GreenDataNet

D3.6 – Analytical Models of Data Centre Components

[Final]

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Rev 1.2

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REVISION SHEET

Revision Number	Date	Brief summary of changes
Rev 0.1	07/09/2015	Baseline document
Rev 1.1	19/11/2015	Integration of reviewing comments. Second version of deliverable
Rev 1.2	30/11/2015	Integration of internal reviewing comments

KEY REFERENCES AND SUPPORTING DOCUMENTATIONS

[1] Schweiger, H.G. and al.: *Comparison of several methods for determining the internal resistance of lithium-ion cells*. Sensors, 10(6), pp. 5604-5625.

[2] Bindner, H. and al.: *Lifetime modelling of lead acid batteries*. Risø-R report, April 2005.

[3] Cugnet, M. and Liaw, B.Y.: *Lead-Acid Battery Technologies: Fundamentals, Materials and Applications, Chapter 9: Mathematical Modelling of Lead-Acid Batteries*. CRC Press, Joey Jung, Lei Zhang, Jiujun Zhang, June 2015, pp. 229-318.

[4] Duffie, J.A. and Beckman, W.A.: *Solar Engineering of Thermal Processes, 4th edition*. John Wiley & Sons Inc, 2006.

[5] Hadj Arab, A. and al.: *Performance of PV water pumping systems.* Renewable Energy, 18 , pp 191-204.

[6] Skoplaki, E. and Palyvos, J.A.: *On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations*. Solar Energy, 83(5), pp. 614–624.

[7] Gray, J.L.: *The Physics of the Solar Cell, Handbook of Photovoltaic Science and Engineering.* John Wiley & Sons Inc, 2011.

[8] *JAP6 60/245-265/3BB Multicrystalline silicon module*. JA Solar, Nov 2013, http://www.jasolar.com/uploads/JAP6%2060%20245-265%203BB.pdf

1. INTRODUCTION

In WP3 of GreenDataNet project, the work is focused on developing the energy management of a data center (DC) for maximizing the self-consumption and self-production rates of photovoltaic (PV) production. Beyond the use of renewables the main goal of the GreenDataNet project is to improve the power efficiency of the urban data centres (i.e. decrease of their Power Usage Effectiveness) for a better sustainability of IT activities.

Part of the Task 3.2.1 (Analytical Models for Data Centre Components), the Deliverable 3.6 of GreenDataNet project aims at formulating the analytical models for the components of the data centre in order to be integrated in the optimization algorithms of the SEMS (Smart Energy Management System, Deliverable 3.7). Some analytical models are also required for the simulation of the GreenDataNet system to evaluate its performances. Beyond the useful analytical models for the optimization process of the SEMS and the AEMS and for the simulation, this document details also the empirical data, used for the models, of the data centre components considering the design of the GreenDataNet prototype.

1.1 DOCUMENT PURPOSE

The analytical models for energy systems are well detailed topics in literature. The purpose of this deliverable is then not to review all the existing models for PV, storage, servers and cooling components and not to propose new ones, but to select the most appropriate ones for the GreenDataNet project and to adapt it if necessary.

Within the Task 3.2.1 the electricity consumption from the servers should be modelled. Due to the IT specificity of the modelling the IT model is used in the DataCentre Energy Controller explained in the Part 3 of the Deliverable 3.2, *Electricity Consumption Forecasting Tool Design and Implementation*. The SEMS and AEMS will not require any model for electricity consumption from the servers. The DataCentre Energy Controller developed by EPFL and UNITN optimizes the IT consumption and directly supplies the forecasting (time series) of data Centre electricity consumption to the SEMS. It proposes a solution for a dynamic power management providing power savings and improved QoS (Quality of Service).

This work is strongly linked to the WP2 (Local Management System: Concept and Algorithms) tasks and especially the development of analytical models that describe the properties of the workload (Deliverable 2.2).

The electricity consumption for the cooling is the other main load in a DC and was foreseen to be modeled in the Task 3.2.1. This cooling load is directly linked to the IT consumption and the cooling design of the data centre; it has been fully described in the Deliverable 3.1, *Analytical Model of Thermal Behaviour of Data Centre*.

Hence the Data Centre components that are discussed in this deliverable are the **renewable generation system** (here PV panel), the **storage system** and the **UPS conversion equipment** following the proposed electrical design for the GreenDataNet (see Deliverable 1.6, *Energy Storage and PV Architecture Specification*). The following Figure 1 is a reminder of the GreenDataNet prototype electrical design.

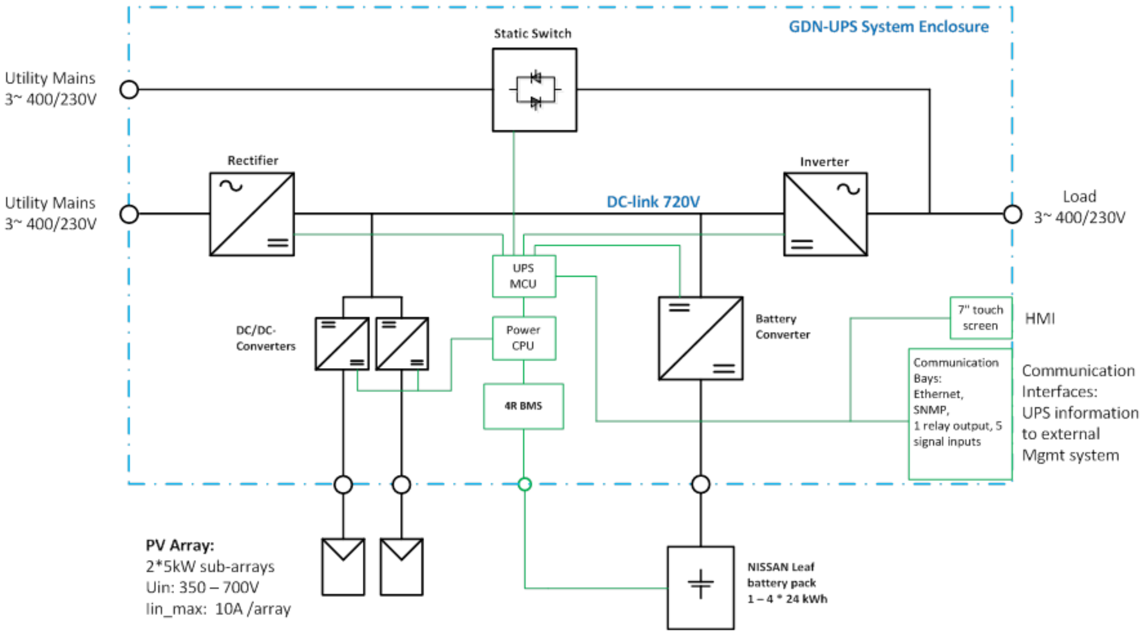

Figure 1. Electrical design of GreenDataNet UPS prototype

The analytical models are needed for solving the energy optimization problem (in SEMS and AEMS) formulated in a mixed-integer linear programming (MILP). The optimization problem for SEMS is formulated in the fourth part of the Deliverable 3.7 as it is integrated in the SEMS. The optimization problem for AEMS will be described in Deliverable 3.11.

Different levels of complexity of the models are possible. The used models have to be good enough for solving the optimization problem with an acceptable resolution but not too complicate to avoid too large time of calculation. A linearity of such model is also required. For this application the main physical behaviours of the system are described by the models but it is not necessary to be faithful of the real physical behaviour of the system. The solutions of the optimization problem are always false; the selected optimization methodology permits to be close to the true solution as much as possible. An important simplification and source of imprecision comes from the time discretization. The shortest is the time step, the closer from the true solution is the optimized solution; but a common time step for such optimization problem is about some minutes or some hours to not be too much time consuming. It has been chosen for GreenDataNet project to have an optimization time step from 30 min to 1h and an optimal solution for several time steps to cover 24h.

Nevertheless it appears **models** are not only required for the energy optimization (at data centre level) tool, i.e. the SEMS and the AEMS, but also **to test the given solution in a simulated environment** taking into account the physical characteristics (at least a part of them) of the components and the PV and electricity consumption forecasts.

For this application the required models need to be as close as possible to the real system depending on the available data.

This simulation framework dedicated to GreenDataNet has been developed in Matlab Simulink environment. A Simulink plant with physical components has been designed following the scheme of Figure 1. Analytical models fed by empirical data through look-up tables are used.

An associated control has been developed taking into account the forecasts, the optimization solution from the SEMS and the real power from PV, ESS and IT+cooling loads. As illustrated in Figure 2 the developed control integrates the SEMS optimization process for power planning for next time steps (to cover 24h) but also the power control for the current time step.

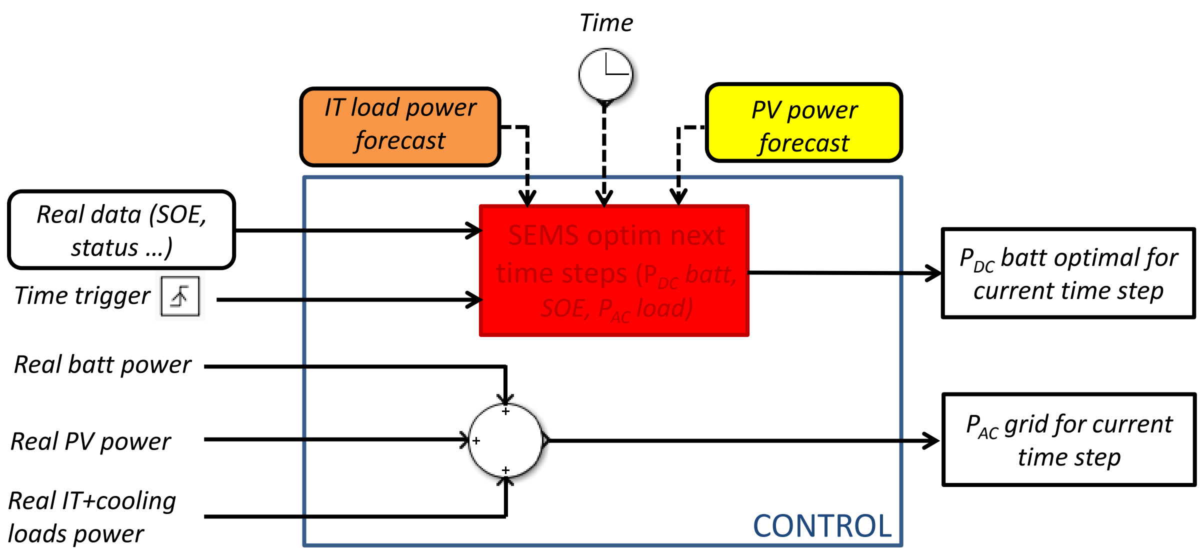

Figure 2. Schematic view of the developed control within the simulation environment

An optimal charging or discharging power for the battery is given as an optimal control (PDC batt optimal) for the simulation time step. Then the battery limitations are considered by the simulation model of the physical plant with limitations in terms of energy, power … A simulated 'real' power (Real batt power, >0 for discharge and <0 for charge) for the battery is generated. Regarding the 'real' simulated PV power (>0) and loads power (<0) a power value for the control of the grid (PAC grid) is calculated; this control power for the grid is given by the following equation:

$$Real\ batt\ power + real\ PV\ power + real\ loads\ power + P_{AC}\ grid = 0$$

The SEMS and AEMS optimization software are developed in C++ and use input and output xml files as explained in Deliverable 3.7 and 3.11; these files cannot be used directly by the developed simulation environment in Simulink. Then a generator for xml file from Matlab files has been developed to build an input file from real data (generated at previous time step by the simulation). A parser is also used to integrate the XML output files of the SEMS and AEMS in the Simulink environment. Within the results of the SEMS/AEMS output file (for the next time steps) the optimal power of the battery for the current time step is considered. The time steps of the simulation could be different from the SEMS optimization time step.

1.2 DEFINITION, ACRONYMS AND ABBREVIATIONS

AC	Alternating Current
AEMS	Aggregated Energy Management System
BMS	Battery Management System
DC	Direct Current
GDN	GreenDataNet
LMO	Lithium Manganese Oxide
LNO	Lithium Nickel Oxide
MPPT	Maximum Power Point Tracker
OCV	Open Circuit Voltage
PV	Photovoltaic
SEMS	Smart Energy Management System
SGCT	Smart Grid Configuration Tool
SoC	State of Charge (of the battery
SoE	State of Energy (of the battery
SoH	State of Health (of the battery)
UPS	Uninterruptible Power Supply
XML	Extensible Markup Language

1.3 DOCUMENT OVERVIEW

The Part 2 of this deliverable deals with the battery component of the GreenDataNet prototype browsing possible analytical models for both applications explained in previous part and reviewing integrated empirical data.

Part 3 and Part 4 explain the models for UPS and PV components respectively.

The specific energy strategy used by the SEMS software for the data centre energy optimization with time steps from 30 min to 1 h is detailed in the Deliverable 3.7. AEMS is described in Deliverable 3.11. Simplified analytical models are considered for both SEMS and AEMS optimization process. They permit also to perform energy time shift strategies in addition of increasing self-production rate.

The control strategies of the simulation environment developed for GreenDataNet is explained in the following part.

Once these first energy strategies will be integrated and tested in the demonstrator with SEMS and AEMS, more advanced strategies (for instance peak shaving, grid support, load following …) could be implemented first in the simulation environment then in the demonstrator. These new strategies will consider the demonstration results in terms of control deployment and also energy management. Simulated results and monitored data from the demonstrator could be compared within the WP3 and WP4 framework..

2. BATTERY COMPONENT

Lots of models are available in literature for the battery component due to the different aim of the model but also due to the high variety of battery technologies.

Multi-physical models are needed to understand electrochemical processes and their impacts in terms of mechanical, material and thermal changes with high accuracy. Sets of analytical models are used for this multi-physical approach.

Electrical models, electrical equivalent circuit, are used to copy the physical electrical behaviour of electrochemical components by determining values and connections of several resistances, capacitances and inductances. These electrical components of the model could have a link with the real behaviour of the battery component or not; their values could be determined through test measurements [1].

Strictly empirical methods based on experiment results are used to approach the general behaviour of the battery and the values of the main battery status (as State of Charge).

Analytical models can also be used to describe general behaviour of the battery component, for instance energy behaviour, without going into accurate physical description.

To date, the battery technology installed in the data centre is lead-acid one due to its maturity and its low cost. They are used in floating mode to supply energy in case of grid failure and before starting the emergency power supply genset. Lead-acid battery is a well-known technology and models detail deeply its physical behaviour and its lifetime [2] [3].

For GreenDataNet prototype it has been decided to use second-life Nissan Leaf lithium-ion batteries. Lithium-ion battery technology is widely studied but stays very complex to understand; it is only a 20-years old technology. Numerous components (electrode, electrolyte, collectors, and separators) are gathered, then large variety of lithium-ion batteries exists depending on the material choice for each of these components.

The Nissan battery is a LMO+LNO/Graphite lithium-ion battery. Understanding the physical behaviour of such technology is not required for GreenDataNet modelling to calculate optimal strategies and to simulate energy flows in the system. Analytical models and empirical data will be respectively used for these two applications, optimization and simulation. Nevertheless even for such general modelling several parameters such as State-Of-Charge (SOC), State-Of-Energy (SOE), charging/discharging rates, temperature have a great impact on the results.

Nissan has provided technical generic specifications at beginning of life of the Leaf battery to help the configuration of the models regarding the impact of such parameters. On-going lab tests on Leaf battery will help to update the models with test measurements at beginning of life but also after ageing process.

For the moment no data are available regarding the SOH (State-Of-Health) of the battery on capacity losses or on internal resistance increases regarding temperature, on charged/discharged energy and on SOE. Laboratory characterization of Leaf battery (Task 1.3.3) could help to get some results and to integrate them in updated battery analytical models fed by empirical data with SOH consideration.

2.1 ANALYTICAL MODELS FOR OPTIMIZATION IN SEMS AND AEMS

The main objective for using the analytical model of storage component for optimization is to calculate the optimal scheduling of storage(s) with short term forecasting. In general, this horizon could go from 24h to 48h with time step from 30 min to 1 hour.

The optimal solution for storage management is calculated with discrete time step ΔT; the horizon H of control contains K periods of ΔT and K is integer number ($K \in$N).

$SOE(k)$ is defined as the state of energy of the storage for the time step k. The SOE index reports the available energy in the battery at a given time regarding the past charging and discharging conditions. It is defined in a similar way than the SOC index used for the available capacity in the battery.

The $E(k)$ is the energy charged in (<0) and discharged (>0) from the storage in the time step k regarding the nominal energy value of the battery; it is unit-less (it is similar to a ΔSOE).

Depending on the technical constraints for the optimization problem (i.e. number of variables or speed of calculation) and the quality of the available technical information on the storage several analytical models with different levels of accuracy can be defined. The more complex the model is, the harder the resolution of the optimization problem is.

2.1.1 100% EFFICIENCY MODEL

First it can be considered that the efficiency value of the storage is 1. Then, the evolution of State Of Energy (SOE) is determined as follows:

$$SOE(k+1) = SOE(k) - E(k)\ \forall k \in [1, K-1]$$

The maximum of charging/discharging energy during a time step is limited regarding the physical constraints of the battery (total energy of the battery and maximal currents in charge and discharge). The simplest way to model it is considering those limits are constant and do not depend on ageing, temperature or charge and discharge rates.

$$E_{min} \leq E(k) \leq E_{max}\ \forall k \in [1, K]$$

In order to limit the ageing of the battery or to always keep the possibility to charge or discharge the battery, some minimal and maximal values of the SOE can be defined. These limits can be considered constant and are described by the following equation:

$$SOE_{min} \leq SOE(k) \leq SOE_{\max} \ \forall k \in [1, K]$$

Hence a first simple analytical model of the battery is defined by the following set of SOE evolution and constraints equations:

$$\begin{cases} SOE(k+1) = SOE(k) - \ E(k) \ \forall k \in [1, K-1] \\ E_{min} \leq E(k) \leq E_{max} \forall k \in [1, K] \\ SOE_{min} \leq SOE(k) \leq SOE_{\max} \ \forall k \in [1, K] \end{cases}$$

2.1.2 CONSTANT EFFICIENCY MODEL

A more accurate analytical model can be defined by considering that the efficiency during charge is different from the one in discharge. It is general the case in practice. The variables $E_{dis}(k)$ and $E_{ch}(k)$ which are the energy of discharging and charging phases should be defined. The efficiency of charging phase is defined as μ_{ch} and μ_{dis} is used for discharging phase ($0 \leq \mu_{ch} \leq 1, \mu_{ch} \in R$ and $0 \leq \mu_{dis} \leq 1, \mu_{dis} \in R$). The same value can be chosen for charge and discharge. These efficiencies are single value for all the conditions regardless the temperature, the SOE or the rates of charge and discharge.

The SOE value at the following time step regarding the condition of the time step k is calculated as follows:

$$SOE(k+1) = SOE(k) - \mu_{ch} \times E_{ch}(k) - \frac{1}{\mu_{dis}} \times E_{dis}(k) \ \forall k \in [1, K-1]$$

As charging phase and discharging phase could not happen at the same time, a logical constraint equation as to be defined:

$$E_{ch}(k) \times E_{dis}(k) = 0 \ \forall k \in [1, K]$$

This more advanced analytical model of the battery is defined with the next set of equations.

$$\begin{cases} SOE(k+1) = SOE(k) - \mu_{ch} \times E_{ch}(k) - \frac{1}{\mu_{dis}} \times E_{dis}(k) \ \forall k \in [1, K-1] \\ E_{ch}(k) \times E_{dis}(k) = 0 \ \forall k \in [1, K] \\ E_{min} \leq E_{ch}(k) \leq E_{max} \forall \ k \in [1, K] \\ E_{min} \leq E_{dis}(k) \leq E_{max} \forall \ k \in [1, K] \\ SOE_{min} \leq SOE(k) \leq SOE_{\max} \ \forall k \in [1, K] \end{cases}$$

The issue of this analytical model is that it is not a linear model due to the second equation.

It could be better to build a new version of this model by using a mixed linear analytical approach with both linear and non-linear variables:

$$\begin{cases} SOE(k+1) = SOE(k) - \gamma(k) \times \mu_{ch} \times E_{ch}(k) - (1-\gamma(k)) \times \frac{1}{\mu_{dis}} \times E_{dis}(k) \ \forall k \in [1, K-1], \gamma(k) \in \{0,1\} \\ E_{min} \leq E_{ch}(k) \leq E_{max} \forall \ k \in [1, K] \\ E_{min} \leq E_{dis}(k) \leq E_{max} \forall \ k \in [1, K] \\ SOE_{min} \leq SOE(k) \leq SOE_{\max} \ \forall k \in [1, K] \end{cases}$$

2.1.3 VARIABLE EFFICIENCY MODEL

The limitation of such analytical model is it does not take into account the impact of SOE and/or charging/discharging powers on the efficiencies. If SOE and charging discharging rates/powers (or the time step energy as the power rate is constant) are considered the model is described as follows:

$$\begin{cases} SOE(k+1) = SOE(k) - \gamma(k) \times \mu_{ch}\big(SOE(k), E_{ch}(k)\big) \times E_{ch}(k) - (1-\gamma(k)) \times \dfrac{1}{\mu_{dis}(SOE(k), E_{dis}(k))} \times E_{dis}(k) \\ \forall k \in [1, K-1], \gamma(k) \in \{0,1\} \\ E_{min} \le E_{ch}(k) \le E_{max} \forall\, k \in [1, K] \\ E_{min} \le E_{dis}(k) \le E_{max} \forall\, k \in [1, K] \\ SOE_{min} \le SOE(k) \le SOE_{\max}\ \forall k \in [1, K] \end{cases}$$

The temperature influence on the results (increasing of internal resistance and decreasing of available energy with cold temperatures) **is not integrated** by this analytical model. However it has been decided that as the battery will be used mainly at room temperature. Batteries will be installed in a temperature regulated room and small charging/discharging rates should not lead to high increase of battery internal temperature. So temperature has not to be considerate in the analytical model for optimization.

No ageing of lithium-ion battery effects on available energy and efficiencies are considered in such analytical model as no ageing data of Nissan Leaf battery are available for now. It could be implemented later.

2.1.4 VARIABLE ENERGY LOSSES MODEL

The **analytical battery model finally used by the SEMS and AEMS software** is close to the previous one. It takes into account the same parameters but instead using charging/discharging efficiencies the **energy losses are modelled**. It has been assumed that these energy losses only depend on the charging/discharging power during the time step (hence on the charged/discharged energy as constant power is applied during a time step) and not on the SOE. The following set of equations presents the approach selected for building the model used for the optimization process of GreenDataNet SEMS and AEMS.

$$\begin{cases} SOE(k+1) = SOE(k) - \gamma(k) E_{DCch}(k) - (1-\gamma(k)) E_{DCdis}(k)\ \forall k \in [1, K-1], \gamma(k) \in \{0,1\} \\ E_{DCch}(k) = E_{DCbusch}(k) - E_{lossesch}(E_{DCbusch}(k))\ \forall k \in [1, K] \\ E_{DCdis}(k) = E_{DCbusdis}(k) - E_{lossesdis}(E_{DCbusdis}(k))\ \forall k \in [1, K] \\ E_{DCmin} \le E_{DCch}(k) \le E_{DCmax} \forall\, k \in [1, K] \\ E_{DCmin} \le E_{DCdis}(k) \le E_{DCmax} \forall\, k \in [1, K] \\ E_{DCbusmin} \le E_{DCbusch}(k) \le E_{DCbusmax} \forall\, k \in [1, K] \\ E_{DCbusmin} \le E_{DCbusdis}(k) \le E_{DCbusmax} \forall\, k \in [1, K] \\ SOE_{min} \le SOE(k) \le SOE_{\max}\ \forall k \in [1, K] \end{cases}$$

E_{DCch} is the energy effectively charged in the battery whereas $E_{DCbusch}$ is the energy supplied at the output of the DC/DC battery converter in order to charge the battery.

In the same way $E_{DCbusdis}$ is the energy at the input in discharge of the DC/DC converter whereas E_{DCdis} is the energy really discharged from the battery.

2.2 POWER-ENERGY EFFICIENCY BASED ANALYTICAL MODEL FOR SIMULATION

The analytical model used for the simulation for the GreenDataNet project is close to the one used for the optimization. Electrical equivalent models could be used but it has been decided to **use a power-energy model with efficiencies consideration** as the focus of GreenDataNet is on energy management and not on electrical simulations.

$$
\begin{cases}
SOE(i+1) = SOE(i) - \int_{i}^{i+1} \frac{P_{DCch}(t)}{3600 *\ E_{nom}} * Eff_{ch}\big(SOE(t), P_{DCch}(t)\big)dt, \qquad in\ charge \\
SOE(i+1) = SOE(i) - \int_{i}^{i+1} \frac{P_{DCdis}(t)}{3600 *\ E_{nom}} * \frac{1}{Eff_{dis}\big(SOE(t), P_{DCdis}(t)\big)}dt, \qquad in\ discharge \\
P_{DCch}(t) * P_{DCdis}(t) = 0 \\
P_{DCchmax}(SOE(t)) \leq P_{DCch}(t) \leq 0 \\
0 \leq P_{DCdch}(t) \leq P_{DCdismax}\ (SOE(t)) \\
SOE_{min} \leq SOE(i+1) \leq SOE_{\max}
\end{cases}
$$

The current simulated time step is defined as *i*. The analytical power-energy model used for GreenDataNet energy simulations is given by the following set of six equations:

Where *t* is the simulation time in seconds, $P_{DCch}(t)$ is the charging power (<0) from DC busbar of the UPS (constant from *i* to *i*+1), $P_{DCdis}(t)$ is the discharging power (>0) to DC busbar during the current simulation time step (constant from *i* to *i*+1), SOE(*t*) is the state of energy of the battery at the beginning of the current simulation time step, E_{nom} is the nominal energy of the battery (given under standard testing conditions in Wh), Eff_{ch} is the charging efficiency of the battery regarding SOE and charging power values, and Eff_{dis} is the discharging efficiency of the battery regarding SOE and discharging power.

It is not allowed to have a charge and a discharge during the same simulated time step and it is transcript by the third equation of the selected model.

The values of the battery efficiencies in charge and in discharge depend on the current SOE value and the current power value (in charge or in discharge). Based on data given by Nissan about electrical characterization of the Leaf battery, such empirical tables of efficiencies regarding SOE and power have been built (see next part 2.3). Efficiencies do not depend on temperature in this model.

The charging and discharging powers of the battery are also limited (4th and 5th equations) by the electrical characteristics of the lithium-ion cells within the Leaf battery but also by the Leaf BMS (Battery Management System). The BMS operation permits to use the battery safely and to avoid fast decrease of battery performances. These limitations of power depend on the SOE value. Empirical tables can also be built based on Nissan information. The temperature is not considered in this model for power limitations as the battery will be mainly operated at room temperature.

It has been decided to allow the limitation of SOE between a fixed maximal and nominal values (6th equation) for slowing battery ageing or for energy management purposes (to keep ability to charge or discharge the battery in case of defined 'emergencies' for instance).

2.3 BUILDING EMPIRICAL SETS OF DATA FOR BATTERY MODELS

2.3.1 INPUT DATA

The developed analytical battery model for simulation is Power/Energy efficiency based one. Energy losses analytical model is also used for SEMS and AEMS optimizations. Both models need some empirical set of data to run. Based on Nissan Leaf electrical characterization these sets of data aim at giving and computing:

- The charging and discharging current and efficiencies, then losses
- The nominal energy Enom
- The maximal charging power regarding SOE value Pmaxch(SOE)
- The maximal discharging power regarding SOE value Pmaxdisch(SOE)

The function used to build the empirical sets of data returns tables of battery charging and discharging efficiencies and charging and discharging currents with reference to the following breakpoints: SOEref brkpts and Pref brkpts

The operational parameters for the Nissan Leaf lithium-ion battery are listed hereafter which are taken as inputs for the building empirical data function.

- Following the Nissan EV Battery Specs provided for GreenDataNet project, the cells used in the Leaf battery are lithium-ion LMO+LNO/Graphite cells with a nominal voltage of 3.75V and a capacity cell-Cnom=32.5Ah. The cell nominal capacity is given for a discharging rate of 0.3C (discharge in 3 hours), at Beginning-Of-Life (BOL) and at 25°C. The resulting cell nominal energy value is about 122Wh with an energy density of 317Wh/l and a specific energy of 157Wh/kg.

- Number of cells in series (for the battery pack): nCellSeries

The Leaf battery is an assembly of 48 modules in series. Each module is composed of 2 cells in parallel and 2 cells in series. So, 96=nCellSeries cells are connected in series in a Leaf battery resulting in a nominal voltage of 360V.

- Number of cells in parallel (for the battery pack): nCellParallel

There are 2=nCellParallel branches of cells in parallel. Nominal capacity of the Leaf battery is about 65Ah and nominal energy about 23 to 24kWh.

• Open circuit voltage (OCV) for different State of Charge (SOC) values from the OCV-SOC graph provided by Nissan (Figure 3). In this case the following SOC points are considered: refSOC=[0%, 5% 10% 20% 50% 70% 80% 90% 100%]. Only the room temperature (25°C) values are considered for GreenDataNet and the size of the matrix obtained in this case is [1 X number of SOC points] = [1 x 9].

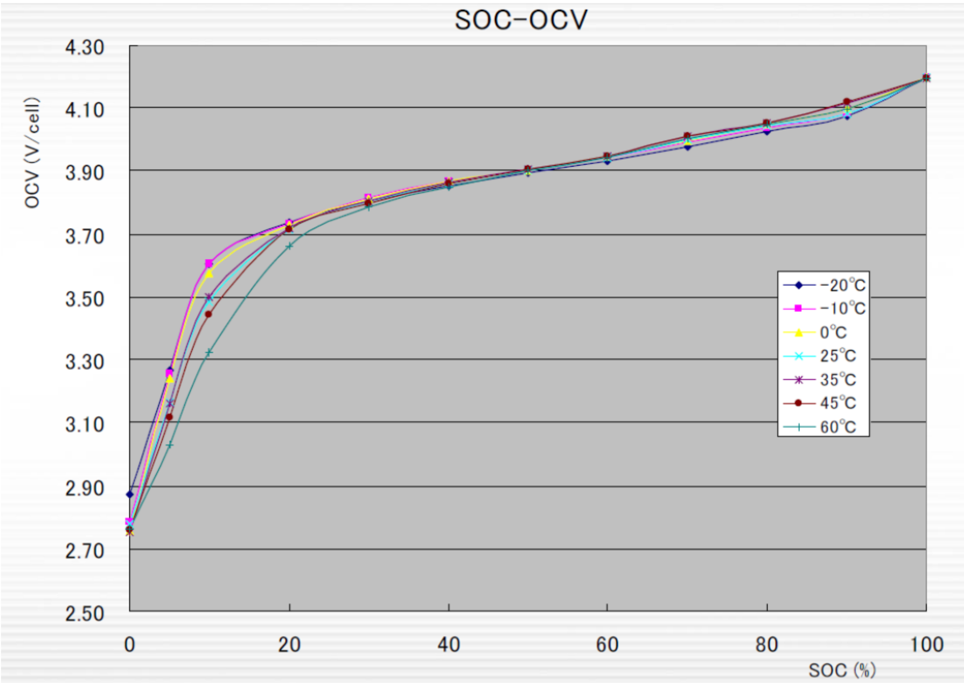

Figure 3. OCV=f(SOC) characteristic for Nissan Leaf battery cell at BOL.

• The minimum cell voltage and maximum cell voltage are also defined in the inputs: CellUmindisch and CellUmaxch. These are the operational voltage limits of the cell which should be always respected. BMS controls them. If cells are overdischarged or overcharged it could result to a fast degradation of cell performances and to security issues (thermal runaway).

Following Nissan specifications CellUmindisch=2.5V and CellUmaxch=4.2V. It leads to a minimal voltage for the battery of 240V=BatteryUmin and a maximal voltage of 403.2V=BatteryUmax.

This minimal voltage stands for SOC 0% value whereas SOC 100% corresponds to the maximal voltage.

• The maximum charging current (cellImaxch) for a cell (for the same SOC points [refSOC] as above) is taken from the Nissan datasheet. It is taken to be maximum at SOC = 0% and at SOC= 100% it is taken to be zero. From SOC 0% to SOC 90% the maximum charging current is set to the cell maximum current given by Nissan which is 100A (200A=BattImaxch for the battery).

It is matrix of size [1 X number of SOC points] = [1 x 9].

• The maximum discharging current (cellImaxdch) for a cell is defined in a similar fashion as cellImaxch with the slight difference that at SOC=0%, cellImaxdch = 0 and at SOC=100% it is the maximum discharging current. From SOC 5% to SOC 100% the maximum discharging current is set to the cell maximum current specified by Nissan which is 200A (400A=BattImaxdch for the battery).

The size of the matrix is [1 X number of SOC points] = [1 x 9].

• The cell resistance during charge for different current rates and different SOC values (refSOC, as mentioned earlier) are inputs in the matrix Rch_bat. In fact this gives charging resistance as a function of current and SOC.

$$Rch_{bat} = f(I, SOC)$$

The resistance is obtained from the I-V characteristics of the Leaf battery supplied by Nissan for different C rates at 25°C and obtained at different SOC levels (Figure 4).

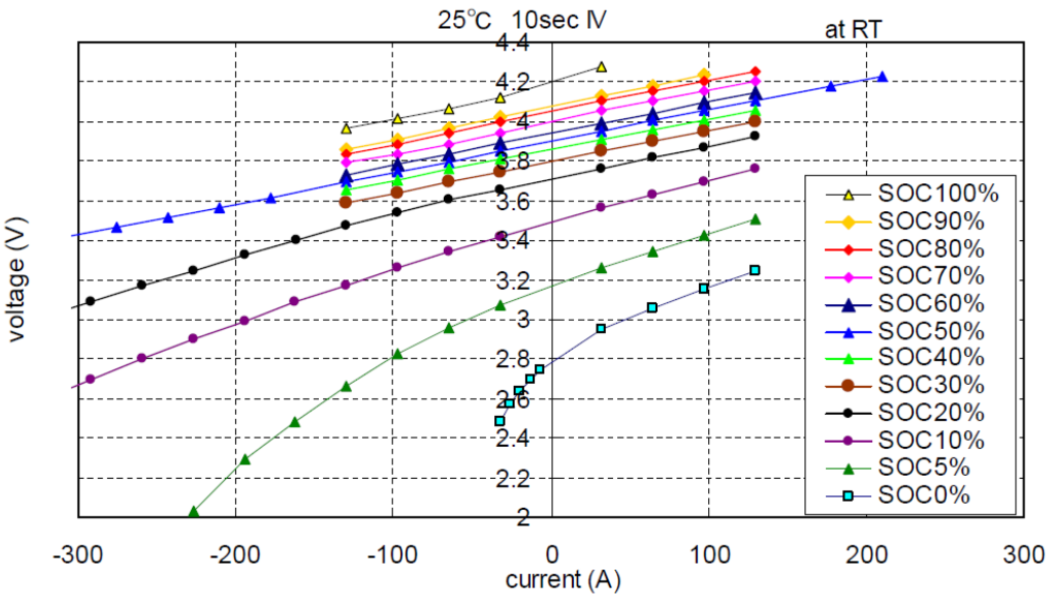

Figure 4. IV-characteristics curves at different SOC for 1 cell of Nissan Leaf battery (I<0 in discharge).

The 10sec charge pulse method is used to calculate the charging resistance following the equation here after:

$$Rch(SOC, I) = \frac{U_{10\text{sec}}(SOC, I) - U_{OCV}(SOC)}{I_{pulse}}$$

Only C rates values that are smaller or slightly higher than the maximal charging current have been considered; the points of previous figure from 0 to 4C (130A) are taken into account. Thus the size of the matrix is: [(number of C rates considered)charging x number of SOC points] = [5 x 9].

Considering the number of cells in series, nCellSeries, and in parallel, nCellParallel, the charging cell resistance matrix for the whole battery is given in the following table. The charging resistance values for 0C are the same than the discharging ones and have been calculated thanks to a linear interpolation between the charging resistance values at 1C and the discharging resistance values at 1C.

Rch_bat (Ω)

Rate \ SOC (%)	0	5	10	20	50	70	80	90	100
0C	0,3415	0,1292	0,1015	0,0831	0,0739	0,0923	0,0831	0,0831	0,1108
1C	0,2533	0,1557	0,1134	0,0713	0,0738	0,0923	0,1029	0,0765	0,1108
2C	0,2097	0,1424	0,1121	0,0726	0,0738	0,0831	0,0884	0,0752	0,1108
3C	0,1890	0,1319	0,1055	0,0730	0,0738	0,0800	0,0774	0,0747	0,1108
4C	0,1741	0,1266	0,1068	0,0778	0,0738	0,0738	0,0765	0,0745	0,1108

Table 1. Charging resistance (in Ohms) values of Nissan Leaf battery regarding different SOC and charging rates.

This matrix is linearized and a function has been created to find the internal charging resistance of the battery whatever SOC and charging current values. The map in Figure 5 illustrates this function. The cell resistance during charge is more impacted by SOC than by charging current.

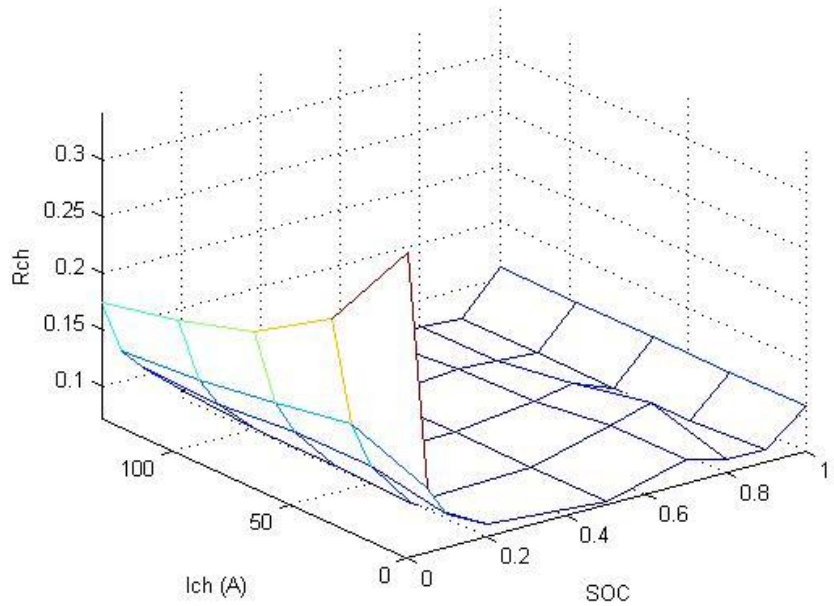

Figure 5. Map of charging resistance (in Ohms) values of Nissan Leaf battery regarding different SOC and charging currents.

- A similar method is employed for determining discharging battery resistance, Rdch_bat, at different C rates and SOC values.

$$Rdch(SOC, I) = \frac{U_{OCV}(SOC) - U_{10sec}(SOC, I)}{|I_{pulse}|}$$

C rates values from 0 to 7C (227.5A) have been considered. It has been decided for presentation purpose that the C rate/current values of the Rdch matrix are reported with positive values (even if Nissan uses the battery convention, I<0 for discharge, for the Leaf battery specifications).

If no 10sec voltage measurements are available in Figure 4 an extrapolated (linear extrapolation) value has been calculated. Thus the size of the matrix in this case is: [(number of C rates considered)discharging x number of SOC points] = [8 x 9]. The next table gives this matrix for the entire Leaf battery, and not only cell.

Rdch_bat (Ω)

Rate \ SOC (%)	0	5	10	20	50	70	80	90	100
0C	0,3415	0,1292	0,1015	0,0831	0,0739	0,0923	0,0831	0,0831	0,1108
1C	0,4298	0,1028	0,0896	0,0948	0,0738	0,0923	0,0632	0,0896	0,1108
2C	0,4335	0,1529	0,1002	0,0843	0,0923	0,0831	0,0778	0,0817	0,1015
3C	0,4298	0,1635	0,1099	0,0808	0,0738	0,08	0,0826	0,0853	0,0862
4C	0,4298	0,1872	0,1147	0,0883	0,0738	0,0738	0,0758	0,0824	0,0877
5C	0,4298	0,2015	0,1176	0,0928	0,0738	0,0702	0,0717	0,0807	0,0886
6C	0,4298	0,211	0,1196	0,0958	0,0738	0,0677	0,069	0,0796	0,0892
7C	0,4298	0,2178	0,1209	0,0979	0,0738	0,0659	0,0614	0,0787	0,0897

Table 2. **Discharging resistance (in Ohms) values of Nissan Leaf battery regarding different SOC and discharging rates.**

This matrix is linearized and a function has been created to find the internal discharging resistance of the battery whatever SOC and discharging current values. The map in Figure 6 illustrates this function and only a slight variation can be observed regarding the discharging current.

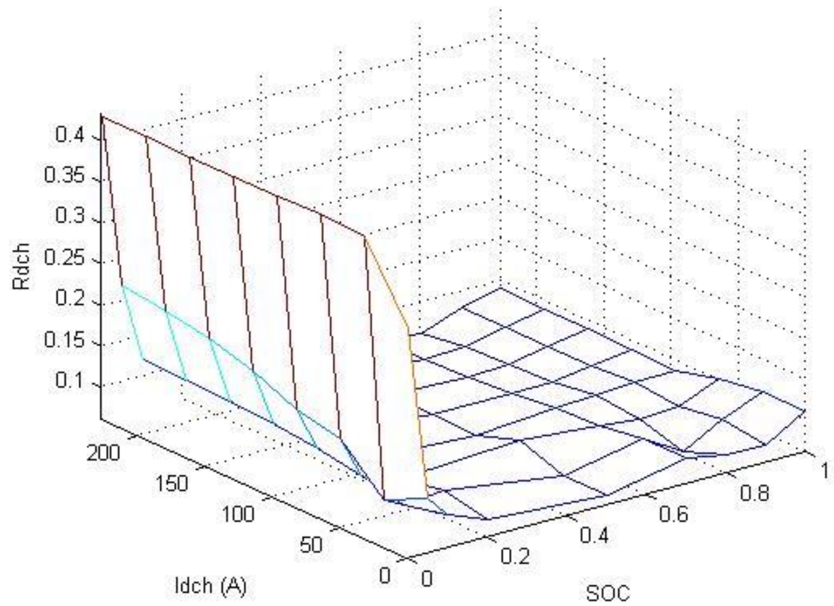

Figure 6. **Map of discharging resistance (in Ohms) values of Nissan Leaf battery regarding different SOC and discharging currents.**

• The faradic efficiencies in charge and in discharge illustrate the losses in the battery due to side reactions that consume current (could be equations of corrosion, passivation …). For lithium-ion cells in normal operation conditions, the faradic efficiencies are generally almost 100%. As no specific values are available for the Nissan Leaf battery, a 100% faradic efficiency has been considered both in charge and in discharge.

•	Finally, the minimum cell SOC and the maximum cell SOC are user inputs under the variable names cellSOCmin and cellSOCmax respectively. Varying these variables increases or decreases the operating range of the battery and the energy available for use. The Leaf battery will not be used in extreme conditions and should not perform lots of charge and discharge cycles per day, so a cellSOCmin value of 0 and a cellSOCmax value of 1 are setup for the moment.

2.3.2 METHODOLOGY

Enom corresponds to the "total nominal DC energy" in the battery. It is defined as the integral of (Idc*Udc)dt, which can also be expressed in the following way:

$$E_{nom}(t) = \int_{t0}^{t} U_{batt}(t) * C_{nombatt} * \frac{dSOC(t)}{dt}\, dt$$

As,

$$I_{batt}(t) = C_{nombatt} * \frac{dSOC(t)}{dt}$$

The nominal energy can also be expressed as the integral under the OCV-SOC curve multiplied by the capacity of the battery Cn_{ombatt} from the input data of cell capacity cellCnom and number of cell in parallel nCellParallel ($C_{nombatt}$= cellCnom* nCellParallel). Only the OCV-SOC curve part between cellSOCmin and cellSOCmax is considered to calculate the nominal energy.

Thanks to this method the calculated nominal energy of the Leaf battery at 25°C for the model is of 23896 Wh. It is consistent with the nominal energy given by Nissan, 23 to 24kWh.

For generating the results, different SOC values than the ones used for the inputs can be set. These new values take into account the SOC min and SOC max value.

Values of SOC as newSOCvalues=[0%, 5%, 10%, 20%, 50%, 80%, 90%, 95%, 100%] have been selected as an example. There is the same number of SOC values than for the inputs but it could be different. These new values are associated to SOC values (refSOC) without integrating SOC limitations of the battery.

$$refSOC = cellSOCmin + (cellSOCmax - cellSOCmin) * newSOCvalues$$

Rather than SOC (State-of-Charge, i.e. related to capacity [Ah]), SOE (State-of-Energy, i.e. related to energy [Wh]) values have to be considered for the results. Regarding the OCV-SOC curves and the nominal energy of the battery, SOE values are associated to the newSOCvalues but also to the reference ones refSOC (used for inputs).

$$SOE(SOC) = \frac{E_{batt}(SOC)}{E_{nom}}$$

The following table gives the corresponding SOE values to the new SOC values.

newSOCvalues (%)	0%	5%	10%	20%	50%	80%	90%	95%	100%
SOE (%)	0%	3,87%	8,21%	17,61%	47,44%	78,57%	89,18%	94,55%	100%

Table 3. Corresponding SOE values to new defined SOC values for generating results.

The first wanted results for the power-energy analytical models (energy losses for optimization and efficiencies for simulation) of the battery component for GreenDataNet are the maximum charging and discharging power regarding the SOE values (see Part 2.2).

At any time the maximum operational voltage of the battery is the minimum of the maximum PCS voltage (PCSubusmax=410V for Eaton battery converter) on DC bus for battery connection and the maximum battery voltage (BatteryUmax=403.2V for Leaf battery as explained in the previous part).

$$Ubatmax = \min(PCSubusmax, BatteryUmax)$$

Similarly the minimum operational voltage limit for the system is defined as the maximum of the minimum PCS voltage on DC bus for battery connection (PCSubusmin=326V for Eaton battery converter) and the minimum battery voltage (BatteryUmin=240V).

$$Ubatmin = \max(PCSubusmin, BatteryUmin)$$

The maximum charging and discharging currents (positive values) are limited by these voltage thresholds and the internal resistance as detailed by the two following equations.

$$Ibatmaxch(SOE) = \frac{Ubatmax - OCV(SOE)}{R_{ch}(SOE, I)}$$

$$Ibatmaxdch(SOE) = \frac{OCV(SOE) - Ubatmin}{R_{dch}(SOE, I)}$$

As some current limitations are also given by Nissan for charging and discharging the battery as inputs, i.e. BattImaxch=200A and BattImaxdch=400A, the maximal operational currents for charging and discharging the battery are the minimal values (positive values).

$$Imaxch(SOE) = \min(Ibatmaxch(SOE), BattImaxch)$$

$$Imaxdch(SOE) = \min(Ibatmaxdch(SOE), BattImaxdch)$$

Then the maximum charging power and discharging power of the battery can be calculated to be implemented in the analytical power-energy model.

$$Pbatmaxch(SOE) = Imaxch(SOE) * (OCV(SOE) + R_{ch}(SOE, Imaxch) * Imaxch\ (SOE))$$

$$Pbatmaxdch(SOE) = Imaxdch(SOE) * (OCV(SOE) - R_{dch}(SOE, Imaxdch) * Imaxdch(SOE))$$

These **maximum powers are absolute values** and depend on SOE but **for the following calculations** the **charging power values are negative** and the **discharging power values are positive** (generator convention and not battery convention). For the maximal power in discharge it is assumed here that it occurs at the maximal discharging current.

The maximum of these two Pbatmax vectors are used to define the power breakpoints (Pbatch_brk and Pbatdch_brk) during charging and discharging as a fraction of them.

These breakpoints are used to calculate battery efficiency and associated energy losses during charging and discharging. The running of the efficiency power-energy analytical model developed for simulation in GreenDataNet is based on a set of empirical data: maximum power vectors in charge and in discharge regarding SOE values, and efficiency matrixes in charge and in discharge regarding SOE and power values. On the other hand the energy losses power-energy analytical model (selected for optimization) is also based on a set of empirical data: maximum power vectors in charge and in discharge regarding SOE values, and energy losses matrixes in charge and in discharge regarding SOE and power values. It is needed then to perform a piecewise linearization of this set of data for optimization software.

Ich is defined as the charging current of the battery (Ich<0 for generator sign convention, at the opposite of battery sign convention). At every SOE and charging power breakpoints defined for building the efficiency matrix, the following equation has to be satisfied.

$$OCV(SOE) * I_{ch} + I_{ch}^2 * R_{ch}(SOE, I_{ch}) - P_{batch_{brk}} = 0$$

A similar equation has to be satisfied in discharge for each (SOE, discharging power breakpoints) pair.

$$-OCV(SOE) * I_{dch} + I_{dch}^2 * R_{dch}(SOE, I_{dch}) + P_{batdch_{brk}} = 0$$

For determining Ich and Idch values, these nonlinear optimization problems are solved using '*fsolve*' optimization tool in Matlab.

The matrixes of efficiency in charge and in discharge are calculated by comparing the charge/discharge power with the internal resistance consideration and the charge/discharge power without the internal resistance.

If no internal resistance exists, the power charged in the battery at the defined SOE and power in charge and in discharge breakpoints, respectively *i*, *j* and *k*, should be:

$$P_{batchideal}(i,j) = OCV\big(SOE(i)\big) * I_{ch}\left(SOE(i), P_{batch_{brk}}(j)\right) * FaradicEfficiency_{ch}(SOE(i), P_{batch_{brk}}(j))$$

And the discharged power should be:

$$P_{batdchideal}(i,k) = OCV\big(SOE(i)\big) * I_{dch}\left(SOE(i), P_{batdch_{brk}}(k)\right) * FaradicEfficiency_{dch}(SOE(i), P_{batdch_{brk}}(k))$$

For lithium-ion batteries, there are almost no parasitic side reactions (corrosion …) and a value of 1 is considered for the faradic efficiency.

The power effectively charged in the battery at the same SOE and power in charge breakpoints is:

$$P_{batch}(i,j) = I_{ch}\left(SOE(i), P_{batch_{brk}}(j)\right) * (OCV\big(SOE(i)\big) + R_{ch}(SOE(i), I_{ch}\left(SOE(i), P_{batch_{brk}}(j)\right)) * I_{ch}(SOE(i), P_{batch_{brk}}(j))$$

Whereas the discharge power is calculated as follows:

$$P_{batdch}(i,k) = I_{dch}\left(SOE(i), P_{batdch_{brk}}(k)\right) * (OCV\big(SOE(i)\big) + R_{dch}(SOE(i), I_{dch}\left(SOE(i), P_{batdch_{brk}}(k)\right)) * I_{dch}(SOE(i), P_{batdch_{brk}}(k))$$

Finally the charging efficiency for the SOE breakpoint i and the charging power breakpoint j is given by:

$$Eff_{batch}(i,j) = \frac{P_{batch}(i,j)}{P_{batchideal}(i,j)}$$

And the efficiencies in discharge for the SOE breakpoint i and the discharging power breakpoint k are calculated thanks to:

$$Eff_{batdch}(i,k) = \frac{P_{batdch}(i,k)}{P_{batdchideal}(i,k)}$$

2.3.3 RESULTS

Following this methodology maximal power values and efficiency values for the Nissan Leaf battery have been generated.

The Table 4 and the Figure 7 report the results obtained for the maximal power values regarding the SOE of the battery.

SOE (%)	0,00	3,87	8,21	17,61	47,44	78,57	89,18	94,55	100,00
Pmax ch (W)	-60311	-65681	-71198	-74426	-77834	-79535	-59377	-23879	0
Pmax dch (W)	0	0	23255	101731	137945	145427	144292	145613	146933

Table 4. Maximal power (in W) allowed in charge (P<0) and in discharge (P>0) for Nissan Leaf battery.

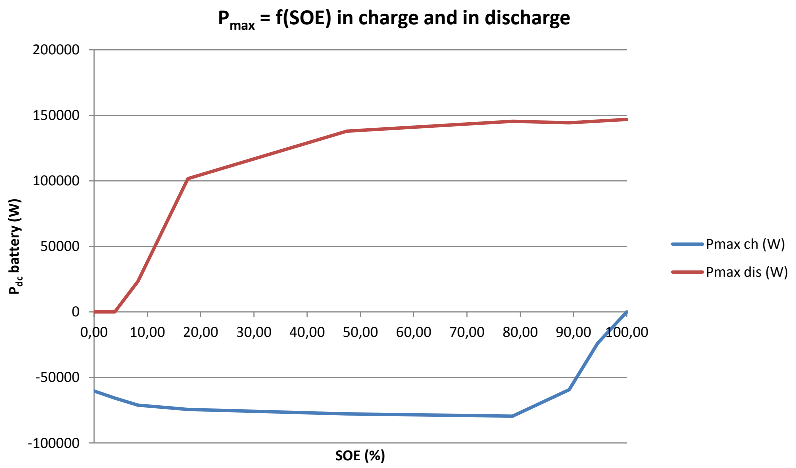

Figure 7. Maximal power (in W) allowed in charge (P<0, in blue) and in discharge (P>0, in red) for Nissan Leaf battery.

The efficiencies calculated for the Nissan Leaf battery and required for the running of the models are gathered in Table 5 regarding power and SOE values. The Figure 8 illustrates these efficiencies during the charge of the battery whereas efficiencies in discharge are plot in Figure 9.

Eff=f(Pdc [W],SOE [%])	0,00	3,87	8,21	17,61	47,44	78,57	89,18	94,55	100,00
-117000	66,67%	83,19%	88,65%	92,79%	93,81%	94,03%	94,31%	94,47%	91,97%
-105300	66,67%	85,02%	89,82%	93,52%	94,43%	94,63%	94,89%	95,03%	92,78%
-93600	73,79%	86,79%	90,98%	94,25%	95,06%	95,23%	95,45%	94,50%	93,59%
-81900	78,29%	88,52%	92,13%	95,06%	95,68%	95,80%	96,02%	95,19%	94,40%
-70200	81,95%	90,21%	93,31%	95,92%	96,30%	96,33%	96,58%	95,88%	95,20%
-58500	85,24%	91,62%	94,42%	96,64%	96,92%	96,73%	97,15%	96,56%	96,01%
-46800	87,46%	93,01%	95,38%	97,32%	97,53%	97,21%	97,71%	97,25%	96,81%
-35100	89,81%	94,48%	96,47%	98,01%	98,15%	97,74%	98,27%	97,93%	97,61%
-23400	92,29%	96,11%	97,63%	98,69%	98,77%	98,42%	98,83%	98,61%	98,41%
-11700	95,40%	98,15%	98,87%	99,29%	99,38%	99,28%	99,39%	99,31%	99,20%
0	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%
11700	92,81%	98,54%	99,00%	99,17%	99,38%	99,42%	99,34%	99,26%	99,20%
23400	82,85%	97,01%	98,07%	98,23%	98,75%	98,99%	98,62%	98,49%	98,38%
35100	69,45%	94,00%	96,87%	97,48%	97,89%	98,36%	97,99%	97,80%	97,63%
46800	50,00%	91,09%	95,51%	96,80%	96,83%	97,57%	97,42%	97,17%	96,94%
58500	50,00%	87,40%	93,96%	96,07%	96,40%	96,80%	96,74%	96,44%	96,39%
70200	50,00%	82,13%	92,38%	95,23%	96,15%	96,01%	95,97%	95,91%	95,98%
81900	50,00%	75,73%	90,72%	94,08%	95,48%	95,45%	95,30%	95,40%	95,43%
93600	50,00%	66,77%	89,00%	92,87%	94,80%	95,00%	94,68%	94,70%	94,69%
105300	50,00%	51,93%	87,20%	91,63%	94,11%	94,52%	94,05%	94,02%	93,94%
117000	50,00%	50,00%	85,30%	90,37%	93,40%	94,05%	93,42%	93,30%	93,17%

Table 5. **Calculated efficiencies of the Nissan Leaf battery in charge (P<0) and in discharge (P>0) regarding SOE and the power.**

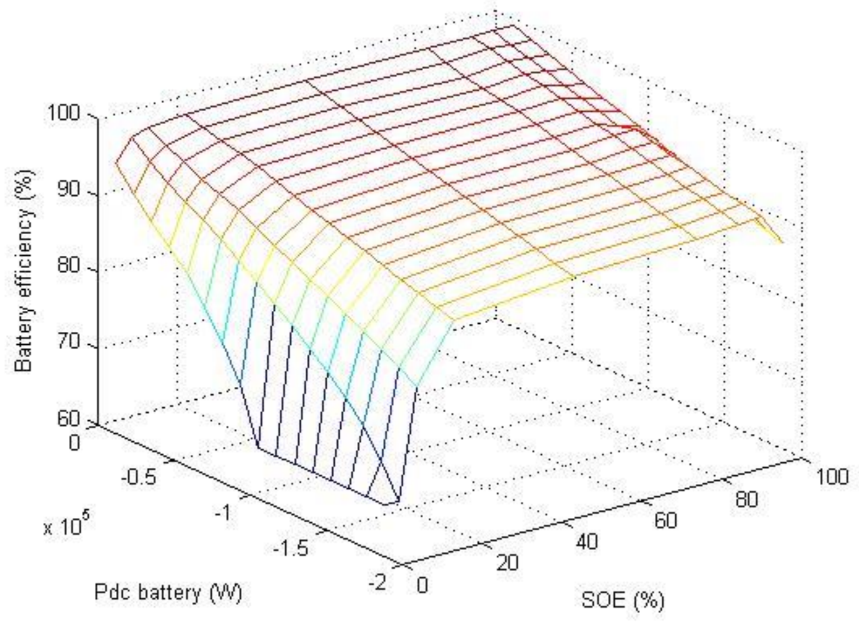

Figure 8. **Charging efficiency regarding charging power (P<0) and the battery SOE.**

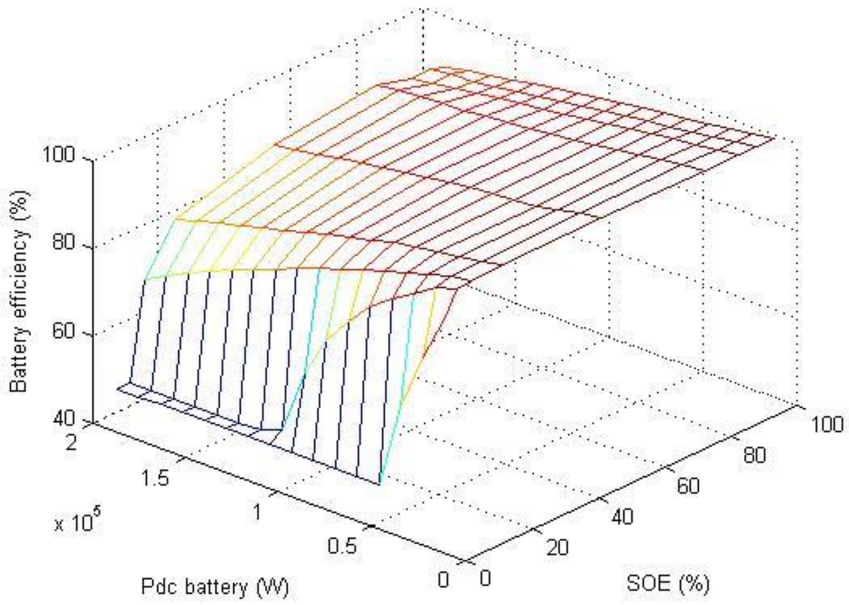

Figure 9. Discharging efficiency regarding discharging power (P>0) and the battery SOE.

As explained in the parts 2.3.1and 2.3.2 these results are based on the data provided by Nissan for the Leaf battery at the Beginning of Life. They could be changed following the laboratory test results on the Leaf battery scheduled during GreenDataNet project (Task 1.3.3).

The Table 4 and Table 5 are directly used for the power-energy analytical model for simulation. The input data of the analytical model used for SEMS/AEMS optimization are generated in order to be as close as possible to the values gathered in these tables while fulfilling integration constraints for optimization problem definition. The losses are directly calculated regarding battery efficiencies in charge and in discharge and a piecewise linearization has been applied on this calculated data.

3. UPS COMPONENT

The UPS is composed of four power converter systems (see Figure 1). A rectifier AC/DC takes power from the grid to the UPS DC bus. An inverter transform DC power from the UPS DC bus to AC power for the IT loads. A DC/DC converter with MPPT of 10kW (2*5kW) injects PV power to the UPS DC bus. Finally a bidirectional battery DC/DC converter allows charging and discharging the battery.

The efficiency of a PCS depends on output operating voltage and input power.

First the efficiencies of each PCS (rectifier AC/DC, inverter DC/AC, converters DC/DC) have been taken to be constant and equal to 98% based on Eaton information. This function can later be used to calculate the input operating power of the converter when the output operating power is known.

For the analytical models of the UPS converters, a similar approach than for the battery analytical model has been applied. Power-energy models based on losses are used for SEMS/AEMS optimization whereas power-energy models based on efficiencies are used for simulation purpose.

The **analytical model** of each power converter for **SEMS optimization** can be illustrated by the following set of equations.

$$\begin{cases} E_{out}(k) = E_{in}(k) - E_{losses}(E_{in}(k))\ \forall k \in [1, K] \\ E_{inmin} \leq E_{in}(k) \leq E_{inmax} \forall\ k \in [1, K] \\ E_{outmin} \leq E_{out}(k) \leq E_{outmax} \forall\ k \in [1, K] \end{cases}$$

E_{in} is the energy input to the converter (>0) whereas E_{out} in the energy output from the converter (>0). It is equivalent to the power as constant power values are applied for each optimization or simulation time steps.

The specific method to linearize these equations is not detailed in this deliverable but it aims to setup the energy losses E_{losses} in order to have an efficiency of 98% for each converter.

For the simulations, the used power-energy models for the different UPS converters satisfy the following equation:

$$\begin{cases} P_{out} = P_{in} * Eff_{conv}(P_{out}) \\ P_{inmin} \leq P_{in} \leq P_{inmax} \end{cases}$$

For calculating the charging and discharging DC power applied to the battery, the following formulas are used:

When charging

$$P_{battch} = P_{inbattconv} * Eff_{battconv}(P_{battch})$$

When discharging

$$P_{battdis} = \frac{P_{outbattconv}}{Eff_{battconv}(P_{outbattconv})}$$

As for the battery analytical models **some empirical data are used** to run the models. Regarding the converter components Eaton has performed the tests and provided the figures.

The minimal power is set to 0 whereas the maximal power is of 50kVA/50kW regarding GreenDataNet prototype specifications for the AC/DC rectifier, DC/AC inverter and DC/DC battery converter for discharge.

The maximum input power for PV DC/DC converter is set to 10kW whereas the maximum input power for charging the battery is limited to 10kW. The real power limitation of the prototype DC/DC converter for battery charging is of 10kW if $P_{ACITloads}$ is inferior to 40kVA, and 6kW if $P_{ACITloads}$ is above 40kVA; but only the 10kW limitation has been implemented for the moment in both analytical models.

As explained in the Part 2.3.2 of this deliverable the minimal and maximal voltage of the battery bus side of the DC/DC battery converter have been considered (PCSubusmin=326V and PCSubusmax=410V following Eaton data) for the battery model.

Beyond the average efficiency value of 98% for each converter, Eaton has certified the double conversion mode efficiency of the prototype (rectifier then inverter) and the battery mode operation in discharge (battery converter then inverter). The more accurate efficiency values are used in the analytical model for simulation.

The hypothesis that the efficiency of both rectifier and inverter is the square root of the certified double conversion mode efficiency was done.

The considering efficiencies of the UPS rectifier and inverter for the power-energy model used for the simulations are gathered in the following table.

Pout (%Pmax)	10	20	25	30	40	50	60	70	75	80	90	100
Efficiency (%)	95,60%	97,52%	97,83%	98,03%	98,23%	98,29%	98,29%	98,29%	98,29%	98,23%	98,18%	98,13%

Table 6. Efficiency of UPS rectifier and inverter regarding output power.

The efficiency of the battery converter can be calculated considering the inverter efficiency values and the battery mode operation of the GreenDataNet prototype. The values are reported in the following table.

Pout (%Pmax)	10	20	25	30	40	50	60	70	75	80	90	100
Efficiency (%)	94,24%	95,16%	95,78%	96,50%	96,61%	97,17%	97,27%	97,37%	97,37%	97,42%	97,37%	97,52%

Table 7. Efficiency of UPS DC/DC converter regarding output power.

These empirical data are directly used for the power-energy analytical model for simulation. They could be slightly adapted for the analytical model used for SEMS (and possibly AEMS) optimization to generate the energy losses. But it has been decided, as mentioned above, for the optimization power-energy analytical models of converters to keep a constant efficiency of 98% for all the converters.

For the software developed to test the electricity consumption forecasting tool (Deliverable 3.2) a polynomial analytical model of the efficiency is used for all the converters. The efficiency is expressed regarding the input power (and not the output power) and a lookup table obtained by interpolation of experimental results is used.

The following equation has been generated for this Deliverable 3.2 and applied to all the GreenDataNet UPS converters.

$$Eff_{conv}(P_{in}) = 1 - \frac{1}{P_{in}} * \left(0.0094 + 0.0043 * P_{in} + 0.04 * P_{in}^2\right)$$

4. PV COMPONENT

The PV cell and PV modul modelling is a widely studied in literature [4] [5] [6] [7]. The aim of this deliverable is not performing a review of the existing model but only to propose one analytical model for GreenDataNet project.

The electrical performances of a PV panel are dependent from the used material characteristics and from the fabrication process. They are illustrated by the PV panel I-V characteristic curve and are impacted by the irradiance level on the module and the temperature of the module (Figure 10).

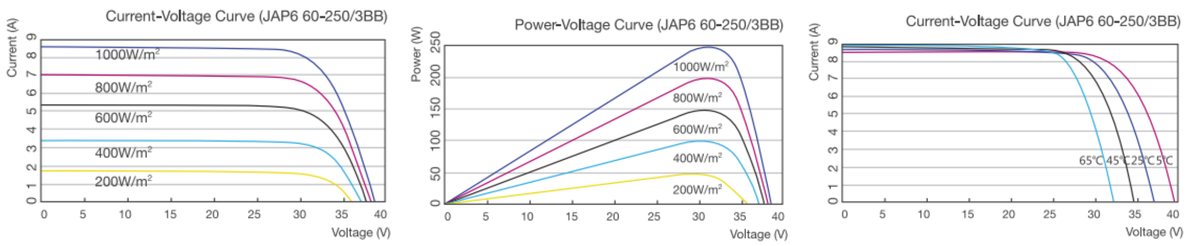

Figure 10. Impact of irradiance and temperature on I-V characteristic curve and power-voltage curve of a PV module manufactured by JA Solar (ref JAP6 60-260/3BB) [8]

Two analytical models are presented in the following parts: under given irradiance and temperature, the first one aims at matching the I-V characteristic curve and the second one permits to generate the maximum PV power. These models are approximate ones and do not stand for the electrical losses due to cabling, shadow effects, real irradiance angle … Other models are widely documented in literature.

4.1 ANALYTICAL EQUIVALENT ELECTRICAL CIRCUIT MODEL FOR PV MODULE

A common approach to model the PV panel consists in an analytical equivalent electrical circuit model in order to provide the I-V characteristic regarding irradiance and temperature. Double diode PV model are presented in literature but in this deliverable only a single diode PV model is detailed, based on [4] and [5]. The global irradiance in the plan of PV panel is used instead of the global horizontal irradiance in order to be adapted to the PV plant features. The ambient temperature is preferred to PV cell temperature as it is easier to monitor (see Figure 11).

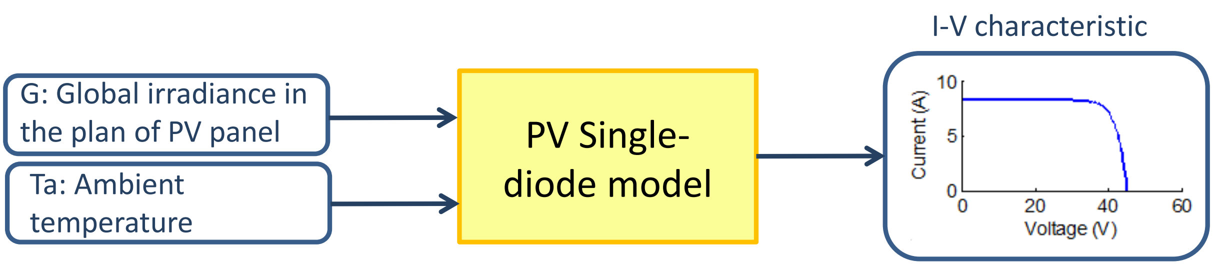

Figure 11. Methodology for PV panel modelling.

The equivalent electrical circuit for the PV single diode model is illustrated in Figure 12 and consists of a photo-current source, a diode, a parallel resistance R_p (or shunt resistance) and a series resistance R_S. I^c_{ph} is the light generated current for the PV cell c, I^c_d is the voltage-dependent lost current to recombination in the cell, I^c_{sh} is the current lost due to shunt (or parallel) resistance in the cell.

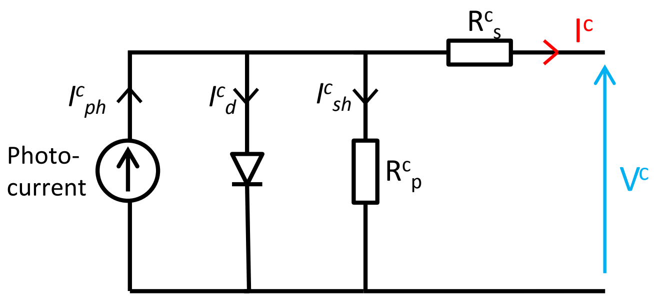

Figure 12. Equivalent electrical circuit for single diode model to model PV cell.

As explained previously, the PV model consists in computing the output current **I** for given global irradiation G, ambient temperature T_a and voltage **V** in order to get the I-V characteristic.

The governing equation for the output current $\mathbf{I^c}$ of the electrical equivalent circuit for PV cell is given by the Kirchoff's law:

$$I^c = I^c_{ph} - I^c_d - I^c_{sh}$$

Applying the electrical laws and considering an ideal diode (Shockley equation can be used), the following equation is obtained for the equivalent circuit of PV cell.

$$I^c = I^c_{ph} - I^c_0 * \left[\exp\left(\frac{V^c + R^c_s * I^c}{V^c_t}\right) - 1\right] - \frac{V^c + R^c_s}{R^c_p}$$

The parameters for the PV cell and panel model used in the previous equation and in the following ones are gathered in Table 8. All parameters with a 'c' exponent are relative to cell level.

Parameters	description	value
I^c_0	Diode saturation current for a PV cell	/
V^c_t	Diode thermal voltage with quality factor for a cell	/
k	Bolzmann's constant	$1.381\ 10^{-23}$ $J.K^{-1}$
e	Charge of the electron (constant)	$1.602{\cdot}10^{-19}$ C
I_{sc}	Short-circuit current at reference conditions	PV panel data sheet
V_{oc}	Open circuit voltage at reference conditions	PV panel data sheet
μ_{Voc}	Temperature coefficient of the open circuit voltage	PV panel data sheet
μ_{Isc}	Temperature coefficient of the short-circuit current	PV panel data sheet
R_s	Series resistance for the PV panel	
R_p	Parallel resistance for the PV panel	
R_{pref} R_{p0} R_{pexp}	Parameters for the parallel resistance	
N_{sm}	Number of cells in series for the module	PV panel data sheet
N_{pm}	Number of cells in parallel for the module	PV panel data sheet
G_a	Working irradiance on PV module plan	
G_{a0}	Reference irradiance (Standard Test Conditions)	1000 Wm^{-2}
G_{min}	Minimum irradiance for the model to be valid	
T_c	Working cell temperature	

T_{c0}	Reference cell temperature	25 °C
T_a	Working ambient temperature	
m	Diode quality factor	
$NOCT$	Normal Operating Cell temperature	PV panel data sheet

Table 8. **Model parameters for the PV cell and panel model.**

Depending on the number of PV cells in parallel N_{pm} and in series N_{sm} in the PV panel the same kind equation can be obtained for the PV panel with **V** its output voltage and **I** its output current [Model equation]. Solving this implicit equation is achieved with a Newton Raphson approach.

$$I = N_{pm} * \left(I_{ph}^{c} - I_0^{c} * \left[\exp\left(\frac{\frac{V}{N_{sm}} + \frac{R_S^c * I}{N_{pm}}}{V_t^c} \right) - 1 \right] - \left[\frac{V}{N_{sm}} + \frac{R_S^c * I}{N_{pm}} \right] * \frac{1}{R_p^c} \right)$$

The relationships between the values of parallel resistance, series resistance, current (and short-circuit current under reference conditions) and voltage (and open-circuit voltage under reference conditions) for the PV module and the PV cell are given by the following set of equations.

$$\begin{cases} R_p^c = R_p * \dfrac{N_{pm}}{N_{sm}} \\ R_S^c = R_s * \dfrac{N_{pm}}{N_{sm}} \\ V^c = \dfrac{V}{N_{sm}} \; and \; V_{oc0}^c = \dfrac{V_{oc0}}{N_{sm}} \\ I^c = \dfrac{I}{N_{pm}} \; and \; I_{sc0}^c = \dfrac{I_{sc0}}{N_{pm}} \end{cases}$$

If the PV cell works in short-circuit then the output current is the short circuit current I_{sc} and the output voltage is 0. The following equation is obtained for the PV cell and I^c_{ph} can be calculated.

$$I_{ph}^c = I_{sc}^c * \left[1 + \frac{R_S^c}{R_p^c} \right] + I_0^c * \left[exp\left(\frac{R_S^c * I_{sc}^c}{V_t^c} \right) - 1 \right]$$

If the PV cell works in open-circuit then the output voltage is the open-circuit voltage VOC and the output current is 0. The following equation is obtained and it allows calculating I_0^c.

$$I_0^c = \left(I_S^c - \frac{V_{oc}^c}{R_p^c} \right) * \exp\left(-\frac{V_{oc}^c}{V_t^c} \right)$$

As explained previously the irradiance and the cell temperature have an impact on I-V characteristic of the PV cell and the PV module.

The open circuit voltage of the PV cell depends on its temperature (if temperature cell increases the open-circuit voltage decreases). It also slightly depends on the irradiation but it is not detailed in this proposed model.

$$V_{oc}^{c} = V_{oc0}^{c} + \frac{\mu_{Voc} * (T_c - T_{c0})}{N_{sm}} = \frac{V_{oc} + \mu_{Voc} * (T_c - T_{c0})}{N_{sm}}$$

And the diode thermal voltage also depends on the temperature of the cell:

$$V_t^c = \frac{m * k * (273 + T_c)}{e}$$

The short-circuit current of the PV cell slightly increases with an increase of the cell temperature and decreases if irradiance decreases.

$$I_{sc}^{c} = \frac{1}{N_{pm}} * \left[I_{sc} * \frac{G_a}{G_{a0}} + \mu_{Isc} * (T_c - T_{c0}) \right]$$

As it is difficult to monitor the cell temperature, it can be modeled through the ambient temperature T_a, the irradiance G_a and the Normal Operating Cell Temperature (NOCT with an irradiance of 800W/m², air mass AM=1.5, an ambient temperature of 20°C and a wind speed of 1m/s) given by the manufacturer. The reference conditions (or Standard Test Conditions) are defined with an irradiance of 1000W/m² but also a cell temperature of 25°C which requires a clod ambient temperature.

$$T_c = T_a + G_a * \frac{NOCT - 20}{800}$$

Finally the parallel resistance (or shunt resistance) R_p also depends on the irradiance and is defined from the associated parameters ($R_{pref}, R_{p0}, R_{pexp}$; based on PV panel manufacturer data) and it can be expressed by the following equation.

$$R_p = R_{pref} + \left(R_{p0} - R_{pref}\right) * \exp\left(-R_{pexp} * \frac{G_a}{G_{a0}}\right)$$

$R_{pref}, R_{p0}, R_{pexp}$ parameters are obtained through optimization methods aiming at minimizing the difference between reference operating points or measurements given by the constructor and operation points obtained through the model including these parameters. These operation points can be either the current or the voltage of the Maximum Power Point, or the different I-V data sets for different weather conditions.

It is obvious that $R_{p0} = R_p \; for \; G_a = 0$ and it can be admitted that $R_{pref} \approx \; R_p \; at \; G_{a0}$.

Other equations can be found in the literature for the parallel resistance of the PV module depending on the available data from the manufacturer.

Hence each combination of ambient temperature and total irradiation leads to an I-V characteristic for a given PV cell and module technology. The characteristics are obtained by solving the model equation for the voltage ranging from 0 to V_{oc}.

4.2 ANALYTICAL POWER MODEL FOR PV MODULE

Instead of calculating the generated current for each output voltage values of the PV module under a given irradiance G_a and a given ambient temperature T_a based on the model of previous part, simplest model can generated the output power of the PV module (and its efficiency). This model aims to give the maximum power of PV module (and not all the I-V curve characteristic) regarding its maximum certified power (under STC conditions), the irradiance G_a and the ambient temperature T_a [6].

The PV inverter (or PV converter) tracks this maximum power point thanks to MPPT algorithms; then this approach is pertinent if the model does not aim to test the MPPT algorithm.

This kind of model is chosen in the Deliverable 3.2 for designing the PV model for the simulation software in order to test the electricity consumption forecasting tool.

For this Deliverable 3.2 PV module model, the following equation gives the output power P_m of the module.

$$P_m = P_{m0} * \frac{G_a}{G_{a0}} * \left(1 + \gamma_{Pmp} * (T_c - T_{c0})\right)$$

With P_{m0} the STC certified maximum power of the PV module given by the manufacturer and γ_{Pmp} the temperature coefficient of P_{max}.

These two parameters are given by the manufacturer of the PV panel. The PV modules that will be used for the GreenDataNet demonstrator at Eaton Le Lieu are manufactured by JA Solar (reference JAP6 60-260/3BB, [8]) and have a rated maximum power at STC of 260W and a temperature coefficient of P_{max} of -0.430%/K.

Similar equation than for the equivalent electrical circuit model is used to calculate the cell temperature from the ambient temperature.

$$T_c = T_a + G_a * \frac{NOCT - 20}{800}$$

Then, the electrical efficiency of the PV module η_m can be simply calculated from the maximum electrical power P_m through the following definition.

$$\eta_m = \frac{P_m}{A * G_a}$$

With A the PV module area in m^2

This formula is used by the manufacturer to give the PV module efficiency under the reference STC conditions. For instance the PV module JAP6 60-260/3BB used for the GreenDataNet demonstrator at Le Lieu has an area of 0.991*1.65=1.635m² and a rated STC maximum power of 260W. It leads to a STC maximum efficiency of 15.9% for this PV module. If the reference JAP6 60-265/3BB is used then rated STC maximum power is of 265W and STC maximum efficiency of the PV module is about 16.21% [8].

4.3 PV MODULE MODEL USED IN SEMS+AEMS AND FOR SIMULATION

As explained in the Deliverable 3.7 *Smart Energy Management System* and its summary (Deliverable 3.8) the SEMS directly used time-series for PV power for the whole PV plant and not only from one single PV panel. Hence there is no need to integrate a PV module or plant analytical model for the SEMS and the AEMS for calculating the output power regarding the ambient temperature T_a and the irradiance G_a on the PV module plan.

Nevertheless, an accurate PV module analytical model is used by the PV production forecasting tool of GreenDataNet (Deliverables 3.4 and 3.5) and is associated with weather forecast methods and self-learning algorithms.

For the PV plant of the GreenDataNet demonstrator at Eaton Le Lieu the parameters of the JA solar PV Panel (reference JAP6 60-260/33B) are used. P_{max} at STC is 260W, temperature coefficient of the open circuit voltage is μ_{Voc}=-0,33 %/°C, temperature coefficient of the short-circuit current is μ_{Isc}=0,058 %/°C, temperature coefficient of P_{max} of -0.430%/K and NOCT is 47 ± 2 °C [8].

Finally a tilt angle of 24,7° and an orientation angle of -36° are considered to generate, for GreenDataNet demonstrator at Eaton Le Lieu, the irradiance on the PV module plan G_a from the global irradiance forecast values.

5. CONCLUSION

This Deliverable 3.6 does not aim at reviewing all the existing analytical models for data centre components (converter, PV module, storage, IT loads, and cooling loads) as it is already well detailed in literature. Only some relevant analytical models that are used for GreenDataNet project are detailed. Obviously, each proposed model has some limitations and does not stand for the real behaviour of the components of the GreenDataNet prototype.

The analytical model of IT loads is addressed by Deliverable 3.2 whereas the analytical model of cooling load is presented in Deliverable 3.1.

Two kinds of analytical models are needed and are detailed in this Deliverable 3.6. **Models of first type** are needed for the **optimization algorithms** of the SEMS. It has been decided to formulate them in a Mixed-Integer Linear Programming (MILP) for solving the optimization problem. Such analytical models can also be used for the AEMS algorithms. **Models of second type** are used in the Matlab Simulink **simulation framework developed for the GreenDataNet project** in order to test the system and the SEMS software. These models are more accurate than the ones used for optimization purposes. Similar ones are also used in the simulation framework developed to test the IT loads optimization and forecasting software.

Testing results on components have been provided by Eaton for the converters and by Nissan for the Leaf battery and permit to generate the empirical data for feeding the analytical models.

For the **lithium-ion battery, an energy losses based power–energy analytical model** for **optimization purpose** and **an efficiency based power-energy analytical model** for **simulation** purpose are proposed in this deliverable. The empirical data used by the models are generated from beginning of life electrical characterization of Nissan Leaf battery. They could be updated following the electrical characterization (Task 1.3.3 of GreenDataNet project) performed after ageing process on a Leaf battery; then, an update of Deliverable 3.6 could be submitted to GreenDataNet partners.

Regarding the **UPS power converters** (rectifier, inverter, PV DC-DC converter, battery DC-DC converter), **same types of analytical models** are also used: an energy losses based power-energy analytical model for SEMS and possibly AEMS optimizations, and a efficiency based power-energy analytical model for simulation.

Finally **no analytical model of PV module** to generate PV power from the irradiance and the temperature **are required** by the SEMS and the AEMS, nor by the simulation framework to test the system and the SEMS. Indeed **PV power time-series**, and not irradiance time-series, are directly provided by the PV production forecasting tool (Deliverable 3.4 and Deliverable 3.5) to the SEMS/AEMS or the simulation framework control.

A power analytical model of PV module has been used to simulate the environment for the development of the IT Loads optimization and forecasting tool (Deliverable 3.2 and WP2). This power analytical model permits to calculate the maximum PV power regarding irradiance and temperature, and is detailed in this deliverable. A more accurate equivalent electrical circuit analytical model for PV module is also described.