery is charged when the price is low, and the stored energy is used to support the load when price peaks. The corresponding battery state of charge can be seen in Figure 4.3.

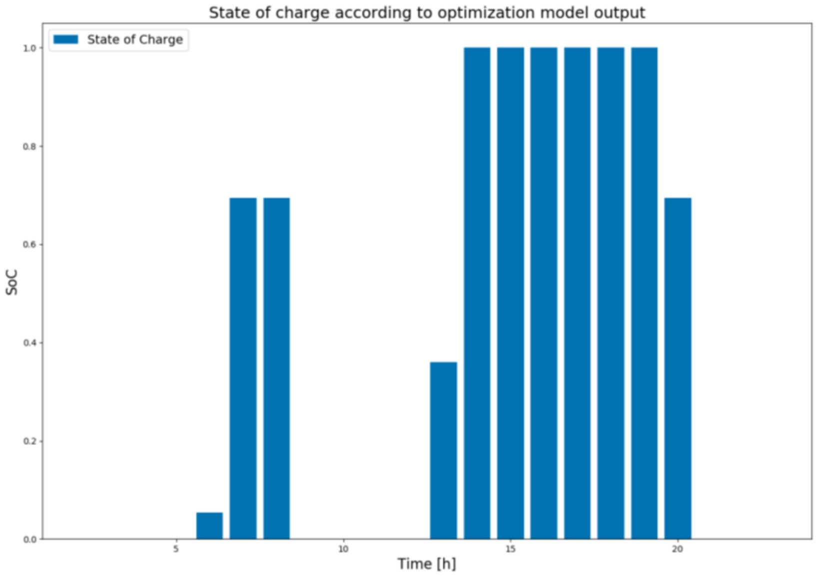

Figure 4.3- Optimization test result of battery state of charge

4.3.1 Optimization algorithm extension

The optimization model is developed with a focus on controlling the battery behaviour only. The next step of the development is including demand side management into the model as requested from the project. Three controllable loads on site, heat pump, sauna, and wastewater pump, will be added into the current model and will be turned on and off according to the optimization result. The on/off control schedule will follow the same format as ESS charge schedule with 24 control set points, and it will be sent to the technician on site for executing the control.

4.4 Implementation

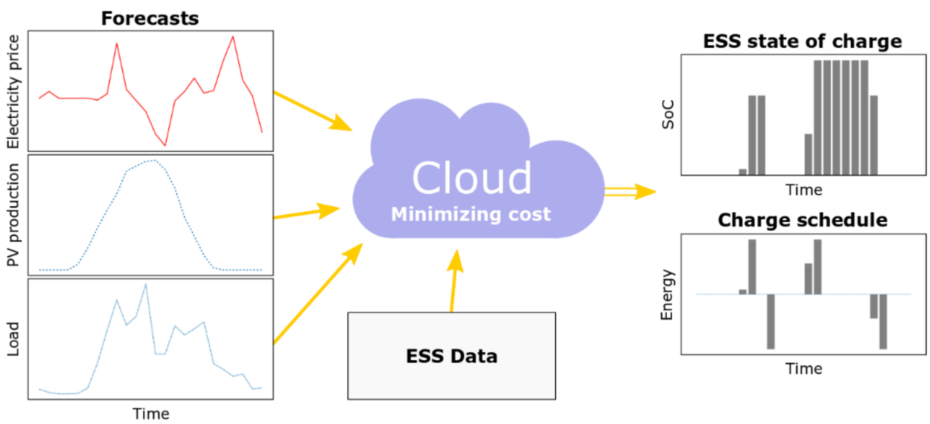

Figure 4.4- A system view of optimization model

The optimization model is implemented in Python as a mix integer linear programming (MILP) problem using the Pyomo [3] package with GLPK [4] as solver. The model contains continuous real variables, integer variables, and binary variables. A number of input parameters such as electricity price, demand forecast, PV production forecast, and feed-in tariff are used to determine the energy storage behaviors and return the optimal BESS charging/discharging schedule for the next day as shown in Figure 4.4. The optimization model solution resides in a docker image based on python:3.6-jessie (linux/amd). In this project an Intel x86 processor has been chosen for the hardware implementation, with an Ubuntu Linux OS and Docker run time installed. In operational mode, the model collects needed data via REST calls from the API endpoints provided by Route Monkey and utilizes MQTT protocol to retrieve needed input data from the site controller such as ESS SoC value. Based on the inputs the optimization model computes the ESS control setpoints and publishes them as MQTT messages through TCP/IP to the site controller.

5 Samsø Ballen Marina

The data set for Marina is provided by Samsø Energy Academy. The overview of Ballen Marina is shown in figure 5.1.

Figure 5.1-Ballen-Marina

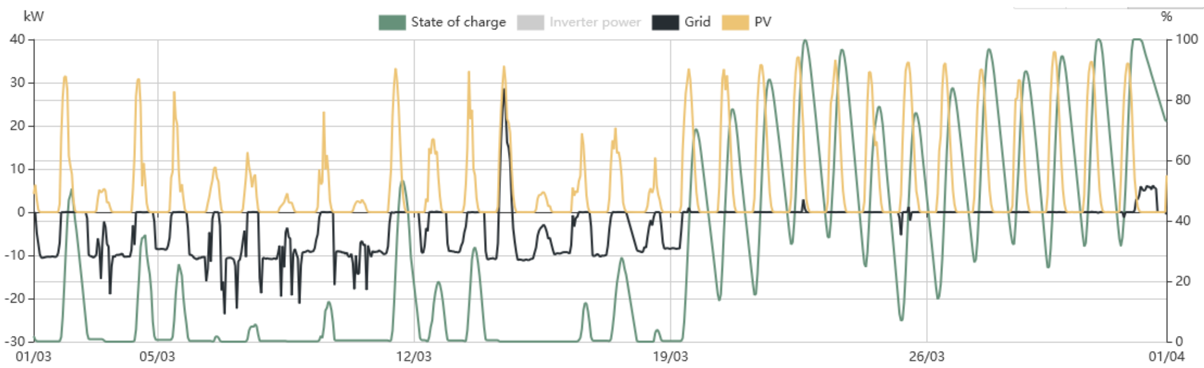

Figure 5.2– Present data in the Marina working system

Figure 5.2 shows the BESS SOC, PV production, Inverter power and grid export/import for March 2020 month. It can be observed that the BESS is charged to 100% from Solar PV production. There are times in the first half of March, where power import from grid has taken place. In addition, the power is also exported into the grid at around Mar 15th. The present data for the BESS and PV system is shown in Figure 5.2. Selling to grid is not encouraged, as the price to sell the electricity is low. So, the BESS is to be scheduled so that it maximizes the self-consumption of solar-PV. Buying from grid is unavoidable due to present size of Solar, which could not be able to cover the annual demand.
The current control operation is based on the following simple algorithm:

***If** PV > demand*

If** BESS < SOC_{max}, charge the battery, **Else** sell to grid, **end

Else

If** BESS > SOC_{min}, discharge the battery, **Else** buy from grid, **end

end

The same algorithm is used for BESS scheduling that will be discussed in Section 6.1. In this way, the self-consumption of solar-PV will be increased and with the introduction of the potential flexible loads that are present in the service building and harbour master's office it is expected to further maximize the local consumption of solar production, thereby reducing the export of solar energy back into the public grid. The details of the Marina site are as given in the Table 5.1.

Table 5.1 – Component details of Ballen-Marina

Specifikationer (dansk)		**Specifications (English)**
Målt selvforsyningsgrad	43%	Measured degree of self-supply
Samme, uden batteri	26%	Same, without the battery
Målt egetforbrug af solcellernes årlige energi	89%	Measured own consumption of annual PV energy
Samme, uden batteri	45%	Same, without the battery
Batteriets nominelle kapacitet	237 kWh (Xolta BAT-79)	Nominal capacity of battery
Batteriets brugbare kapacitet	211 kWh	Accessible capacity of battery
Årlig system-virkningsgrad (AC-AC)	85%	Annual system round-trip efficiency (AC-AC)
Batteri-konverterens effekt	49 kW (ABB ESI-S)	Battery converter power
Solcellernes nominelle effekt	60 kWp (Eurener)	PV plant nominal power
Solcelle-inverternes effekt	49 kW (Fronius, Enphase Energy)	PV inverter power
Solcellernes beregnede ydelse	56 000 kWh/year (Better Energy)	PV plant estimated annual yield
Solcellernes areal	155 m2 (Better Energy)	PV plant area
Lystbådehavnens elforbrug (2016)	105 000 kWh/year (NRGi)	Marina annual demand (2016)
Antal stik til bådene	340 (CompuSoft, Seijsener)	Sockets for the boats
Hvert stik har en elmåler og en fjernstyret afbryder	(Compusoft, Seijsener)	Each socket has a meter and a remotely controlled switch
Maximal tilladelig eksport til det offentlige elnet	49 kW (KONSTANT Net A/S)	Max allowed export to the grid
Antal varmepumper	5 (Daikin)	Number of heat pumps
Varmepumpe dækning i havnekontoret	100 %	Heat pump coverage in harbour master's office
Fjernvarmeforbrug i toiletbygningen	18 000 kWh/year (Ballen-Brundby Fjernvarme amba)	District heating consumption of the service building
Spildevandstank	2 m3 (Xylem, Inc.)	Wastewater tank
Sauna i badebygningen	15 kW (SAWO, Inc.)	Sauna in the service building
Ladestik til havnefogedens elbil	11 kW	Charging point for the harbour master's electric vehicle
Ladestik til 3 dele-elbiler	16 amp (Lasses Auto)	Charging sockets for 3 rental electric vehicles
Link til betalingssystemet	cpay.dk/site/marsamb	Link to the payment system

5.1 Model predictive control-based BESS scheduling

The Samsø Energy Academy have published a research paper that is partially supported by the SMILE project and the work focusses on Model Predictive Control (MPC) based energy scheduling [5]. Model Predictive Control has recently become particularly attractive for the control of smart energy systems due to its principles of feedback control and numerical optimization. In effect, MPC can use both predictions of future disturbances (e.g., demand fluctuations, weather, etc.) and given requirements (e.g., comfort ranges), to anticipate the energy needs of a system and optimize its operations on the basis of the defined goals.

Generally speaking, the MPC technique is based on three elements: (1) an explicit dynamical model of the system, which is used to predict the system behavior in response to future actions, (2) two time horizons over which the behavior of the system is predicted and controlled (often the two horizons coincide), (3) a time step, in which an optimization problem, based on the dynamical model, is solved so as to optimize the performance of the system over the chosen control horizon. At each time step, the system behavior is observed and information on its state is collected and used to update the corresponding dynamical model. Then the optimization problem is stated and solved over the time horizon and the results are applied to the system in a closed-loop control fashion. The results of the optimization consist in proper control actions that are applied to the system only in the subsequent time step. The procedure is then iteratively executed until the end of the time horizon.

The reason for applying a scheduling algorithm is illustrated by the following examples: (1) If the PV forecast for tomorrow is low, it is better to charge the battery from the grid during the night when the price is low; (2) even though the wastewater tank is not totally full, it is better to operate the pump at night when the price is low. It is to be noted that the MPC approach relies on models (e.g., model of the BESS based on the charge level as state variable, model of the wastewater tank based on the level as state variable) and prediction data (e.g., PV production curve, wastewater inflow profile, energy pricing). The energy import/export for these four approaches with optimal BESS scheduling are as shown in Figure 5.3.

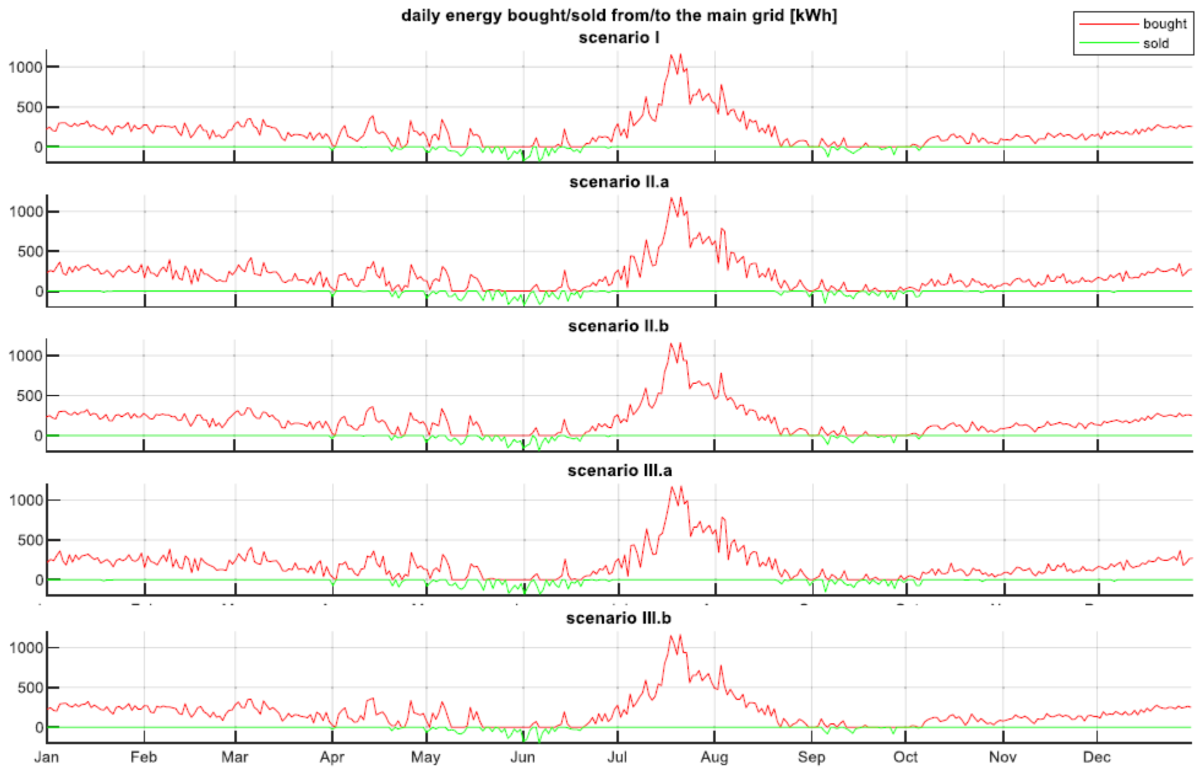

Figure 5.3– Energy import and export for four scenarios (kWh)

Four scenarios are considered corresponding to four objectives. (1) cost optimization BESS only; (2) self-reliance optimization, BESS only; (3) cost optimization with controllable loads included; and (4) self-reliance optimization with controllable loads included.

It is to be observed that with given system specifications, there is considerable amount of import from grid during peak hours. In general terms, the MPC optimizer *without DSM of controllable loads* already saves operational costs. Whether the savings outweigh the costs of installing and operating the MPC optimization remains to be calculated, but the optimizer will provide 6.5% savings on annual costs according to the simulation. In addition, DSM of controllable loads improves the savings to 8.5%.

The smart energy system may change over time, and staff must be trained to change the algorithmic constraints accordingly. It will also be necessary to build a fail-safe mechanism, which switches to naïve control mode in case of failures. Even the naïve mode utilizes the photovoltaic plant well (up to 94%).

The simulation study indicates that an MPC optimizer improves the economic viability at the expense of the self-supply with solar energy. There is trade-off simulation between economy and self-supply. The improvement of the economy is larger, in percentages, than the loss of the self-supply. The economy will be the more important of the two. Should it turn out, in the worst case, that an investment in an MPC controller is infeasible, this simulation study has already taught the energy manager of the marina of Ballen some advantageous control strategies, which could be implemented in an inexpensive manner based on a calendar. The calendar predicts the number of boats according to the harbour master’s experience, holidays and time of the year.

6 Verification of Algorithms

The inputs from Route Monkey and Lithium Balance were used by University of Aalborg (Department of Energy Technology) to simulate the Marina system for demonstrating the functioning of BESS along with PV system for two cases. One is optimal scheduling of BESS for maximizing the self-consumption of Solar PV [6] and other case is flexible operation of Marina loads using DR. The electrical network in the site is as shown in Figure 6.1.

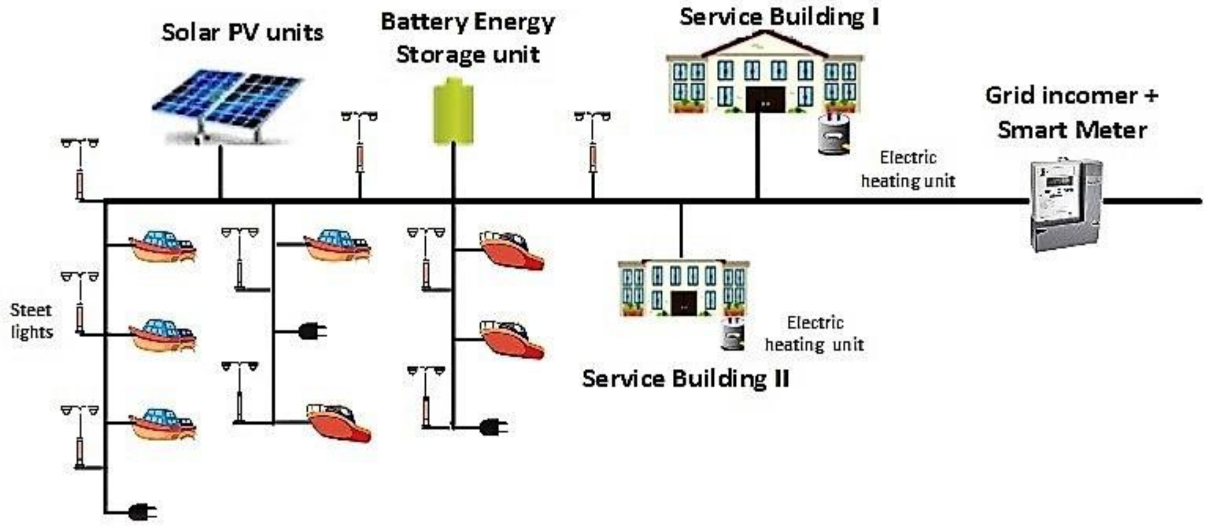

Figure 6.1– Ballen-Marina electrical network

6.1 BESS scheduling for maximizing the self-consumption of Solar-PV

BESS plays a key role for maximizing the energy consumption locally by intelligently defining the charging/discharging patterns of BESS with respect to the production of Solar-PV. The idea is to create a real-condition smart grid system with renewable energy sources, storage and electric loads. The flagship case concerns the boats that are main consumption in the marina, where they are encouraged to be charged with the electricity from renewable energy sources (RES) by an intelligent charging/discharging system.

6.1.1 Optimization formulation

The mathematical formulation is as given in Eq. 6.1,

$$
\begin{aligned}
&\text{Minimize } P_{inj}^{t} \\
&\text{subject to} \\
&\qquad SOC_{\min} \le SOC \le SOC_{\max},\ \text{BESS SOC limits} \\
&\qquad r_{ch} \le Inv_{cap} \le r_{dch},\ \text{rate of charge and discharge limits} \qquad \textbf{(6.1)} \\
&\qquad P_{PV}^{t} - P_{L}^{t} > 0,\ \text{charge from PV} \\
&\qquad P_{PV}^{t} - P_{L}^{t} < 0,\ \text{discharge to meet load} \\
&\qquad P_{inj}^{t} < 50kW,\ \text{injection into public grid} \\
&\qquad P_{PV}^{t} + P_{bat}^{t} < P_{L}^{t},\ \text{import from grid} \\
&\qquad P_{PV}^{(t+1)=t_{pk}} + P_{bat}^{(t+1)=t_{pk}} - P_{L}^{(t+1)=t_{pk}} < 0,\ \text{charge from grid}
\end{aligned}
$$

The objective function is minimizing the power injection from Marina network into grid for constraints including BESS charge/discharge rates, state of charge limits etc., as given in Eq. (6.1). The optimization problem is solved using integer linear programming function in Matlab. The real data set from Jul till Sep 2019 that is provided by Samsø partners was used. Two cases were simulated, Case-1 is optimal scheduling of BESS for maximizing yield from Solar-PV and Case-2 is optimal scheduling of flexible loads using DR and BESS for maximizing the Solar-PV production.

6.1.1.1 Simulation results

The total Marina consumption data received is as shown in Figure 6.2. The estimated Solar-PV production from irradiance data is shown in Figure 6.3 .The import/export of energy obtained from the optimization problem is shown in Figure 6.4. It is very clear from Figure 6.4 that with optimal scheduling of BESS the injection is reduced. The SOC of the BESS is shown in Figure 6.5. The BESS is charged for two conditions, ***a)*** Charge when there is excess PV and ***b)*** Charge from grid when the forecasted Marina load is higher than production combined with storage. In the formulation, last constraint shows charging of BESS for condition ***b)***.

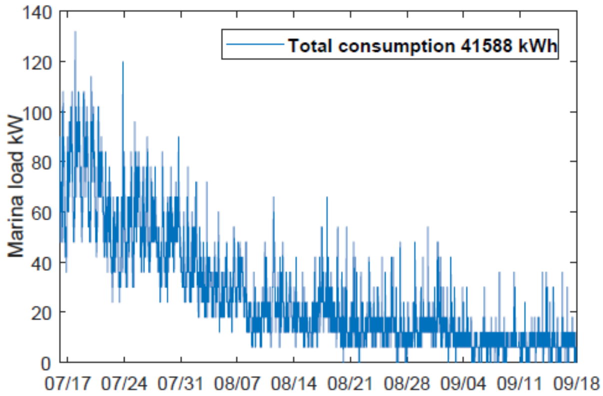

Figure 6.2–Total Marina consumption

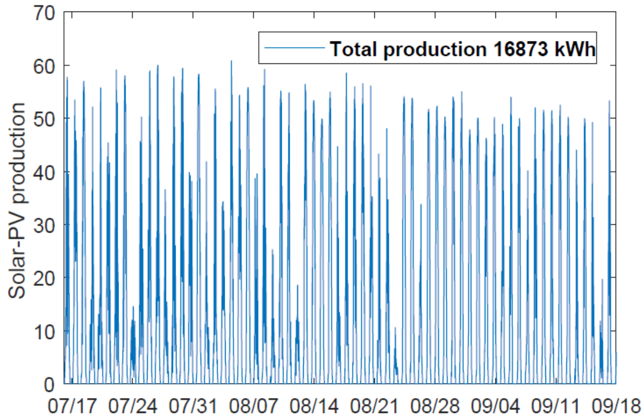

Figure 6.3 – Estimated Solar PV production of 60 kWp

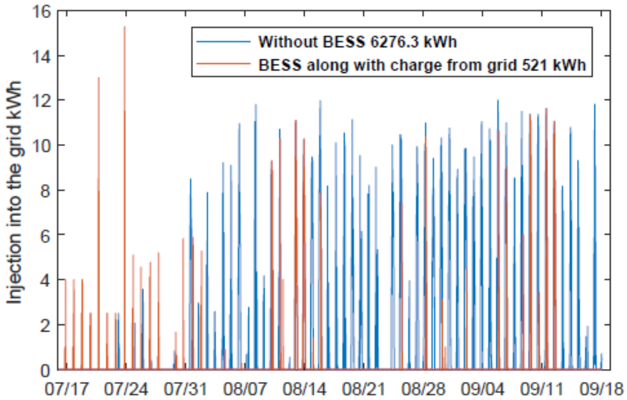

Figure 6.4–Electricity injection to public grid

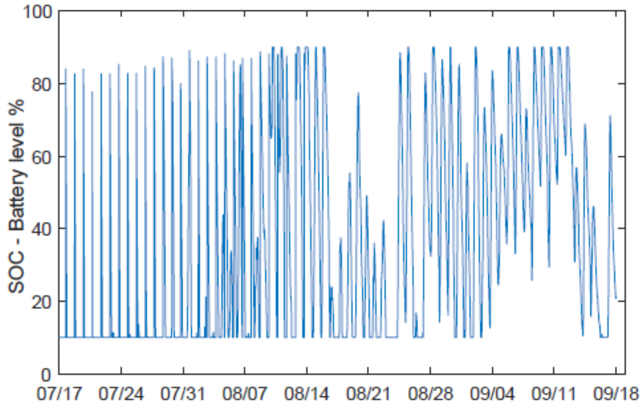

Figure 6.5–SOC of BESS

The simulations results giving the amount of energy and its associated costs and revenue for import/export, respectively are given in Table 6.1. The last scenario is interesting to analyze as the BESS is charging whenever there is excess solar-PV production and also from grid if the future forecasted peak demand exceeds the available generation (Solar-PV+BESS). In scenario-4, the import is more than in scenario-3, but the cost of import is less due to the fact that import has taken place only during off-peak hours.

Table 6.1– Costs and revenue for the import/export from Marina

Scenario	Energy import		Energy export	
	kWh	€	kWh	€
Without PV-BESS	41588	98501	-	-
With PV and without BESS	30991	14231	6276.3	426.93
With PV-BESS and charge from only excess PV	24543	10915	682.36	20.470
With PV-BESS and charge from both excess PV and grid	25236	7918.8	521	15.63

In this case, optimal BESS scheduling is carried out for increasing the utilization factor of Solar-PV production. The results show that there is considerable reduction of dependence on the main grid, making Samsø-Marina self-sustainable most of the time during a day. For the Marina site, the buying price is 0.21 e/kWh and the selling price is 0.03 e/kWh and the electricity buying price during peak hours is considered to be 1.17 e/kWh. The price data is taken from D3.4 “Requirements Specification”

6.2 Optimal scheduling of boats and other flexible loads using DR and BESS

The data set for boat consumption is divided for four piers at aggregated level as shown in Figure 6.6.

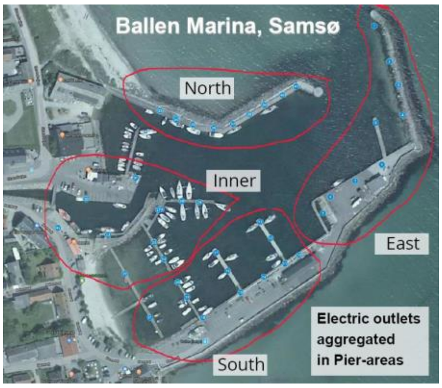

Figure 6.6– Aggregated piers at Marina site

The aggregated boat consumption on east, inner, north and south piers is as shown in Figure 6.7, Figure 6.9, Figure 6.10 & Figure 6.10 respectively.

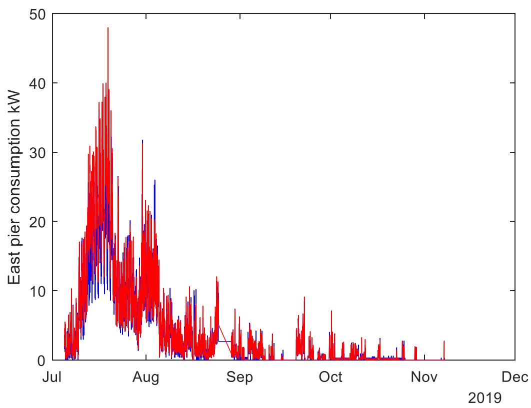

Figure 6.7– Boats load on east pier

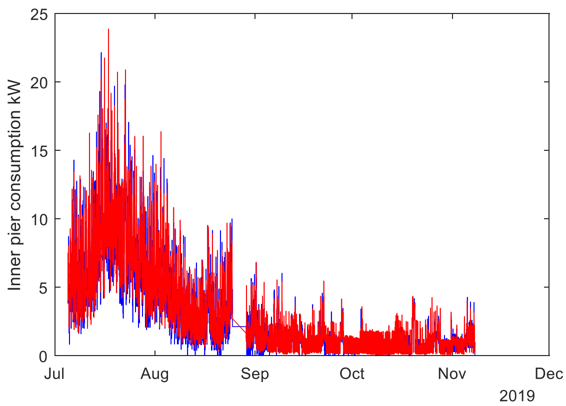

Figure 6.8– Boat load on inner pier

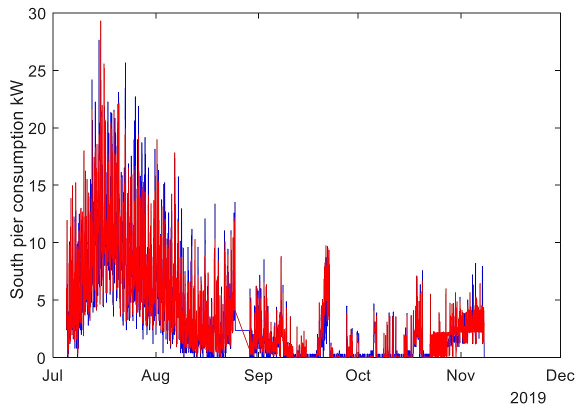

Figure 6.9– Boat load on north pier

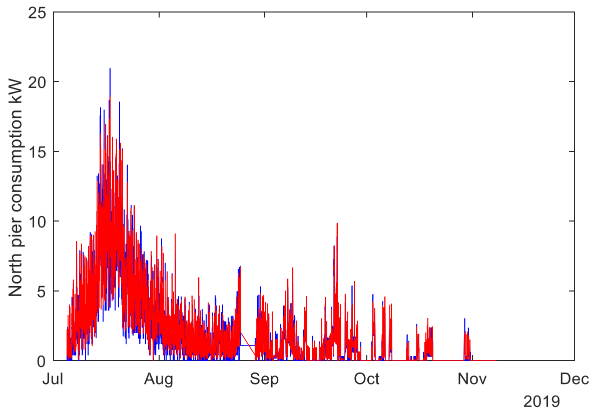

Figure 6.10– Boat load on south pier

The peak load is coming out to be 125 kW in the mid of July 2019, due to a greater number of tourist sailors. Other flexible loads include heat pump at harbour master's office of 2.5 kW, sauna in the service building of 15 kW and an electric vehicle (EV) owned by Samsø municipality of 11 kW charging capacity. The EV is used only by harbour master and his staff. The electricity spot price for the year 2016 that is provided by Samsø Energy Academy is as shown in Figure 6.11.

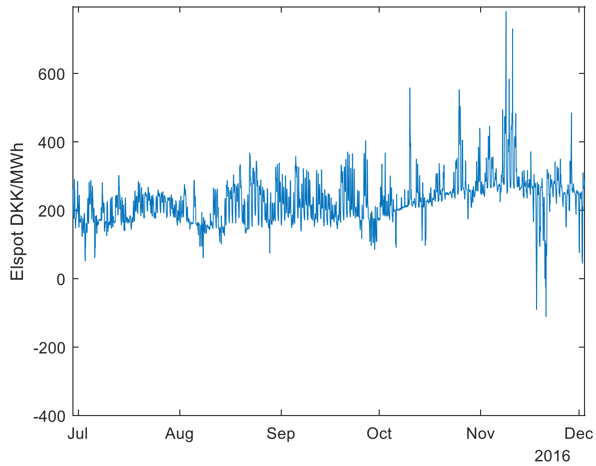

Figure 6.11– Elspot prices

With the data, the Marina load forecast, Solar-PV forecast and Elspot prices, again optimization problem is formulated and is given as algorithm.

6.2.1 Optimization problem

The objective function is to find the optimal scheduling of flexible loads using DR and BESS for maximizing the self-consumption of Solar-PV. The intelligent algorithm is as follows,

- *Collect data of forecasted load, Solar-PV and Elspot prices.*
- *Adjust the loads and charge the BESS, to match with Solar-PV production.*
- *Switch ON flexible loads,*
    - ***Heat pumps**, depending upon season,*
        - *In summer, if temperature rises above 28 degrees*

- *In winter, if temperature falls below 14 degrees*
    - ***Sauna**, depending upon outdoor temperature (Temp<24 degrees)*
    - ***EV**, when there is excess PV and battery is full, only in the daytime*
- *Send green/yellow signals to boat loads, which will be associated with discounts when they respond back. Case -1 if they respond, Case-2, If they chose not to respond.*
- *Repeat the above steps for daily scheduling.*

6.2.1.1 Simulation results for DR

The DR that is defined for this Ballen-Marina case is Time of Use (TOU) DR. This means that the electricity price is decided by the usage time in a day. The algorithm is demonstrated for single day case i.e., July 16th as shown in Figure 6.12, Figure 6.13 and Figure 6.14. It can be observed from the Figure 6.12, the spot price witnessed quick rise from 17:00 hrs till midnight, which will be an interesting scenario to analyse where the Solar-PV is available only until 18:00 hrs and in addition, power consumption from boats is high during this period. The total energy yield from Solar-PV is 368.81 kWh on July 16th and the profile is shown in Figure 6.13, whereas the total energy consumption from boat loads is 1285.08 kWh. For the current installation capacity, the production from Solar-PV cannot completely meet the total load but can handle the peak load to a certain extent.

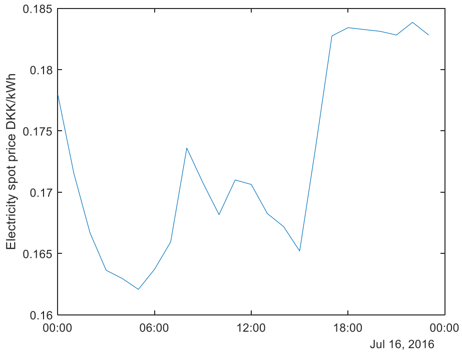

Figure 6.12– Electricity spot price to buy from grid

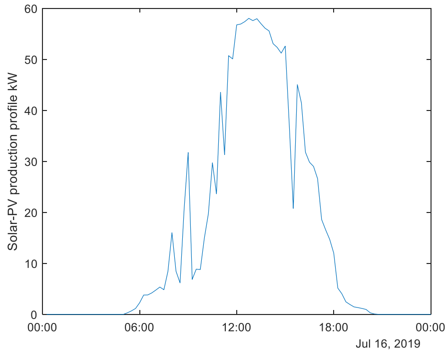

Figure 6.13– Solar-PV production profile

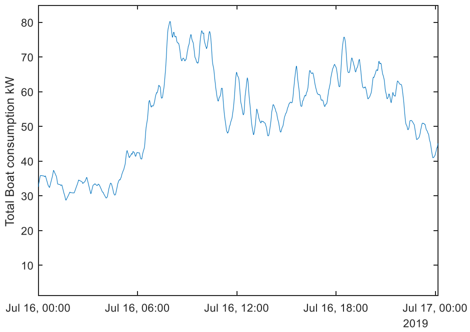

Figure 6.14– Total boat load before DR

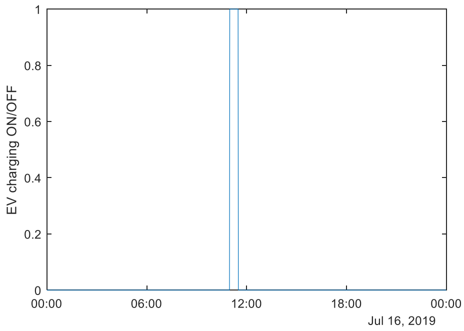

Figure 6.15–EV load switch ON

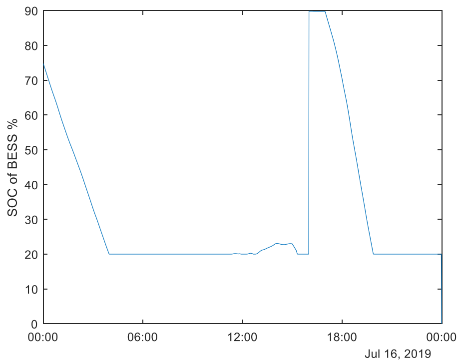

Figure 6.16–BESS SOC in '%'

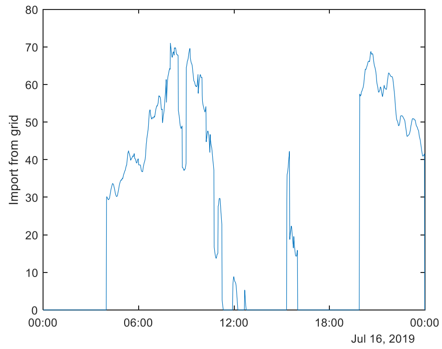

Figure 6.17– Grid import

It is to be noted that for the considered day, the EV as a part of flexible is switched ON to charge from excess solar-PV generation after meeting the boat load. Also, the BESS is charging both from solar (if there exists excess generation after meeting the Marina load) and the grid (during Off-peak hours). It is obvious that there is large amount of load is met by importing from grid due to the limitation of present Solar-PV installation. But it is a good idea to use BESS and DR for maximizing the self-consumption of Solar-PV for both domestic and commercial installations.

7 DR evaluation and market perspectives in Marina

This section describes the actual implementation of demand response and market perspectives as realised by simulations in the previous sections. The battery system on the Ballen's marina is grid connected, which means it can exchange power with the public grid. It is still unusual in Denmark to have a large battery connected with the distribution grid. The overview in Figure 7.1 shows the electric connections between the grid and the components of the system. In the default mode, the photovoltaic plant produces electricity for boats and other electric loads. The battery stores excess electricity on sunny days. The battery delivers it back during periods of shortage, for instance during the night. In default mode the battery operates as a one-day buffer storage. The following power balance governs the power flow (Kirchhoff's node law),

PV + battery + grid = demand

The PV production is somewhat unpredictable, so is the demand. Therefore, the battery and the grid both act as balancers in the power balance equation. They can both react fast enough, when the PV production differs from the demand, which is nearly always the case. The demand usually comes from yachts, motorboats, and land load such as streetlights and pumps. In addition, the visiting sailors and the citizens can use the sauna, which, electrically speaking, is a large load (15 kW). Five heat pumps cool, heat, or dry three buildings (0.6 kW each).

Figure 7.2 shows a grave mismatch between solar production and load. The PV production increases during the sunny hours of the day, where the production exceeds the consumption. The figure shows two situations: shortage of PV – when the PV supply is lower than the demand – and excess PV – when the PV supply is larger than the demand.

The generated excess power (kW) is over time stored as energy in the battery (kWh). Figure 7.3 shows the battery's state-of-charge (SOC) on the same day. In case of PV shortage, the battery level decreases, opposite in the case of PV excess. The first crossing point between PV and demand (Figure 7.2) is the time instant where the battery starts to charge (Figure 7.3). The second crossing point (Figure 7.2) is where the battery starts to discharge (Figure 7.3). A plot of the inverter flow would show the flow changes its sign. The battery level at time 01:00 results from previous days' history. All times refer to the end of the hour. For instance, the SOC at 01:00 is the result of the SOC at midnight and the flow streams between midnight and 01:00. The plot covers 24 hours, so it starts at 01:00, and it ends at 24:00. The battery meets its objective, in this example, because the marina does not exchange power with the public grid at all.

The system has a supply side and a demand side as shown in Figure 7.1. All components connect to a common busbar on the marina side of the public meter. The upper part, above the busbar, is the supply side, and the lower part, below the busbar, is the demand side. The inverter acts as a two-way valve for the battery. It controls whether to charge, discharge, or leave the battery idling. The inverter controls the flow between the two sides. Even the demand side is controllable, to some extent. It is possible to control the sauna and one heat pump, remotely. They are controllable loads, that can be turned on or off at times when it is useful. For example, the following is a rule of thumb for demand side control:

IF (PV production > demand) and (SOC is high) THEN dry shower room with the heat pump from 14:00 to 16:00. Another option is to preheat the sauna early in the morning if the weather forecast predicts excess PV energy during the following afternoon.

There are three objectives for the demand side control according to the following priority list:

1. To maximise the sailor's comfort,
2. to minimise the operating cost, and
3. to maximise the renewable energy share.

Priority 1 is a matter of service. The marina is a service enterprise, and the municipality wishes to see more visiting boats in the marina to improve its economy. Priority 2 is more important to the municipality than priority 3, because the economy is evaluated every year at a budget seminar between the politicians. Priority 3 is a nice-to-have objective, but not necessary for the operation.

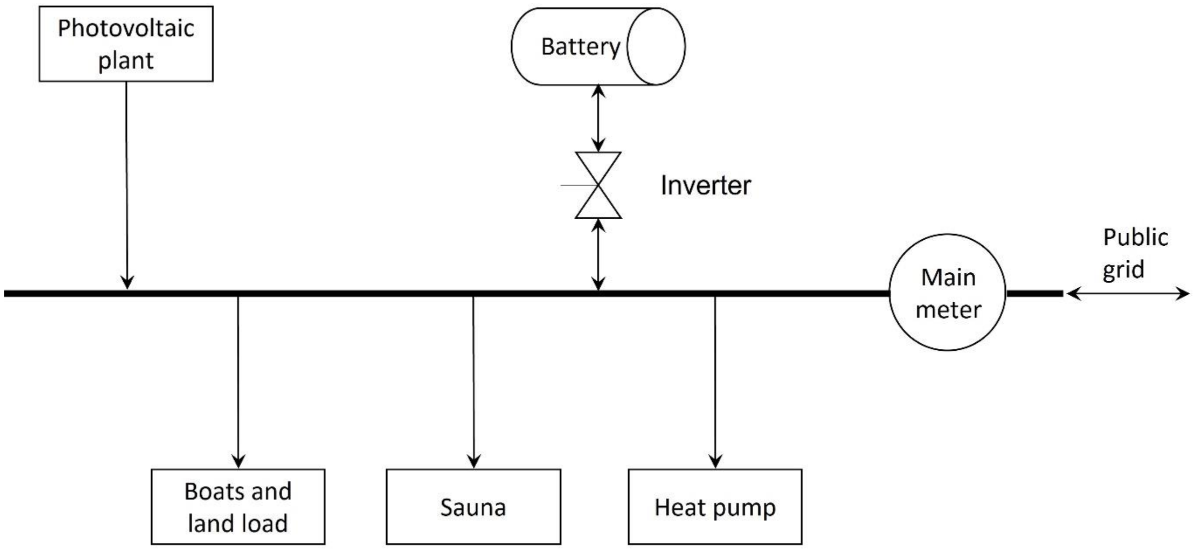

Figure 7.1. Overview of the solar battery system for the Ballen marina.

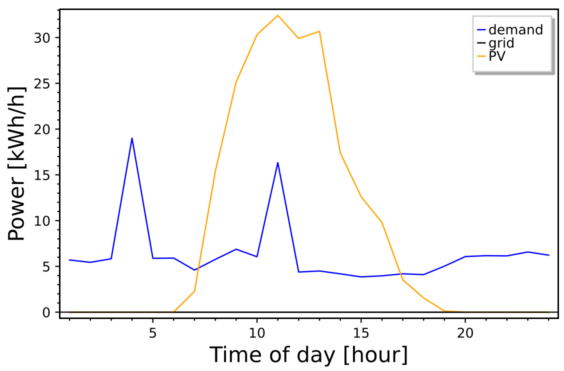

Figure 7.2. Demand and PV production on a sunny day. The PV production was highest around 11 that day. The sauna caused two distinct peaks in the consumption.

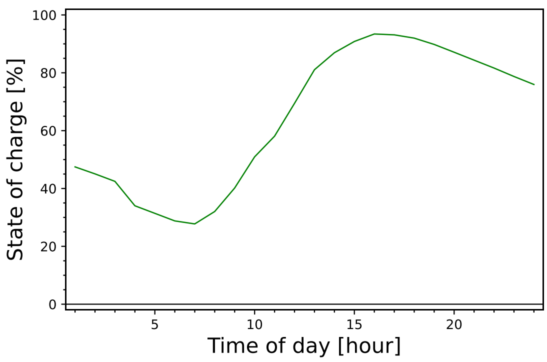

Figure 7.3. The battery's state-of-charge on the same day. The end state is higher than the initial state thanks to excess PV energy.

The following subsections describe the actual implemented control methods for both BESS and flexible loads including sauna, heat pump etc. The developed control algorithms have shown that the BESS storage system can nearly double the effectiveness of the PV system. However, the complex yearly demand profile makes it difficult to fully utilize the BESS system with smart algorithms and forecasting.

7.1 Controllable loads – control algorithm

Lithium Balance developed graphical user interface (GUI) and application programming interface (API) for the controlling loads: heat pump and sauna, as shown in Figure 7.4. The electricity price is illustrated with colored bar chart, which indicate the high (red colour) and low-price (green colour) region of the day.

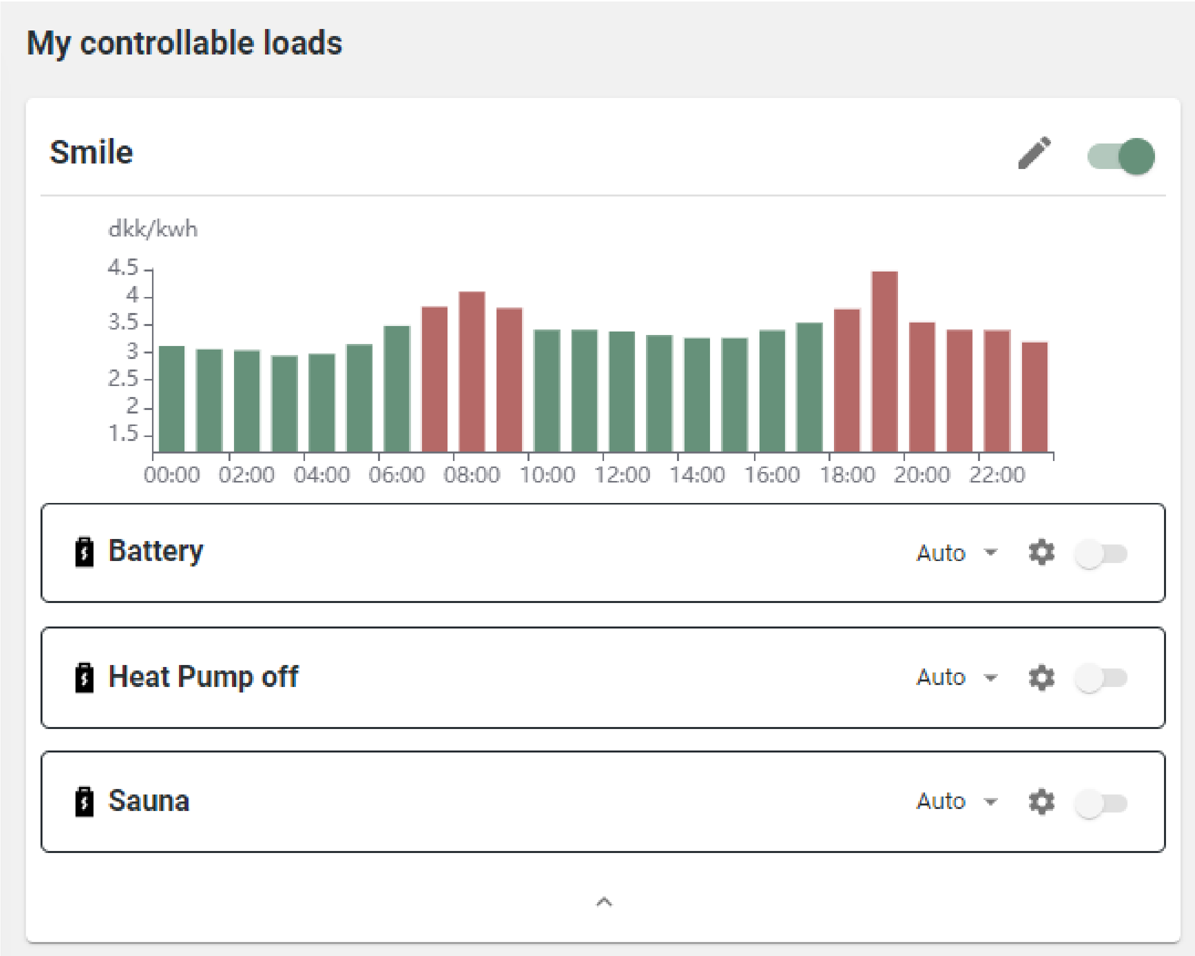

Figure 7.4. SMILE control settings graphical user interface.

After the load characteristic has been studied and in agreement with Samsø Energy Academy, the following control strategy has been implemented as described in Table 7.1 and Table 7.2.

Table 7.1. Samsø heat pump control strategy (turn off only).)

Condition	Comment
For h=23:00pm – 4:00am Turn off request every two hours. This means send turn off request 3 times in the night at 23.00, 1.00, 3.00.	No need to maintain temperature during the night.
For h in range (5, 23): If El_Price (h) >= 75% top EL price and Δh >= 4: Turn off for two hours	Constrain to turn off at high price and assure user comfort. Δh means the time in between the 2 requests

Table 7.2. Samsø sauna control strategy with annual card scenario (turn on only).

Condition	Comment
For h in range (3, 6): Turn on sauna when the 2 continuous hours price combination are the lowest in this period For h in range (6, 14): If Δh >= 5 and SoC >= 80% and $P_{PV}(t) > P_{load}(t)$: Turn on sauna For h in range (14, 22): If Δh >= 5: Turn on sauna when the 2 continuous hours price are the lowest in this time period	Constrain to turn on at low price, high battery charge and assure user comfort. Between 3.00 and 5.00, sauna will be turned on once for the morning user, During the day (6.00 to 13.00) when battery charge is high, sauna will be turn on once more. But the second turn on time will be at least 5 hours later than the previous time. During the evening (14.00, 21.00), sauna will be turned on once more for night user. This ensures sauna will be turned on at least 2 times a day, and with maximum 4 times a day.

The heat pump is a small load with consumption of 1kW power. It has a build-in software (Tado) and can regulate the room temperature, and this will ensure the user comfort. On Lithium Balance side, the main control will be focusing on lowering the energy cost. This means the heat pump will be turned off in unnecessary time period and during high price periods. Lithium Balance has set up communication to the heat pump digital control software (Tado). It is able to switch the heat pump between auto mode and off. The intention of heat pump control is to avoid having it running during high price region.
The control of sauna is slightly different. Sauna is a lager load, around 15 kW. Lithium Balance is only able to turn on the sauna through remote control, and it will be switched off by itself after 1-2 hours. Based on the harbor operation, the sauna will be operated with an annual subscription bases, this means user pattern is important for the control and Lithium Balance should take care of both user comfort and economic while controlling to the sauna. The sauna communication has been set up through calling the REST API with credential provided by Compusoft.

7.2 Optimal battery control

Depending on the situation, it may be an advantage to time-shift a necessary exchange with the public grid. For instance, it saves money to delay buying from the grid until the price is low. There are two main optimisation criteria.

- *Technical optimisation*. Maximise the share of renewable energy, which is equivalent to minimising the exchange (import and export) with the grid.
- *Economic optimisation*. Minimise the overall cost of buying and selling energy to the grid.

They lead to different results, generally; an optimal share of renewable energy is generally different from the most economical solution. There may be other criteria as well, such as minimising just export to the grid letting import free. In either case, an optimiser needs foresight; more precisely, it needs knowledge of the future prices, an estimate of the future PV production, and an estimate of the future demand. If the battery is large enough, it absorbs uncertainties in the forecasts.
With a 24-hour time horizon, it is almost impossible to find an optimal solution by hand calculations and intuition alone. The search space is too large. However, the problem is a *linear programming* problem, which can be solved in several programming languages.
While the optimiser solves the problem, it also points to a boundary condition to consider.

- SOC at 00:00. The initial level of charge affects the optimisation severely. For instance, if the battery is full at midnight, it may be necessary to export power to the grid later. Oppositely, if the battery is empty at midnight, it is necessary to import power from the grid to cover the nightly load.
- SOC at 24:00. This is the end state-of-charge. If this is free, the optimiser may decide to sell all stored energy to increase income. The end state is the initial state of the following day, and it is prudent to leave some energy for the following night.

The optimiser impressively finds a solution, even when fixing the initial and the end states. An online program would have to rely on forecasts of demand and PV production. The spot price, however, is known from the power exchange Nord Pool at around 12:00 for the following day's 24 hours. The sampling period is 1 hour, and each variable will have a time index k associated with it (k = 1, 2, ..., 24). The data are discrete-time measurements because the energy is accumulated hour-by-hour. Grid import (positive) must be separate from grid export (negative) because they have different prices. The battery state-of-charge and the power flow through the inverter are also unknown.
There are two sets of equality constraints. The first set concerns the dynamics of the state-of-charge,

$$\mathbf{s}(k) = \mathbf{s}(k\text{-}1) + \mathbf{f}(k)$$

where

- **s** contains the states-of-charge of the battery (24-by-1 vector), and
- **f** contains the inverter flow (24-by-1 vector).

The equation just expresses that the increase in state-of-charge at the end of period k equals the state-of-charge at the beginning of the period plus the energy that flowed through the inverter during the period k. The second set concerns the power balance,

$$\mathbf{f}(k) + \mathbf{g}_{\mathrm{i}}(k) + \mathbf{g}_{\mathrm{e}}(k) + \mathbf{p}(k) = \mathbf{d}(k)$$

where

- $\mathbf{d}(k)$ is the demand during the kth hour,
- $\mathbf{p}(k)$ is the PV production,
- $\mathbf{g}_{\mathrm{i}}(k)$ is the grid import, and
- $\mathbf{g}_{\mathrm{e}}(k)$ is the grid export, which will have a negative sign.

All amounts are in kWh per hour. The excess energy flows to the battery, with a contribution from the grid. The grid balances any mismatch between production and demand.
The optimiser must find a solution within certain bounds:

- The state-of-charge is bounded by $0 \le s \le 211$ kWh,
- the inverter flow is bounded by $-49 \le f \le 49$ kW,
- the grid import is bounded by $0 \le g_{\mathrm{i}} \le 500$ kW, and
- the grid export is bounded by $-49 \le g_{\mathrm{e}} \le 0$ kW.

The cost vector (EUR/kWh) contains the buying and selling prices toward the grid. The buying price is the spot price on the Nord Pool market plus taxes and fees. The selling price is the bare spot price. The buying price is, roughly, seven times the selling price. However, if one wishes to optimise, not cost, but grid import or grid export, the associated costs can be set to 0 or 1 as fitting.

Linear programming is attractive, because it finds an optimal solution to a complex problem, while considering prices and constraints. It finds a solution, not by a mathematical formula, but by searching a space of feasible solutions. However, the search space is limited, and the elapsed time for finding a solution is relatively short. However, the accuracy depends on forecasts, which may be inaccurate. It is difficult to predict the boat arrivals to the Ballen marina for every hour of the day 24 hours ahead. It is also difficult to predict the solar production every hour during the daylight period of the following day. Even though linear programming is a strong method, it is jeopardised by poor quality of forecasts.

7.3 Peak load from boat loads scenario

The real time simulation of a scenario where peak load is observed from boats on a day in July 2020. The voltage profile at various charging stations without demand response are shown in Figure 7.5, where the voltages are falling beyond operational limits i.e., 0.95 p.u. – 1.05 p.u.

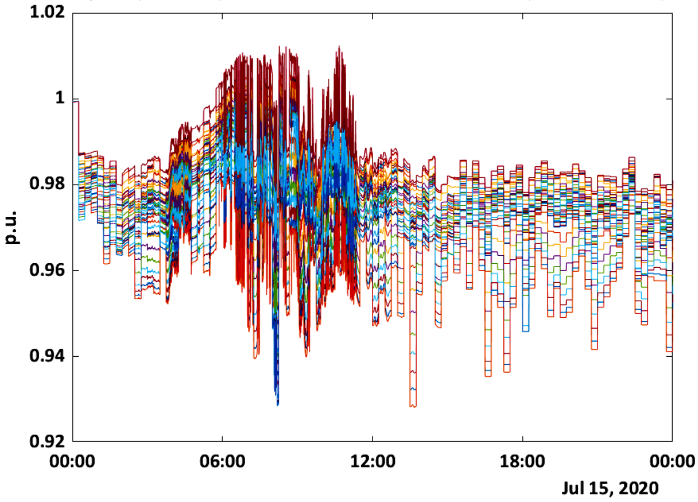

Figure 7.5: Voltage profiles at various charging stations without optimal boat load schedule

With the optimal scheduling of boat loads, the voltage profiles were brought back to normal operating limits as shown in Figure 7.66. It is clear that there exists a fair chance that Marina grid can be subjected to voltage limit violations with uneven distribution of loads at various piers. It is an important grid constraint that has to be considered while considering any of the three objectives including sailor's comfort, cost effective operation and maximizing solar-PV utilization.

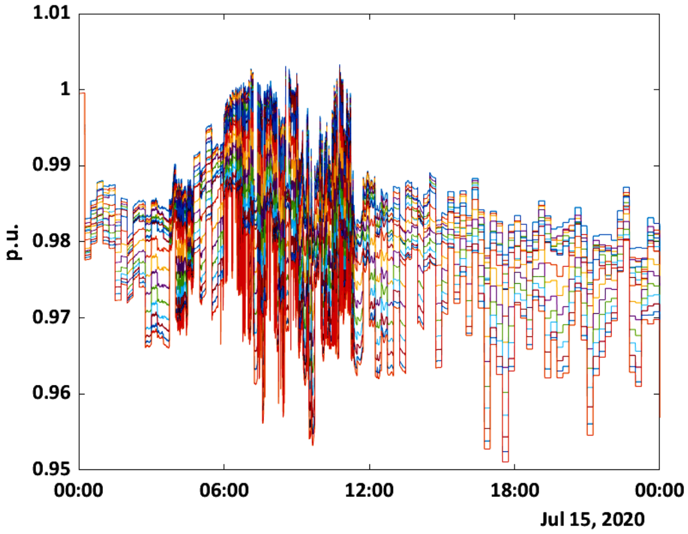

Figure 7.6: Voltage profiles at various charging stations with optimal boat load schedule

7.4 Solar-PV forecasting method

DTI has developed an alternative forecasting methods with respect to the one of Route Monkey. The forecasting of solar-PV production using Route monkey's algorithm is as shown in Figure 7.7. It can be observed that the forecasted value always underestimates the peak power leading to unwanted import from the grid that adds to cost of operation. A simple forecast method has been proposed by DTI as shown in Figure 7.8, where the solar profile is assumed to be identical to the previous day.

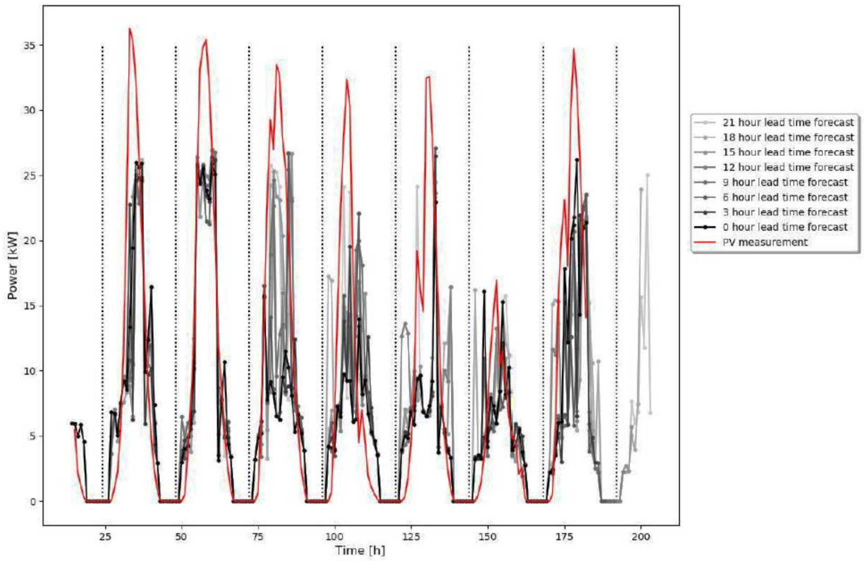

Figure 7.7: Route Monkey's forecast methods using different lead time compared to PV measurement

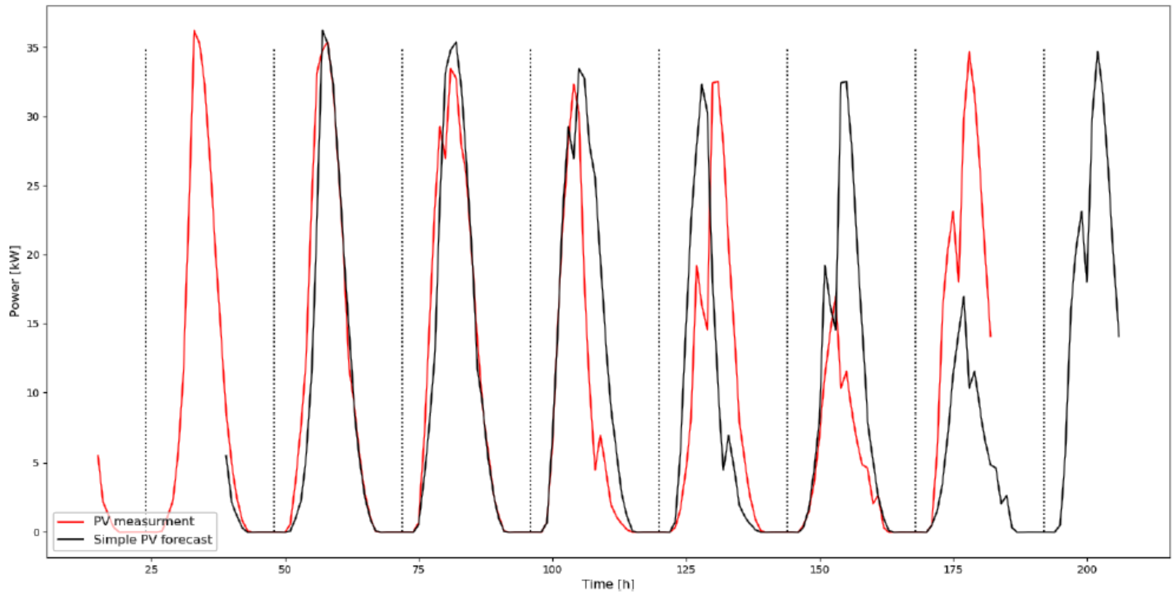

Figure 7.8: Simple solar-PV forecast by DTI

However, the forecasting method proposed by DTI proved highly effective at capturing the seasonal changes since these vary on a longer time scale but resulted in higher inaccuracies for days with cloudiness and unforeseeable weather. From comparison with the two forecasting models the result is a similar accuracy is achieved with an average deviation of 0.48 and 0.53 kWh for the simple forecast and the historical forecast, respectively.

7.5 Evaluation of methods

Several methods that have been considered in the SMILE project were evaluated with respect to advantages and disadvantages.

- *Linear programming*: Packages exist in several languages, it is computationally fast, and it finds an optimal solution. The constraints can be tailored to direct the method to find a technical optimum or an economic optimum. It can be applied to historical data to provide a reference for comparisons [9]. However, the forecasts have apparently been unreliable (confidential deliverables D3.7 and D5.7), and the method was abandoned for real-time use.

- *Machine learning for forecasting*: These methods, including neural networks, do not require any assumptions about an underlying model structure. They need a set of training data, and other sets of test and validation data to estimate the accuracy of the extracted model. However, the extracted model is a 'black box model', which is impossible to interpret physically. The method gave poor forecasts, possibly because it did not find regular patterns in the marina load and the PV production.
- *Autoregressive model for load prediction*: This method uses previous data from a time series to predict the next future value. It relies on the 'least squares method' to estimate the parameters of the model, and that is computationally fast. Tests indicate that it finds a good load prediction, for instance, 79 percent correct on the 17th of July. However, it requires trial-and-error tuning to find the best model structure. It cannot foresee events, because it relies on past values only; the only chance to predict an event is if it is recurring at the same time, as a pattern. It is not documented in SMILE.
- *Model predictive control*: The method uses the past to predict the future, and it then finds an optimal solution. But it only uses the solution one time-step ahead. Then it includes real data measurements to make the next prediction and optimal control. It continues step-by-step. The predictions are better, because it uses actual data as soon as they appear [7, 8]. Although the intermediate solutions are optimal, there is no guarantee of a globally optimal solution.
- *Price-based control*: To overcome unreliable forecasts, a buying and selling strategy can be based on the known spot prices. If one knows beforehand that it will be necessary to buy from grid during the next day's 24 hours, the algorithm buys on the times of the day when the buying price is low. It would be feasible to implement as a time-of-day tariff, but the anthropological study showed that tariffs are unpopular (see confidential deliverable D5.7). The method does not consider all the constraints known from linear programming. Furthermore, the span between the highest and lowest price the following day must be large enough to compensate for the cycle loss in the battery system (15 percent).
- *Rule-based control*: IF-THEN rules are versatile and can be applied in almost every situation. When the conditions in the IF-part are fulfilled, the actions in the THEN-part are executed. The price-based control is based on rules with logical conditions. However, the rules in Lithium Balance dashboard are only accessible to the design engineer, not to the expert operator or any other user. Rule-based control gives no guarantee of optimality, it is a heuristic approach based on experience. It is a fallback solution when the more mathematical methods fail.
- *Controllable loads strategy*: The controllable loads (sauna, heat pump) are turned on or off at favourable times, presumably without disturbing the users. It works well in theory, in combination with for instance linear programming. However, if these methods fail for other reasons, the remaining possibility is manual scheduling in the calendar. This is implemented in Lithium Balance dashboard. The controllable loads are in the order of 15 kW in total, which is small compared to the capacity of the battery (original nominal 240 kWh, adjusted to 237 in datasheet kWh, useable part 210 kWh), and the effect is weak. In fact, the battery itself is the most powerful controllable load, and it is possible to force it to discharge or charge at times defined in the calendar.
- *Voltage violation strategy*: A part of the marina is susceptible to low voltage, which could disturb the equipment on the boats. The proposed solution is to force the boats to change their pattern of usage, to shave peaks. However, this is unpopular, and a better solution would

be to rewire the cables in the distribution board, to distribute the load evenly on all the main fuses.

- *The EnergyPLAN/energy system perspective*: the energy system analysis in WP8 suggest operation of the BESS according to technical feasibility, hence, renewable energy is given priority over imports, yet also system integration across the whole island's energy system is given attention, where excess electricity from wind or PV can be used to charge vehicle batteries or heat water in a thermal energy storage. The system perspective has limits for the DR evaluation of the particular marina set-up, yet, variable tariffs according to local production and demands is recommended to 'force' flexibility in line with fluctuating production through DR, where availability to production, storage and consumption technology is fundamental. [10].

8 Conclusions

This deliverable dealt with the demand response evaluation for Ballen-Marina of Samsø demonstrator. First of all, the envisage DR services were presented. Then the forecasting algorithms and the scheduler to be used for Samsø demonstrator in both simulation and real-time environments were illustrated.

In accordance with this task, both Samsø Energy Academy and Aalborg University (AAU/ET) have devised the algorithms for optimal BESS scheduling, which can be implementable at the Ballen-Marina demonstrator. In particular, the results in section 6 illustrates the method for not only maximizing the Solar-PV self-consumption but also optimal scheduling of flexible loads using demand response and BESS through computer simulations. Due to covid situation, the real time evaluation took place in the summer 2021, and therefore in this deliverable D3.8, the real demand response systems have been now included by amending the preliminary draft version of this deliverable (D3.6) prepared in April 2020.

Indeed, Section 7 is included in this version describing the actual implementation of demand response programs at Ballen-Marina and evaluating the proposed methods in market perspectives. Lithium Balance has made a power purchase calendar for the Marina, which gives the spot price details that helps the harbour master in taking reliable decisions. Through the Lithium Balance studies, it is determined that the day-ahead forecast of both consumption and production profiles will be leading to better cost-efficient operation of Marina grid that considering hourly basis, where any prediction of sun-deficit for the upcoming day can be filled up between midnight before day and six in the morning same day. All in all, several methods have been evaluated by identifying pros and cons.

Apparently, it is difficult to forecast load and PV production accurately enough to bring in powerful methods such as linear programming and least squares optimisation. On the other hand, it is possible to perform manual control through the scheduler (Lithium Balance calendar), which is an impressive practical achievement.

An alternative approach is to change viewpoint from hourly based forecasts to daily based forecasts. Daily forecasts are more accurate; being summations over 24 hours, they absorb zero-mean variance. Most of the days experience PV shortage, and most of the days the buying price is low between midnight and 6 in the morning. It is therefore more or less safe to always buy during this period of the day. In case of PV excess (which happens in springtime after equinox, but not often) the only option is to drain the battery as much as possible by turning controllable loads on. This is a heuristic strategy and there is no guarantee it will always improve the default mode of operation. The PV production is already utilised to 89 percent in buffer mode, so there is only 11 percent left for improvements. This indicates that it will be difficult and expensive to capture the remaining percentages by optimisation.

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