Stochastic-Predictive Energy Management System for Isolated Microgrids

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***Abstract*—This paper presents the mathematical formulation and control architecture of a stochastic-predictive energy management system for isolated microgrids. The proposed strategy addresses uncertainty using a two-stage decision process combined with a receding horizon approach. The first stage decision variables (Unit Commitment) are determined using a stochastic Mixed-Integer Linear Programming formulation; whereas the second stage variables (Optimal Power Flow) are refined using a Nonlinear Programming formulation. This novel approach was tested on a modified CIGRE test system under different configurations comparing the results with respect to a deterministic approach. The results show the appropriateness of the method to account for uncertainty in the power forecast.**

***Index Terms*—Microgrid, stochastic programming, energy management system, model predictive control, optimal dispatch, OPF.**

NOMENCLATURE

Parameters

Δt_{k_t} Time between steps k_t and k_t+1
$\eta_{g_{ESS}}^{in}$,$\eta_{g_{ESS}}^{out}$ ESS charge & discharge efficiencies
π_ω Probability of scenario ω
A_1, A_2, A_3, b_1, B_1 Recourse matrices in SUC
d_p, d_c, d_s Costs of power generation, curtailment and load shedding
I_c Matrix to extract the commitment variables from x_t
I_{rw} Matrix to extract the RE-based generators from $\widehat{P}_t^\omega$
n Number of hours for SUC look-ahead window
R_{up}, R_{dn} Maximum ramp-up and ramp-down of units
a_1 Parameters relevant to first-stage restrictions on SP
b_{2_ω}, b_3 Parameters relevant to second-stage restrictions on SP

Variables

$\overline{E}$ Vector of steady-state internal voltage phasors of synchronous generators [p.u.]
$\overline{I}$ Vector of steady-state line current phasors [p.u.]
$\overline{V}$ Vector of steady-state line voltage phasors [p.u.]
$\widehat{P}^\omega$ Vector of power generation in scenario ω [p.u.]
$\widetilde{P}_{g_{rw}}^\omega$ Vector of RE power generation in scenario ω [p.u.]
P^{out},P^{in} ESS output/input power [p.u.]
P_{curt}, P_{shed} Generation curtailment and load shedding [p.u.]
SoC State of charge of an ESS [p.u.]
u_g Binary start-up decision variable
v_g Binary shut-down decision variable
w_g Binary commitment status variable
x_t First stage variables on the SP

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I. INTRODUCTION

MICROGRIDS have received great attention from the research community over the last decade [1]. This interest is driven by their potential to reliably integrate intermittent Renewable Energy (RE) sources in a decentralized fashion, and enable the realization of the smart grid concept.

Several contributions to Energy Management System (EMS) controls in microgrids have been presented in the literature, ranging from decentralized approaches mainly focused on grid-connected microgrids to centralized approaches that are more suitable for isolated microgrids [2]. For grid connected applications the, EMS is only required to allocate the energy sources economically within certain power quality standards, because voltage levels and frequency are determined by the main grid. In stand-alone microgrids, the task of keeping the generation-load balance requires the Distributed Energy Resource (DER) units to control voltage and frequency while allocating the resources in the most efficient and secure way, which becomes more challenging.

Given the multiple control tasks and different requirements of isolated microgrids, a hierarchical structure is the natural choice for their adequate operation and control [3]. Figure 1 shows the different control actions and variables assigned to each layer in a centralized hierarchical control structure; time frames associated with the tasks in each layer must be properly separated in order to prevent interference. For these isolated microgrids, the dispatch algorithm should be designed to ensure reliable and economical operation of the system [4], [5]. Given this requirement, the EMS should be able to account for the uncertainty associated with intermittent energy sources, and efficiently dispatch the available Energy Storage Systems (ESSs).

The present work concentrates on the secondary control level, also known as the microgrid EMS for applications in isolated microgrids, as illustrated in Fig. 1, following the definitions in [6]. Thus, dynamics of the system in the order of seconds or faster (e.g., transient stability, voltage and frequency regulation), which are typically addressed at a primary control level, are not considered in this work. A

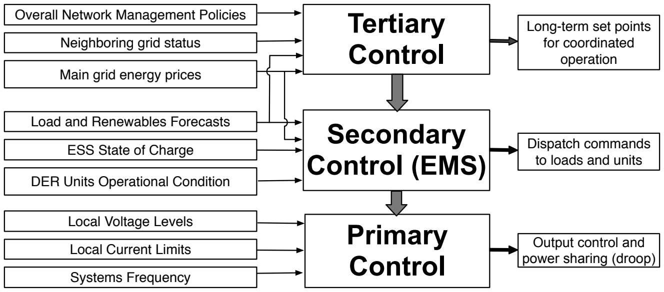


Fig. 1: Hierarchical centralized approach to control of microgrids.

centralized EMS operates by solving an optimization problem. Previous works have used various optimal dispatch formulations such as linear programming [7], non-linear programming [8] and meta-heuristic methods [9], to determine the least-cost solution. A more detailed power flow model is used in [10], where the authors study the effect of imbalance by using a three-phase power flow model and Receding Horizon Control (RHC). However, these approaches do not consider the uncertainty explicitly in the mathematical formulation; instead, they use an arbitrary reserve equation combined with RHC. The management of uncertainty in generation dispatch is a challenging problem, particularly in the context of isolated microgrids, in view of the need of demand-supply balance. Given the relevance of this particular issue for this paper, a detailed discussion of uncertainty handling in power systems and the various proposed approaches are presented in Section II.

The EMS architecture and algorithm herein proposed have been designed to produce the most suitable dispatch strategy for an isolated microgrid, while considering a detailed representation of the intermittent and dispatchable DERs, loads and distribution network. With this in mind, a two-stage decision process is proposed in order to obtain mathematical formulations suitable for real-time applications. The proposed approach builds on existing EMS developments by presenting a novel stochastic-predictive EMS architecture that directly accounts for uncertainties in the problem formulation, and features a highly detailed representation of the network and DERs. Also, a thorough analysis of different operational conditions and EMS options, and their impact on the EMS performance is presented. The forecasting and scenario generation techniques are important elements in the operation of the proposed approach; however, the development of such tools is outside the scope of the paper. Thus, the analysis of the performance of the forecasting and scenario generation engines is not discussed here.

The rest of the paper is structured as follows: Section II presents a review of different approaches to address uncertainty in power systems dispatch, justifying the proposed EMS architecture, operational requirements, and the underlying control principles to manage uncertainty. The description of the algorithm, mathematical models and implementation are discussed in Section III. Section IV presents the test microgrid and discusses the simulation results for various case studies. Finally, in Section V, relevant conclusions and the main contributions of this paper are highlighted.

II. EMS Architecture and Operational Characteristics

A. Review of the EMS Problem Under Uncertainty

Managing uncertainty in power systems operation is a cumbersome task, as it requires a combination of flexibility, robustness and security criteria [11]. The most common approaches can be classified under the following four categories:

- *Deterministic with close tracking*: This methodology consists of a close tracking of the realization of uncertain variables in the problem with small time steps (i.e., 5-minutes), solving the dispatch problem using the most current information, and including an explicit reserve requirement [12]. This approach handles uncertainties indirectly by frequently updating solutions in small time steps, whose size depends on the particular application, in order to closely follow the changes in uncertain variables. However, it requires the forecasts to be refreshed at every calculation, making this type of method very data-intensive and difficult to implement.
- *Robust Optimization*: In this technique, a suboptimal solution is obtained by optimizing the decision variables considering a single worst case scenario over an uncertainty set, the size of this set is adjusted to balance optimality and robustness [13], [14]. There are important challenges related to the structure and description of the uncertainty set and its relation with the RE power (generation from RE sources) forecast accuracy. If not conveniently defined, the structure of the uncertainty set may lead to computationally intractable problem formulations.
- *Chance-constrained Optimization*: This method minimizes the dispatch cost given a probabilistic description of uncertainty without considering recourse actions, and is hence a single stage approach. The method assumes that random variables have known PDFs, or that can be reasonably approximated by a number of scenarios [15]. These models include constraints that do not need to hold surely, but instead hold with some probability [16]. One important drawback of this method is that, if the decision maker chooses high confidence levels, it requires an accurate representation of the uncertainty in the tails of the distribution to produce meaningful results.
- *Two-stage Stochastic Optimization*: This type of formulation minimizes the cost of the first stage plus the expected cost of the recourse, given a discrete representation of the uncertain variables, which may lead to large-scale problems. The solution is obtained by breaking down the problem into first and second stages, in such a way that first-stage variables must guarantee feasibility for all second-stage scenarios [11], [17]. As discussed later in the paper, advanced scenario generation techniques can be used that do not require precise information of the probability distribution of the forecast error, and intrinsically consider the accuracy of the forecasting systems, while respecting the inter-temporal correlation of the variables.

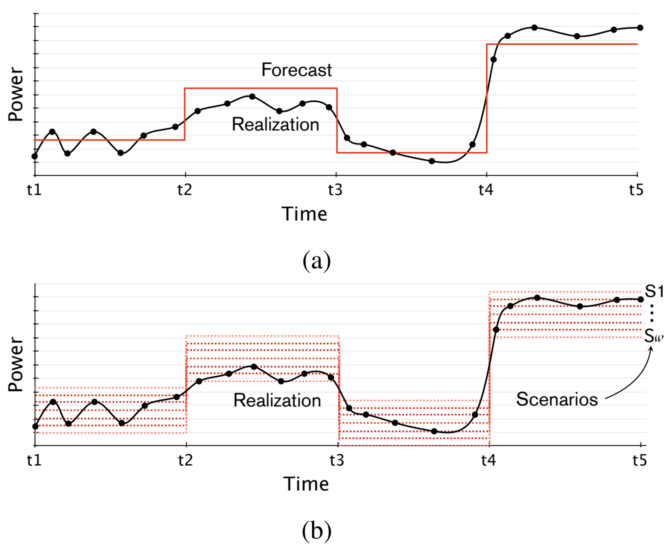


Fig. 2: (a) Deterministic vs (b) Stochastic approach to UC

The later approach used in this paper accounts for uncertainty directly in the formulation, combining the benefits of Stochastic Programming (SP) and RHC into a two-stage decision making process. This architecture is capable of obtaining the least-cost dispatch while complying with requirements of the EMS regarding uncertainty and ESS management. The application of the these two principles in Unit Commitment (UC) and dispatch applications is discussed next.

1) UC SP approach: In principle, a deterministic UC implicitly considers that a prediction will hold for a given time step Δt; however, the realization of such prediction will not necessarily correspond to the forecasted value. Furthermore, using a smaller time step Δk_t, the power fluctuates around the forecasted value. These deviations and mismatches have to be corrected, otherwise they lead to expensive load shedding, generation curtailment or even infeasibility. Figure 2 showcases the differences between the stochastic and deterministic UC approaches.

Thus, a two-stage SUC formulation is an MILP problem able to find a first-stage solution that provides probabilistic guarantee of feasibility for a finite set of possible scenarios, thus, improving the ability of the system to perform corrective actions without requiring load shedding and generation curtailment. Fig.2-(a) shows a wind power forecast with hourly time steps and the realization of the wind power in a higher time resolution. Even though hourly-average forecasts, such as the ones considered in the SUC, can be very close to the realization, when looked at with a higher time resolution, the wind power might have greater fluctuations; this can render the solution of a deterministic UC infeasible for certain intra-hour wind power scenarios. In contrast, Fig. 2-(b) shows that by using several hourly-average scenarios, it is also possible to provide immunization against intra-hour resource variations, assuming that the intra-hour ramping rates are not an issue and fluctuations are contained within the extreme scenarios. The Stochastic Unit Commitment (SUC) should be able to satisfy the constraints in the look-ahead window for any scenario in Fig.2, generated with the information available at time t.

The solution of an SUC vis-a-vis the solution of a deterministic UC may produce a more expensive realization of first-stage variables, but will reduce the need for load shedding or generation curtailment to compensate for deviations in the second-stage problem. This is known as the difference between the price of perfect information and the value of the stochastic solution [18].

A stochastic version of UC, proposed in [19], seemed unattractive due to its computational complexity; however, this has changed with the appearance of more powerful computational tools. Thus, in [20], the authors formulated a two-stage stochastic programming model for reserve commissioning using weighted scenarios, solving it using a dual decomposition algorithm. In [21], a short-term market clearing algorithm is developed accounting for variations from power forecasts, and presenting a comprehensive comparison with the worst-case approach. A system operation tool based on security constrained SUC is presented in [22], considering random disturbances such as outages and load forecasting inaccuracies.

In spite of the advancements and wide range of applications, SUC has not been applied to real-time dispatch of large power systems due to the computational burden and solution times. Nonetheless, in the case of microgrids, these obstacles are less of an issue due the smaller problem scale. For instance, a two-stage stochastic MPC model is proposed in [23] for operational planning of the microgrid considering a multi-objective framework to account for emissions; in this work, the authors consider linearized models in order to maintain the tractability of the problem as an MILP. A multi-objective operation planning model is presented in [24], where the authors propose a stochastic dispatch model to determine the day ahead purchases from the grid as the first-stage, and the uncertainty associated with the RE sources is represented using discrete scenarios; the result is a Pareto front available to the decision maker to select the final operating point. A scenario-based EMS model for grid-connected microgrids is proposed in [25], where a heuristic logic combines a master SUC with a slave distribution system OPF solved by a third-party software, and the model is tested generating the dispatch signals with a 24-hour look-ahead window; however, the authors rely on historical samples as scenarios for both solar and wind power without further discussion.

2) Model Predictive Control in Dispatch Problems: The control mechanism where the instantaneous solution is obtained by solving an online finite-horizon open-loop optimal control problem is known as Model Predictive Control (MPC) or RHC [26]. The optimization problem is solved for a sequence of control actions over the whole finite horizon at each time-step, so that a selected performance criterion is optimized; however, only the command for the next time-step $(t+1)$ is implemented.

This type of formulation has been reported in [27] as a means to optimally dispatch all available resources, including intermittent energy sources. The application of MPC as a control technique to efficiently optimize microgrid operation is presented in [28], where the authors discuss the issues of

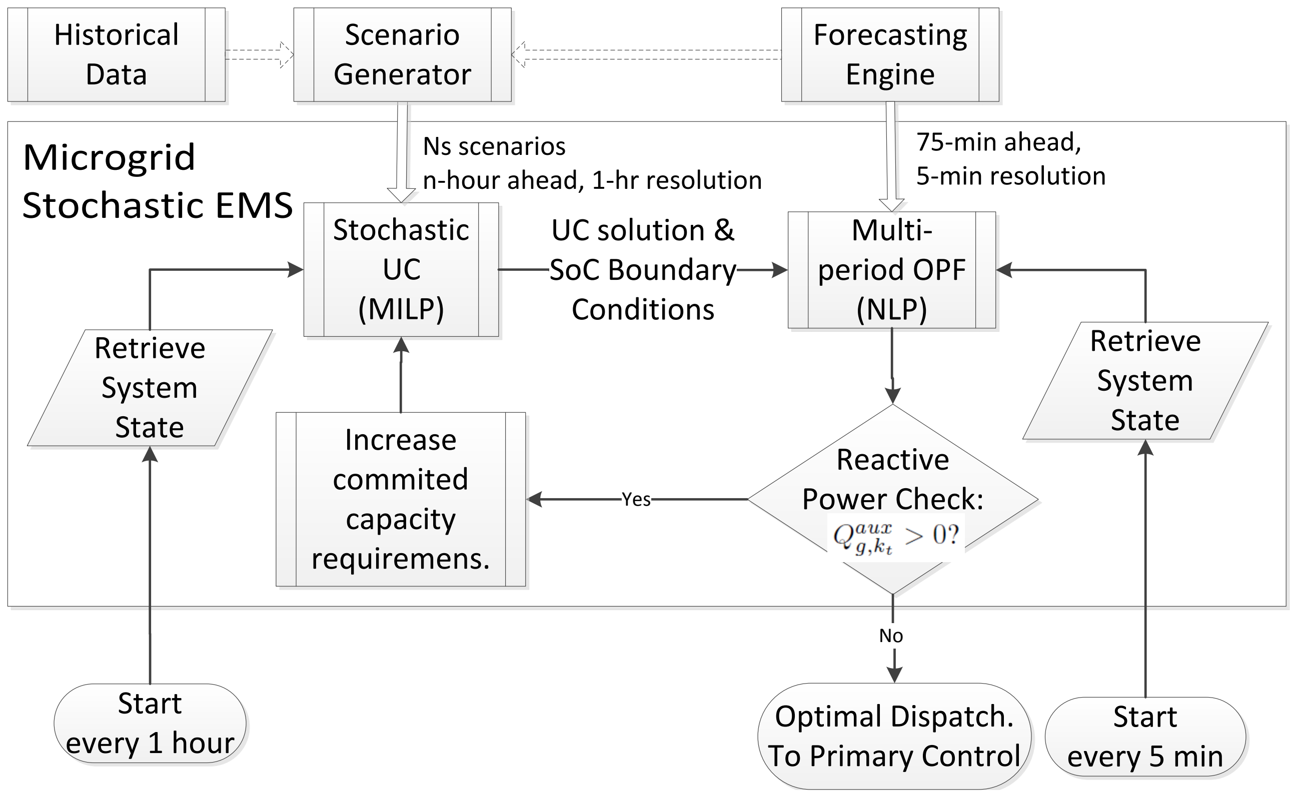


Fig. 3: Proposed EMS internal structure.

ESS modeling.

The use of RHC in EMS applications considers the impact of future conditions on the present operation of the microgrid, and accounts for the uncertainty of input data (forecasts of load and intermittent generation) by continuously updating the optimal dispatch of units based on the most recent information available. The impact of future conditions needs to be considered in order to handle time-coupling constraints, and make a proper use of storage resources in time. In [29], this technique is used for the dispatch of hydrogen storage together with a wind power plant in a power market, where updated wind and market price forecasts are available at each time step.

3) Shrinking Horizon Control Optimal Power Flow: Shrinking Horizon Control (SHC) or Batch- process control is a variant of the classical MPC, where the look-ahead window is reduced with each successive control action. This characteristic of SHC might produce undesirable effects such as reducing the ability of the algorithm to improve solutions as the horizon is reduced, which could also lead to infeasibility; however, this approach can be useful in cases where it is necessary to maintain a boundary condition at a fixed moment in time [30]. This control technique is commonly used in chemical engineering processes, and extensively discussed in [31], [32].

In power systems applications this technique has been recently used in [33], where the authors develop a bi-level model for mitigation of cascading failures using energy storage. SHC is applied in order to address the short-comings of MPC when new measurements are not available after a transmission line trips, and allows limiting the use of load shedding only to a fixed moment in time, at the last step in the look-ahead window.

In the present work, a SHOPF is proposed in order to optimally accommodate intra-hour dispatch variations while maintaining a fixed boundary condition for the SoC of ESSs given by the solution of the SUC. This mechanism prevents the SHOPF from using all the energy stored in the ESS, ensuring a minimum SoC for the operation of the microgrid beyond the horizon of the SHOPF. The proposed approach considers three-phase unbalanced power flow constraints and operational limits of the microgrid.

The underlying idea of using SHC is similar to the one presented in [33]. That is, given that the commitment decisions and target SoC may change with every calculation of the SUC, extending the horizon beyond the next SUC calculation may result in a false perception of future system conditions by the SHOPF. The detailed sequence of calculations in the proposed algorithm is presented in the next section.

B. Proposed EMS Architecture

The proposed algorithm features a two-stage decision making process, where a linear SUC is used to determine the commitment, and a non-linear Shrinking Horizon Optimal Power Flow (SHOPF) performs the final dispatch. As illustrated in Fig. 3 two look-ahead windows are used simultaneously depending on the stage of the process. This structure allows to have different time resolutions and levels of detail for these two problems, and enables the use of appropriate forecasting techniques, depending on the required resolution and look-ahead window length as described in [34].

To accommodate the two time resolutions, different time-step are used for each problem; a 1-hour step (t) is used for the SUC and a 5-minute step (k_t) is used for the SHOPF. The algorithm time-lines shown in Fig. 4 are the following:

- The SUC is solved for time t with a n-hour look-ahead window in order to obtain the commitment decisions and the State-of-charge (SoC) of the storage for time $t+1$, which serves as boundary condition for the SHOPF dispatch to meet all possible scenarios. The solution is issued to the SHOPF with a 15-minute lead to the corresponding time t. The scenarios are generated every hour, with every new n-hour look-ahead forecast.
- Based on the SUC solution, an SHOPF is executed 15 minutes before the t, providing sufficient time for calculations and corrections if required. Thus it starts with an initial 75 minute or 15 5-minute k_t steps look-ahead window, see Fig. 4, this window shrinks as time gets closer to the next hour, in order to maintain the same frontier condition (a lower limit of the SoC of ESSs). Thus, the SHOPF does not consider other than the nearest hour, until a new solution of the SUC is available. The forecast used by the SHOPF has a 5-minute time resolution and is updated every 5 minutes, in order to use the best information available. The frontier condition obtained from the SUC solution allows the SHOPF to indirectly consider future system conditions (beyond the nearest hour) in the operation of ESSs, and prevent the charge of ESSs to be depleted within the SHOPF horizon. The SHOPF calculates the final dispatch every 5 minutes, and requests corrective actions in case reactive power shortages are detected within its look-ahead window. The corrective action is performed by adding auxiliary variables that provide very expensive reactive power support, which is not physically available from the units committed by the SUC stage. When this variable is non-zero in the solution of the SHOPF, additional units are committed by a new run of the SUC in order to provide the required levels of reactive power support.

1) Length of time-step and look-ahead windows: By limiting the length of Δk_t to five minutes, the EMS is able to incorporate in the decision making process relevant operational constraints such as ramping limits, time-delays bigger than 5-minutes, short-term reactive power limitations and handle intra-hour variations of wind power; without conflicting with system dynamic controls that operate in smaller time frames. The selection of a 15-minute lead time for solving the SUC is directly related to the overlap between the look-ahead windows of the SHOPF when transitioning between the shortest and the longest look-ahead window. In this way, the architecture reduces the chances of the SHOPF not providing a new solution, or "giving up" [33], given the short length of the look-ahead window. Also, this characteristic provides spare SHOPF solutions in cases where the SHOPF with the longest look-ahead window faces convergence problems.

III. Mathematical Formulation

Developing the proposed algorithm in the form of a single mathematical program will result in a large-scale mixed-integer non-linear problem with no realistic applicability, particularly for real-time dispatch; thus, the execution of the aforementioned EMS architecture is described with independent mathematical formulations for each stage. The SUC assumes a network-less model of the microgrid, whereas the SHOPF is formulated as an ac unbalanced power flow formulation with ABCD matrix representation of the network elements. The non-linear model is presented next, followed by the stochastic formulation.

A. Non-Linear Modeling for SHOPF

To fulfill the requirements for proper system representation, the proposed SHOPF features a three-phase model of the network, and is capable of accounting for the effect of system unbalances and reactive power requirements of the microgrid. This model is based in the three-phase ABCD parameter matrices with phasors in rectangular coordinates presented in [35], [36]. A thorough description of the equations used in the SHOPF model is presented in [10], and some of the key modeling details are described next.

The synchronous generators can be seen as a special case of an element in series, with an ABCD matrix relating terminal and internal currents and voltages. This ABCD matrix can be built using the internal impedance matrix of the generator, which in turn is obtained from the sequence-frame reactances of the machine [37]. This internal and terminal currents and voltages in a synchronous generator are related by:

$$\begin{bmatrix} \overline{E}_{g_s} \\ \overline{I}_{g_s} \end{bmatrix} = \begin{bmatrix} \mathbf{I} & Z_{g_s,abc} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \overline{V}_{g_s} \\ \overline{I}_{g_s} \end{bmatrix} \quad \forall g_s \tag{1}$$

The following equations are required to ensure a positive sequence internal voltage in the synchronous machine:

$$E_{a,g_s} + E_{b,g_s} + E_{c,g_s} = 0 \tag{2}$$

$$|E_{a,g_s}| = |E_{b,g_s}| = |E_{c,g_s}| \tag{3}$$

Inverter-interfaced DERs are modeled as an equivalent voltage source per-phase, with a limit on the maximum neutral current, which is set to zero in the case of 3-wire voltage-sourced-converters. Inverter losses are modeled as a function of the output current, using a quadratic term (resistive losses) plus a constant loss factor.

Directly-connected induction generators are modeled as a special case of series element. In this case, the featuring ABCD matrix relates terminal voltages and currents with internal voltages and currents at the negative resistance used in the induction machine equivalent circuit to represent the power input:

$$\begin{bmatrix} \overline{V}_{g_i} \\ \overline{I}_{g_i} \end{bmatrix} = \begin{bmatrix} \overline{V}_{st,g_i} \\ \overline{I}_{st,g_i} \end{bmatrix} = \begin{bmatrix} A_{g_i} & B_{g_i} \\ C_{g_i} & D_{g_i} \end{bmatrix} \begin{bmatrix} \overline{V}_{rt,g_i} \\ \overline{I}_{rt,g_i} \end{bmatrix} \quad \forall g_i \tag{4}$$

The entries of the ABCD matrix can be obtained from the sequence-frame model of the induction generator, by properly applying a sequence-to-phase transformation [37]. The induction generator model is completed by the relation between

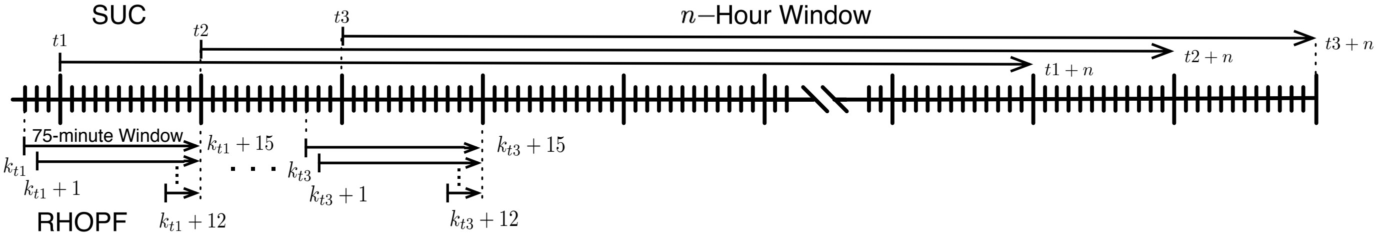


Fig. 4: EMS horizon variable time-steps.

voltages across and currents through the equivalent internal resistances of the machine.

For energy storage, two positive variables, $P^{out}_{g_{ESS}}$ and $P^{in}_{g_{ESS}}$, are created to capture charging and discharging cycles of ESS separately, as follows:

$$P_{g_{ESS}} = P^{out}_{g_{ESS}} - P^{in}_{g_{ESS}} \quad \forall g_{ESS} \tag{5}$$

And the required SoC balance constraints are represented as follows:

$$\begin{gathered} SoC_{g_{ESS},k_t+1} = SoC_{g_{ESS},k_t} + \\ \left(P^{in}_{g_{ESS},k_t} \eta^{in}_{g_{ESS}} - \frac{P^{out}_{g_{ESS},k_t}}{\eta^{out}_{g_{ESS}}} \right) \Delta t_{k_t} \quad \forall g_{ESS}, \forall k_t \end{gathered} \tag{6}$$

In order to avoid simultaneous charging and discharging of the battery, the following complementarity constraint is included in the SHOPF:

$$P^{out}_{g_{ESS},k_t} P^{in}_{g_{ESS},k_t} = 0 \quad \forall g_{ESS},\ \forall k_t \tag{7}$$

This constraint is normally fulfilled even if not included in the model, as discussed in [10]; however, in some rare cases the SHOPF might use simultaneous changing and discharging of ESS units in order to absorb power from the system without affecting its SoC [38].

Additionally, the SoC of each ESS is limited by its maximum and minimum storage capacity. This model captures several ESS technologies such as batteries and electrolyzers, hydrogen-storage and fuel-cell sets, using different efficiency parameters and the addition of conversion factors in each case.

Other operational constraints are necessary to ensure the ramp-up and ramp-down limits of DERs are not exceeded, as follows:

$$\begin{aligned} &P_{g,k_t+1} - P_{g,k_t} - u_{g,k_t+1} P^{max}_g \\ &\qquad \leq R_{up,g} \Delta t_{kt} \quad \forall g, \forall k_t \end{aligned} \tag{8}$$

$$\begin{aligned} &P_{g,k_t} - P_{g,k_t+1} - v_{g,k_t+1} P^{max}_g \\ &\qquad \leq R_{dn,g} \Delta t_{kt} \quad \forall g, \forall k_t \end{aligned} \tag{9}$$

Maximum and minimum DER power output constraints are also included in the models, and the output is forced to zero if the unit is not committed by the SUC.

Finally, the following objective function considers both DERs' heat-rates and the cost of generation curtailment and load shedding.:

$$\begin{aligned} z = \sum_{k_t} \Big[\Big(\sum_g & a_g P^2_{g,k_t} + b_g P_{g,k_t} + c_g w_{g,k_t} \\ & + C_{sup} u_{g,k_t} + C_{sdn} v_{g,k_t} \Big) \\ & + d_s P_{shed,k_t} + d_c P_{curt,k_t} \Big] \Delta t_{k_t} \end{aligned} \tag{10}$$

where renewable energy-based DERs and ESSs are assumed to be zero cost, and the binary variables (w_{g,k_t}, u_{g,k_t}, v_{g,k_t}) defined the SUC algorithm and fixed for all k_t. The positive variables P_{shed,k_t} and P_{curt,k_t} are included in the problem definition in order to provide the SHOPF with enough resources to handle load-generation imbalances, given that the microgrid operates in an isolated fashion. The SHOPF problem then consists on the minimization of the total cost z in (10), subject to the aforementioned constraints, and corresponds to a non-convex Nonlinear Programming (NLP) problem. As with classical OPF formulations, non-convexity is introduced by the power balance equations at each bus of the system, which involves the calculation of real and reactive power from bus voltages and current injections [10]. Thus, the solution of the SHOPF is only guaranteed to find a local optimum if proper initial guesses are provided.

B. SUC Model

The SUC is formulated as a fixed-recourse, two-stage stochastic problem. This type of models are based on the concept of first and second stage actions, where the first stage is minimized given the knowledge of a finite set of discrete scenarios. The results is an equivalent Mixed-Integer Linear Programming (MILP) problem, which in the case of the proposed microgrid EMS, the objective is to minimize the cost of the UC as a function of the binary variables (w_g, u_g, v_g), and calculate the target SoC of the ESS for the next time step $t+1$.

Each scenario is defined by the pair $\{(\widetilde{P}^{\omega}_{g_{rw}})_t, \pi_\omega\}$, where $(\widetilde{P}^{\omega}_{g_{rw}})_t$ is a sequence of vectors $\widetilde{P}_{g_{rw},t}$ representing the generation of RE-based units at time t for scenario ω, and π_ω is its probability. The recourse matrices (A_1, A_2, A_3, B_1) are assumed fixed, i.e. not affected by the outcomes of the random variables [39], [16]. Hence, for this particular application, the two-stage, fixed-recourse SP can be formulated as follows:

$$\min \quad \sum_{t=1}^{T} \Big[c^{\intercal} x_t + \dots$$

$$\sum_{\omega\in\Omega}\pi_\omega\cdot\left(d_p^\intercal\widehat{P}_t^\omega+d_cP_{curt,t}^\omega+d_sP_{shed,t}^\omega\right)\Big] \quad (11a)$$

$$\text{s.t.}\quad A_1I_cx_t\le 0 \quad \forall t \quad (11b)$$

$$\sum_{\bar{t}=t-M_{time}}^{t} A_2^{\bar{t}}x_{\bar{t}}\le a_1 \quad \forall t \quad (11c)$$

$$b_1\widehat{P}_t^\omega+P_{shed,t}^\omega-P_{curt,t}^\omega\le b_{2\omega,t} \quad \forall t \quad \forall\omega \quad (11d)$$

$$\widehat{P}_{t+1}^\omega-B_1\widehat{P}_t^\omega\le b_3 \quad \forall t \quad \forall\omega \quad (11e)$$

$$A_3I_cx_t+P_{g,t}^\omega\le 0 \quad \forall t \quad \forall\omega \quad (11f)$$

$$I_{rw}\widehat{P}_t^\omega=\widetilde{P}_{g_{rw},t}^\omega \quad \forall t \quad \forall\omega \quad (11g)$$

where x_t corresponds to the first-stage variables: binary variables for shut-down, start-up and commitment status of a generator, and SoC of the ESSs at $t+1$. The cost function (11a) has the following parts: the commitment cost and, for each scenario, the linearized generation cost function for every unit, and penalties for load shedding and generation curtailment used to avoid infeasibilities in the second stage; thus, the SUC formulation has complete recourse. The constraint (11b) corresponds to restrictions relevant to the binary variables, such as start-up and shut-down logic, and constraint (11c) corresponds to the restrictions for the minimum-up and minimum-down times. Constraints (11d)-(11f) correspond to all the restrictions relevant to the dispatch variables that are subject to uncertainties power balance, max-min limits of the units and ramping rates given by (8) and (9). Constraint (11e) includes the ESS restrictions, given by (5) and (6), for steps greater than $t+1$. Finally, (11g) forces the generation from RE sources to be equal to their expected values, for each scenario, where I_{rw} is a matrix used to extract the RE-based units from $\widehat{P}_t^\omega$. In the proposed approach, $b1$ is a row vector of ones used to add up all the generation from the units to perform power balance.

Formulation (11) will produce a different solution for every possible $S\in\Omega$, where Ω is the set of RE power scenarios. The solution will also include the load shedding and generation curtailment for each scenario, which will be used to asses the adequacy of the dispatch. The lack of additional stages of uncertainty unveiling (multi-stage formulation) is compensated by the iterative solution of the SUC using an MPC approach. This helps to reduce the size of the SUC model and associated computational burden, also facilitating the representation of wind power profiles using state-of-the-art scenario generation techniques that respect the inter-temporal correlations.

1) Scenario Generation and wind prediction: The quality of the decision making process from an SP is highly dependent on the characterization of the probability space of the uncertainty. SP requires a discrete set of scenarios that represent a discrete approximation of the Probability Distribution Function (PDF) [39]; a probability space poorly represented by the scenarios will yield an unreliable solution, and thus the generation of scenarios has to be carefully done.

In general, among the many techniques available to generate scenarios to represent uncertainty, the following has been demonstrated to generate credible RE power scenarios:

- Moment matching techniques [40], where a limited number of discrete outcomes are generated that satisfy predefined statistical properties.
- Internal sampling, which corresponds to a form of Monte Carlo scenario generation [41].
- Statistic ensembles, which uses the information from the confidence intervals within a prediction to generate credible scenarios [42].

The selected method for the present work is statistic ensembles, since it intrinsically consider the accuracy of the forecasting algorithm. The method also respects the temporal correlation of forecast errors by embedding them in all the scenarios for the horizon of interest [43]. This technique is not computationally expensive; thus, once a forecast is issued, it can be immediately applied.

In case a forecasting system for RE power is not available, or if it is not possible to produce scenarios, the EMS can be also provided with historical data. This approach may yield more conservative results, as demonstrated in Section IV.

C. Implementation

The model is coded in the high-level optimization modeling language GAMS [44], where the UC MILP problem and the SHOPF NLP problem are solved using CPLEX 12.1 and COIN-IPOPT 3.7 solvers, respectively. IPOPT requires the user to provide a starting point with all variables within bounds. In case this starting point is not provided, or if it lies outside bounds for some variables, IPOPT runs a routine to adjust the values until a valid starting point is found [45]. However, due to the iterative nature of the approach, a natural warm-start at each time-step is given by the solution of the previous iteration. The EMS is assumed to have full control over the dispatch of every DER in the microgrid, and is provided with updated load and intermittent generation forecasts according to its requirements. Hence, updated 24-hours forecasts with 1-hour time-steps are assumed to be available at each iteration of the SUC, whereas 75-minutes forecasts with 5-minute time-steps are assumed to be available for each iteration of the SHOPF.

The available methods to solve SP problems are discussed in [16]. For this particular case, a direct Branch-and-Bound algorithm is used instead of the more commonly used decomposition techniques [46]. Although Branch-and-Bound is not preferred for large scale systems due to computational costs [47], it can be faster and more precise than the Bender's decomposition as reported in [48], which is also the case in this paper, given the size of the microgrid dispatch problem.

IV. Test System

The designed stochastic-predictive EMS is tested on a modified version of the medium-voltage grid connected microgrid presented in [49], which is a CIGRE distribution network benchmark. A single-line diagram of the 16-bus, 12.47 kV test system is shown in Fig. 5. This modified test system features 2 extra diesel units, with a combined capacity of 2,800 kW, replace what was originally a connection to the main grid. This configuration is typical of isolated microgrids, where diesel generators are connected to the medium-voltage network for distribution purposes, through a step-up transformer. The

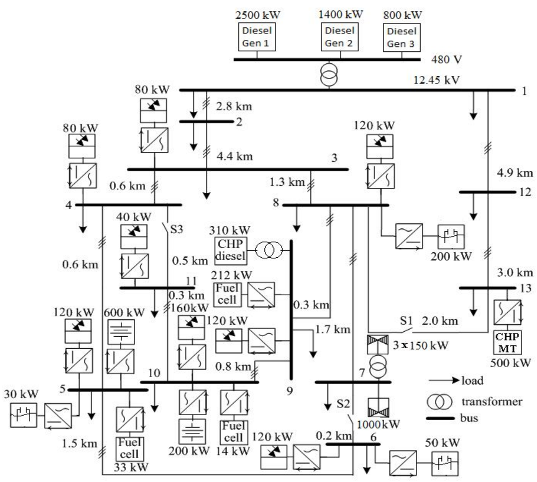


Fig. 5: Modified CIGRE microgrid benchmark.

system's total installed capacity is 6,860 kW, including ESS units and intermittent RE sources. The microgrid's load is unbalanced, with phase-a feeding 30.1%, phase-b 35.7%, and phase-c 34.2% of the total load. Loads are considered a combination of constant-impedance (Z) and constant-power (PQ) loads, for a peak load of approximately 4,650 kW. All the forecasts required for load and RE are obtained from real data from real forecasting systems used in an isolated microgrid in Huatacondo, Chile [50]. Load shedding and generation curtailment from dispatchable generators were penalized strongly in the objective function with costs of $ 5/kWh and $ 3/kWh, respectively; RE-generation curtailment was alos allowed at zero cost.

In this test system, the uncertainty is assumed to be associated with the wind power forecast only, since the load and solar power forecasts have narrow uncertainty bounds, and hence have little impact on the resulting dispatches, which are dominated by the wind uncertainty; thus, scenarios are generated only for wind power profiles. However, the models presented are general and can incorporate several sources of uncertainty simultaneously.

It should be noted that, in order to better analyze the ability of the stochastic EMS approach to determine suitable reserve levels based on the uncertainty of the wind power forecast, no deterministic reserve requirements have been used. However, in a realistic application of the proposed algorithm, a minimum reserve requirement should be included.

A. Study Cases

A number of study cases are presented in order to analyze the performance of the proposed EMS under different system conditions. The following study cases address important aspects that may impact the performance of the system, i.e. available storage capacity, scenario generation approach, and length of the optimization window (horizon) of the SUC:

- *Base Case*: This corresponds to the test system presented above. For the SUC, 100 scenarios are generated at each hour based on the given 24-hour forecast. The SUC horizon is set to $n = 24$ hours in order to capture complete cycles of the load, solar and wind profiles. The SHOPF uses a varying optimization horizon, ranging from 75 minutes to 15 minutes, with 5-minutes time-steps, as per Fig. 4.
- *Deterministic Approach*: For the purpose of benchmarking the benefits of the stochastic formulation in the controller, a comparison is made with respect to a deterministic UC formulation (*Det.Case*), using the same system and parameters as the *Base Case*.
- *Perfect Information*: This study case is a special case of the deterministic approach, where the UC uses the hourly-average of the wind power realization as a forecast (*Perf.Case*). This is equivalent to having a "perfect" 24-hour forecast with hourly resolution, which is a theoretical exercise to assess the value of the SUC compared with a deterministic approach using the best possible forecast.
- *ESS Capacity*: A higher ESS capacity is expected to positively impact the operational costs of the microgrid, due to the higher operational flexibility, and may also have an effect on the allocation of system reserves. Thus, 2 scenarios with different additional ESS capacities are analyzed: 250 kW–1,250 kWh (*B250*) and 500 kW–2,500 kWh (*B500*), which represent a total battery-ESS capacity of 1050 kW and 1300 kW, respectively. In each case, the additional capacity is included as a single battery-ESS unit located at Bus-1.
- *Scenario Generation Approach*: The approach used for generation of scenarios may have an impact on the determination of system reserve and operational cost. In the study case *Hist.Data*, the data from wind power profiles of the 30 preceding days are used as scenarios in the SUC, with all of them assumed to have the same probability. Scenarios based on unfiltered historical data (*Hist.Data*) do not take into account the performance of the forecasting system. This may lead to more conservative results (pessimistic scenarios); hence, the suitability of using historical data needs to be evaluated in case by case basis.
- *SUC Optimization Window*: The use of extended optimization horizons can be expensive in terms of computation times. An alternative to reduce the solution times is to reduce the horizon considered in the optimization; however, this alternative may negatively impact the unit commitment decisions and proper management of energy storage resources leading to more expensive solutions. To analyze this effect, 2 study cases with different SUC horizons are presented: $n = 8$-hour (*Var8*), and $n = 12$-hour (*Var12*).

The impact of the imbalance has been taken into account using the model discussed in [10], and hence not discussed in this paper as part of the results.

B. Simulation Results

Results of the optimal dispatch of diesel units and battery-ESS for the *Base Case* scenario are shown in Fig. 6 using a stacked-area plot; the total load profile is shown, with the remaining power (in white) being provided by the RE sources. The optimal dispatch of battery-ESSs has been plotted in a way to properly show charging and discharging cycles; thus, negative areas in the figure correspond to charging cycles of the batteries. Daily-average reserves, minimum instantaneous

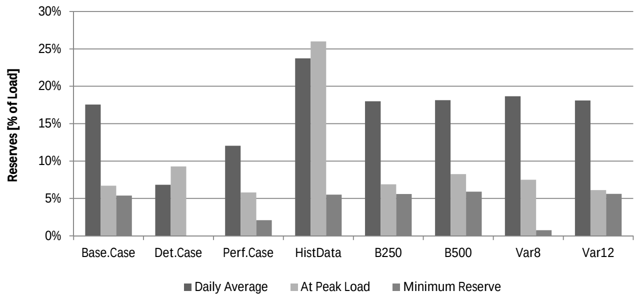


Fig. 7: System Reserves for Different Scenarios

reserves, and reserves at peak-load for each case are shown in Fig. 7. Reserve levels are calculated based on the unused capacity of committed diesel generators and micro-turbine, which corresponds to the classical notion of spinning reserves, without including available ESS capacity.

In order to evaluate the performance of the proposed EMS in terms of robustness, two indices are defined: $eLOLE$ and $eLOEE$. These indices are obtained from the solution of the SUC, and are inspired in the Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE) indices [51], respectively, and defined as follows:

- $eLOLE$: Represents the number of scenarios for which the SUC produces load shedding at $t = 1$, for the whole simulation period of 24 hours ($h = 1, ..., 24$), divided by the number of scenarios, as follows:

$$eLOLE := \frac{\sum_{h=1}^{24} \sum_{\omega \in \Omega} (P_{shed,1}^{\omega,h} > 0)}{K_\Omega} \tag{12}$$

where:

$$(P_{shed,1}^{\omega,h} > 0) = \begin{cases} 1 & \text{if } P_{shed,1}^{\omega,h} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

- $eLOEE$: Corresponds to the total energy shed in all the scenarios at $t = 1$, for the whole simulation period of 24 hours, divided by the number of scenarios, as follows:

$$eLOEE := \frac{\sum_{h=1}^{24} \sum_{\omega \in \Omega} P_{shed,1}^{\omega,h}}{K_\Omega} \tag{14}$$

It is important to note that by using a receding horizon approach in the SUC, each hour of the simulated day corresponds to $t = 1$ of one of the iterations of the SUC. Also, these indices assume that the uncertainty is properly represented by the scenarios utilized; therefore, the indices are only comparable if they are based on the same scenarios. With this in mind, indices for study cases *Hist.Data*, *Det.Case* and *Perf.Case* cannot be directly compared with the rest of the study cases, since they use different scenarios. Indices $eLOLE$ and $eLOEE$ for each scenario, together with the actual loss of load over the 24-hour simulation, are presented in Table I. The operational cost of the microgrid for each study case, defined as the total cost of fuel plus the cost of load shedding, is presented in Table II, together with the percent cost deviations with respect to the *Base Case*.

TABLE I: Estimated Adequacy Indices

	$eLOLE$	$eLOEE$	Loss of Load
	[hours/day]	[kWh/day]	[hours/day]
Base Case	0.93	131.7	0
B250	0.35	9.8	0
B500	0.02	0.5	0
Var8	1.57	272.5	0
Var12	0.84	129.1	0
Hist.Data	N/A	N/A	0
Det.Case	N/A	N/A	1.1
Perf.Case	N/A	N/A	0

TABLE II: Operation Costs

	Diesel Cost	Load Shedding	Total	Deviation
	US$/day	US$/day	US$/day	%
Base Case	13,097.1	0.0	13,097.1	0.0
Det.Case	13,555.0	1,283.4	14,838.3	13.3
Perf.Case	13,498.4	0.0	13,498.4	3.1
Hist.Data	13,176.4	0.0	13,176.4	0.6
B250	12,980.3	0.0	12,980.3	-0.9
B500	12,944.1	0.0	12,944.1	-1.2
Var8	13,285.4	0.0	13,285.4	1.4
Var12	13,232.9	0.0	13,232.9	1.0

C. Discussion

Observe in Table II that the proposed stochastic formulation (*Base Case*) outperforms the deterministic case (*Det.Case*) in terms of operation cost. From the reserves point of view, note that *Det.Case* is not able to commit enough reserves to compensate for variations on the instantaneous wind power with respect to the forecast, which results in the need to use expensive load shedding.

The perfect information case (*Perf.Case*) performs better than *Det.Case* in terms of total cost of operation, which is expected since this approach uses the hourly averages of the wind power realizations as forecast in the UC stage. However, *Perf.Case* is also outperformed by the *Base Case* due to its deterministic nature which is unable to consider the intra-hour variations in the commitment. From the reserves perspective this case also underperforms when compared to stochastic formulations *Base Case*, *Var12* and *Hist.Data* for the same reason.

Cases with increased ESS capacity (*B250* and *B500*) show a reduction of costs as compared with the *Base Case*, without affecting the levels of reserve, which is attributed to a reduction in the use of more expensive diesel units due to a more flexible operation of the system. Nevertheless, note that the reduction of cost due to increased ESS capacity is not directly proportional, since it depends on several other factors such as the level of penetration of intermittent sources, its correlation with the load profile, and the accuracy of the forecasting system.

The *Hist.Data* case shows the effect of a more pessimistic representation of the uncertainty, yielding more conservative results, as can be seen from the high levels of reserve in Fig. 7. This also yields slightly higher operation costs, due to the over commitment of more expensive units. Note in this case that the small difference in cost with respect to the *Base Case* is due to the the particular cost characteristics of the units in the

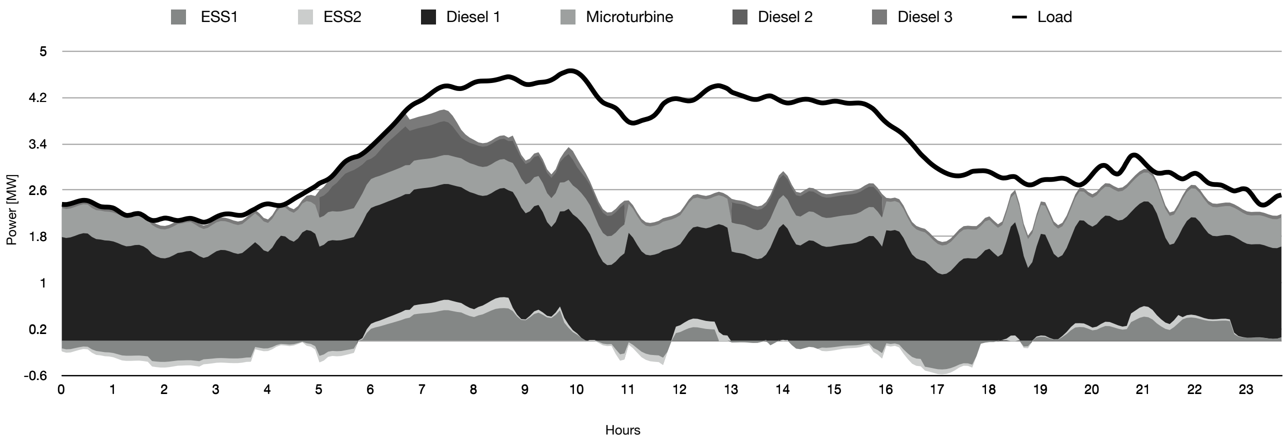


Fig. 6: Optimal dispatch obtained by the EMS: *Base Case*.

test system, and may increase in system with more dissimilar generators' costs.

Study cases with reduced SUC look-ahead windows (*Var8* and *Var12*) show poor performance in terms of operation costs, making them comparable to *Det.Case*; however, they do not yield actual load shedding. The higher costs of these study cases are associated with their limited ability to foresee future system conditions.

In terms of system adequacy, the proposed indices show that higher levels of ESS capacity will yield lower $eLOLE$ and $eLOEE$ indices, improving the reliability of the system. Also, observe that study cases with reduced look-ahead windows, although more expensive, do not necessarily improve the system adequacy.

1) Primary Controllers: The results shown in Section IV-B represent an approximation of the actual microgrid dispatch based on 5-minute updates of the SHOPF routine; defining the set-points of local (primary) controllers of DG units. The actual system conditions of the microgrid in real time are a result of the actions of local controllers (e.g., droop controllers) [6], with the stability of the microgrid depending on their parameters, which can be adjusted to ensure grid stability taking the dispatch settings obtained by the SHOPF as a given.

2) Non-convexity of the SHOPF: As previously mentioned, the formulation of the SHOPF yields a non-convex NLP formulation; thus, the NLP solver (IPOPT) is only able to find locally optimum solutions of the problem. In addition, due to the inherent sub-optimality of the solution, the non-convexity of the SHOPF might also produce inconsistent solutions if the solver "jumps" between local minima in consecutive solutions of the algorithm, yielding varying dispatch commands. This problem is minimized by providing an appropriate starting point to the NLP solver as follows: in every run of the SHOPF in the simulation, the previous solution is used as a starting point, since the new solution is likely to lie in the neighborhood of the previous one.

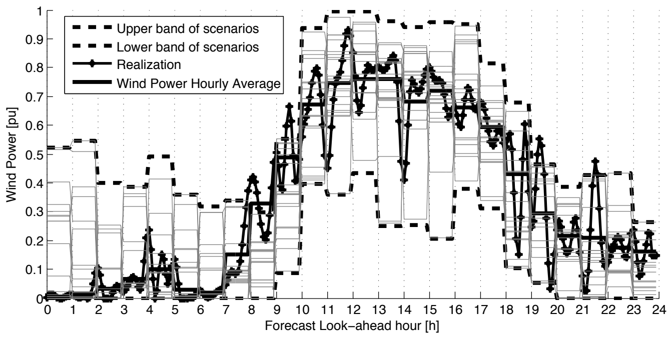
3) The value of SUC vs perfect information: As discussed in Section II-A, the use of a SUC approach is able to consider not only the forecast errors with hourly resolution, but also the intra-hour power fluctuations, which is described by Fig. 8. Figure8-(a), analogous to Fig.2-(a), shows the wind power realization together with a sample of the scenarios and their bounds for the 24-hour look-ahead window, at time step $t = 1$. Observe that even if the forecasting system was able to predict the hourly average of the realization, the system would still be subject to the intra-hour variations. Furthermore, the close up in Fig.8-(b) shows that the scenarios are able to capture most of these variations, yielding hedged commitment solutions. The advantages of the SUC approach are also confirmed by the results shown in Table II. Moreover, the extra hedging is reflected by the reserve margin results in Fig. 7, which show that using an SUC approach provide better reserve performance.

D. Computational Performance

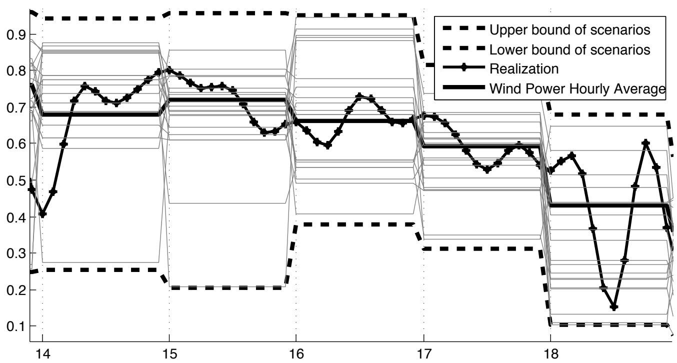
The EMS performance was tested for each study case and 24 hours of operation. Computational times averaged 11s per iteration of the NLP (SHOPF), and 93s per iteration of the MILP (SUC). Solution times of the SUC were fairly constant over the 24 hour simulation periods, whereas solution times for SHOPF ranged from approximately 60s for the largest window (15 time-steps, after an SUC update) to approximately 2s for the shortest window (4 time-steps, right before the SUC update and window extension). Note that these times can be considered realistic, since the EMS was tested on a fairly large isolated microgrid with a wide variety of DGs, and allow the implementation of the proposed approach for real-time applications, since the results can be obtained in less than the considered 5-minute window for the EMS.

E. Implementation Considerations

The actual implementation of the proposed algorithm in a real microgrid should take into account potential convergence issues of the SHOPF problem, which are more likely to appear when the SHOPF transitions from a small look-ahead window to a larger one. In this regard, it is important to note that during the transition, the shortest horizon overlaps with the longest one, meaning that the EMS has a solution available for the



(a)



(b)

Fig. 8: SUC scenarios and wind power realization for (a) 24-h window, and (b) close-up.

following 10 minutes. In case of a convergence failure, additional heuristics can be included in the implementation, such as keeping the best available solution, and letting the primary controllers adjust the mismatches, or solving the SHOPF with a shorter look-ahead window to ease convergence.

V. Conclusions

This paper has presented a novel EMS architecture and algorithm for isolated microgrids with the presence of intermittent energy sources. The proposed approach combined the advantages of stochastic mathematical formulations and close tracking of variations in order to produce an economical and reliable microgrid dispatch. The decomposition of the energy management problem allowed to obtain UC decisions and dispatch commands with different strategies and levels of detail, according to the requirements of each optimization problem.

The proposed EMS was tested under different configurations in order to obtain the most suitable combination of parameters, obtaining the best results when used with a 24 hour look-ahead window and scenarios generated with a technique that best represents the uncertainty. The results show a superior performance in terms of total operation cost of the cases where a stochastic formulation of the UC problem is used instead of a deterministic one (see Table II), which justifies using the proposed approach.

The main contributions of this work can be summarized as follows:

- The paper extends on the recent paper [10] on deterministic EMS of isolated microgrids by including a stochastic UC formulation within the proposed EMS architecture, using an MPC approach. This required a modification of the previously proposed architecture to accommodate different time steps of the SUC and SHOPF formulations, and the implementation of a shrinking horizon for the SHOPF in order to properly use the ESSs as a hedging mechanism against uncertainty. The resulting architecture is unique in terms of the modeling detail, and the combination of techniques to provide the best performance of the microgrid EMS under uncertainty.
- The performance and feasibility of the proposed stochastic-predictive EMS was tested and demonstrated for different configurations in a realistic microgrid test system.

Developing algorithms with different approaches to handle forecasting information and uncertainty is the next step in this research.

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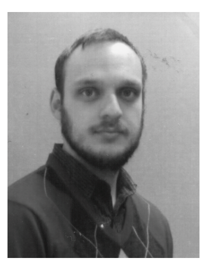

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