DEALING WITH UNCERTAINTY IN PV-POWERED MICROGRIDS: AN OPTIMAL CORRECTIVE APPROACH

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ABSTRACT

With the aim of increasing the penetration of renewables in the energy matrix, microgrids could play a major role. However, microgrids powered by renewable energy sources bring along a higher level of uncertainty, derived from the stochastic nature of this type of energy sources. The fact of having an uncertain production along with the usually-uncertain consumption in this type of electric systems, poses different challenges for their management in terms of power quality, planning and scheduling, among others. This work presents an approach to deal with this uncertainty in a PV-powered microgrid, particularly for its energy management, with the aim to improve its performance.

INTRODUCTION

The general problem addressed in this work concerns most of microgrids that use renewable energy sources (RES). Due to the stochastic nature of the weather and consumers, the net-demand (ND) of any microgrid that includes RES is uncertain. This means that there is always a difference between the real and forecasted ND. The ND is defined in this case as the difference between the total consumption and total generation. That said, if a predictive energy management approach is used (i.e. using ND forecasts to obtain the optimal setpoints of resources in advance), it is required to have one element to compensate differences between real and forecasted ND. This implies that this element will not be following any optimal strategy whatsoever. If the use of this element has a marginal cost (as it is normally the case), this will lead to a suboptimal performance of whole the system. A great part of the state-of-the-art energy management systems (EMS) for microgrids work using this **predictive-managemen**t approach [1][2][3]. The present proposal addresses the uncertainty problem differently. Given that the ND (for a given time period *T*), becomes known once *T* has already passed, a method is proposed to use this **past information** in the EMS, so that it can optimally take it into account in the planning for the next timestep *T+1*.

This is possible by adding an extra element called the **uncertainty reserve (UR)** and by changing the paradigm of working based on a predictive approach to a deferred (corrective) one. In the following sections the study-case, experimental setup and tests performed are described and results are discussed.

CLOSED-LOOP UNCERTAINTY RESERVE

The approach hereby presented has been called *Closed-Loop Uncertainty Reserve* (**CLUR**), as it succinctly alludes to the operating principle behind it. As depicted in *Fig.1* the key element in this proposal is an additional energy storage unit, called **uncertainty reserve (UR)**.

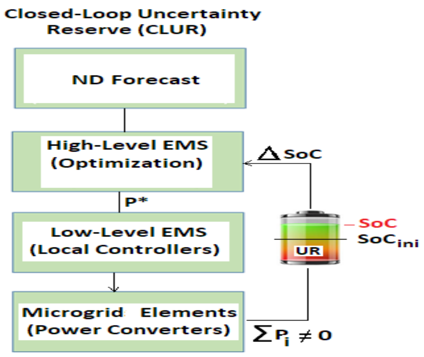

Fig.1: Integration of the operating reserve in the EMS of a microgrid under a closed-loop approach

Main storage vrs uncertainty reserve

One of the most popular technologies used as **main energy storage (MES)** in microgrids nowadays are batteries, due to their high energy density and lower cost [4]. Batteries have a nominal cycling life (charge/discharge cycles) that is reduced as a function of the depth-of-discharge (Dod) and rate-of-discharge (Rod) of every cycle. The levelized-cost-of-electricity (LCOE) produced in a MG (that includes batteries as MES) strongly depends on the lifespan of the battery unit, as it represents one of the most expensive elements in the balance of system; thus, the importance of doing an optimal management of it. There are other energy storage technologies whose nominal cycling-life is much higher than batteries and not dependent on the Dod. One example of these technologies is supercapacitors (SCs). The required capacity of the UR is expected to be small enough as to allow the use of SCs (or an equivalent technology) in a cost-effective way. Given the little dependency between the lifespan and Rod/Dod in SCs, it is considered valid to assign only a capital cost to the UR, given that that the marginal cost derived from its usage is negligible. The latter point, introduces the most important difference between the MES and the UR which is that the MES is scheduled by the EMS whereas the UR is not. The reason is that the MES has a marginal cost-of-use whereas the UR does not, making dispensable the optimal management of the latter.

The uncertainty reserve in the energy management loop

The UR can be considered almost invisible to the EMS, except for its ΔSoC, which is the only feedback that links the UR and the EMS. Any EMS that performs optimal scheduling should include, as one of its constraints, the power balance of the system. It is precisely in this constraint, where the ΔSoC of the UR is included as an additional term, as seen in *Eq. (1)*. In this manner, every time the EMS performs the optimization for the next time step *T+1*, the system tries to bring back the SoC of the UR to its initial state. This is expected to assure convergence of the SoC of the UR, as long as the optimization period *T*, and the capacity of the UR are properly chosen. This is also the reason why this proposal is considered a closed-loop approach, as the changes on the SoC of the UR are fed back into the EMS control loop.

$$\sum P_i - \Delta SoC = 0 \qquad (1)$$

where P_i represents the power of every resource of the MG.

This constraint must be assured at any moment during operation and includes the information about the uncertainty of the ND forecasts through the ΔSoC.

Advantage of the CLUR approach

The inclusion of the UR permits all the other resources of the MG to be optimally scheduled and dispatched, regardless of the mismatch between forecasted and real ND. In this way, the system finds the optimal route of action for the MG as a whole, taking into account the real ND conditions, and assures that all the elements of the MG actually follow that optimal plan. It is also important to highlight that CLUR is not an EMS in itself; it acts in parallel to it. This allows CLUR to be implemented independently of the EMS algorithm being used, to improve the performance of the system. However, the EMS must meet some conditions that are pointed out in the following section.

Conditions of applicability

The CLUR proposal here presented, might lead to an increased performance of a MG that has implemented an EMS, independently of what performance objectives are sought. However, some conditions should be met so that it makes sense to use the CLUR approach. These conditions are:

EMS

Currently, energy management systems can be divided in three main categories: ruled-based (i.e. fuzzy logic), optimization-based (i.e. LP or MILP) and statistical (i.e. machine learning) [1]. The CLUR approach is meant to work with energy management systems of the second category, assuring a global optimal solution.

UR technology

The technology chosen for the uncertainty reserve, has to be one whose lifetime is barely influenced by Dod, Rod or number of cycles during operation. As mentioned in a previous section, there are some technologies that meet these requirements such as SCs.

Forecasts

It is required to have access to forecasts of generation and consumption with an acceptable level of accuracy and with estimations of their uncertainty.

Stochastic variables

The CLUR approach must be applied to all the stochastic variables of the system. In the particular study-case presented here, the only stochastic variable considered is the net demand.

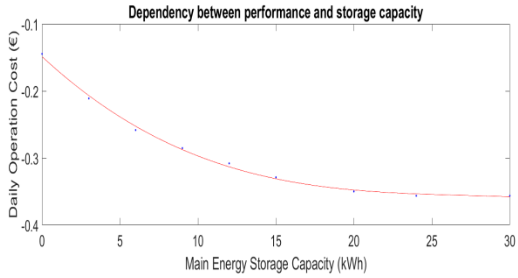

Fig.2: Dependency between the daily operation cost and the capacity of the MES in the study-case MG.

Potential increase of performance

Since the CLUR approach proposes to add an extra energy storage element in the MG (the UR), one could question what would be the performance of the MG if this UR capacity is assigned to the MES, instead of implementing the CLUR approach. To answer that question it is important to note that almost every MG has a characteristic curve of performance as a function of the capacity of its MES. That relation depends on many factors such as the resources and architecture of the MG, the EMS being used and performance objectives, among others. *Fig.2* shows the characteristic curve of the study-case MG used in this work. It can be noted that the system achieves a certain state of saturation after which, further increases in the MES capacity do not necessarily bring further increase of performance. Since every MG responds differently, only a case-specific test would confirm the usefulness (or not) and advantage of the CLUR implementation over the simple increase in the MES capacity.

STUDY CASE

Description of the system, data and experimental setup

The study-case MG is composed of a load (1.5kWp), photovoltaic generation (1.5kWp), a battery (6kWh), a bidirectional grid connection (1.5kWp) and the UR. The system is depicted in *Fig.3*.

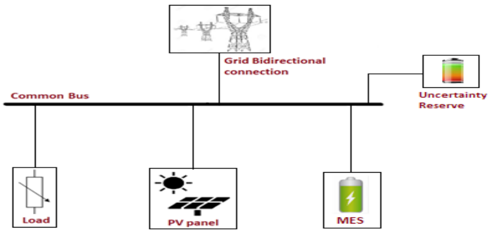

Fig. 3: Resources of the proposed study-case microgrid

The battery is allowed to work between 20-90% of its nominal capacity and its initial SoC is 55%. For this test UR is considered to have an unlimited capacity. All the elements of the microgrid are emulated using 2.2kW fully-programmable bidirectional inverters and a DC power source. Tests are performed in the Microgrids Laboratory at Aalborg University, Denmark. A picture of the hardware setup described above is shown in *Fig.4*.

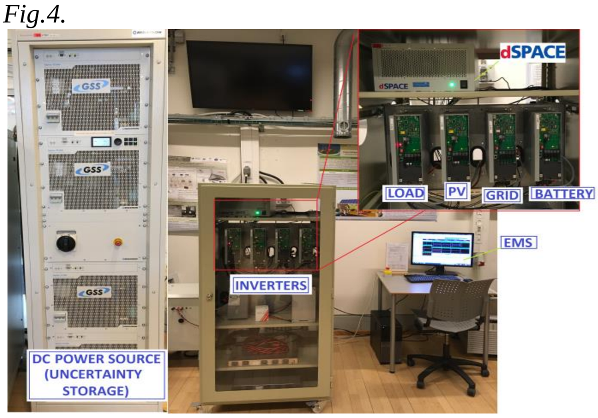

Fig.4: Experimental setup (Microgrids Lab, AAU)

The hourly electricity prices used are considered deterministic and available day-ahead. For the sake of simplicity, prices are considered equal for buys and sells. Day-ahead spot prices in Denmark are used and taken from the Energinet group website (*https://www.energidataservice.dk*). Measurements of solar irradiance to compute the PV production for the Aalborg University site are taken from the AAU weather station of the PV Systems Laboratory. The solar irradiance forecasts for the same site are provided by the European Centre for Medium-Range Weather Forecast (ECMWF). Two sample weeks are used regarding PV production (7-13 Jan & 8-14 Jul 2013). A sample week dataset of individual-household electric power consumption (in 5-minute intervals) is taken from the Center for Machine Learning and Intelligent Systems (*http://archive.ics.uci.edu/ml*). For the sake of simplicity, consumption is considered deterministic. Production and consumption data is scaled to respect the maximum limits of the power inverters.

EMS and optimization problem

A simple optimization-based EMS has been implemented as a linear programming problem, whose objective function is to minimize the operation cost (OC) of the MG. In this case, the OC is reduced to the cost of the electricity exchanged with the main grid (that allows buys and sells). This is stated in *Eq. (2)*.

$$Min\ f(P_{grid}) = \sum_{h=1}^{H} \Delta t \cdot Power_{grid}^{h} \cdot Price^{h} \qquad (2)$$

where the optimization horizon H is 24h (or the rest-of-day) and the *Power* is an hourly average.

The constraints imposed for the optimization are presented in *Eq. (3a-3f)*. This set of constrains are met for every time step and assure: the energy balance of the system, sustainability in time of the SoC of the MES, respecting the maximum and minimum SoC limits of the MES and respecting the power limits of the inverters (i.e. power limits of the lines).

$$E_{MES} + E_{grid} + E_{PV} + E_{load} + \Delta SoC_{UR} = 0 \qquad (3a)$$
$$SoC_{MES}^{ini} = SoC_{MES}^{end} \qquad (3b)$$
$$SoC_{MES}^{t} + \Delta t \cdot Power_{MES} \leq SoC_{MES}^{max} \qquad (3c)$$
$$SoC_{MES}^{t} + \Delta t \cdot Power_{MES} \geq SoC_{MES}^{min} \qquad (3d)$$
$$P_{MES}^{min} \leq P_{MES} \leq P_{MES}^{max} \qquad (3e)$$
$$P_{grid}^{min} \leq P_{grid} \leq P_{grid}^{max} \qquad (3f)$$

TESTS AND RESULTS

Two sample weeks (summer and winter) in the AAU site are chosen to emulate the scenarios. Day-ahead forecasts are considered to be available at midnight of each day, when the first optimization is run. When CLUR is implemented, this optimization is run every hour (with a time horizon up to the end of the current day) in order to compensate the changes on the SoC of the UR of the previous hour. Tests are run for the entire week after which, the total operation cost is computed. This is the metric of performance chosen for this experiment. For the sake of simplicity, no cost or aging due to battery usage is considered.

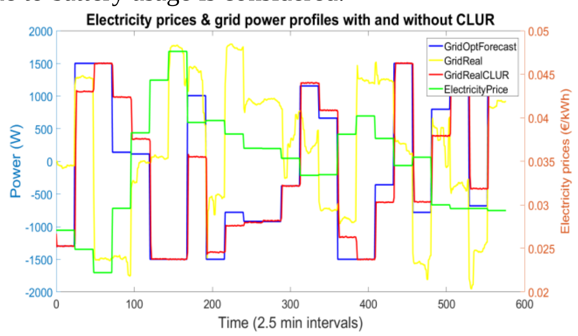

Fig.5: Grid power profiles and electricity prices with and without the CLUR implementation

Performance tests

In the first part, an optimal scheduling for the battery and grid usage is obtained based on day-ahead PV production forecasts. This is done for 7 days for each sample week. In *Fig.5,* the grid power profiles for one day in summer are shown. In blue is the optimal power profile obtained based on day-ahead forecasts; in yellow is the profile of the grid when is left free as the compensating element (only battery power profile fixed) and in red is the grid power profile when the CLUR is implemented. It is also shown in green the hourly electricity prices along the day. It is interesting to note how the grid power profile, once CLUR is implemented and run in real conditions, follows very closely the profile obtained with the day-ahead forecasts, leading even to a slightly better performance by the end of the week. When the grid is left free as the compensation element, it ends up following a sub-optimal profile with respect to electricity prices and surpassing the power limits imposed, which is reflected on its poor performance by the end of the week (winter and summer), as shown in *Table 1.*

Table 1: Weekly operation cost of the MG

Optimal cost(€/week)*	Summer week	Winter week
Real ND (CLUR)	-1.05	0.52
Real ND	-0.8 (-19.3%)	0.77 (-32.5%)
Forecasted ND	-0.99 (-6%)	0.55 (-5.4%)

*Negative prices account for sales of electricity, profits.

The operation costs reflect the expected behavior in which the MG with the CLUR implementation performs better than the system when the grid is not following any optimal strategy. It is also interesting to note that the CLUR implementation make the MG perform better even with respect to the optimal case (when only forecasts are used for the scheduling). However this cannot be generalized and more tests under different ND scenarios are required to validate this result.

UR SoC stability

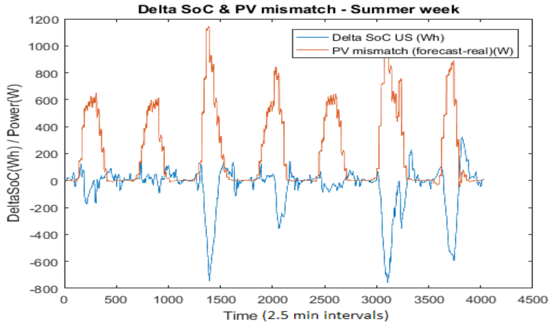

Fig.6: Correlation between changes in the SoC of the UR and PV-mismatch between forecast and real data

The first attempt to implement CLUR was on a daily basis (run the optimization only once a day). In this case, divergence on the SoC of the UR was the norm. Mismatches in the daily ND become too big for the optimizer to find a feasible solution. Then, the optimization period is reduced to one hour and the system becomes stable (for the sample weeks studied). In *Fig.6* the changes on the SoC of the UR are shown throughout the summer week, as well as the mismatches in the PV production. It is clear the correlation between variations in the SoC and mismatches between forecasted and real ND. It is important to recall that in this experiment consumption is considered deterministic; being PV production the only variable that adds stochasticity to the ND. During operation, the UR shows its capacity to recover from strong variations on its SoC due to mismatches in the ND and come back to (almost) its initial SoC by the end of the week. However, further tests under different ND scenarios are required to validate this condition. The peak-to-peak ΔSoC of the UR found is around 1kWh (16% of the nominal capacity of the MES), which would be the minimum capacity required for its proper operation in this particular study-case.

SUMMARY AND FUTURE PERSPECTIVES

The CLUR approach led to a better performance of the MG compared to the deterministic EMS used as reference, in both summer and winter weeks. However, it is clear that this cannot be taken as complete validation of the proposal, as many other state-of-the-art EMS (including stochastic ones) should be tested out and compared with the hereby presented approach. Also, different arquitectures of MG, with different optimization and performance objectives should be explored. A more detailed model of the MG including losses and battery cost and aging models would be desirable. Regarding stability, the system shows convergence of the SoC of the UR for the two weeks tested, when optimizing every one hour. On the contrary, the system becomes unstable when optimization is run once a day. A sweep is desirable to find out the optimal time period to perform the optimization, to achieve the best results in terms of convergence, performance and costs (capacity of the UR). The online sizing of the UR, based on uncertainty estimations of ND forecasts, is another subject to explore, in order to optimize the usage of the storage capacity available, with the aim to attain further improvements in performance of the MG.

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