Estimation and integration of net demand uncertainty in a microgrid management

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***Abstract*—The subject addressed in the proposed paper is the estimation of uncertainty of deterministic forecasts of net demand, and a proposal to incorporate this information in the energy management system of small scale microgrids. This with the aim to decrease CO2 emissions. The information regarding the uncertainty of the forecasts is used for the scheduling of resources during the optimization stage of the energy management system. Results are compared with a base case deterministic and perfect forecast scenario to evaluate the usefulness of the method.**

Keywords—uncertainty, microgrids, energy management system, CO2 emissions, rolling horizon

I. Introduction

One of the key aspects that make electrical systems including renewable energy sources (RES) difficult to manage is the impossibility to foresee their precise output. The longer the forecasting horizon, the less accurate the forecast becomes. This makes planning, scheduling and management of resources in a microgrid a non-trivial issue if an optimal result is expected. Inaccuracies in net-demand (ND) estimations (difference between production and consumption) can lead to a variety of issues, going from stability problems to sub-optimal utilization of resources and performance of the system (i.e. low self-consumption/self-sufficiency rates or high CO_2 emissions levels). An optimal management of a microgrid is also imperative to lower its LCOE, which in turn is a key aspect in achieving grid-parity for distributed energy systems (DES). With sinking feed-in-tariffs in many countries, self-consumption and self-sufficiency are incentivized and viewed as the way-to-go by many specialists in small-scale DES [1]. Also, with the climate crisis the need of decreasing CO_2 emissions in energy systems worldwide has gain major importance in recent years. In order to decrease CO_2 emissions, the best possible matching between RES production and consumption shall be attained, minimizing the use of electricity from the main electric network, that -depending on the country- might carry a strong CO_2 content. Therefore, the imperative need of reliable and meaningful forecasts. An important percentage of the state-of-the-art EMS's require deterministic/discrete forecasts of ND as inputs to perform the optimal scheduling [2]. Due to the intrinsic stochasticity of RES and electricity consumption, a measure of accuracy of the forecasts could make them more meaningful for the EMS, eventually allowing it to find a better scheduling, with a better matching between production and consumption that eventually help to lower CO_2 emissions of the system.

II. Methodology

The microgrid upon study is supposed to serve a tertiary building that is isolated from the main grid with 15kWp of solar panels and a 42 kWh of battery storage with a carbon footprint of around 40 gCO_2/kWh assuming average values of cycling life and carbon footprint during production of the battery [4]. The consumption has been recorded from the Drahi-X site École Polytechnique for several years and can be accessed in real time to perform the simulations. The system is assumed to have a backup 30kWp diesel generator (Genset) whose carbon footprint is 1270 gCO_2/kWh [5].

A database of forecasts and measurements for net demand is build using PV production and electricity consumption ground measurements. PV production data is supplied by the SIRTA laboratory and meteorological station (Ecole Polytechnique site) for the years 2016 to 2018 while electricity consumption data is taken from the Drahi-X building at the same site and for the same period of time, all in an hourly-average basis. With these ground measurements, net demand is computed as the difference between PV production and consumption for every hour of the dataset. Regarding the ND -deterministic- forecasts, a simple weekly-persistence is used in order to generate the forecasts for the entire study period. The dataset is divided in two subsets, a 'training-subset' of one year (2016/08-2017/08) and a 'test-subset' of one year (2017/08-2018/08). Due to the heavy computational burdens and time limitations, a sample of the test-set is used composed of four equally-spaced sample days per month (7^{th},14^{th},21^{th} and 28^{th} day of each month) summing up a total of 1152 samples (hours).

A rolling horizon (RH) strategy is used for the scheduling of the battery power delivery with different optimization time horizons, going from one to thirty-six hours ahead. This means that the scheduling optimization algorithm is run every hour and optimizes for a given time horizon utilizing the ND forecasts. The objective of the energy management system (EMS) is to reduce the CO_2 emissions of the electricity delivered by the microgrid. Three different types of forecasts are compared: perfect forecast (PF), deterministic forecast (DF) and the inter quartile adjusted mean (IQAM). With the PF the EMS has the exact information about the upcoming ND. With the DF, EMS is supplied with the weekly-persistence forecast to perform the optimization and scheduling. The IQAM forecast consists on obtaining the mean value between quartiles Q2.5 and Q97.5 of the ensemble of analogs which provide a confidence of 95.7% (97.5% of the measurements in the training-subset fall within the two percentiles). This mean is adjusted proportionally with a factor that is experimentally determined to minimize the error between real and forecasted ND in the training set.

An analogs ensemble method is used to convert the deterministic forecast provided by the weekly-persistence into a probabilistic one that is used to obtain the IQAM. This method is chosen due to its versatility as a data post-processing method [3] and ability to produce probabilistic information out of past ground measurements. The workflow principle of the method is shown in Fig. 1, and it lies on the availability of two datasets with historical data of ground measurements and forecasts. When a new forecast is available, it is compared with the forecasts database and a certain number of past "similar" forecasts are chosen. This number is optimally chosen to achieve the best trade-off between resolution and reliability. The corresponding ground measurements to those "similar" forecasts are then taken as the ensemble of analogs. The dispersion of the samples contains information about the uncertainty of the forecast. From the same ensemble IQAM is obtained.

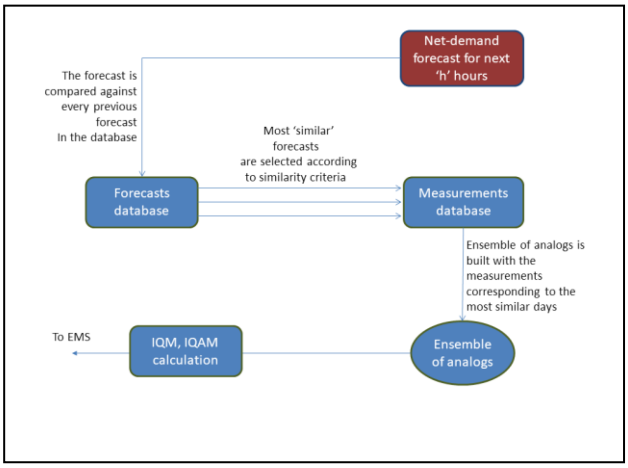

Fig 1. Flow diagram of the analogs ensembles algorithm

Once the forecasts are produced with the three different approaches (PF, DF, IQAM) for the test period, the EMS is run over the same test period, using different optimization horizons (6h, 12h, 24h). An hourly RH strategy is used hence the optimization is repeated every hour taking into account the latest information available regarding the state of the system (state-of-charge (SoC) of the battery) and the forecasts (in case they are updated). Simulations are run over the sample test period and an average-hourly cost is found and used as the measure of performance of each strategy.

III. Analogs Ensembles

To serve as base case to compare the performance of the AE to produce meaningful probabilistic forecasts, a climatology-like approach is used to produce an ensemble of samples too. The climatology ensemble (CE) takes its name from the climatology approaches used in the meteorological domain to produce a baseline for probabilistic forecasts out of historical data of

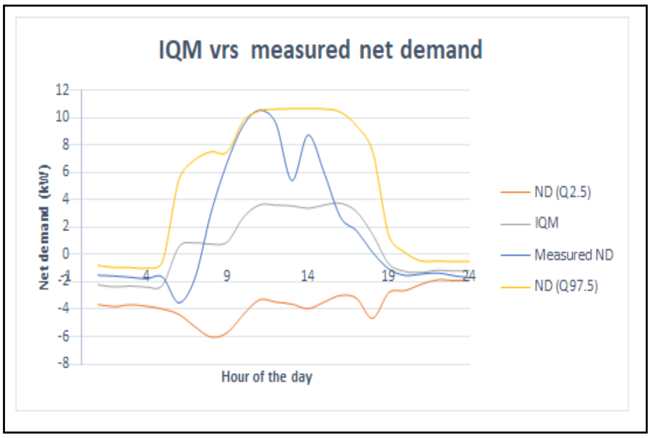

Fig. 2 Example of the output of the AE method (2017-08-14)

meteorological variables such as windspeed, solar irradiance, temperature and rainfall, among others. The CE are formed by taking the hourly ND measurements of the training set forming an ensemble of 365 samples for every hour of the day. Once the twenty-four CE are formed, symmetric quantiles are found so that the ensembles present a confidence of 95%. The confidence is defined as the percentage of samples (of measured ND) on the test-subset that fall within the two quantiles. The quantiles Q3 and Q97 present an average confidence over 95% and a resolution of 12.98kW for the CE of all the hours of the day. In this approach the resolution is defined as the absolute difference between Q3 and Q97 (in kW). Then, the analogs ensembles are formed by taking from the training dataset the most similar 60 samples of ND for each hour of the test-subset. Similarity is found between the forecast for the upcoming '*t*' hours (optimization time horizon) and the forecasts in the training set. The similarity criteria is defined in Eq. 1.

$$\|F_t, A_{t'}\| = \sum_{i=1}^{N_v} \frac{W_i}{\sigma_{f_i}} \sqrt{\sum_{j=-tw}^{tw} (F_{i,t+j} - A_{i,t'+j})^2} \quad (1)$$

where $\|F_t, A_{t'}\|$ is the distance (score/similarity) between the forecast for time t and the analog forecast at time t' in the database, W_i is the weight of the i^{th} variable, N_v is the number of variables, σ_{f_i} is the standard deviation of the time series of past forecasts of a given variable, $F_{i,t+j}$ is the forecast of the ith variable at time t+j, $A_{i,t+j}$ is an analog forecast sample of the ith variable at time t+j and *tw* is the time window.

To achieve an average confidence above 95% with the AE (as with the CE), the quantiles Q2.5 and Q97.5 have to be used yielding an average resolution of 9.57 kW, which is 26% less with respect to the CE. Given that resolution can be interpreted a measure of uncertainty of the forecasts (or forecasting skill), one can conclude that the AE method produce less-uncertain ensembles than climatology. An example of the AE output can be seen in Fig. 2.

IV. ENERGY MANAGEMENT SYSTEM

The forecast of ND has to be fed to the EMS in order to perform the scheduling. The algorithm takes this forecast and optimizes for a given time horizon the best strategy for the battery and Genset power delivery (optimization variables). Given that in reality ND is different than the forecasted one, both variables cannot be fixed in the real system, otherwise it would collapse as the power balance of the system would not be fulfilled. Hence, the genset will be left free to compensate differences between forecasted and real ND (in case differences are negative) and PV production is curtailed in the case the differences are positive (more production than consumption). The cost of curtailed PV energy is considered as the difference between the genset energy cost and the battery energy cost, as the PV energy that is curtailed (not stored in the battery) shall be replaced in the future by energy taken from the genset at the genset cost, as per Eq. 2.

$$C_{curt} = C_{gen} - C_{batt} = 1270 - 40 = 1230 \ (gCO_2/kWh_{curt}) \quad (2)$$

The cost of charging the battery is considered to be zero, as all the CO_2 emissions of the battery are charged to the energy delivered by the battery, as stated in section II. The objective function for the optimization accounts for the costs in terms of CO_2 emissions per kWh of the system as per Eq. 3.

$$C_t(P_b,P_g) = C_b*P_b*dt + C_g*P_g*dt \quad (gCO_2) \quad (3)$$

where C_b, C_g are the battery and grid cost in terms of CO_2 emissions, P_b, P_g are the battery and grid hourly average power and *dt* is the timestep of the data (1 hour); where C_b = 39 gCO_2/kWh when $P_b > 0$ (when battery discharges) and $C_b = 0$ when $P_b < 0$ (when battery charges); and similarly C_g = 1270 gCO_2/kWh when $P_g > 0$ (when Genset delivers power) and $C_g = C_{CURT}$ when $P_g < 0$ (when PV energy is curtailed).

The constraints of the optimization consist in the upper and lower limits for the variables, the state-of-charge (SoC) of the battery plus the energy balance of the system. An additional constraint is added, to study the behavior of the system with and without it, which is the 'sustainability of the SoC' meaning that the system is forced to leave the battery by the end of the optimization horizon with the same SoC that it had at the beginning. These constraints are formulated in Eqs. 4 to 8.

Battery limits: $P_b < P_{b\,max}$, $P_b > P_{b\,min}$ (4)
Genset limits: $P_g < P_{g\,max}$, $P_g > P_{g\,min}$ (5)
SoC limits: $SoC < SoC_{max}$, $SoC > SoC_{min}$ (6)
Energy conservation: $P_b + P_g + ND = 0$ (7)
SoC sustainability: $SoC_{final} = SoC_{initial}$ (8)

Where $P_{bmax} = -P_{bmin}$ = 15kW, $P_{gmax} = -P_{gmin}$ = 30kW, SoC_{max} = 100, SoC_{min} = 0. As mentioned in section II, once the forecasts for the test-subset have been generated, the optimization is run to generate the optimal scheduling for the battery and genset power, for different time horizons, including and excluding the SoC sustainability restriction (Eq. 8). When Eq. 8 is excluded, the time horizons considered are 6h, 12h and 24h. Once the optimal strategy has been found ($P_{b\,opt}$ and $P_{g\,opt}$), $P_{b\,opt}$ is imposed in the system (simulated) in real conditions (with the real ND). The difference between the real and forecasted ND will cause P_g to be different than $P_{b\,opt}$ which yields different total costs for each of the forecasting strategies. P_g is chosen as the pivot variable due to its higher power (and energy) capacity (flexibility).

V. RESULTS

The results of the different case scenarios are summarized in tables I and II.

TABLE I. ERROR AND COST FOR DIFFERENT FORECAST SCENARIOS (CASE 1: SOCINI=SOCFINAL)

	MAE (kW)	MBE(kW)	RMSE(kW)	Cost(gCO2/kWh)
Time horizon: 6 hours				
PF	0	0	0	4679
DF	2.277	-0.109	3.64	5033
IQAM	2.082	0.372	2.949	5155
Time horizon: 12 hours				
PF	0	0	0	3976
DF	2.275	-0.097	3.641	4873
IQAM	2.073	0.395	2940	4892
Time horizon: 24 hours				
PF	0	0	0	3926
DF	2.289	-0.108	3.656	4996
IQAM	2.083	0.398	2.952	4898

* The cost is an hourly average value over the entire test-subset

TABLE II. ERROR AND COST FOR DIFFERENT FORECAST SCENARIOS (CASE 2: SOCINI≠SOCFINAL)

	MAE (kW)	MBE(kW)	RMSE(kW)	Cost(gCO2/kWh)
Time horizon: 6 hours				
PF	0	0	0	2463
DF	2.277	-0.109	3.639	4046
IQAM	2.082	0.372	2.949	3658
Time horizon: 12 hours				
PF	0	0	0	3463
DF	2.275	-0.097	3.641	4693
IQAM	2.073	0.395	2.94	4539
Time horizon: 24 hours				
PF	0	0	0	3788
DF	2.289	-0.108	3.656	4890
IQAM	2.083	0.398	2.952	4722

* The cost is an hourly average value over the entire test-subset

As expected, the perfect forecast yields the best results on both scenarios (with and without SoC constraint), being the difference higher for shorter time horizons in case 2 and the opposite behavior is observed in case 1. The fact of having the real information about what is about to happen in the future allows the system to follow exactly the optimal strategy therefore obtaining the minimal cost. IQAM performs better than DF in case 2 for all time horizons, with differences ranging from 3% to 9%. This is reasonable when taking into account that IQAM is the result of collecting similar samples to the expected ND, yielding an overall smaller error between forecasted and real ND. On the other hand, in case 1 it is for longer time horizons when IQAM performs better than DF; this behavior can be better appreciated in Fig. 3. In this case, for the short term, the fact of having the restriction of the SoC, seems to counteract to some extent the advantage of more accurate forecasts of IQAM, which can be caused by the non-linearity of the cost function. This means that, over and underestimation of the ND weight different in terms of cost. However, the precise reason of this behavior for shorter time horizons (observed in Fig. 3) is yet to be analyzed.

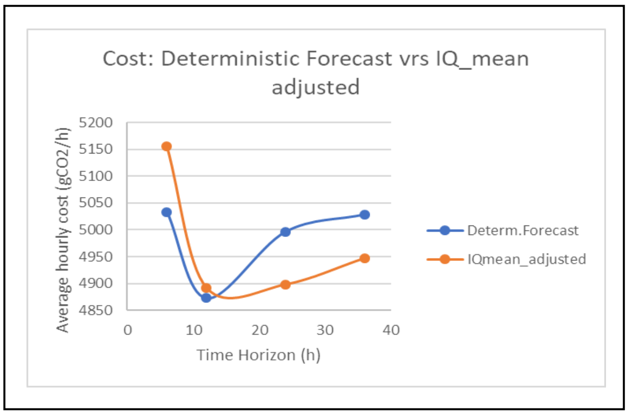

Fig 3. Comparison between costs using DF and IQAM (case 1: SoCini=SoCfinal)

Overall costs are higher in case 1, which suggest that leaving the battery with no restriction regarding the final SoC allows the system to do better in the scheduling. This can be the result of having this arbitrary constraint that not necessarily is optimal from the point of view of cost, and not necessary from the point of view of the SoC as the algorithm always keeps it within the allowed limits. The costs decrease with time horizon in case 1 and the opposite behavior can be observed in case 2. This is observed in Fig. 4.

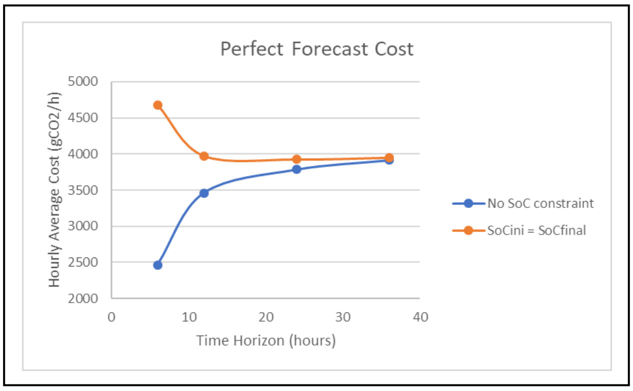

Fig 4. Average cost of the system using perfect forecast with and without the SoC constraint

It is interesting to note in Fig. 4 that the difference for 6h time-horizon surpasses 2kW, while for 36h it is practically zero. From the same figure it seems that the best combination is case 2 (no SoC restriction) and shorter time horizons for optimization. This could be explained by the fact that by optimizing for longer periods of time, will make the systems to take decisions that are good for the long term but not for the short term. Given that the system is run every hour (RH strategy), the only value that is actually used (out of all the future optimal-values obtained by the scheduling algorithm) is the one for the next hour. If this value is optimized for a longer period of time, it is understandable that could not be the optimal in the short term (i.e. next hour).

VI. CONCLUSIONS

-The AE method present an advantage over ND-climatology in terms of resolution (for equal confidence level), being a viable alternative to produce probabilistic information out of deterministic ND forecasts, regardless the source of the latter.

-IQAM is a viable alternative to take into account the uncertainty of a deterministic ND forecast (reflected in the spread between quantiles) and to convert it in a single value that can be input in a linear-programming-based EMS, that performs power scheduling.

-Shorter optimization time horizons seem to perform better in terms of CO2 emissions than longer ones, which can be explained by the fact that optimal strategies made with a long-term view, are not necessarily optimal in the short-term (which takes more importance when a RH strategy is used).

-The restriction of the SoC (SoC_{ini} = SoC_{final}) seems to be unnecessary and counterproductive as it yields overall higher costs in terms of CO2 emissions. The boundary constraints (upper and lower limits for the SoC) are sufficient to keep the battery within its working limits.

-For the present case study, putting no constraint on the final SoC and a 6h optimization horizon is the combination that yields the lowest levels of CO2 emissions per hour.

VII. ONGOING WORK

The study of an grid connected system with the ability to send energy to the main grid is one of the next steps of the study. This will be accompanied by the utilization of the CO2 emissions of the main grid in real time which are variable (some times higher and some times lower than the battery value), which opens the possibility of doing CO2 trading; specially in moments when the solar production is low hence, utilization of the battery for peak shifting is useless.

Besides, we want to study different objectives for the optimization, such as operation costs and self-consumption/self-sufficiency. The objective is to study how the optimization for one objective affect the other ones, either in a positive or a negative way.

A real microgrid is being deployed in order to test the algorithms developed and to observe other constraints and issues that might not be visible in the simulations.

Demand side management is being implement as part or the EMS as a way to deal with diurnal variability in the PV production to try to minimize the requirement of storage and/or optimize its use. The study is being carried out following a real case of a microgrid being deployed in a tertiary sector building.

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