A Stochastic Optimal Power Flow for Scheduling Flexible Resources in Microgrids Operation

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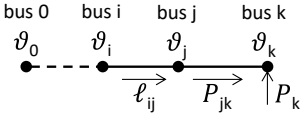
Abstract

Microgrid operations are challenging due to variability in loads and renewable energy generation. Advanced tools capable of taking uncertainty into account are essential to maximize microgrid benefits when operating microgrid owned DERs. This paper proposes a novel optimization model for day-ahead economic dispatch of flexible resources within a microgrid environment, considering uncertainty of PV and loads.This model is conceived to support the microgrid supervisory control layer, providing a security-constrained day-ahead strategy to operate three types of microgrid flexible resources: PV, electric storage and controllable loads. The work presented in this paper introduces a novelty in microgrid operations by presenting a stochastic version of the day ahead scheduling of microgrid DERs to deal with uncertainties associated with PV, load and temperature while considering microgrid network limits and end-user comfort as optimization constraints. An annual analysis quantifies the benefits of to the microgrid-owner of a stochastic formulation over a deterministic one both in terms of ensuring end-user comfort and decreasing operation costs.

***Keywords*: demand response, microgrids, optimal power flow, photovoltaics, stochastic optimization, storage**

NOMENCLATURE

Summary of notation:



A. Indices:

t	period
ij	branch
j	node
pv	PV system association
ul	uncontrollable load
cl	controllable load
st	storage system association
hvac	heating, ventilation, and Air-Conditioning systems
ewh	electric water heater systems
$\overline{\Delta\theta}_{low}$	maximum degrees of under-heating tolerated (^oC)
$\overline{\Delta\theta}_{high}$	maximum degrees of overheating tolerated (^oC)
ext	external air temperature
int	internal air temperature of each house
w	property of water
d	controllable device
s	scenario-dependent variables
+	positive domain
c_w	water specific heat (J/g°C)
R_d	thermal resistance of device (^oC/kW)
-	negative domain
0	substation node point of common coupling

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B. Constants:

c_e cost of wholesale electricity (€/MWh)
c_c cost of wholesale electricity plus distribution and transmission costs(€/MWh)
c_{cf} cost of comfort constraint violation (€/°C · h)
r_{ij} resistance of a specific branch (Ω)
x_{ij} reactance of a specific branch (Ω)
η efficiency of a device
C_d thermal capacity of a device (kWh/°C)
α heat loss coefficient of building (kW/°C)
$\overline{P}$ maximum active power value allowable (MW)
$\overline{S}$ maximum apparent power value allowable (MVA)
$\underline{V}$ minimum voltage constraint of grid (V)
$\overline{V}$ maximum voltage constraint of grid (V)
$\overline{soc}$ maximum state of charge of battery (MWh)
$\underline{soc}$ minimum state of charge of battery (MWh)
$\underline{\theta}$ minimum temperature (°C)
$\overline{\theta}$ maximum temperature (°C)

C. Variables:

P active power (MW)
ℓ squared current magnitude (A)
Q reactive power (MW)
ϑ squared voltage magnitude (V^2)
soc state of charge of a battery system (MWh)
θ temperature (°C)
$v_{d,t}$ electric hot water consumption (l)
θ_{in} inlet water temperature(°C)
θ_{out} desired outlet water temperature (°C)
$\Delta\theta_{low}$ degrees of under-heating (°C)
$\Delta\theta_{high}$ degrees of overheating (°C)

I. Introduction

At the distribution grid level, uncertainties in renewable generation and load consumption represent a challenge to network operation, namely for day ahead planning of Distributed Energy Resources (DERs), such as grid connected storage, controllable loads or photovoltaic (PV) control strategies, implemented in real time by a distribution management system (DMS). These challenges are magnified in microgrids, where uncertainties are higher due to minimal aggregation and smoothing effects. Since microgrids are more easily perturbed by DERs, an accurate control is needed to manage multiple electric storage systems, load devices and generation units, while ensuring a stable and reliable operation of the microgrid network and minimizing costs [1] [2].

Due to high uncertainties in load and renewable generation, microgrid control requires advanced forecasting tools and robust scheduling of controllable devices to guarantee power quality and security of supply. In particular, the control of individual loads, e.g. heating, ventilation and air-conditioning (HVAC) systems [3], brings new sources of uncertainty to the day ahead planning of DERs, such as ambient temperature, building occupancy and consumption habits. This uncertainty has a modest impact on grid operations when aggregated at the distribution level but it becomes relevant at the microgrid scale where a finer control is needed.

Optimization algorithms have been presented in the literature to solve the problem of day ahead scheduling of microgrid dispatchable resources. Numerous examples of deterministic [4] [5], stochastic [6] [7] and hybrid [8] [9] approaches to plan and operate renewable intensive microgrids are presented in the literature. Optimization methods include quadratic programming (QP) [10], as well as heuristic and meta-heuristic techniques [4] [11]. In the optimal scheduling of DERs in multi-node microgrids, heuristics have the advantage of enabling exact network constraints [4], while QP requires a convex relaxation of power flow equations [9]. Due to the random aspect of search techniques in heuristic methods, calculation time can be high and the global optimal is not guaranteed. However, QP methods perform significantly better in terms of computational time. Thus, when combined with techniques that guarantee accuracy of the power flow calculations, e. g. linear cuts [12], they become a better solution.

Stochastic approaches have been used in optimal operation of microgrids to capture uncertainties of renewable sources [13]. Primarily, these strategies include either scenario trees [14] [7] or statistical parameters of the stochastic variables [15] [11] [16] that are integrated into the optimization problem.

Monte Carlo simulation along with the distribution functions for generators and load are used to generate scenarios in [15]. Scenarios are constructed by analyzing the mean, standard deviation and probability density functions of load and generation in [11]. Upper and lower bounds on generation and load are considered in [16]. A scenario tree is developed to represent stochastic variables such as temperature, electricity prices and consumer occupancy through the calculation of quantiles and consideration of the probability density function (PDF) of historical data [7].

The day ahead operation of microgrids includes optimal scheduling of multiple DER technologies. Besides the generation and storage control solutions, demand response (DR) has been a valuable resource to compensate the variability of the renewable sources, especially through the control of thermal loads, such as HVAC and Electric Water Heaters (EWH). In fact, as shown in [8], load control can significantly reduce microgrid operation costs as well as CO_2 emissions. Two primary modeling strategies are presented in the literature for DR consideration: an aggregated model or individual modeling of devices. Aggregated models make acceptable assumptions about individual devices [14] and improve aggregated controllability of the microgrid, but the comfort of individual end users is not modeled in detail. Thus, individual load models become more appropriate for small scale applications (e.g. buildings) where a detailed comfort representation is required. In [9], individual load models are used in optimization of building operations with DR. A deterministic approach that considers end-user comfort constraints and PV for a 3 building micro-grid is detailed in [5]. An algorithm proposing an economic penalty for violations in thermal comfort constraints is presented in [7] however, this paper does not consider the electric network and instead performs only an energy balance.

A majority of the mentioned citations take into account the losses in the electrical lines in a two-step process and do not integrate a full AC optimal power flow (AC-OPF) into the optimization problem [13] [11] [15].

This paper presents a novel method for day ahead scheduling of loads and DERs that has a low calculation burden while considering network constraints. To the authors knowledge, it is the first time that a full AC-OPF algorithm is used while considering thermal comfort constraints of end users. Moreover, the presented model adds on recent innovations in the field of stochastic AC-OPF [17], by expanding the formulation to accommodate multiple sources of uncertainty relevant for microgrid operations: PV generation, load and ambient temperature.

The algorithm uses the second order cone program (SOCP) convex relaxation of the power flow equations proposed in [12] to ensure accuracy in load flow constraints with a relatively low computational burden. Also, to avoid relaxations to be inexact, especially in periods of high DER injection, linear cuts are added to the problem to guarantee exactness on load flow constraints.

The microgrid flexible resources considered in the optimal scheduling model are electrochemical storage and thermal loads, namely space heating/cooling and EWH devices. To include thermal loads in the formulation, this paper integrates into the stochastic OPF different developments on individual load models [9], thermal comfort constraints [18] and uncertainty in ambient temperature [7]. The result is a suitable DER scheduling method, based on one of the most detailed formulation of its kind – combining first-order thermal models with second order security constraints – to support control at the microgrid level. Thus, the main contributions of the paper are the following:

- a multi-period SOCP adapted to consider uncertainties through scenarios of generation, load, hot water consumption and ambient temperature to account for thermal loads;
- the optimal day-ahead scheduling of microgrid flexibilities, considering grid constraints, end-user comfort constraints, and the multi-temporal dispatch of different DER technologies;
- the behind-the-meter individual loads devices modeling and scheduling for optimal DR strategies, constrained by the comfort of end-users, and integrated with the microgrid stochastic dispatch.

By combining these contributions in a single stochastic AC-OPF, the authors aim at providing a valuable discussion on the implications of generation and load uncertainties for microgrids control and the

resulting effects on end-user comfort while considering demand side management. Following this introductory section, section II describes the novel formulation introduced by this paper. Section III describes a case study to demonstrate the utility of the day-ahead scheduling strategies produced, and section IV discusses final conclusions.

II. Stochastic Optimal Power Flow Method

A. Methodology Overview

This section proposes a multi period stochastic optimization method for the day ahead scheduling of DERs in a microgrid. The DERs considered are electric storage and controllable (CL) buildings' water and space heating/cooling loads, such as EWH and commercial HVAC units. This stochastic approach considers uncertainty in the baseline uncontrollable loads (UL) (such as lighting, cooking appliances, electronic devices and phantom loads), PV generation, ambient temperature and hot water consumption. These uncertainties are considered in the form of forecast scenarios which are generated from probabilistic forecasts taking into account the spatial and temporal correlations in the processes. High and low scenarios for each variable are selected through a scenario reduction strategy and are assumed equally probable as described later in section II C.

The benefit introduced by the stochastic approach is measured by the value of the stochastic solution (VSS).This consists of comparing the expected value of perfect information (EVPI) given the stochastic solution and the deterministic average solution [19].A schematic showing the methodology as a flow chart is shown in Fig. 1.

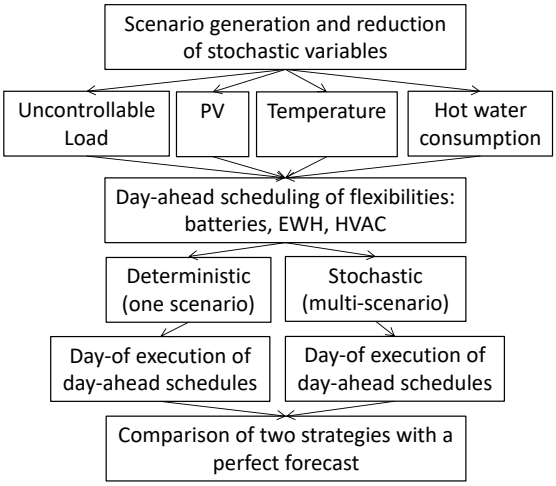


Fig. 1. Flow chart of proposed methodology

B. Formulation

The proposed formulation (1)-(22) is a multi-period (t) multi-scenario (s) optimal power flow that aims at reducing the day ahead microgrid operation costs through scheduling of batteries ($P_{\mathrm{st,j,t}}$) and controllable thermal loads, EWH ($P_{\mathrm{ewh\ ,j,t}}$) and HVAC ($P_{\mathrm{hvac\ ,j,t}}$), located at the nodes (j) of the microgrid.

1) Objective function

The operation cost function (1) considers differentiated rates for energy imports and exports, following the current regulatory mechanisms adopted by several European countries to promote self-consumption. Hence, the energy exports at the point of common coupling are remunerated at wholesale electricity market price, while the energy consumption costs are charged at the final electricity price, which corresponds to the hourly electricity market price with fixed rates, e. g. due to transmission and distribution cost. The comfort constraints of space heating systems are also considered in the objective

function through a cost function associating a price penalty with under heating and overheating.

$$min. \sum_{s} \sum_{t} \left[c_{c,t} tP_{0+,s,t} + c_{e,t} tP_{0-,s,t} + \sum_{d} c_{cf} \left(\Delta\theta_{low,d,t} + \Delta\theta_{high,d,t} \right) \right] \quad (1)$$

2) Power flow constraints

The constraints of the problem include the nodal power balance considering different DER units (2)-(5). Equation (6) describes the convex relaxations of the line constraints. The result of each OPF calculation for each time step is compared to a forward backward sweep power flow calculation to verify that the convex relaxation of the line constraint equation (6) is exact. If the solution is not exact, linear cuts are added to the problem to guarantee exactness as explained in [12].

$$P_{ij,s,t} = P_{ul,j,s,t} + P_{cl,j,t} + \sum_{k} P_{jk,s,t} + r_{ij} \ell_{ij,s,t} + P_{pv,j,s,t} + P_{st,j,t} \quad (2)$$

$$Q_{ij,s,t} = Q_{ul,j,s,t} + Q_{cl,j,s,t} + \sum_{k} Q_{jk,s,t} + x_{ij} \ell_{ij,s,t} + Q_{pv,j,s,t} \quad (3)$$

$$\vartheta_{j,s,t} = \vartheta_{i,s,t} - 2\left(r_{ij} P_{ij,s,t} + x_{ij} Q_{ij,s,t} \right) + \left(r_{ij}^2 + x_{ij}^2 \right) \ell_{ij,s,t} \quad (4)$$

$$\underline{V}^2 \leq \vartheta_{j,s,t} \leq \overline{V}^2 \quad (5)$$

$$\ell_{ij,s,t} \geq \frac{P_{ij,s,t}^2 + Q_{ij,s,t}^2}{\vartheta_{i,s,t}} \quad (6)$$

3) Battery system constraints

Equations (7)-(10) represent the battery limits regarding power and state of charge.

$$-\overline{P}_{st,j} \leq P_{st,j,t} \leq \overline{P}_{st,j}$$

$$\underline{soc}_{st,j} \leq soc_{st,j,t} \leq \overline{soc}_{st,j} \quad (8)$$

$$P_{st,j,t} = P_{st+,j,t} + P_{st-,j,t} \quad (9)$$

$$soc_{st,j,t} = soc_{st,j,t-1} + t\eta_{st} P_{st+,j,t} + \frac{t}{\eta_{st}} P_{st-,j,t} \quad (10)$$

4) Thermal comfort constraints

The thermal comfort constraints associated with the individual HVAC and EWH controllable devices are shown in (12)-(19). The division of over and under heating in equation (20)-(22) allows for a piecewise linear penalty function of thermal constraint violations in the objective function.

$$P_{cl,j,t} = P_{hvac,j,t} + P_{ewh,j,t} \quad (12)$$

$$\sum_{d} P_{ewh,d,t} = P_{ewh,j,t} \quad (13)$$

$$0 \leq P_{ewh,d,t} \leq \overline{P}_{ewh,d} \quad (14)$$

$$\underline{\theta}_{w} < \theta_{ewh,d,t} < \overline{\theta}_{w} \quad (15)$$

$$\theta_{\mathrm{ewh},d,t} = \theta_{\mathrm{ewh},d,t-1} + \frac{t}{C_d}\left[-\alpha_d\left(\theta_{\mathrm{ewh},d,t-1} - \theta_{\mathrm{int},d,t}\right) - \nu_{d,t} c_w (\theta_{\mathrm{out}} - \theta_{\mathrm{in}}) + P_{\mathrm{ewh},d,t}\right] \quad (16)$$

$$\sum_d P_{\mathrm{hvac},d,t} = P_{\mathrm{hvac},j,t} \quad (17)$$

$$0 \le P_{\mathrm{hvac},d,t} \le \overline{P}_{\mathrm{hvac},d} \quad (18)$$

$$\theta_{\mathrm{hvac},d,t} = \theta_{\mathrm{hvac},d,t-1} - \frac{t}{C_d R_d}\left[\theta_{\mathrm{hvac},d,t-1} - \theta_{\mathrm{ext},t} + \eta_d R_d P_{\mathrm{hvac},d,t}\right] \quad (19)$$

$$\underline{\theta}_{\mathrm{hvac},d} - \overline{\Delta\theta}_{\mathrm{low},d} \le \theta_{\mathrm{hvac},d,t} \le \overline{\theta}_{\mathrm{hvac},d} + \overline{\Delta\theta}_{\mathrm{high},d} \quad (20)$$

$$\underline{\theta}_{\mathrm{hvac},d} - \theta_{\mathrm{hvac},d,t} = \Delta\theta_{\mathrm{low},d,t} \quad (21)$$

$$\theta_{\mathrm{hvac},d,t} - \overline{\theta}_{\mathrm{hvac},d} = \Delta\theta_{\mathrm{high},d,t} \quad (22)$$

These thermal equations are the first order physically-based load modes – considering the thermal capacity (C), resistance (R), and heat loss constant (α) - to describe the temperature behavior of thermal systems.

5) Stochastic variable and scenario generation

Controllable variables include the active power of EWH for residential buildings and HVAC thermal loads for commercial buildings ($P_{\mathrm{ewh},d,t}$and $P_{\mathrm{hvac},d,t}$) and the active power of battery systems ($P_{\mathrm{st},j,t}$).On the other hand, the baseline uncontrollable load ($P_{\mathrm{ul},j,t}$) is also is considered as a state variable. A table summarizing the controllable variables, stochastic variables and scenario dependent variables is found in Table I.

The stochastic variables are represented in the linear constraint matrix of the optimization problem through parallel multi-period scenarios. This technique to integrate uncertainties into and OPF is classified as a probabilistic scenario-based technique for taking into account uncertainties in power systems as classified in [20] a.k.a. a deterministic equivalent formulation of the stochastic problem. Here we apply the approach proposed in [21], where a similar scenario representation in an OPF scheduling algorithm has been implemented. Two main steps are necessary, the generation of scenarios and the reduction of scenarios. That paper uses a Monte Carlo scenario generation method applied to wind turbine generation and load profiles based on [22]. The scenario reduction technique that is used is based on probabilistic distance and fast-forward selection as described in [23].

Table. 1
Variable types

Type	Applicable Variables
Controllable Variables	P_{st} ($P_{\mathrm{st+}}$, $P_{\mathrm{st-}}$), P_{cl} (P_{hvac}, P_{ewh})
Scenario Dependent Variables	P_{ij}, ℓ_{ij}, Q_{ij}, ϑ_{i}
Stochastic Variables	P_{pv}, P_{ul}, $v_{d,t}$, θ_{ext}

Here we use the same scenario generation technique as [22] for the UL, ambient temperature and EWH scenarios. A three-month historical period is used to calculate the quantiles and the covariance matrix to generate normal Gaussian scenarios.

This technique is less effective when applied to PV production scenarios due to the fact that PV production profile has a very strong correlation associated with the irradiation which depends on the course of the sun during the day. This strong correlation with irradiation may dilute the other causes of variation in PV production such as cloud cover. The PV production profiles were therefore normalized by

the clear sky index before applying the scenario generation method. This allows for a more precise analysis of inter-temporal variation due to cloud cover or other phenomena that are not correlated with irradiation. For further discussion on the necessity to stationnarise PV production time-series when modeling spatio-temporal correlations and more sophisticated stationnarisation techniques for that purpose, refer to [24].

Table. 2
UL, CL and DER characteristics per node

Node	0	6	10	12	14	15	19	23	28	29	32
Average UL (kW)	28	-	95	62	95	64	76	66	-	21	8
Maximum UL (kW)	68	-	212	156	212	155	183	159	-	52	20
Nominal PV Power (kW)	-	313	-	819	428	-	518	-	542	-	-
Nominal Battery Power (kW)	-	250	-	250	250	-	250	-	250	-	-
Nominal Battery Capacity (kWh)	-	500	-	500	500	-	500	-	500	-	-
Number of EWH devices	4	-	7	5	4	4	6	6	-	10	3
Number of HVAC devices	0	-	0	2	1	2	2	1	-	3	0

It is noted that a limitation of the approach in [21] concerns the fact that the scenario generation techniques does not consider possible correlations between the stochastic variables considered. This could be part of the perspectives of the current work. The stochastic OPF optimization, through the use of multiple scenarios as input, aims at finding a solution that provides “hedging” to the considered physical system against uncertainties. This means that the system is prepared to face more situations than when optimized through the simpler deterministic approach. This strategy may consequently involve higher costs. To be able to evaluate this risk for higher costs we have adopted a simple but intuitive scenario reduction method that is based on choosing the “extreme” upper and lower scenarios resulting from the scenario generation step and then combine these opposite situations that these scenarios reflect. This can be considered as a pessimistic approach that could lead to amplified “hedging” costs compared to the deterministic case. Depending on the system this does not necessarily mean that there is no margin to reduce costs through the deterministic approach. It is a matter of tradeoff between the hedging cost mentioned above and the impact of the deviations from a deterministic schedule. The overall approach remains though generic as one can replace by scenarios resulting from more sophisticated reduction method (i.e. from in [23]) as done by the authors in [21]. More precisely, here, three scenarios were selected based on the total cumulative values of the day. The three scenarios are chosen by selecting the maximum, minimum and closest to average value of the cumulative values in order to produce a high, low and average scenario for each variable.

C. Performance Evaluation of Stochastic Method

The stochastic approach is evaluated through VSS and EVPI. To calculate these performance indicators, the day-ahead schedules obtained in the deterministic approach and those obtained in the stochastic approach are benchmarked against the actual observation of day-of conditions.VSS is the difference between the stochastic method and the deterministic one. The expected value of the actual observation, EVPI, is the absolute difference between the expected value *with* the data of the actual observation, and the expected value *without* the actual observation – either the stochastic solution or the deterministic solution.

When evaluating each of these cases, the set points for EWH, HVAC and battery power are implemented with no intra-day adjustments for the real conditions. The thermal equations are used to simulate the evolution of temperatures in the buildings and in the hot water tanks. A forward backward sweep power flow calculation is performed to calculate the current and voltage of each node at each time step. Energy costs, grid constraint violations and thermal comfort profiles are then analyzed to assess the comfort of end-users in comparison with the economic performance of the optimization strategies.

III. Case Study

In this section, the proposed methodology presented above is applied to a realistic community microgrid, located in France in the area of Grenoble city. To facilitate the interpretation and to allow the replicability of the results, the microgrid network is assumed to be the well-known IEEE 37 nodes distribution circuit(Fig. 2). However, generation and load were modified as described below.

A. Generation and Load Data

Load profiles including EWH, HVAC and uncontrollable loads are generated using a bottom up load simulator detailed in [25]. This simulator produces a group of individual commercial and residential building load profiles. These profiles are generated to be statistically accurate representations of residential and commercial customer proportion, electric heating, building surface area and population using the INSEE building inventory database of France, and distributed randomly across the network. The medium voltage feeder is assumed to have a 5 MVA transformer serving 5 low voltage substations for a total of 312 clients, of which 300 are residential and 12 are commercial. Of the 300 residential clients, 49 residential hot water heaters are controllable. It was assumed that all 12 commercial clients have controllable HVAC systems. In addition, a total of 1.2 MW uncontrollable load, 155 kW of controllable EWH and 308 kW of controllable HVAC are considered.

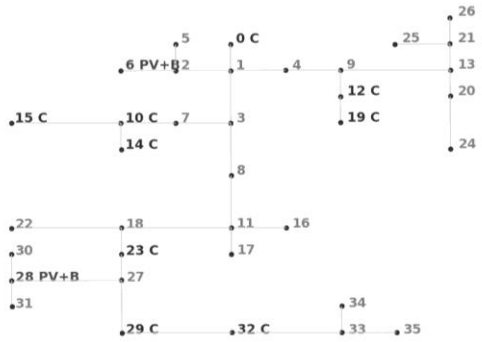


Fig. 2. Medium voltage microgrid case study feeder. C indicates a node with customer load, PV + B indicates nodes with PV and batteries

A total capacity of 2.62 MW of PV is distributed over 5 nodes, with production curves based on a real PV plant in Grenoble [26], normalized by the nominal power installed in each node. In addition, all 5 PV nodes are assumed to have a battery system with 250 kW nominal power and 500 kWh nominal capacity, totaling 1.25 MW and 2.5 MWh. The UL, CL and DER characteristics for each node can be found in Table II. The parameters used for the HVAC and EWH units are as follows: for EWH, the maximum power per device is between 2.0-6.0 kW, thermal capacities and heat loss coefficients are within 0.0877 – 0.2925 kWh/^{o}C and 0.0004-0.0012 kW/^{o}C, respectively. Cold water intake temperature (θ_{int}) and usage temperatures (θ_{out}) are12^{o}C and65 ^{o}C, while temperature limits are between 60 ^{o}C and 80 ^{o}C. For individual buildings HVAC systems, the maximum power is between 2.44 – 158.67, C and R values are within 0.2244 – 1318.4959 kWh/^{o}C and 0.0127-21.0012 ^{o}C/kW, respectively. The comfort temperatures are between19^{o}C and 26^{o}C.The cost of discomfort for under heating and overheating was considered to be

Table. 3
Case study labels

Scenario	St No CL 2 S	St No CL 4 S	St w T 10 €	St w T 1 €
1	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{H} \theta_{ext}^{L}$	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{H} \theta_{ext}^{L}$
2	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M} v$	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{L} \theta_{ext}^{H}$	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{L} \theta_{ext}^{H}$
3	-	$P_{pv}^{H} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{H} P_{ul}^{H} P_{ewh}^{H} \theta_{ext}^{H}$	$P_{pv}^{H} P_{ul}^{H} P_{ewh}^{H} \theta_{ext}^{H}$
4	-	$P_{pv}^{L} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{L} P_{ul}^{L} P_{ewh}^{L} \theta_{ext}^{L}$	$P_{pv}^{L} P_{ul}^{L} P_{ewh}^{L} \theta_{ext}^{L}$

Scenario	St 2 S	St C	St PV	St 4 S
1	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{M} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{H} P_{ul}^{M} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{L} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$
2	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{M} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{L} P_{ul}^{M} P_{ewh}^{M} \theta_{ext}^{M}$	$P_{pv}^{H} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$
3	-	-	-	$P_{pv}^{H} P_{ul}^{H} P_{ewh}^{M} \theta_{ext}^{M}$
4	-	-	-	$P_{pv}^{L} P_{ul}^{L} P_{ewh}^{M} \theta_{ext}^{M}$

10€/°Ch or 1€/°Ch for different case studies. The case study uses historical variable market prices for electricity cost in France for 2012.

B. Results

The results presented below focus on three primary topics: i) economic benefit of using a stochastic approach over a deterministic one, ii) economic benefits of combining stochastically managed storage devices with controllable loads and iii) thermal comfort improvements with stochastic techniques.

The annual operational costs of the microgrid are calculated using both the stochastic and deterministic day-ahead scheduling strategies. The deterministic case (denoted as "Det" in the figures) uses the average daily cumulative value of the available forecasts for all stochastic variables. The stochastic case (denoted as "St" in the figures) uses combinations of high and low forecasts for each stochastic variable shown in Table I.

Multiple case studies are tested to quantify the effect of each stochastic variable on the total annual operational cost. The cases consider high (H) and low (L) scenarios and combine different stochastic variables to analyze the effects of each stochastic variable independently as well as their compounded effects. Cases when a stochastic variable is not being evaluated the average scenario is used (M). Table III details the labels for each case study evaluated in this section.

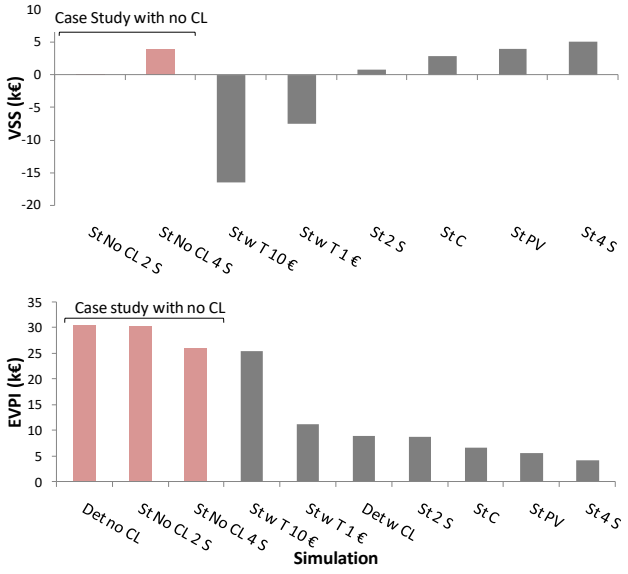


Fig. 3. Annual VSS (top) and EVPI (bottom) costs of case studies

Fig. 3 shows the stochastic performance measures of the annual operational cost. The case study with CL shows that stochastic strategies result in lower annual costs. However, no major economic advantage is seen in using 4 scenarios instead of 2. In fact, the 2 initial scenarios already represent extreme conditions of PV and UL and they have a dominant impact in the stochastic optimization.

As seen in Fig. 3, when integrating controllable load into the optimal scheduling problem, annual costs are reduced. This reduction is primarily due to shifting HVAC and EWH to less expensive periods.

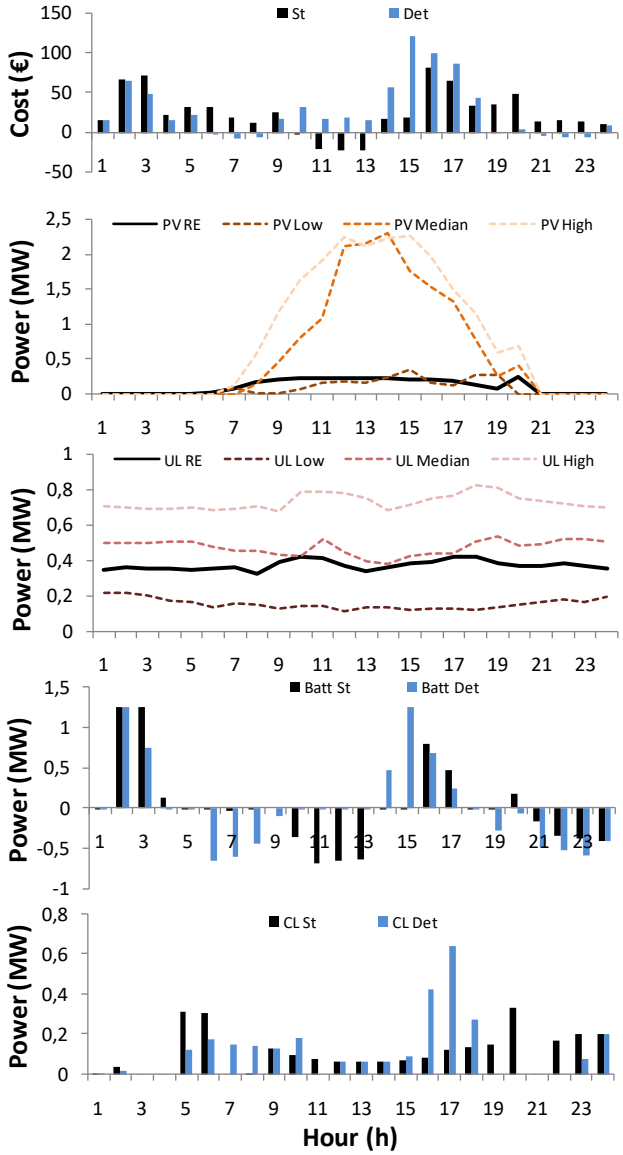


Fig. 4. Example day where stochastic scheduling results in lower operational costs than the deterministic one. From top to bottom: cost of electricity (1), PV scenarios and real PV production (2), uncontrollable load (UL) scenarios and real UL (3), stochastic and deterministic battery schedule (4), stochastic and deterministic controllable load schedule (5).

Figure 4 shows the daily operation of the microgrid, presenting a comparison of costs, battery and load scheduling between deterministic and stochastic approaches. The stochastic day ahead strategy significantly improves the operation costs of the microgrid system when simulated with real day of conditions. This improvement can be explained by the observation of the microgrid operation during the transition between hours 6 to 9 and 14 to 19. In these periods deterministic approach is unable to respond

accurately to situations where PV production deviates from the predicted average. For example, the deterministic scheduling solution suggests discharging the battery between 6 and 9 AM, preparing it to store the PV surplus during the expected sunny day. However, the observed PV generation is significantly lower than expected and this decision has a negative economic impact in the subsequent periods. In contrast, since the stochastic approach considers from the beginning the scenario of low PV generation, it suggests a more conservative discharge during the early morning. Instead, the battery is significantly discharged in the period10-13 hours, where the electricity price is higher.

From the analysis performed, a tradeoff was observed between annual operational costs and thermal comfort of the users. This tradeoff can be represented as a Pareto-optimality state with annual operational costs and end user comfort defining the Pareto-frontier.

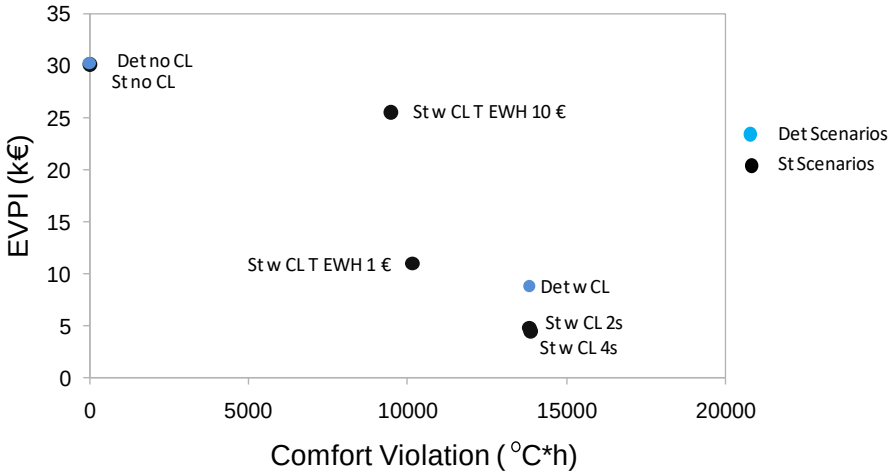


Fig. 5. EVPI vs comfort constraint violations of HVAC and EWH systems

To evaluate the trade offs of annual operational costs and user comfort additional scenarios are considered. These scenarios include high and low ambiant temperature scenarios and high and low hot water consumption scenarios. The cases 'St w T 1 €' and 'St w T 10 €' associates a 1 €/°Ch or 10 €/°Ch penalty for comfort constraint violations. The high and low temperature scenarios with economic penalties results in a more robust management of the heating and hot water loads. This robust management tends to keep the temperatures in a middle range as opposed to only heating the minimal amount. Therefore, increasing annual operational costs and improving user comfort. As shown in Fig. 5, considering uncertainties in ambient temperature is a Pareto improvement for end user comfort in HVAC loads while not considering these uncertainties is a Pareto improvement for annual costs. The value chosen for the cost penalties, 1 €/°Ch and 10 €/°Ch, effected the optimization differently. With higher cost penalties for temperature violations, annual costs were higher but fewer comfort violations resulted. In all cases the stochastic algorithm results in lower annual operational costs for the same number of comfort constraint violations when comparing stochastic and deterministic approaches.

C. Algorithm Performance

The algorithms presented in this paper have been implemented in Python and solved using the MOSEK SOCP solver on an 8-core, 3.4 GHz CPU. Due to the fact that the stochastic algorithm takes into account multiple scenarios the calculation time of this algorithm is higher. A performance analysis was completed to compare the time of calculation for the deterministic algorithm and varying amounts of scenarios in the stochastic algorithm. The average calculation time of stochastic and deterministic methods for 24 coupled time steps is shown in Table IV. Therefore, the stochastic algorithm is about 3 times slower with the consideration of 2 scenarios and 6 times slower with the consideration of 4 scenarios.

Table. 4
Algorithmic performance

Analysis	Number of Scenarios	Coupled Timesteps	CL present	Time (s)
Deterministic	1	24	No	3
Stochastic	2	24	No	8
Stochastic	4	24	No	14
Deterministic	1	24	Yes	7
Stochastic	2	24	Yes	15
Stochastic	4	24	Yes	45

IV. Conclusion

This paper presents a multi-temporal stochastic method that performs a centralized day-ahead economic scheduling of storage and controllable loads in a microgrid. The method considers network constraints using a SOCP approach in order to guarantee the security of the microgrid operation. Moreover, end-user comfort is ensured during the optimal scheduling of thermal loads, by considering first order thermal constraints. Finally, the stochastic formulation considers different scenarios, generated based on a Monte Carlo technique that takes into account spatio-temporal correlations of the variables.

The use of a stochastic approach resulted in a reduction of the microgrid operation costs in comparison with the deterministic strategy, especially in periods where weather conditions and baseline load deviate from the average. The results also show that significant savings can be achieved by harnessing thermal controllable loads in day-ahead scheduling of microgrids. In particular, considering detailed physical models and end user comfort constraints is important to effectively implement load scheduling without affecting end user comfort. However, especially in stochastic applications, meeting comfort constraints in all possible scenarios can lead to extreme conservative scheduling solutions with higher costs. Therefore, formulations based on comfort penalties, also explored in paper, prove to be suitable alternatives for this kind of constraint.

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