D5.6 - Initial DSF Predictive Models

Deliverable ID	**D5.6**
Deliverable Title	**Initial DSF Predictive Models**
Work Package	**WP5**
Dissemination Level	**PUBLIC**
Version	**1.0**
Date	**2018/08/30**
Status	**Final**
Type	**Report**
Lead Editor	**LIBAL**
Main Contributors	**LIBAL, ISMB**

Published by the Storage4Grid Consortium

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 731155.

Document History

Version	Date	Author(s)	Description
0.1	2018-06-15	LIBAL	First ToC proposed
0.2	2018-07-10	ISMB	ToC update and contribution assignment
0.3	2018-08-21	LIBAL	Input to section 1 and 2
0.4	2018-08-22	ISMB	Input to section 3
0.5	2018-08-24	LIBAL	Conclusion and finalized the report.
0.6	2018-08-29	ISMB	Changes based on EDYNA's review
1.0	2018-08-30	LIBAL	Adapted changes according to the review Ready for submission to the EC

Internal Review History

Review Date	Reviewer	Summary of Comments
2018-08-29 (v0.6)	Marco Baldini (EDYNA)	Approved: • General minor corrections
2018-08-30 (v0.5)	Sisay Chala (FRAUNHOFER)	Approved: • When comments in the document are applied

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Executive Summary

D5.6 - Initial DSF Predictive Models will provide the initial inputs of the predictive models' development activities carried out by the two involved entities, LiBal and ISMB.
These models are meant to empower S4G DSF and GESSCon with reliable forecasts and estimations, that in turn would optimize the ESS and RES exploitation.

GESSCon, based on Remaining Useful Life (RUL) and State-of-Health (SoH) estimation pattern would adapt the operational scheme for each individual ESS to extend service life and efficiency for those systems. These models are being designed, developed and implemented within LiBal's Battery Management System (BMS) product.
State of health and remaining useful life predictive algorithms have been studied and selected in this deliverable. Two methods of each are detailed described in this report and will be investigated more later. The final chosen algorithm will be present in D5.7 - Final DSF Predictive Models in M33.

DSF as the main component for storage analysis and planning requires an anticipated view over the state of the grid, this requirement essentially refers to the electricity consumption and generation in terms of power for near future and energy for the long-run pictures. Distributed generation tied with the environmental aspects, load consumption bound directly to the human behaviour and storage status data a combination of both. These models will be provided to assist the DSF make decision, analysis and scheduling.

1 Introduction

This deliverable document presents the ongoing efforts towards predictive models' development, within T5.4 framework. We divide the predictive algorithms in two major categories which coincide with the division of activities:

1. Feature oriented: to develop estimation algorithms for electrochemical energy storage system (ESS) behaviour such as RUL and SoH, an effective feature has to be extracted from the measurement data. The term feature-oriented, refers to such features for SoH and RUL prediction.

2. Observation oriented: load consumption, RES production and ESS status forecasts are based on the human behaviour, climate and environment. These might be modelled either from the recorded/observed data in the past and can also be enriched with the reliable forecasts from 3rd parties which are obtained from numerous terrestrial and satellite measurements and observations.

Battery health predictive model will be operated in LiBal's BMS and update related energy storage system (ESS) parameters through SMX to PROFESS and to GESSCon for more accurate and optimized operation result [D4.2] [D4.4]. Observation-oriented predictive models determine few key inputs for GESSCon optimization framework. There is high dependency between GESSCon and DSF Predictive Models. In this deliverable LiBal and ISMB provide the relevant inputs for these two prediction categories respectively.

1.1 Scope

The main goal for the T5.4 is to develop predictive algorithms for the DSF system given that a large number of entities in the DSF grid models are statistically predictable, and therefore can be described with sufficient confidence by means of simple probabilistic or even deterministic model. But also, most of the load, RES and storage systems are not known or predictable a priori [D3.2].
This task will integrate advanced lifetime estimation algorithms on Lithium Balance novel BMS platform. The advanced lifetime estimation includes Remaining Useful Life (RUL) and State-of-health (SoH) specific for stationary energy storage systems. These algorithms are not currently available for off-the-shelf battery management systems. These algorithms could predict End of life of the battery packs for easier maintenance and battery swap planning.
Alongside the ESS related estimation models, load consumption, RES production and ESS status predictive models are being developed within this task in order to supply DSF with reliable data.

1.2 Related documents

ID	Title	Reference	Version	Date
[D2.5]	Initial Lessons Learned and Requirements Report	D2.5	1.0	2017-05-30
[D3.1]	Initial S4G Components, Interfaces and Architecture Specification	D3.1	1.0	2017-09-15
[D3.2]	Updated S4G Components Interfaces and Architecture Specification	D3.2	1.5	2018-08-08
[D4.2]	Updated User-side ESS Control System	D4.2	1.0	2018-06-14
[D4.4]	Grid-side ESS control System	D4.4	1,0	2018-08-30

2 Battery Health Prediction

In this section, the methods that diagnose the battery health status will be presented. The State of Health (SoH) and Remaining Useful Life (RUL) of the battery are introduced, the possible solutions for this project are analysed.

2.1 Overview of Battery Health Prediction

With the degradation of the Lithium-ion battery, the loss of lithium leads to the capacity fade, and the growth of the SEI layer increases the impedance. Therefore, the variation of the capacity and resistance during the aging process can be used to calculate the battery SoH. Generally, in the degradation process, the battery capacity gradually decreases, and the internal resistance increases. The definition of SoH are,

$$SOH = \frac{r_{bat} - r_{EOL}}{r_{new} - r_{EOL}} \cdot 100\% \tag{1}$$

$$SOH = \frac{Q_{bat} - Q_{EOL}}{Q_{new} - Q_{EOL}} \cdot 100\% \tag{2}$$

where r_{new}, Q_{new} are the resistance and capacity from new cell; r_{bat}, Q_{bat} are the measurements at present; r_{EOL}, Q_{EOL} are the measurements at the battery's end-of-life [1], [2]. Normally, the battery end-of-life is defined as 160% of the internal resistance of the fresh cell or the 80% of the capacity of the new cell [1], [2].

RUL is the length of the period from now to the end-of-life of battery. RUL can be transformed to predict the probability when a battery reaches its end-of-life. In addition, RUL can mean the number of cycles still left before the end of the battery's lifespan. Therefore, RUL has some connections with SoH. For example, if the current capacity/resistance of the battery is measured, the SoH can be calculated. Afterwards, on the basis of the relationship between the capacity and the cycling numbers of battery, RUL can be predicted from the health monitoring results.

2.2 State of Health (SoH)

A brief introduction of the SoH estimation methods is presented in the next subsections. Afterwards, the possible solution for SoH estimation in this project is discussed.

2.2.1 Capacity/internal resistance offline measurement

A straightforward way to estimate the battery SoH is directly measuring the resistance and capacity of the battery. Measuring the capacity needs one fully charge or discharge of the battery at the present health status. The power fade of the battery can be measured through the current pulse test as Figure 1.

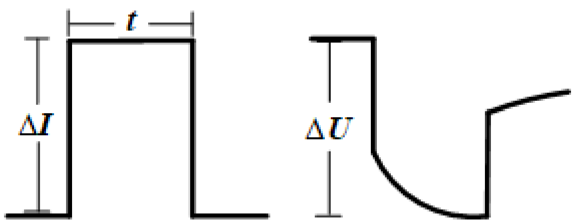

Figure 1. Current and voltage in the current pulse test

The current pulse in Figure 1 lasts only a few seconds. The internal resistance of the battery can be calculated by the following equation

$$r_{bat} = \frac{\Delta U}{\Delta I} \tag{3}$$

After calculating the internal resistance r_{bat} from Eq.(3), the battery SoH can be estimated from Eq.(2).

2.2.2 Online capacity/resistance identification

Despite the offline methods, the capacity and resistance are also possible to be calculated online with only few samples of the measurement. Algorithms, such as, Recursive Least Squares (RLS), Kalman filter, Total Least Squares (RTLS). have been used to identify the battery resistance and capacitance online. The principle of the online capacity/resistance identification method is illustrated as follows [3],

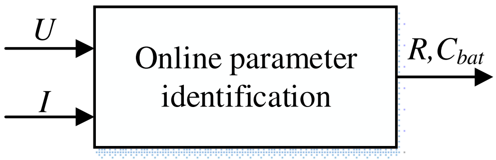

Figure 2. Principle of online parameter identification

The current and voltage in a short period are collected as the input of the identification algorithm. After the calculating steps of the algorithm, the resistance and capacity are identified online. Generally, the resistance can be identified from the measurement in the current and voltage sensors. The capacity estimation relies on the battery SoC.

Recently, machine learning methods are also popular in the SoH estimation area. machine learning methods are based on large amount of training datasets, which need time and manpower to collect the datasets from a certain application. Another problem is that the generalization of the machine learning algorithms is doubtful. For example, the production of renewable energy is different from area to area, and the people's life also varies. If machine learning based SoH estimation model is established by the dataset collected from one area, the estimation results may not always be suitable for another area.

2.2.3 SoH estimation solutions

Online parameter identification of the resistance suffers from the noise in the current and voltage measurement. The capacity estimation is related with SoC, however, accurate SoC estimation is still an issue. In addition, the online parameter identification needs the computing power of the microprocessor, which definitely increases the cost of the hardware platform.

In S4G project, the current profile may not be as aggressive as that in an electrical vehicle. Hence, there is a high chance that the battery is fully charged or discharged. Since the SoH will not change in short period, we can calculate the capacity according to one fully charge or discharge from our BMS. Moreover, compared to capacity, resistance is easier to be calculated through a current pulse test. We can perform several current pulses in certain conditions to receive the internal resistance of a battery, and according to Eq.(1) and Eq.(2), the battery SoH at present is calculated from our BMS.

The steps of our SoH estimation solution are summarized as follows:

Step 1. Calculate the battery capacity from one fully charge or discharge process, SoH is calculated according to Eq.(1);

Step 2. Calculate the battery resistance from the specific current pulse tests, calculate the resistance from Eq.(3). SoH is calculated according to Eq.(2).

Step 3. Fuse the SOH from Eq.(1) and Eq.(2) as the final battery SoH estimation.

2.3 Remaining Useful Life (RUL)

In the following subsections, two categories of RUL methods are mainly introduced. The possible solution for this project is discussed afterwards.

2.3.1 Empirical model

In different RUL, the electrical properties of the battery are also different, such as the charge/discharge curve of terminal voltage, the capacity, and the internal resistance [4]. Thus, the RUL of the battery is possible to be predicted according to the connections between above mentioned aging indexes and the RUL. The methods in this category utilize the features of the parameters. Exponential function is usually used to fit the battery capacity variation with different cycling numbers. Internal resistance is also selected as the indicator to predict the battery RUL after the curve fitting. Instead of using simply one parameter for SoH estimation, two or more influential indicators are also possible to be used to establish the prediction model. Therefore, the typical empirical models are summarized as follows [5], [6],

$$RUL = f_1(Q_{bat}) \tag{4}$$

$$RUL = f_2(R_{bat}) \tag{5}$$

$$RUL = f_3(R_{bat}, Q_{bat}) \tag{6}$$

2.3.2 Data driven method

In order to involve more new features, such as, the shape information from the battery voltage charge curve, sample entropy, and so on, machine learning methods are also used to predict the battery RUL. One advantage of these data driven methods is that different new features extracted during the battery degradation are easily used to the RUL prediction. Artificial Neural Networks (ANN), Support Vector Machine (SVM), Relevance Vector Machine (RVM), etc. have already proposed to predict RUL with different kind of features extracted from the battery degradation [7].

The steps of the data driven method are shown in Figure 3. The effective features are extracted from the raw measurement data at first. Then, the RUL estimator is trained through a training process offline. Finally, RUL at present is predicted from the coming features online. Normally, it's not easy to find an effective feature from the raw data, and the generalization of the offline trained estimator is difficult to be validated.

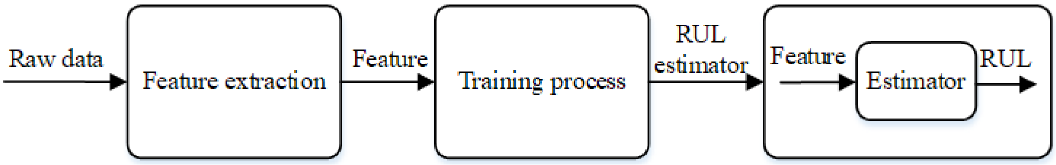

Figure 3. The process of data driven RUL prediction

The data driven method is possible to combine with nonlinear filter, such as, Unscented Kalman filter (UKF), Particle Filter (PF). to form the model-based estimation. However, it's quite time consuming to predict the RUL with this kind of model-based estimation methods in a microprocessor.

2.3.3 RUL prediction solutions

It's possible to predict the RUL on the basis of battery SoH. In S4G project, the battery packs may be fully charged or discharged, by considering the SoH prediction solution proposed in the previous section, the RUL prediction in this project can utilize the capacity and resistance from the SoH estimation to establish an empirical model. Moreover, the fully charge or discharge cycles are also counted to assist the RUL prediction. The steps of the RUL prediction are as follows:

Step 1. Count the numbers of full charge or discharge cycles in the BESS;

Step 2. Establishing an empirical model between the capacity/resistance and RUL and predict RUL online with the information from SoH.

Step 3. Fuse the RUL from Step 1 and Step 2 to form the final RUL prediction of the BESS.

3 DSF Predictive Models

In this chapter we will provide an overview of the state-of-the-art predictive technics and models, then bring the conclusion based on which we choose the right method (more adapted) to work with for each specific issue. Finally, we provide some results obtained from the initial models.

3.1 State-of-the-art predictive models

Load consumption, RES production and ESS status are subject to study as the evolutions of the variables in the time domain in the determined horizons. Looking at this pattern as time series, there exist various methods to deal with this kind of prediction, such as Fast Fourier Transformation (FFT), Autoregressive (AR), Moving Average (MA), Autoregressive Integrative Moving Average (ARIMA), Recurrent Neural Network (RNN), etc.
We will demonstrate these technics' theory and matching use case for each.

3.1.1 Fast Fourier Transform (FFT)

The FFT has been used for the time series forecasts, in various applications where the seasonality is evident. This method would provide acceptable performance only if the periodical patterns built up the resulting progress form. The FFT basically decouples a time series (signal) into various periodic repeating components (frequencies). One practical prediction method using FFT is to do apply FFT to the data set and obtain harmonics spectrum and their coefficients. The next step is to filter those spectrums based on their amplitude. So the largest ones can rebuild the signal (time series).
This method can be interesting where the periodically is very dominant like for medium temperature case over entire year.
FFT would provide good forecast for long term intervals where the seasonality of the data is guaranteed, but has low precision and very rich training dataset might be needed for acceptable results.

3.1.2 Autoregressive Model (AR)

Most of time series prediction models are based on the observed data in the previous samplings, given that the variable's current value x_k is dependent on the past ones. The *AR(p),* where *p* indicates the auto-regression order or in other word maximum lag order, is a linear regression of the variable x_{k-p} up to x_k. The obtained linear regression model is then being used for further steps such as x_{k+1}, x_{k+2} and so forth. An *AR(p)* is expressed as following:

$$x_k = \varphi_0 + \sum_{i=1}^{p} \varphi_i x_{k-i} + \varepsilon_i \tag{7}$$

Where φ_i are the model coefficient, φ_0 is the constant (intercept) and the ε is the error
An important key in previous state dependent predictions is Autocorrelation function (AFC), which indicates how the sampling variables in a time series are dependent and is measured by correlation between current observation x_k and the observation *p* lag step from *k* sampling point. The correlation between the actual observation and lag sampling points can be obtained from the Eq.(8);

$$corr(x_k, x_{k-p}) = \frac{cov(x_k, x_{k-p})}{\sqrt{var(x_k)}\,\sqrt{var(x_{k-p})}} \tag{8}$$

Then normally a threshold is being defined to preserve significant correlations in the past.
This type of prediction model is useful especially when the variable evolution follows a slow dynamic and the forecast horizon is rather small. The AR is extremely simple and provides acceptable precision for the small prediction horizon within some few next slot.

3.1.3 Moving Average (MA)

In the *MA (q)*, where the *q* represents the order of MA model and indicates the span of horizon for getting average. Simply the expecting value in the next step is calculated from the average of the past *q* steps. The equation (9) expresses a simple description of MA:

$$x_k = \theta_0 + \frac{\sum_{i=1}^{q} \theta_i x_{k-i}}{q} \tag{9}$$

In practice, a Partial Autocorrelation Function (PACF) that takes into account all lag values down to *k-q*, might be used, either for AR, MA and ARIMA.
This model is also very simple but again, is adapted mainly to the very small prediction horizon within some next slot.

3.1.4 Autoregressive Integrated Moving Average (ARIMA)

ARIMA is a class of statistical models for analyzing and forecasting time series data and an *ARIMA (p, d, q)* is actually a combination of *AR(p)* and *MA(q)* where *d* is the degree of differencing. It is a generalization of the simpler combination of Autoregressive Moving Average and adds the notion of integration.
This family models or Seasonal ARIMA (SARIMA) provide more sophisticated results gaining the same elementary concept of AR and MA

3.1.5 Recurrent Neural Network (RNN)

RNN is an artificial neural network that additionally uses the past state(s) to calculate the output. In other word, the *recurrent network* is a network with feedback; some of its outputs are connected to its inputs. One type of discrete-time recurrent network is shown in Figure 4. Recurrent Network.

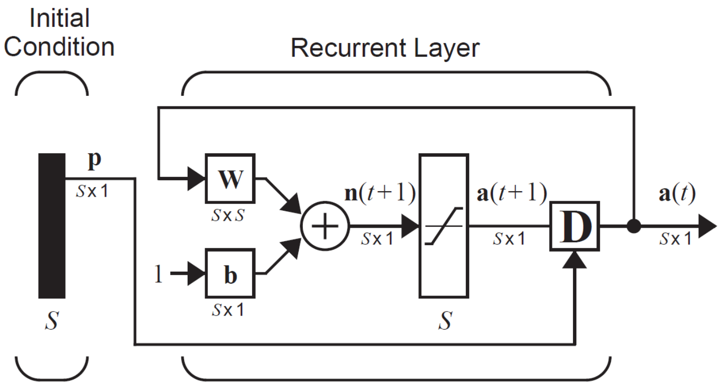

Figure 4. Recurrent Network

Building a complex RNN with mode nodes and hidden layers and forwarding all the past state (memory) means in the training phase that the entire network is being updated in forward and backward propagations, a huge memory would be needed if the training set was not brief enough (long gap of dependencies). Other computational cost is penalized because of vanishing and exploding gradients in a long sequential dataset.
That is why in practice **Long Short Term Memory Recurrent Neural Network (LSTM RNN)** is being used.
The LSTM RNN evaluates which past state(s) might be preserved as memory and learns long-term dependencies, thus resolves the gradient problem over all data.
The decision of what to keep and what not, is being set trough hyper-parameters of memory module and also the type of activation functions. In this way a LSTM RNN learns most relevant events in the past and keeps only them as state (memory).
A LSTM RNN is shown in Figure 5.

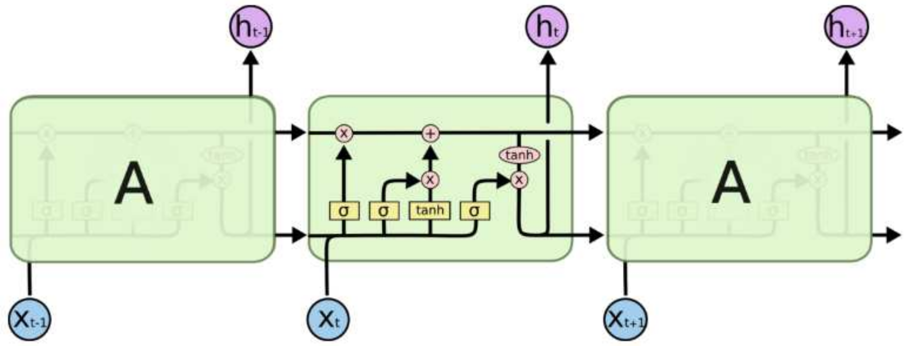

Figure 5. LSTM RNN and internal module structure

3.2 Load Pattern Recognition

We tried the different models presented in the state-of-the-art part. All these methods in general learn the sequence of events and tend to follow the most recent trends and correlate them with the actual state in a stochastic way. Some methods also use hybrid models, combining these methods and gain good results. For instance, an ARIMA may recognise the seasonal pattern and alongside that a LSTM RNN would predict short term dynamics.

In single house/building level, the load consumption pattern is strictly tied with the human needs that on its turn is affected by the environmental conditions. For instance, lights are being switched on and off with a shift in the time in winter with respect to the summer. The heater or air conditioner are dependent on the external temperature, what is predictable from some few days before. One part of a long-observed load consumption is reported in the Figure 6.

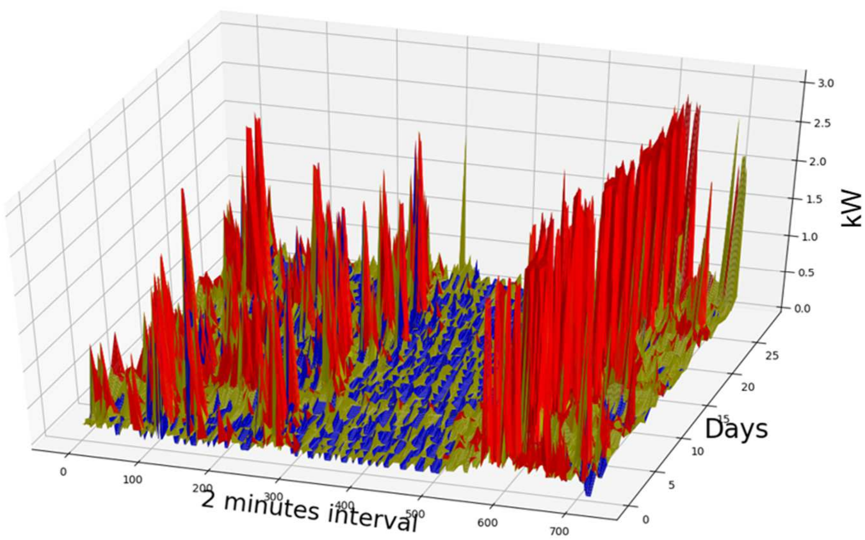

Figure 6. One month consumption of a single house

The pick consumption around the 8:00 p.m. is the one for dish washing machine, the others for various appliances such as refrigerator, iron etc.

A longer period of that dataset is shown in Figure 7 as a heat map graph that might be more intuitive.

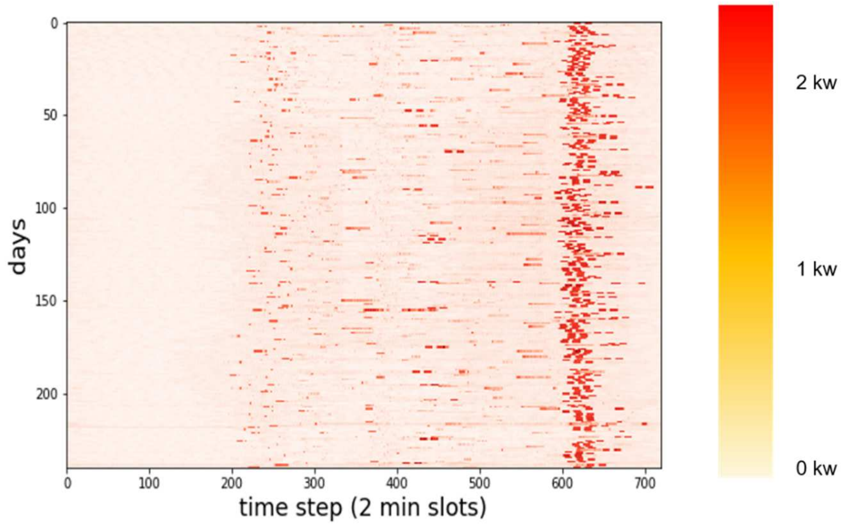

Figure 7. Load consumption observation for 250 days

Once a model could recognise and decouple all these consumption components, would be able to reconstruct them according to the external variables and finally put them up together to obtain house load profile.
The objective model would classify the single appliance operation based on the external environment condition, working days/holidays and the decision-dependent classes.
We instead will build the Load Predictive Model based on human behaviour prediction. In this way we will gain a higher level of knowledge, where the consumption pattern is originated from.

For district/substation level load profile, the conventional method in the dispatching operations where the output is calculated mainly from the last year observation taking into account some trend and environmental condition is valid and highly reliable.

3.2.1 Non-Intrusive Load Monitoring (NILM)

The NILM - also called Non-Intrusive Appliances Load Monitoring (NIALM) – classifies the electric appliances switching on/off, level and consumption time. The learning process however uses various technics such as machine learning and deep classifier network.
Once such functionality is obtained, the predictive model will learn house inhabitants' behaviours and applies the appropriate shifting and rules to get the expecting consumption pattern.
Besides the accuracy, NILM training dataset can be started from just a few load profiles. Once for a single home the appliances are known (what can evidently be expected from a smart home) the training dataset can be virtually generated by random combination of the single appliances. This is precious for not matured datasets like the S4G case that is a young project overall.
The measurement sampling in S4G is in 1 *Hz* order, that is we will propose a slow-NILM model. We design a deep network with appropriate filters to capture different features, for example, active and reactive power and transients.
A home load consumption profile with some example of dominant power consumer is depicted in the Figure 8. Note that the sampling frequency is 1/120 Hz, but in S4G use case measurement such graph is clearer.

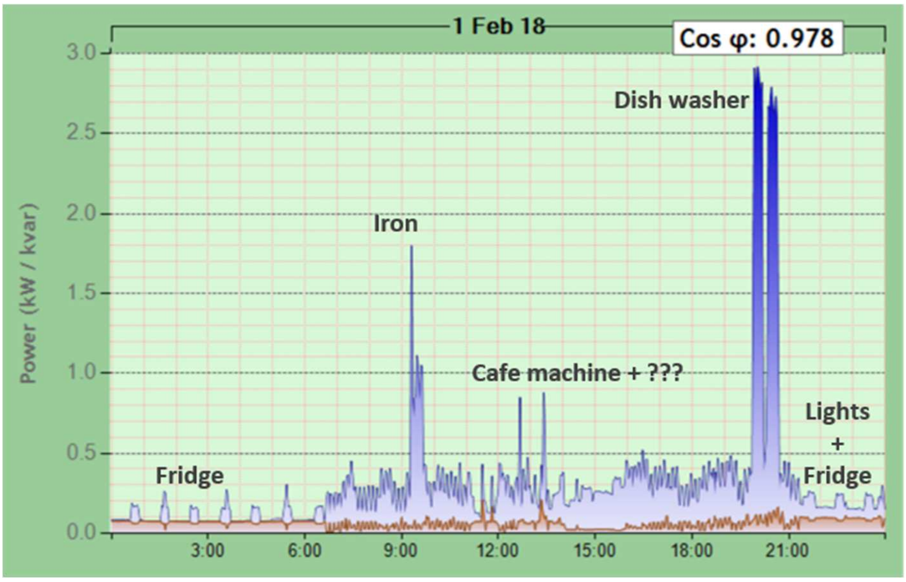

Figure 8. NILM method example

3.3 RES Production

The RES production within S4G framework is referring to PV power generation, that is in operational condition and fixed position is a function of season, time, cloud density and temperature. There are other variants as well, however those are not dominant.
To achieve reliable PV generation forecast we get use of most reliable sources for the weather forecast and hence cloud density and temperature, and calculate the irradiation based on the location and time.

The process is as following; based on the geographical location of the simulation, date and period, tilt angle and etc. a perfect irradiation profile is being calculated in terms of azimuth degree and $\frac{W}{m^2}$. this profile basically means the irradiation as if it was not any cloud and temperature is 25° C constant. Then a designed connector request weather forecast from weatherunlocked [8], a 3rd party weather forecast service provider. The cloud density then is being applied to the perfect irradiation profile as a noise with specific coefficients. Finally one further step provides the final form of irradiation profile for the requested time. This must be considered that the weather forecast are available only for the next 7 days from the request time on.

Figure 9 shows an output example of model for the different sites (UNINOVA, UPB, EDYNA and LiBal sites), on 20/06/2018. The scale is normalized so one can deduce solar irradiation from the graphs.

This model will be improved by updating some coefficients according to the measurements in the real condition.

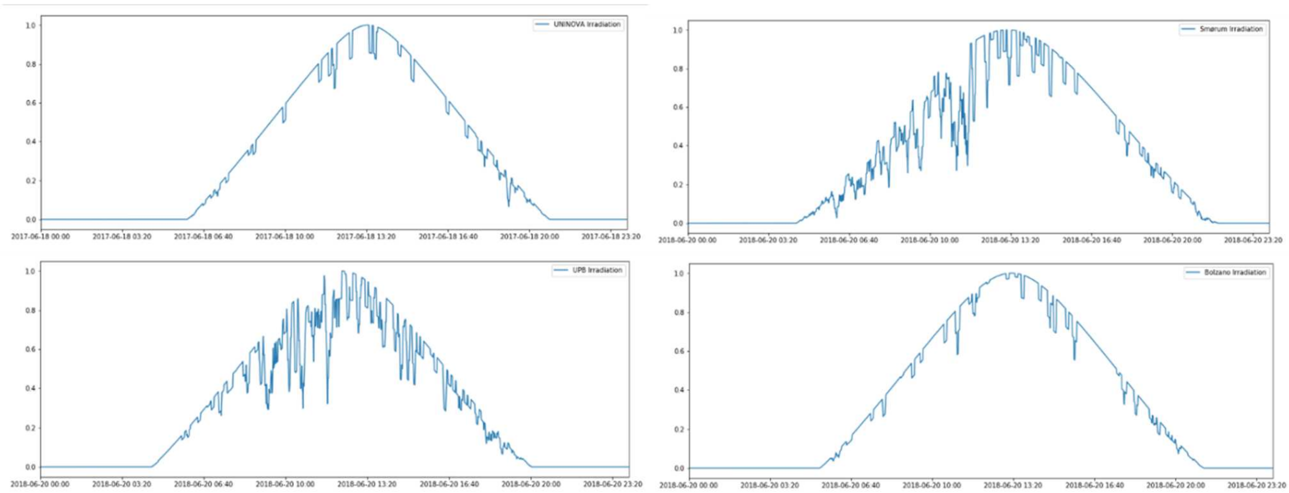

Figure 9. Normalized irradiation level for UPB, UNINOVA, EDYNA and LiBal sites

3.4 ESS Status Predictive model

In a S4G compliant use case, the ESS status indeed is a function of load profile, RES production and a decision factor (ESS controlling entity). This is valid for either house/school level and commercial/DSO owned ESS. The first two profiles will be available within the DSF prediction module. The third one, the decision of the ESS owner in house case, would be made based on economic aspects such as returning benefits and the ESS status can be varied based on who is controlling that. A simple machine learning or stochastic model can provide this input once two other and financial aspects are clearer.
As a result, we provide a simple machine learning or stochastic model that receives the PV electricity generation, load consumption and price forecast as inputs and gives the ESS status profile as its output.

4 Conclusions

This deliverable presented the algorithms of predictive models that is implemented in DSF and LiBal's BMS. Further investigation and development will be conducted following the user needs and requirements collected in WP2 and documented in the issue-tracking software JIRA. Additionally, the predictive models will be improved and evaluated to ensure a high-quality output forecast which enhance the GESSCon performance. Further updates will be presented in D5.7 Final DSF Predictive Models (M33).

Acronyms

Acronym	Explanation
BESS	Battery Energy Storage System
BMS	Battery Management System
DSF	Decision Support Framework
DSO	Distribution System Operator
DWH	Data Warehouse
ESS	Energy Storage System
GESSCon	Grid ESS Controller
PROFESS	Professional Realtime Optimization Framework for Energy Storage Systems
PV	Photovoltaic
RES	Renewable Energy Sources
RUL	Remaining Useful Life
S4G	Storage4Grid
SEI	Solid Electrolyte Interphase
SMX	Smart Meter eXtension
SoC	State of Charge
SoH	State of Health

List of figures

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