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Economic optimization of micro-grid operations by dynamic programming with real energy forecast

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Abstract. Optimal management of micro-grids requires anticipating the supply-demand unbalance. This work aims at developing a method to integrate real day-ahead deterministic forecasts of photovoltaic (PV) production and of system loads in the management of an ESS integrated inside a micro-grid. Dynamic Programming (DP) has been chosen to optimize the cost of the micro-grid operation. To test the developed method, a real educational Net Zero Energy Building equipped with a PV roof is considered. Compared to a management that does not take advantage of forecasts, the developed method allows decreasing the operating cost of the system.

	Variable		Variable
Measured and forecasted load (kWh)	$E_{LOAD}, \overline{E_{LOAD}}$	Energy transfers with grid (kWh)	E_{GRID}
Measured and forecasted PV (kWh)	$E_{PV}, \overline{E_{PV}}$	Global irradiation (kWh/m ²)	I
Energy injected to the grid by the ESS (kWh)	$E_{ESS-GRID}$	PV surface (60 m ²)	S
Energy injected to the grid by the PV (kWh)	$E_{PV-GRID}$	PV efficiency (10%)	η_{PV}
Price of purchased electricity (€/kWh)	C_1	Feed-in tariff (10.85 c€/kWh)	C_2
PV temperature coefficient (0.005 °C ⁻¹)	cT_{PV}	Converter efficiency	η_{inv}
State of charge (SOC _{min} = 40% and SOC _{max} = 90%)	SOC	ESS capacity (30 kWh)	C_{ref}
ESS charge and discharge energy (kWh)	E_{ESS}	ESS round-trip efficiency (82%)	η_{ESS}
Inverter nominal power (25 kW)	$P_{inv rated}$	ESS aging coefficient (2.10 ⁻⁴)	Z
ESS state of health (SOH _{min} = 70%)	SOH	Outdoor temperature (°C)	t_0
ESS investment cost (130 €/kWh)	BIC	PV production cost (6.90 c€/kWh)	C_{upv}

1. Introduction

Microgrids are rising worldwide because they contribute to better integrate renewables in energy systems [1]. A micro-grid is a system with its own generation means such as PV rooftop, loads and frequently an energy storage system (ESS). Its architecture aims to improve energy production and delivery to load. By their variable nature, intermittent RES such as PV generate fluctuations that destabilize supply and demand balance, reduce the power quality and therefore the system reliability. The main challenge facing the microgrids is to find the most effective way to manage the generation and the load. This work focuses on a centralized microgrid with few controllable devices.

Considering non-dispatchable RES such as PV, the use of an ESS allows balancing the supply-demand of electricity and add flexibility [2] to the system. The objective is to reduce the operation costs



and increase the local self-consumption. Regarding recent works [3], the management of the ESS state of charge (SOC) is one of the most used methods. Scheduling of the SOC while taking into account the future loads and production permits to reach the lowest operating cost. In the state of the art [3], this operational problem is commonly divided in two optimization loops: predictive scheduling of the production systems (PV and ESS) commitment and real-time control of the system. This work only addresses the predictive scheduling step. Most of the works on the topic [3] use unrealistic forecasts from perturbed measured data. The use of the perfect forecasts as input of the optimization process also permits to evaluate the maximum expected improvement, as instance they allow decreasing the peak demand from the grid and can cut off by 13% the system operating cost of a small microgrid with PV, lead-acid batteries and a local electricity demand.

This work proposes a strategy based on the integration of operational day-ahead forecasts into the optimization process required to generate an optimal scheduling of the ESS. Then, an analysis of the contribution of the forecasts on the operation of the microgrid is carried out. DP is used to optimize the control of the ESS using operational forecast retrieved from the European Centre of Medium range Weather Forecasts (ECMWF) with a 1-hour time step for several days ahead.

2. Methods and tools

2.1. Load and PV forecasts

The building load forecasts are based on average weekdays. $E_{LOAD}(h, D)$ is the energy consumed by the building for the week day D (i.e. Monday to Sunday) and hour h. The forecasted load $\widehat{E_{LOAD}}(h, D)$ corresponds to the average load of the building over the N weeks of the year as follow:

$$\widehat{E_{LOAD}}(h, D) = \frac{\sum_i^N E_{LOAD}(h, D)}{N} \quad h \in (1, \dots, 24) \quad D \in (1, \dots, 7) \quad \text{and } N = 51 \quad (1)$$

Using this method, we generate 7 averages weekdays, which are representative of the building schedule use during an average week. As a consequence, all forecasted weeks are identical.

To forecast the PV output, day-ahead forecasts with a 1-hour granularity of relevant weather parameters, i.e. solar irradiance and dry-bulb air temperature are retrieved from the IFS run launched at midnight and available at the ECMWF portal. The simplified model proposed by [4] is used to compute the generation of the PV plant:

$$\widehat{E_{PV}}(t) = \eta_{PV} \times S \times \widehat{I_{ECMWF}} \times (1 - cT_{PV} \times (\widehat{t_{ECMWF}}(t) - 25)) \times \eta_{inv} \times \Delta t \quad (2)$$

Where η_{PV} is the conversion efficiency of the solar cell array, cT_{PV} the temperature coefficient of the PV module, S the PV field area, $\widehat{t_{ECMWF}}$ and $\widehat{I_{ECMWF}}$ are respectively the forecasted dry-bulb temperature and the global solar irradiance. Regarding the inverter, the efficiency is calculated using the model proposed by [3]:

$$\eta_{inv} = 1 - \frac{P_{inv rated}}{P_{PV}} \times (0.0094 + 0.043 \times In + 0.04 \times In^2) \quad (3)$$

2.2. ESS model

The architecture of the system is based on the model introduced by Riffoneau [3], composed by a load, a PV generator, an ESS and a connection to the main grid. A lead-acid batterie is used for this work, with the assumption that no self-discharge occurs over time. For the AC-DC (bidirectional) conversion, we will use the same type of converter as the one used for the PV generator and its efficiency is given by see eq. 3. The round-trip efficiency of the batteries is estimated to be a constant value η_{ESS} of 82%[5]. The State of Charge ($SOC = C(t)/C_{ref,nom}$) is the ratio of the current capacity C(t) to the reference capacity $C_{ref,nom}$ and its variation over the time is $\Delta SOC(t) = SOC(t - \Delta t) - SOC(t)$. The energy that flows in and out to the ESS is given by:

$$E_{ESS}(t) = \begin{cases} E_{ESS}(t)^{DISCHARGE} = \eta_{inv} \times \Delta SOC(t) \times C_{ref,nom} & \text{if } \Delta SOC(t) > 0 \\ E_{ESS}(t)^{CHARGE} = \frac{\Delta SOC(t) \times C_{ref,nom}}{\eta_{inv} \times \eta_{ESS}} & \text{if } \Delta SOC(t) < 0 \end{cases} \quad (4)$$

From a technical point of view, the lifespan of this type of storage is linked to the number and the depth of the cycles of charges and discharges. The considered model estimates the deterioration of the

state of health (SOH) as a linear relationship between the depth of the discharges and a coefficient of aging Z . ΔSOH , which corresponds to the diminution of the SOH after a discharge, is given by following equation:

$$\Delta SOH(t) = \begin{cases} Z \times \Delta SOC(t) & \text{if } \Delta SOC(t) < 0 \\ 0 & \text{in other case} \end{cases} \quad (5)$$

2.3. Optimization

In energy planning, there are numerous methods dedicated to the operating cost optimization [6,7]. Here, we chose the Dynamic programming (DP) because our problem can be convex or concave. Furthermore, [8] showed that DP is a good candidate for the optimal management of an ESS. Last, as forecasts could be probabilistic, the use of the stochastic version of the DP will be the next step to achieve a robust ESS management.

The current SOH of a battery depends variation of the SOC and on various random factors such as manufacturing variance. Since our hypothesis does not take into account these random processes, it is assumed that the degradation is simply a function of the SOH. If the SOH reaches the minimum value SOH_{min} , the ESS is disabled. The operating cost $C_{ESS}(t)$ of the ESS depends on its SOH and on the investment cost BiC of the ESS.

$$C_{ESS}(t) = BiC \times \left(\frac{-\Delta SOH(t)}{1 - SOH_{min}} \right) \quad (6)$$

Costs of PV $C_{PV}(t)$ and of purchased electricity from the grid $C_{GRID}(t)$ are calculated using linear relationships based on unitary costs. The production cost of the PV field $C_{PV}(t)$ is calculated as follow: $C_{PV}(t) = E_{PV}(t) \times Cu_{PV}$, where Cu_{PV} is the unitary cost of energy production $E_{PV}(t)$ of the PV generator. This unitary price of energy produced by the OPV is derived from the levelized cost of electricity (LCOE [9]). Considering the economical context of the study case, the unitary price is $Cu_{PV} = 0.069 \text{ Euros/kWh}$. In this study we assume constant values of the feed-in-tariff C_2 and variable grid cost C_1 of electricity are considered (see eq. 7).

$$C_{GRID}(t) = E_{GRID}(t) \times Cu_{GRID} \begin{cases} Cu_{GRID} = C_1 & \text{if } E_{GRID}(t) > 0 \\ Cu_{GRID} = C_2 & \text{if } E_{GRID}(t) < 0 \end{cases} \quad (7)$$

The cost function of the optimization problem is the economic costs of the micro-grid operation taking into account the costs of the different sources (i.e. PV, ESS and grid). The optimal operation cost is obtained from the global minimization of the following objective function where the unique decision variable is the ESS energy (E_{ESS}):

$$J = \min \sum_{t=1}^T C_{PV}(t) + C_{ESS}(t) + C_{GRID}(t) \quad (8)$$

Constraints are by nature related to the operation and to physical limitations of the system. The first constraint is the supply-demand balance of the micro-grid, which implies that the sum of the energy flows is null:

$$E_{LOAD}(t) = E_{PV}(t) + E_{ESS}(t) + E_{GRID}(t) \quad (9)$$

The system also experiences technical constraints related to ESS limitations and to the grid contribution. Considering an electro-chemical battery, the technology itself implies that it is not possible to use the storage in the extremums (totally empty or full). As a result, an operating range between a minimum SOC_{min} and a maximum SOC_{max} is necessary to avoid damaging the ESS.

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (10)$$

As described in section II, the SOH of the ESS gradually decreases with the depths of the discharges. To keep the system working, a minimal level of SOH of the ESS SOH_{min} is required.

$$SOH(t) > SOH_{min} \quad (11)$$

3. Implementation

The control of the ESS consists in scheduling the SOC of the ESS with time step of 1 hour. Therefore, the SOC of the ESS is scheduled every hour of the next day. For the study, two management strategy will be compared: instantaneous or ruled based management and controlled with forecasts.

The ruled based is an instantaneous management, depending on the SOC of the battery, the supply-demand imbalance and the charges/discharges of the ESS. The operation of this strategy can be summarized by few rules. The PV can only charge the ESS when PV output excess the load. The ESS supplies the energy to the load when the PV is not enough. If the ESS is empty, the grid supplies the load. And finally, if the ESS is full, the excess of energy is injected to the grid.

This second management mode uses the forecasts as input of a receding horizon method. At 00h00 of simulated day D , 3 days of PV and load forecast are produced. Then, the optimization schedules the operation of the ESS for the next 72h of with a 1-hour granularity. Only the first 24 hours are considered to operate the ESS but the use of a longer horizon in the optimization permits to define an optimal SOC at the end of the first day. Without this receding horizon method, the ESS would have been empty at the end of every day. During the realization of the schedule of the ESS, the grid counterbalances the deviations from the forecasts. First, perfect forecasts, corresponding to the recorded historical data, will provide an assessment of the best performance that could be achieved while introducing forecasts to elaborate the scheduling of the ESS. Second, real forecasts, as described in section II, will give realistic results.

The operation cost of the micro-grid is obviously the first indicator generated by the two management strategies. Beside the economic assessment, the evaluation of the quality of the management of the micro-grid, will be done by the following indicators proposed by Simpure [10]:

$$\text{Self consumption: } \tau_{CS} = \frac{\sum_{t=1}^T (E_{PV-LOAD}(t) + E_{ESS}(t)^{CHARGE})}{\sum_{t=1}^T E_{PV}(t)} \quad (12)$$

$$\text{The rate of injections to the grid: } E_R = \frac{\sum_{t=1}^T (E_{PV-GRID}(t) + E_{ESS-GRID}(t))}{\sum_{t=1}^T E_{PV}(t)} \quad (13)$$

4. Data

The load data come from a building called EnerPOS, which is located in St-Pierre in the island of Reunion, a French overseas territory in the Indian Ocean. It is a building in a tropical environment of the southern hemisphere. The building is intended for administrative and school uses. It is a Net zero energy building [11] with integrated photovoltaic systems and a low energy consumption. The meteorological data comes from a meteorological station installed on the same site. The cost of electricity in Reunion Island is subsidized by the state and the selling prices are strongly lower than the real cost of electricity production. Considering these artificially low tariffs, the development of renewables must be grant-aid. In this work, we shifted the current prices applied to the studied building to correspond to the annual and real cost of energy provided by the unique local distribution operator, including taxes (Table 1). The timetable of the peak, off peak and normal hours used to compute the electricity bill of the building can be consulted on EDF website [12].

Table 1. French context electricity price from extrapolated value at January 2018

	Fixed part (€/kW)	Peak (c€/kWh)	Summer (c€/kWh)		Winter (c€/kWh)	
			LRH	NH	LRH	NH
Average	47,640	41.49	13.83	15.17	18.38	25.87

Normal hours: NH

Low rate hours: LRH

5. Results and discussion

For a sample day (see figures 1 and 2), we can see that the ESS operation of the ruled based strategy differs significantly from the control with forecasts. Considering the same initial SOC=0.5, the latter outperforms the ruled based method. The optimal control with forecasts uses the difference of prices between peak and off-peak hours to maximize the gains. The storage only stores the energy required to avoid purchasing of electricity from the grid during the peak hours. Regarding more specifically the use of real forecasts, the behaviour of the ESS is almost the same as for perfect forecasts. But due to forecasting errors, mismatches in supply-demand balance occur and increase the operating cost. As

expected, in case of supply-demand imbalance of the micro-grid, the rule-based strategy systematically charges or discharges the ESS. As a consequence, the storage accumulates the extended of energy from the PV till its full and when the PV is not enough, the storage discharges to compensate the deficit. So, the ruled-based management uses intensely the storage and the operation cost is more important because of strong and frequent discharges.

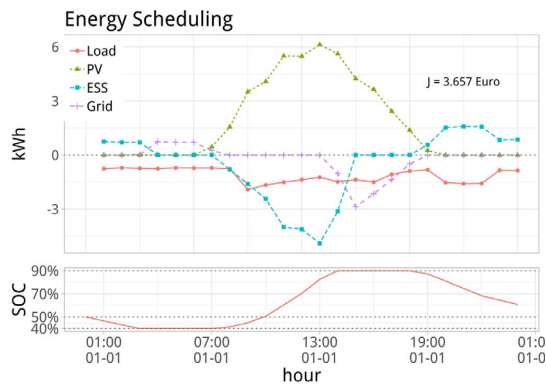


Figure 1. Rule-based management

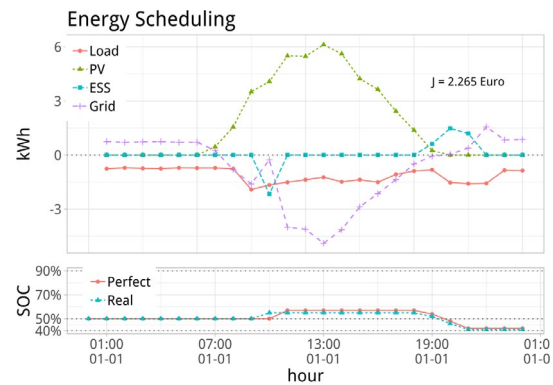


Figure 2. Real forecast scheduling

The forecast quality [13] is computed for an entire year of operation of the building. Table 2 gives the yearly metrics of error for the PV, the load and the net-load forecasts. This former corresponds to the net consumption of the building when considering the PV production, $E_{Net-LOAD} = E_{LOAD} - E_{PV}$. The forecasts experience a low bias. One can also notice that the PV forecasts are less accurate than the load forecasts with lower RMSE and MAE. Finally, the net-load forecasts are strongly worse than both PV and load forecasts. The evolution of the hourly operation cost as a function of the hourly forecasting error of the net-load indicates that an overestimation of the net-load leads to an increase of the operation cost. Moreover, if the error is close to 0, there are high cost values, which mean that at some points, we have to exploit the storage or the network as much as possible.

Table 2: Annual error metrics

	RMSE (Wh)	MAE (Wh)	MBE (Wh)
Load	0.469	0.305	-0.003
PV	0.909	0.332	-0.107
Net-load	2.499	1.834	0.104

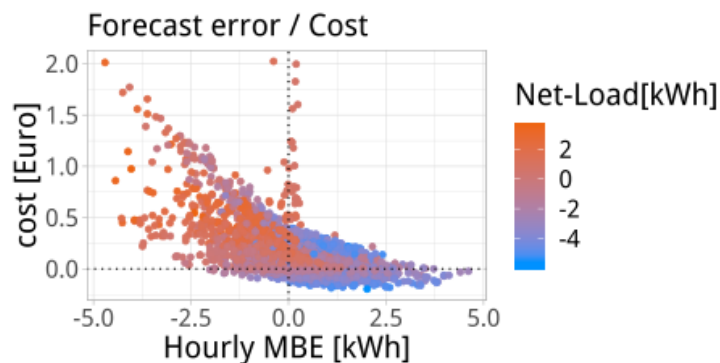


Figure 3: Relationship between hourly forecast error and operation cost of the microgrid.

In table 3, annual indexes show that the knowledge of the future can reduce the operating cost by 22% using perfect forecast and 15% with real forecast. So, the quality of the forecast increases the economic gains. Regarding the self-consumption rate, the values are almost the same for the perfect and real forecasts. However, the ruled-based has a higher self-consumption rate because the ESS is

systematically charged when there is a surplus of PV production and then this surplus is shifted to the night hours to supply the building. The control with forecasts sells more energy to the grid to increase the gains and thus the injection to the grid is higher than the rule-based management.

Table 3: Performances of the microgrid for 1 year of operation

	Self-consumption τ_{cs} [%]	Injection to the grid E_R [%]	Max Energy from grid	Annual operating cost J [€]
Perfect	49.482	38.746	10.488	1086.054
Forecast	48.215	44.239	14.258	1189.498
Rule-based	55.758	9.432	3.534	1402.965

6. Conclusion

This work sets up the optimal control of an ESS with the aim to minimize the operating cost of a real microgrid. The specificity of the approach is to use real forecasts for the load and for the PV production. The use of the forecasts permits establishing the day-ahead schedule of the ESS and to minimize the operating cost. First, the results show that dynamic programming optimization allows detailing efficiently the microgrid features even if they assume non-linear behaviour. Second, the use of the ECMWF forecasts to predict the PV production improves significantly the yearly gain compared to a rule-based management strategy. Then, this study highlights that an underestimation of the future resources (PV) has less effects on the operating cost reduction than an overestimation.

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