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Abstract

This paper aims at optimizing the energy management of a smart power plant composed of wind turbines coupled with a Lithium Ion storage device in order to fulfill a power production commitment to the utility grid. The application of this case study is typically related to islanded electric grids. Our work particularly investigates and compares two classes of energy management strategies for design purpose: a first capable of providing the global optimum of the power flow planning from a Linear Programming (LP) approach thanks to *a priori* knowledge of future events in the environment; a second, based on a classical control heuristic without any *a priori* knowledge on the future, applicable in real time. Beyond the future objectives in terms of system design (techno-economical sizing optimization), the comparison of both approaches also aims at improving the predefined heuristic from the analysis of the ideal reference provided by the global LP optimizer. In this scope, a linear power flow model of the power plant is developed in compliance with a LP solver (Cplex). A particular attention is paid to the techno-economic optimization including storage cost evaluation, commitment failure penalties and exploitation gains. Simulations and optimizations are carried out over one year in order to take variability and seasonal features of the wind potential into account.

Keywords: Smart wind power plant; Storage management; Linear programming; Optimization; Heuristic method

1. Introduction

Integration of renewable energy sources (RES) in electric grids is of great concern especially in islanded networks as in Guadeloupe [9]. Currently the penetration rate of RES is limited for stability reasons. Technologies such as wind and solar power are stochastic and intermittent which limits their participation level in the electric grid despite the related cost reduction and contribution to sustainable development. Increasing the participation rate of RES in islanded electric grids is a key issue which may be achieved through the concept of "smart grids" with participation

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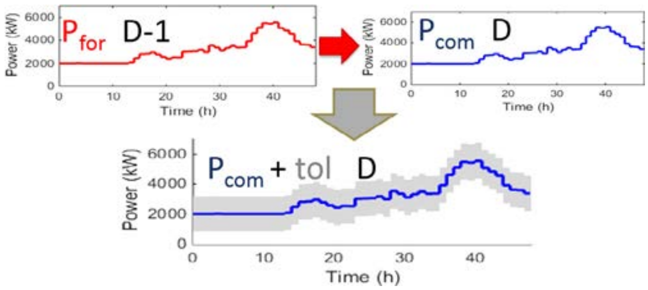

Fig. 1. Commitment assimilated to the forecast power.

to grid services in order to contribute to the whole grid stability [5,20] despite sources intermittence. Adding energy storage systems with corresponding energy management, which are used to create virtual inertia [4,5,32], is one of the major solution to face intermittent character of RES. A lot of studies have been carried out on this topic [10,15,22,24,26,32] for which the main points are the sizing and the management of the storage system. The sizing problem will not be the aim of this paper which is focused on the energy management of the storage device. Inside the energy management issue, many studies can be done as absolute optimization [24] or statistical analysis [10] and different kinds of problems can be processed. Among them, two classes of management strategy using optimization problems can be distinguished:

- Firstly, rule based heuristics without "*a priori*" on future events are often proposed, as for example with fuzzy logic management [7,12]. Those methods are clearly applicable in real time. Optimal control based approaches (as the example of Pontryagin's maximization principle) are also used on certain systems with the same characteristics even if actual applicability is often more complex. The first category of problems based on heuristics is clearly the most commonly used especially in the industrial context;
- Secondly, "global optimization" management where all database are known: "*a priori*" knowledge on past, present and future events is here assumed. Genetic algorithms [6], particle swarm optimization [28] or linear programming (LP) [15,18,22,26], are among the class of methods that can be used which guarantee to reach the global optimum of management performance under modeling assumptions: it gives an "absolute answer" on what should be done at each step. This second class of method is clearly not applicable in real time but may be useful for tuning heuristics or to be used during the sizing process of the system design.

In this article, a linear model for Mixed Integer Linear Programming (MILP) optimization of a smart grid energy management is thus presented. The modeling approach is based on power flow models used to run the energy management of the smart power plant including renewable sources (wind turbines) and a Lithium Ion storage device. The problem statement will be firstly presented. Then a linear model of the system will be proposed with the associated hypothesis. The results obtained over one year of simulation will be exposed and more specifically the impact on some indicators will be presented. The general behavior of the optimal solution will be studied to improve the heuristic management and to develop a new one.

2. Problem setting

The problem is simplified with only one power source (wind turbines, WT) and only one storage technology (Li-Ion). Many studies have been performed on this kind of grids [14,17,19,25] with different storage technologies but on a shorter time horizons: from a few seconds for the frequency control to a few hours. This paper intends to evaluate the proposed method over one year of simulation for a more global evaluation. The concrete goal of this study is to comply with a grid service consisting in a "day ahead power commitment" issue as can be seen in [16,31].

The commitment is generally related to the wind power production forecast; here, in order to focus on the comparison of management strategies, the choice has been made to assimilate power flows for the day ahead forecast (P_{for}) with commitment: $\mathbf{P_{for}}(D-1) = \mathbf{P_{com}}(D)$ as displayed on Fig. 1. A tolerance layer (*tol*) around the commitment power (P_{com}) is allowed and the storage device coupled with an energy management strategy (EMS) have to correct

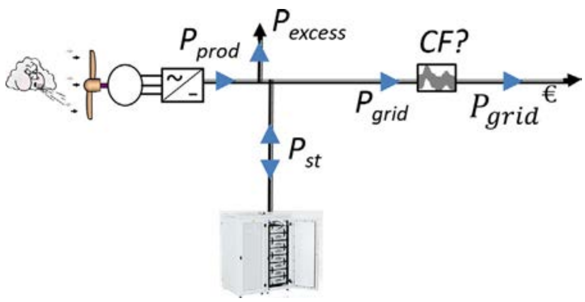

Fig. 2. Power flows.

forecast errors in real time (for the D day) to keep the grid transferred power inside the tolerance band. The study is done in collaboration with industry and the requirements related to smart windfarms with storage for islanded networks are provided by the CRE (https://www.cre.fr) [8]. In the case study, the tolerance (*tol*) is required to be decreased during the three first years (for a 15 year contract) and this study will deal with the third year which is the hardest in terms of commitment with a tolerance band of 15% of the total sizing power of WT sources.

If the mean power transferred to the grid (P_{grid}) does not fulfill this commitment during 1 min, a Commitment Failure (CF) is triggered and the energy supplied to the grid is not paid for 10 min. Regarding the complexity of system analysis (number of variables and long period of time) simulations have been run with a 10 min time step. Reducing this time step to 1 min will be the purpose of further studies. Preliminary tests showed a low difference between 1 vs 10 min time steps.

2.1. *Context of the system*

The studied grid connected system is simplified with respect to a real smart grid: both commitment and actually produced powers (P_{prod}) are not based on physical models: power flow vectors $\mathbf{P_{prod}}$ and $\mathbf{P_{com}}$ are considered as input data. At each time step, the management strategy has to decide which part of the produced power will be sent to the grid ($\mathbf{P_{grid}}$) and which power will be charged or discharged by the battery ($\mathbf{P_{st}}$: where $\mathbf{P_{st}} > 0$ stands for discharge and $\mathbf{P_{st}} < 0$ stands for charge). The wind turbine production is normally maximized (MPPT mode) but a power reduction (curtailment mode) is expectable if excessive production with respect to the power commitment ($\mathbf{P_{prod}} > \mathbf{P_{com}} + \mathbf{tol}$) is obtained and if the battery is not able to charge the power excess. For the simulation, this power flow excess ($\mathbf{P_{excess}}$) is considered as dissipated and lost for the economic balance. The Fig. 2 displays all corresponding power flows related to the power balance (1) for each time step:

$$\mathbf{P_{prod}} + \mathbf{P_{st}} = \mathbf{P_{excess}} + \mathbf{P_{grid}} \tag{1}$$

2.2. *Comparative study between two EMS*

Our objective is firstly to use LP for the energy management optimization in order to find the best trajectory for $\mathbf{P_{st}}$ knowing the whole trajectory of production and forecast data. $\mathbf{P_{st}}$ is the unique unknown variable in (1) that leads to the grid transfer $\mathbf{P_{grid}}$. $\mathbf{P_{prod}}$ and $\mathbf{P_{com}}$ being known, and by considering the battery limits (state of charge and maximum charge power), $\mathbf{P_{excess}}$ can be determined with respect to the tolerance band (*tol*).

This linear optimization will be compared to a rule-based heuristic method. The heuristic is a management method applicable in real time and which follows rules as shown in Fig. 3 where $SOC_{\text{Li-Ion}}$ represents the State Of Charge of the storage system. This strategy is a good compromise between complying with the day-ahead commitment and an efficient use of the storage system. $\mathbf{P_{target}}$ is the power targeted to be transferred to the grid ($\mathbf{P_{grid}}$):

Different heuristics have been tested, but all of them had the same rules when $\mathbf{P_{prod}}$ is out of the tolerance band. In the low production case with $\mathbf{P_{prod}} > \mathbf{P_{com}} - \mathbf{tol}$: $\mathbf{P_{target}}$ is set to the bottom value of the tolerance band and the difference is discharged with storage ($\mathbf{P_{st}}$) if enough energy is available in the battery. A CF penalty is triggered in the opposite case. On the contrary, when the upper limit of the band is exceeded, $\mathbf{P_{target}}$ is set to the upper value of

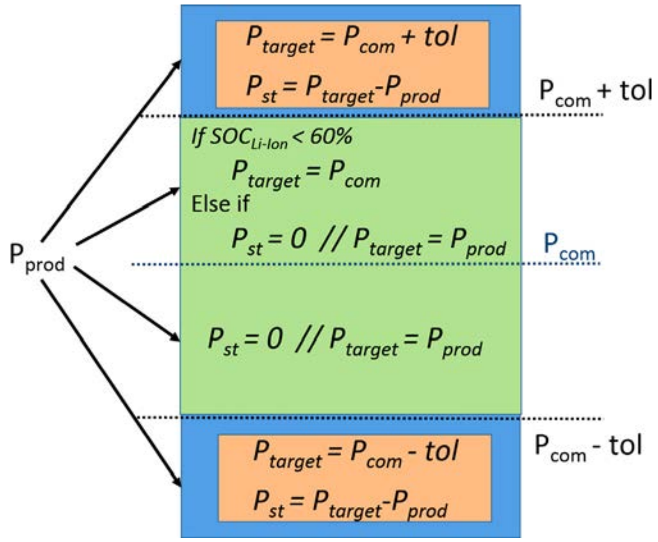

Fig. 3. Heuristic algorithm.

the band and the difference is stored in the battery within its limits in energy and power. If the one part of the excess power cannot be charged due to storage limits, an excess power ($\mathbf{P_{excess}}$) is wasted fulfilling Eq. (1) but no CF penalty is triggered assuming that wind power production is reduced. This heuristic is a bit more complex when $\mathbf{P_{prod}}$ is inside the tolerance band:

- if $\mathbf{P_{com}} - \boldsymbol{tol} < \mathbf{P_{prod}} < \mathbf{P_{com}}$ the storage is off;
- if $\mathbf{P_{com}} < \mathbf{P_{prod}} < \mathbf{P_{com}} + \boldsymbol{tol}$ and if SOC<60% then $\mathbf{P_{target}} = \mathbf{P_{com}}$; $\mathbf{P_{prod}} - \mathbf{P_{com}}$ is then stored in the battery.

This heuristic has been tested with a nonlinear model of the system taking account efficiency of static converters and involving the Tremblay Dessaint model [29] for the battery. In order to run linear programming, a linear derivation has been developed from the nonlinear model, but subsequent results will be tested with the non-linear model. Indeed the point is to assess the ability of the LP to find an optimal storage trajectory ($\mathbf{P_{st}}$) with the linear model and to keep a robust performance for the non-linear and more accurate model.

3. Linear model of the power plant

In this part, the model used in the linear programming optimization is presented. The linear model of the battery is given in details, especially the constraints imposed by the grid and the objective function linearized vs decision variables. The model is presented for a discrete simulation of N time steps of Δt, k being the current step. Equations derived in the following part have to be verified for each step k belonging to the whole profile $[1..N]$.

3.1. Battery linear model

The modeled storage is a Li-Ion battery but its linear model [2] could be easily transposed to any other technology with a simple rated energy E_{nom}. A simple power flow model with charge (η_{ch}) and discharge (η_{dis}) efficiencies has been considered to be enough accurate in view of this comparative analysis of EMS performance. Further analysis made with finer models [14,28] have shown that it does not affect the performance ranking of the EMS. In order to get a linear function vs efficiency, the $\mathbf{P_{st}}$ variable has to be split into 2 parts:

$$\mathrm{P_{st}}\,[k] = \mathrm{P_{st}}^{+}[k] + \mathrm{P_{st}}^{-}[k] \tag{2}$$

where $\mathbf{P_{st}}^{+}$ is the positive part and $\mathbf{P_{st}}^{-}$ is the negative part of $\mathbf{P_{st}}$ in (2). With this separation the efficiency can be linearly introduced. The $\mathrm{P_{bat}}$ variable is used to express the power effectively extracted (stored) from (into) the battery taking account of the losses:

$$\mathrm{P_{bat}}[k] = \eta_{\mathrm{ch}}.\mathrm{P_{st}}^{-}[k] + \frac{\mathrm{P_{st}}^{+}[k]}{\eta_{\mathrm{dis}}} \tag{3}$$

Different linear constraints related to efficiencies (3) or saturations (4), (5) can be assigned for charge or discharge powers and SOC.

$$\mathrm{P_{bat}}[k] \leq \mathrm{P_{dis\ max}}[k] \tag{4}$$

$$\mathrm{P_{bat}}\,[k] \geq \mathrm{P_{ch\ max}}[k] \tag{5}$$

where η_{ch} and $\mathrm{P_{ch\ max}}$ (respectively η_{dis}, $\mathrm{P_{dis\ max}}$) represent the efficiency and power saturation during the charge (respectively the discharge) of the battery (absolutes values). The discrete linear implementation of SOC becomes:

$$\mathrm{SOC}\,[k+1] = \mathrm{SOC}\,[k] + \frac{\mathrm{P_{bat}}[k]\Delta t}{E_{\mathrm{nom}}} \tag{6}$$

Accordingly to the requirements of the battery provider, the SOC is constrained with saturations to maintain the battery lifespan:

$\mathrm{SOC_{min}} = 30\%$ and $\mathrm{SOC_{max}} = 90\%$

The constraints needed to run the optimization with the context described above are detailed in the next part.

3.2. *Linear constraints*

Even with this simplified system, several conditions such as "$if\,\mathrm{P_{prod}} < \mathrm{P_{com}}{-}tol$" are not linear and mathematical tricks have been used. Operators "max" and "min" can be processed as long as they do not operate on decision variables. To solve certain problem binary variables have also to be defined. The Mixed Integer Linear Programming (MILP) approach is used [30].

The first constraint is related to (1) but with linear variables:

$$\mathrm{P_{prod}}\,[k] + \mathrm{P_{st}}^{+}\,[k] + \mathrm{P_{st}}^{-}\,[k] = \mathrm{P_{grid}}\,[k] + \mathrm{P_{excess}}\,[k] \tag{7}$$

All members of this equation are related to decision variables except $\mathrm{P_{prod}}[k]$. Considering $\mathrm{P_{grid}}$ as a decision variable with the equality constraint (7) is equivalent to defining its value. Variables $\mathrm{P_{st}^{+}}/\mathrm{P_{st}^{-}}$ seem convenient to define the battery management. But in order to ensure that charge and discharge cannot simultaneously take place, a binary variable $D[k]$ ($D[k] = 1$ for discharge) is introduced and the following constraints are imposed:

$$0 \leq \mathrm{P_{st}}^{+}\,[k] \leq (\eta_{\mathrm{dis}}\mathrm{P_{dis\ max}}) \times D\,[k] \tag{8}$$

$$\max\left(-\frac{\mathrm{P_{ch\ max}}}{\eta_{\mathrm{ch}}}, -\mathrm{P_{prod}}[k]\right) \times (1 - \mathrm{D}[k]) \leq \mathrm{P_{st}^{-}}\,[k] \leq 0 \tag{9}$$

If $\mathbf{D} = 0$, (8) ensures $\mathrm{P_{st}^{+}} = 0$, i.e. a battery charge operating. If $\mathbf{D} = 1$, (9) ensures $\mathrm{P_{st}^{-}} = 0$ imposing the battery to be discharged.

Eq. (7) and the following constraint define $\mathbf{P_{excess}}$:

$$\mathrm{P_{grid}}\,[k] \leq \mathrm{P_{com}}\,[k] + \mathrm{tol} \tag{10}$$

Indeed, imposing $\mathbf{P_{grid}}$ below the upper band $\mathbf{P_{excess}}$ fulfills the missing power as explained with (1).

$$\mathrm{P_{excess}}\,[k] \leq \max\left(\mathrm{P_{prod}}\,[k] - \mathrm{P_{com}}\,[k]\,, 0\right) \tag{11}$$

Eq. (11) is an upper bound for $\mathbf{P_{excess}}$ in order to reduce the search space of the solver.

Saturations of the SOC become for each time step ($k \in [1..N]$):

$$-\left(\sum_{i=1}^{k} \frac{\mathrm{P_{st}}^{+}(i)}{\eta_{\mathrm{dis}}} + \eta_{\mathrm{ch}}\mathrm{P_{st}}^{-}(i)\right) \leq \frac{E_{\mathrm{nom}}}{\Delta t} \times (\mathrm{SOC_{max}} - \mathrm{SOC_{init}}) \tag{12}$$

$$\sum_{i=1}^{k} \frac{\mathrm{P_{st}}^{+}(i)}{\eta_{\mathrm{dis}}} + \eta_{\mathrm{ch}}\mathrm{P_{st}}^{-}(i) \leq \frac{E_{\mathrm{nom}}}{\Delta t} \times (\mathrm{SOC_{init}} - \mathrm{SOC_{min}}) \tag{13}$$

with (13) equivalent to $\mathrm{SOC_{min}} \leq \mathrm{SOC}[k]$ and (12) to $\mathrm{SOC}[k] \leq \mathrm{SOC_{max}}$.

A constraint on the SOC is added to keep its value at the end of the day equal to the initial value:

$$\mathrm{SOC}\,(N) = \mathrm{SOC}_{\mathrm{end}} = \mathrm{SOC}_{\mathrm{init}} = 50\% \tag{14}$$

This debatable choice has been made in order to decouple planning cycles (i.e. planned days here) from each other. More reasons related to this choice will be detailed in Section 4.

$\mathbf{P_{miss}}$ is another variable introduced to help defining the CF condition: CF is a binary variable equal to 1 in case of commitment failure and 0 otherwise.

$$\mathrm{P_{grid}}\,[k] \geq \mathrm{P_{eng}}\,[\mathrm{k}] - \mathrm{tol} - \mathrm{P}_{miss}\,[k] \tag{15}$$

$$\mathrm{BIGM} \times CF[k] \geq \mathrm{P}_{miss}[k] \tag{16}$$

when $\mathbf{P_{grid}}$ is not inside the tolerance layer, $\mathbf{P_{miss}}$ has to be non-zero to verify (15). The value of $\mathbf{P_{miss}}$ is not really relevant, a non-zero value triggers **CF**=1 thanks to Eq. (16). This method called “Big M” is classically used in LP: the constant BIGM is the big M used to control the value of a binary variable: here **CF**.

The last constraint is here to prevent the use of the available power to charge the battery during a CF. Indeed, the producer is not paid for the energy provide during a CF period as explained in the introduction. So, during that time, the available power is wasted from the economic point of view.

$$\mathrm{P_{st}}^{-}\,[k] \geq -\,(1 - CF\,[k]) \times \mathrm{P_{prod}}[k] \tag{17}$$

This behavior is due to the time step of 10 min used for optimization and which does not allow to define CF more accurately, since its real value is based on the mean value on 1 min followed a possible penalty over 10 min. The trick used in (17) is from the Big M method too which sets **CF**=1 to impose $P_{st}^{-} \geq 0$ and so$P_{st}^{-} = 0$.

With the modeling tricks used, a total of 7 variables are necessary to fully derive the problem instead of one ($\mathrm{P_{bat}}$) for a nonlinear optimization. Those 7 decision variables are: $\mathbf{P_{st}}^{+}$, $\mathbf{P_{st}}^{-}$, $\mathbf{P_{miss}}$, $\mathbf{P_{excess}}$, $\mathbf{P_{grid}}$, **CF** and **D**. **CF** and **D** being binary a MILP solver is run. Simulating 24 h with a 10 min time step (144 steps) involves 1008 (7×144) decision variables to be optimized.

The objective function needed to define the optimal solution is detailed in the following section.

3.3. Linear objective function

As explained in introduction, the issue of this linear optimization is to satisfy a grid service for day ahead market and of course to maximize energy producer profits. Multi-objective optimization approaches being sometimes adequate but more complex [11], the choice has been made to minimize a whole cost gathering the process efficiency and the battery use cost. The fulfillment of the grid service is thus shifted in a monetary cost from the CF penalty consequence. The cost function has been decomposed into 4 parts:

– A first part includes the “deviation cost” due to the CF: the producer is not paid for power to the grid ($\mathbf{P_{grid}}$) if **CF**=1, the associated cost being defined as:

$$\mathrm{Cost_{dev}}\,[k] = \mathrm{FIT} \times CF[k] \times \mathrm{P_{grid}}[k]\varDelta t \tag{18}$$

where FIT denotes the Feed in Tariff in [€/kWh]. However, $\mathbf{P_{grid}}$ and **CF** are both decision variables so this expression is not in accordance with the linear programming. If CF = 1, then $\mathbf{P_{grid}}$ is below the lower limit of the tolerance layer so $\mathbf{P_{excess}}$= 0. The constraint (16) prevents against any charge and there is no interest to discharge the battery if we are not remunerated for the energy provided so $\mathbf{P_{st}}$ = 0. $\mathbf{P_{grid}}$= $\mathbf{P_{prod}}$ in the case of **CF** = 1 can be deduced from (1), where $\mathbf{P_{prod}}$ is an input data of the problem and the expression of $\mathrm{Cost_{dev}}$ becomes:

$$\mathrm{Cost_{dev}}\,[k] = \mathrm{FIT} \times CF[k] \times \mathrm{P_{prod}}[k]\varDelta t \tag{19}$$

– A second part consists in the ‘‘wasting cost” where energy is lost with $\mathrm{P_{excess}}$:

$$\mathrm{Cost_{was}}[k] = \mathrm{FIT} \times \mathrm{P_{excess}}[k]\varDelta t \tag{20}$$

– the third and fourth parts represent the costs due to the battery use, especially related to losses and life cost of this storage device. The third part related to efficiency is similar as previously:

$$\mathrm{Cost}_{\eta\ Li\text{-}Ion}\,[k] = FIT\left[(\eta_{\mathrm{ch}} - 1)\,\mathrm{P_{st}}^{-}\,[k] + \frac{1-\eta_{\mathrm{dis}}}{\eta_{\mathrm{dis}}}\mathrm{P_{st}}^{+}\,[k]\right]\varDelta t \tag{21}$$

The importance of separating $\mathbf{P_{st}}$ to express this cost linearly with decision variables is shown here. Finally, the fourth part related to the life cost of the battery is based on the maximum exchangeable energy $E_{exc\text{-}max}$ [kWh] as detailed in [11]. This last model calculates a percentage of the lifespan already consumed which is multiplied by the cost of one battery $\mathrm{Cost}_{Li\text{-}Ion}$ to obtain the life cost during battery use. This "lifetime model" is based on the cycle to failure curve [3] provided in datasheets which specifies the battery aging with respect to the DOD. This approach is relevant if thermal operation of the battery shelter is controlled as in our case study. A more accurate model counting cycles during operation is sometimes used but this simplification proposed by [1] based on the exchanged energy with the battery during its operation is enough accurate in order to assess the performance of an EMS, especially for comparing performance of several strategies. This model is then considered as enough accurate to show a tendency and will not allow the optimizer to use the battery without affecting the cost function Furthermore, this simplification allows deriving an analytical model which can be linearized as:

$$\mathrm{Cost_{life}}\,[k] = \mathrm{Cost}_{Li\text{-}Ion}.\,\frac{\left(\frac{\mathrm{P_{st}}^{+}[k]}{\eta_{\mathrm{dis}}} - \eta_{\mathrm{ch}}\mathrm{P_{st}}^{-}\,[k]\right)\Delta t}{E_{\mathrm{exc-max}}} \tag{22}$$

The total cost function is obtained by adding all considered costs:

$$\mathrm{Cost}_{tot}\,[k] = \mathrm{Cost_{dev}}\,[k] + \mathrm{Cost_{was}}\,[k] + \mathrm{Cost}_{\eta\ Li\text{-}Ion}\,[k] + \mathrm{Cost_{life}}\,[k] \tag{23}$$

The MILP solver minimizes this total cost and seeks the optimal trajectory for $\mathbf{P_{st}}$. Results obtained are exposed in the following and last part of this paper.

4. Simulations results

Results are obtained using the following method:

We first used GLPK as a unique solver but then switched to CPLEX which is much faster. One year of simulation nearly take 3 min of CPU time. Once all the results ($\mathbf{P_{bat}}$ trajectory) are obtained, the system simulation is performed on the non-linear model and the cost criteria are extracted. Results obtained over a full year with a succession of 365 day MILP optimizations raise several issues. In comparison, one year is also simulated with the heuristic algorithm for energy management. The comparative analysis is based on several criteria:

– Cost: as shown in Section 3.3 (Eq. (18) to (23)) but calculated with the non-linear model.

– Gain: the complementary function of the cost represents the money earned by the energy producer:

$$Gain = \mathrm{FIT}\,(1 - CF)\,\mathrm{P_{grid}}.\Delta\mathrm{t} - \mathrm{Cost_{life}} \tag{24}$$

Also expressed as:

$$Gain = \mathrm{FIT} \times \mathrm{P_{prod}}\,\Delta\mathrm{t} - \mathrm{Cost}_{tot} \tag{25}$$

where the complementarity is shown. The Cost indicator allows us to optimize the Gain with a greater sensibility.

– Commitment Failure is a relevant criterion for grid services. Indeed agreements are made to increase the penetration rate of intermittent renewable sources with reliable and stable operation of islanded grids.

4.1. Model adaptation

The heuristic management strategy is a step by step algorithm which can be applied over a full year of simulation without any problem. The linear optimization is done day by day to be closer to the real commitment problem. In order to be able to simulate one full year, the SOC continuity between two successive days has to be ensured, which is related to (14): $\mathrm{SOC_{end}} = \mathrm{SOC_{init}}$. But even if this constraint is satisfied with the linear model it may be slightly different with the non-linear. The choice has been to calculate the gain available with a $\Delta\mathrm{SOC} = \mathrm{SOC_{end}} - \mathrm{SOC_{init}}$ as if this energy would be sold at the FIT price and then would be added to the global gain:

$$Gain_{\mathrm{SOC}} = \mathrm{FIT}\,(\mathrm{SOC_{end}} - \mathrm{SOC_{init}})\,E_{\mathrm{bat\ tot}} \tag{26}$$

This choice is questionable, but differences between the linear vs non-linear models were not important so this way of correction was seen as relevant to our study. If this correction is not done, the complementarity between gain and cost is not respected anymore.

Table 1
Comparison between linear optimization and heuristic management.

	Heuristic management	Linear optimization	Relative difference
Gain	4 018 k€	4 134 k€	3%
Cost	535 k€	418 k€	28%
CF	8.3%	5.8%	30%

The following results presented are obtained with 4 wind turbines of 2MW each and 3 battery shelters (SAFT batteries model Intensium Max 20M) of 580 kWh each (P_{chmax}=600kW and P_{dismax}=1100kW per battery). This represents a total estimated investment of 14 900 k€(used for the economic model). Detailed economic data cannot be provided due to confidential issues.

4.2. Cost comparison

The costs related to the use of Lithium Ion storage are gathered:

$$\mathrm{Cost}_{sto} = \mathrm{Cost}_{\eta\ LiIon} + \mathrm{Cost}_{\mathrm{life}} \tag{27}$$

Simulations obtained over one year show the ability of the MILP to provide better results than a heuristic even on the same non-linear model. The MILP uses battery twice as much as the heuristic management to reduce wasted and deviation costs. Fig. 5 well emphasizes this issue.

Underusing the battery causes a significant increase of the other parts of the cost function. If only the deviation and storage costs are analyzed, it seems that the battery just has to be used more in a far-sighted approach. But the fact that the wasted cost is increased with heuristic shows that the battery was more often overloaded than for MILP management.

4.3. Other comparison on gain and CF

One goal of the study is to focus on the energy producer point of view for which gain is the most important criterion. Furthermore, the grid point of view is another goal of this study, so that the CF will also be a relevant criterion (see Table 1).

The MILP optimization improves all criteria. The sensitivity of the cost function with regard to the gain is clearly demonstrated here. A significant increase of 28% has been made on the cost but only 3% on the gain. This latter gives the total amount of money theoretically earned during one typical year. This result shows the improvement potential on the gain which cannot be more than 10% “even if the cost would be zero” which would correspond with a perfect production forecast. Results on the CF factor show the MILP capability to also enhance the production forecast of this smart wind power plant, the global CF over one year being almost reduced by 30%. It should be noted that the global CF is reduced, but not on every single simulation step. For some particular days, the LP optimizer is able to reduce the cost by slightly increasing the CF. This particular case occurs because the associated deviation cost is weighted by $\mathbf{P_{grid}}$. This aspect is not absurd even on the grid point of view: indeed CF is all the more problematical when the energy producer does not comply with a high power commitment.

The power flow simulation over one year has been extended to a 10 year economical study with the calculation of Levelized Cost Of Energy (LCOE), which represents the minimal price of energy to refund the initial investment, and the Net Present Value (NPV) which shows a measure of the project’s profitability. The method used is presented in [27] and an example can be seen in [21].

NPV and LCOE are more significant indicators than the cost which is more convenient for the linear optimization. The results over a longer range (10 years) are positive. The linear optimization shows a great improvement with 13% on the NPV and 4% on the LCOE. Data used for those calculations are summarized in Table 3.

Table 2
10 years economics results.

	Heuristic management	Linear optimization	Relative difference
NPV	7 074 k€	7 964 k€	13%
LCOE	113 €/MWh	108.5 €/MWh	4%

Table 3
Economics data.

Name	Value
CAPEX wind turbine	1 700 000 [€/MW]
OPEX wind turbine	3.5 [% CAPEX]
CAPEX Li-Ion storage	750 [€/kWh]
OPEX LI-Ion storage	3.98 [% CAPEX]
Annual inflation rate	2 [%]
Nominal actualization rate	7 [%]
Income taxes	33.3 [%]
Time of the study	10 [years]
Depreciation coefficient	2.25/years [-]

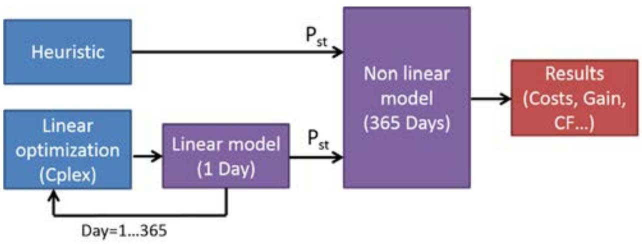

Fig. 4. Simulation method.

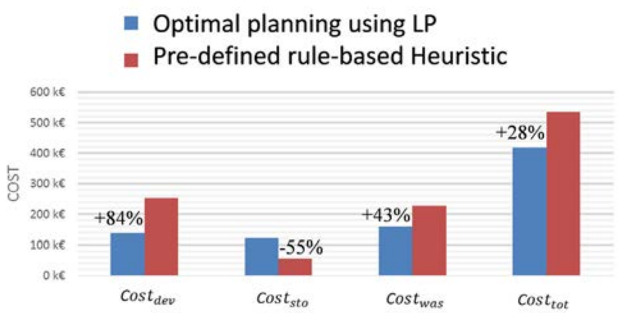

Fig. 5. Cost comparison for both optimization approaches of energy management.

4.4. *Day by day analysis*

The cost deviation between the LP optimal planning and the rule-based heuristic is now analyzed for each day of the simulated year. This will show if the optimal LP solver is capable of reducing each day cost or if the difference is due to critical days which concentrate all the improvement.

Fig. 6 shows a reconstruction of the probability density and the cumulative density functions associated with this cost deviation by considering a day by day comparison between the heuristic and linear programming optimization.

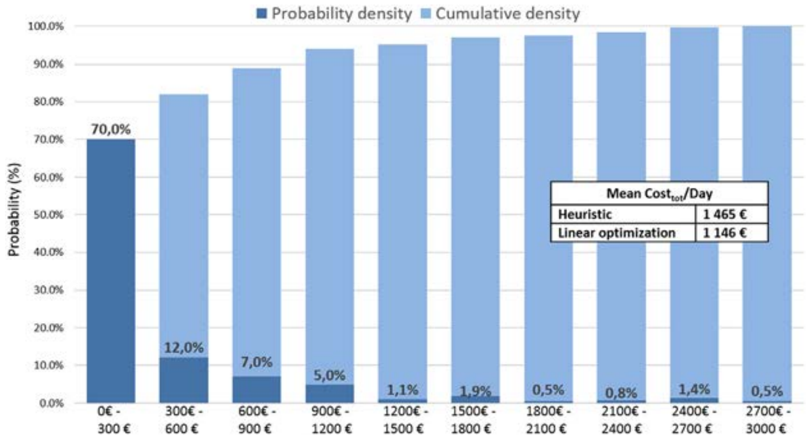

Fig. 6. Cost deviation between the optimal LP planning and the Heuristic on the data set.

Table 4
Linear optimization with different SOC_{init}.

	Linear optimization						
SOC_{init} (%)	30%	40%	50%	60%	70%	80%	90%
$Cost_{tot}$ (k€)	439	425	418	416	415	416	419
$Cost_{sto}$ (k€)	122	123	122	122	121	123	123
$Cost_{dev}$ (k€)	157	143	137	135	132	131	131
$Cost_{was}$ (k€)	160	159	159	159	162	162	165

The figure shows that for 70% of the days the improvement is less than 300 €. Indeed, for a lot of days, forecasts are very low which reduces the impact of the energy management in the global cost. If the power forecast is below half the size of the tolerance layer, $P_{com} = P_{for}$ would induce a negative part of the tolerance layer. In this case the tolerance layer is set at the minimum from 0 to 30% of the installed power (tolerance layer being +/- 15%) which gives more flexibility than usual and prevent from any CF. For 30% of the days, the improvement is beyond 300 €which is quite important compared to the mean total cost per day over the year.

As previously mentioned (Fig. 4), one important difference between both management methods resides in the fact that the heuristics plays the 365 days in a row while the LP separately plays each of the 365 days before being assembled. To ensure the continuity of the SOC in that case, the constraint (14) is applied. One of the consequences is that each day of the optimal solution begin with SOC_{init} = 50% while this level depends on what happened the previous day for the heuristic. A study of the impact of SOC_{init} has been realized to analyze the day by day difference between linear programming optimization and heuristic.

4.5. Impact of SOC_{init}

Several simulations have been performed with different values on the SOC_{init} constraint. The results are summarized in Table 4.

It should be reminded that 30% and 90% are the low and high limits considered in the energy management for the storage system. Table 2 results show that the impact of SOC_{init} is low. Indeed, except when the constraint is set on a saturation level the difference of costs is negligible which comforts our previous hypothesis.

4.6. One particular Day analysis

One particular day (low level of production vs forecast power) where the cost difference is quite important is analyzed. Other typical days studied but not presented showed the same difference of behavior between both strategies.

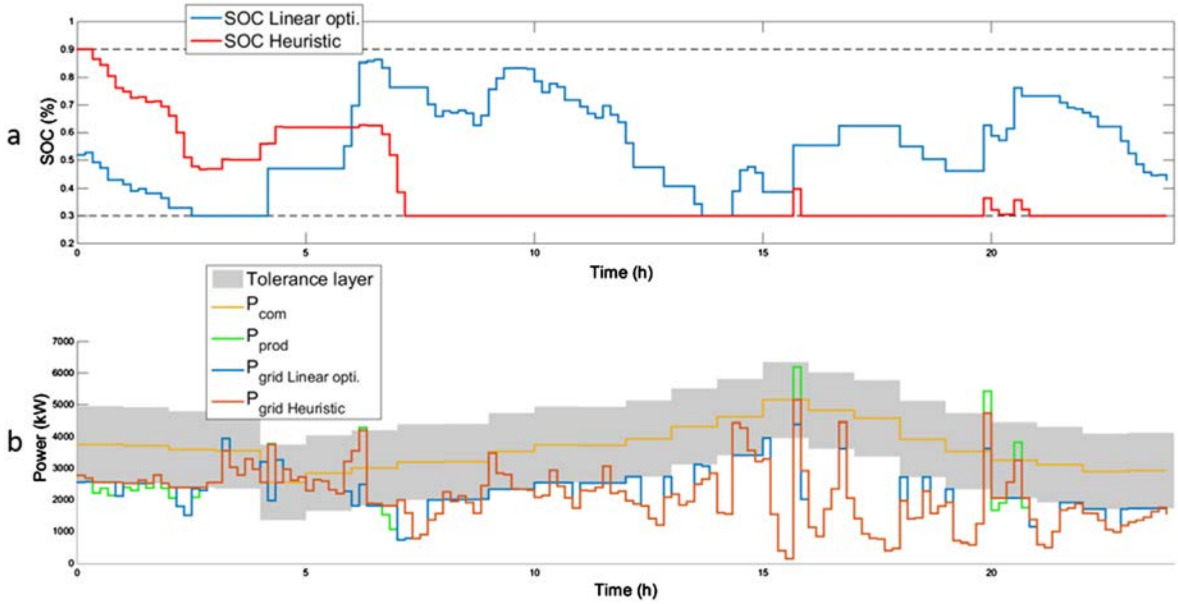

Fig. 7. Comparison between LP and Heuristic strategy a. SOC b. Power flows.

Table 5
Costs' details for Heuristic and linear optimization.

Day 133	Storage cost	Wasted Cost	Deviation cost	Total cost
Heuristic	297 €	0 €	5 235 €	5 532 €
Linear optimization	659 €	0 €	2 528 €	3 188 €
Difference	−362 €	0 €	2 707 €	2 344 €

Fig. 7 shows the variations of SOC with both strategies for a 24 h sample and the corresponding grid power flow.

In the first part of the day, the difference between both strategies is due to the SOC_{init} which is favorable to the heuristic. This results in a similar behavior of both management strategies which use the stored energy to prevent CF. After 7 a.m. the heuristic trajectory is locked due to the SOC saturation at the lower limit whereas the LP optimal planning is capable of exploiting the storage over the whole SOC range reducing the commitment failure when the forecast error is higher. It should be noted, contrary to the heuristic management, that LP optimal planning charges the battery even in the low part of the tolerance layer in order to have back up energy and prevent further CF. Table 5 details the different parts of the $Cost_{tot}$ for this particular day:

Those results show that the battery has to be used more intensively than for the current heuristic. The storage cost is a bit higher in the linear optimal solution in order to reduce a lot the C.F. However, knowing the future production during the day allows the MILP to use the battery exactly when necessary. These trends are useful for future heuristic tuning as it will be developed in the next part of this article.

5. New heuristic deduced from the behavior of the lp optimal planning

The LP optimization has been developed in the scope of two different purposes. It can be firstly used during the design step as an energy management for sizing the smart wind power plant components [23]. Secondly, as an "ideal" reference, it can also be exploited for improving rule-based heuristics or optimal control laws without *a priori* on the future for real time applicability.

Fig. 8 shows the new heuristic developed compared with the initial one.

The rules outside the tolerance layer are the same for both heuristics but the behavior inside the tolerance layer is completely opposite. Indeed the initial heuristic was based "on common sense" to charge the battery in case of overproduction inside the tolerance layer, and directly transfer the produced power through the grid in case of under

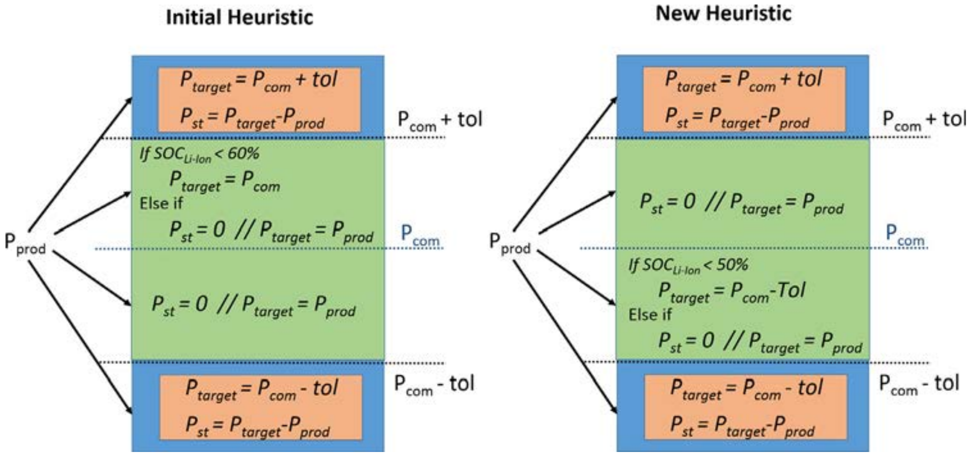

Fig. 8. New Heuristic algorithm.

Table 6
Comparison of the costs obtained with the initial and new heuristics for the considered year.

	Storage cost	Wasted cost	Deviation cost	Total cost
Initial Heuristic	55 k€	227 k€	252 k€	535 k€
New Heuristic	66 k€	224 k€	221 k€	511 k€
Difference	−11 k€	3 k€	31 k€	24 k€

production. The analysis of the data set revealed "a bias" between wind forecast and production: in particular, a situation of underproduction is most likely to happen again in the following step times increasing the CF occurrence probability. Therefore, in case of a production lower than the forecast the choice is made to charge the battery with the new heuristic in order to be able to prevent future CF by using this stored power. The threshold on the SOC ($SOC_{LiIon} < 50\%$) is here in order to prevent overusing the battery. The behavior in the upper part of the tolerance layer is symmetrical. In case of overproduction, the storage is not used so as to absorb this overproduction and avoid wasted power. This relation between P_{prod} and P_{for} could be justified by persistence effects [13].

One cannot conclude on the optimality of this second heuristic but it clearly outperforms the initial one as shown in Table 4 and Fig. 9. In this figure, the wasted power is expressed as a percentage in relation to the power produced, and the CF probability is calculated over the whole year duration. The LP optimization has also been added as the ideal reference (see Table 6).

The changes implemented in the new heuristic strategy have the desired effect on the costs. First of all, the total cost is reduced by almost 5%. The behavior of the new heuristic is closer to the optimal dispatching resulting from the LP optimization. The battery is more efficiently used with regard to the commitment failure reduction. Even if the wasted cost is not strongly reduced, it remains better with the new heuristic.

Wasted power and CF are complementary quantities and it was easy to find a heuristic which reduce one but increase the other one (by playing with the SOC threshold for example). The power of this new heuristic is to be able to reduce both which shows the fundamental improvement.

6. Conclusion

İn this paper, a smart wind power plant composed by a wind farm and a Li-ion battery is studied in the context of island networks. A linear model has been developed to be used with a MILP optimization solver. A comparative study has been made with a rule based heuristic method: even if this latter is applicable in real time the comparison shows that heuristic may be significantly improved. The ability of a linear programming to give optimal results on linear model but exploitable on a non-linear and more accurate model has been proven. Those results have been used to improve decision making for heuristic algorithms. A second heuristic algorithm has been developed based on LP

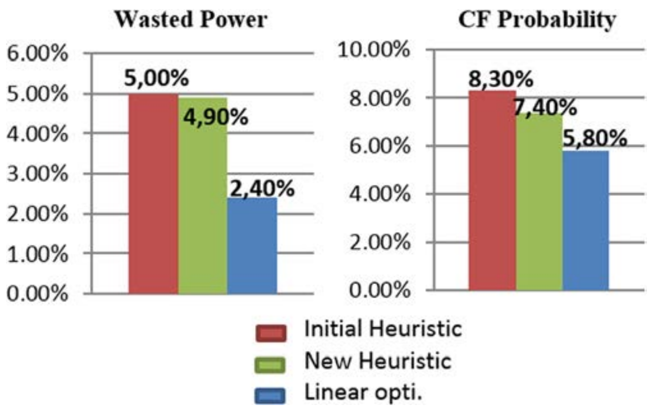

Fig. 9. Comparison between initial and new Heuristic.

behavior showing major improvements in particular by reducing the CF without increasing the wasted power by using the storage system more efficiently. Those results will be used in further studies investigating the co-optimization of component sizing and energy management in the smart wind power plant.

Acknowledgment

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