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Stochastic Optimization for Security-Constrained Day-Ahead Operational Planning under PV Production Uncertainties: Reduction Analysis of Operating Economic Costs and Carbon Emissions

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ABSTRACT Intermittent renewable energy sources (RES) generate variable power that cannot be fully predicted by advanced forecasting tools. Fortunately, re-schedulable conventional generators can contribute to the power balancing. However, the rescheduling usually leads to abrupt operations of fuel-based fast generators, which will induce an increase of fuel costs and CO_2 emissions. This paper presents a general operational planning framework for controllable generators, one day ahead, under uncertain renewable energy generation. The planning objective consists on minimizing operating costs and/or equivalent carbon dioxide (CO_2) emissions. The uncertainty is handled by a two-stage method: past error predictions are analyzed by a probabilistic approach and then possible future error predictions are considered through scenarios. Based on distributions of forecasting errors of the net demand, a loss of load probability-(LOLP) based risk assessment method is proposed to determine an appropriate amount of operating reserve (OR) for each time step of the next day. The effect of photovoltaic (PV) power generation uncertainty on operating decisions is examined by incorporating expected possible uncertainties into a two-stage unit commitment optimization. In a first stage, a deterministic optimization within a mixed-integer linear programming (MILP) method generates the unit commitment of controllable generators with the day-ahead PV and load demand prediction and the prescribed OR requirement. In the second stage, possible future forecasting uncertainties are considered. Hence, a stochastic operational planning is considered and optimized in order to commit enough flexible generators for reserve provision to handle unexpected deviations from predictions. Most of all, through the presented security-constrained two-stage optimization, OR is optimally scheduled (by using PV generators and conventional generators) to reach the minimum costs and CO_2 emissions by considering PV panel characteristics and stochastic nature of PV production. The proposed methodology is implemented for a local energy community. Results regarding the available operating reserve, operating costs and CO_2 emissions are established and compared. About 15% of economic operating costs and environmental costs are saved, compared to a deterministic generation planning while ensuring the targeted security level.

INDEX TERMS Decision making, generator scheduling, probabilistic modelling, renewable energy, reserve allocation, stochastic optimization, uncertainty, unit commitment, urban energy system

NOMENCLATURE

A. ACRONYMS

BPNN	Back-propagation neural networks
CCUC	Chance-constrained unit commitment
CHP	Combined Heat and Power
CI	Confidence intervals
DUC	Deterministic unit commitment
LOLP	Loss of load probability

MGT	Micro gas turbine
MIP	Mixed-integer programming
MILP	Mixed-integer linear programming
MPP	Maximum power point
OR	Operating reserve
pdf	Probability Density Function
RES	Renewable energy sources
RUC	Robust unit commitment
SD	Standard deviation
SUC	Stochastic unit commitment
PV	Photovoltaic
PV AG	Photovoltaic active generator
UC	Unit commitment

B. DECISION VARIABLES

$\delta_{m,\omega}(t)$	Commitment of generator m in scenario ω at time step t; $\delta_{m,\omega}(t) \in \{0,1\}$
$u_{m,\omega}(t)$	Generator m is starting up at the beginning of time step t in scenario ω; $u_{m,\omega}(t) \in \{0,1\}$
$d_{m,\omega}(t)$	Generator m is shutting down at the beginning of time step t in scenario ω; $d_{m,\omega}(t) \in \{0,1\}$
$p_{m,\omega}(t)$	The power generation set point of generator m in scenario ω at time step t.
$r_{m,\omega}(t)$	The allocated reserve power of generator m in scenario ω at time step t.

C. TIME SERIES

$D_{\omega}(t)$	The net demand forecast in scenario ω at time step t, the difference between the total load demand forecast and photovoltaic generation forecast.
$\underline{r}_{\omega}(t)$	Expected operating reserve requirements for the electrical system in scenario ω at time step t.

Parameters

ε	The risk index of LOLP (Loss of Load Probability).
$\underline{p}_m$, $\overline{p}_m$	The minimum and maximum power generation limits of generator m.
π_{ω}	Probability of scenario ω.
c_m^u	The start-up penalties on operating costs.
c_m^d	The shutdown penalties on operating costs.
ce_m^u	The start-up penalties on emission costs.
ce_m^d	The shutdown penalties on emission costs.

D. SETS AND INDICES

$\mathcal{M}$	Set of conventional generators.
$\mathcal{M}^{SLOW}$	Set of slow-start conventional generators.
$\mathcal{M}^{FAST}$	Set of fast-start conventional generators.
$\mathcal{T}$	Set of time steps.
$\mathcal{W}$	Set of scenarios.
Δ	Feasible set of $\delta_m(t)$ under deterministic algorithm, or $\delta_{m,\omega}(t)$ under stochastic algorithm.
p	Feasible set of $p_m(t)$ under deterministic algorithm, or $p_{m,\omega}(t)$ under stochastic algorithm.
r	Feasible set of $r_m(t)$ under deterministic algorithm, or $r_{m,\omega}(t)$ under stochastic algorithm.
$\mathcal{F}$	Set of feasible solutions, $\Delta, p, r \in \mathcal{F}$.

E. COSTS

$c_m(p_m(t))$	The operating costs for generator m producing $p_m(t)$ or $p_{m,\omega}(t)$.
$ce_m(p_m(t))$	The CO_2 equivalent emission costs for generator m producing $p_m(t)$ or $p_{m,\omega}(t)$.

I. INTRODUCTION

Renewable energy sources (RES) like wind or solar power generation are sensible to meteorological changing, which makes it unrealistic to forecast them accurately. Because of their pollution free characteristic and decreased costs, small-scale RES generators are more and more used for residential applications. They increase local profits in energy self-production and self-consumption for citizens, limit greenhouse emissions and differs infrastructure investments in transmission & distribution capacities [1]. Classically, with forecasting data of load demand and renewable generation, determinist unit commitment methods find the optimal scheduling of all controllable generators to balance the electrical system while minimizing the operating cost at each time step of the next day [2]. However, uncertainties in generation and consumption forecasting induce unavoidable deviations between scheduled and optimal generation decisions.

In isolated micro grids and balancing areas, the large-scale development of small-sized variable RES increases local dynamic power imbalances between power generation and consumption [3]. Primary frequency controllers of existing conventional generators are strongly solicited to provide operating reserve (OR) in order to compensate unexpected power imbalances [4] [5]. Therefore, sizing and providing OR requirement is essential to ensure the power system security [6]. OR must be well quantified to avoid extra operational costs due to unnecessary scheduled commitments of generators. Moreover, an optimal reserve allocation among available controllable generators is required by considering a trade-off between their dynamic response and operational cost.

In order to ensure the security of the electrical system, a risk level is usually prescribed before the operation decision of the electrical system. Based on a probabilistic analysis of forecasting errors, additional reserve power is determined and implemented in a deterministic unit commitment (DUC) as an additional and potential power that could be used during the operation [7]. For example, in [8] the reserve is optimized by a constrained unit commitment optimization with a loss of load probability index. A probabilistic method for quantifying the required OR by using forecast errors quantiles of wind production has been presented in [9].

A stochastic unit commitment (SUC) uses a representation of the uncertain forecasting by various possible scenarios in the UC formulation and, so, include uncertainties in the solution search [10]–[13]. The uncertainty behavior of variables and their interactions that may potentially change the state of the system are represented. This modelling enables the determination of possible system's states and consequences when constraints are not satisfied. Fundamental concepts of SUC, including different problem formulations and the most common decomposition techniques applied to solve the problem can be found in [14]. In contrast with scenario-based stochastic programming models, robust unit commitment (RUC) methods try to incorporate uncertainty without the information of underlying probability distributions, and instead with only the range of the uncertainty. In place of minimizing the total expected cost as in SUC, RUC minimizes the worst-case cost regarding all possible outcomes of the un-certain parameters. Certainly, this type of models produces very conservative solutions, but computationally it can avoid incorporating a large number of scenarios. In [15], a robust interval uncertainty method and a scenario-based method are detailed and compared. The results conclude that the performance of interval-based approach is greatly dependent on interval choices, while the computational cost is low. Compared to interval-based robust optimization, the scenario-based method leads to solutions with higher accuracy, but with higher computational complexity. A great challenge of scenario-based SUC is the speed up of the problem solving. To tackle this problem, we propose the determination of a limited number of scenario and the refined exploitation of fast generators to counter pass probable uncertainties.

In chance-constrained unit commitment (CCUC), certain constraints are only satisfied under a preset probability in [16]. To avoid the overestimated costs caused by extreme worst-case that are unlikely to happen, a trade-off is performed between cost and robustness by means of setting a probability of the selected solution to be feasible. Despite the computational difficulty, a joint CCUC is considered in UC with a joint probabilistic constraint for the RES uncertainty in [17]. However, a drawback of CCUC is that probabilistic constraints can be nonconvex and hard to evaluate, thus making these approaches potentially computationally demanding. By comparison with RUC and CCUC, it is clear that SUC adds an acceptable extra computational complexity in solving methods while preserving accuracy of results.

However, the quantification and pre-allocation of the reserve power one day-ahead in a SUC is still a problem since efficiency and reliability when solving such a problem is greatly dependent on the number of scenarios. To overcome these disadvantages, [18] merges a probabilistic reserve constraint technique and a SUC approach with a limited number of scenarios to overcome the problem of computational cost. In [19], by considering different distribution functions, load forecast uncertainty and wind power forecast uncertainty are represented, then two objectives regarding minimal cost and minimal emission are considered for market clearing of electrical energy as well as spinning reserves. A trade-off between emission and cost objectives is proposed in [20] to find the solution of an optimal power flow problem under RES uncertainty in a wind-thermal power system. In [21], to find the economic dispatch solution, the optimal spinning reserve requirements are calculated under consideration of wind uncertainty in a wind-thermal power system. By considering the additional stochasticity from RES, [22] proposes a conditional value of risks during the SUC procedure to deal with RES uncertainties but without distinguishing the dynamic response of generators.

The interest of conventional generators with fast dynamic response (called "fast generators") is that they can be used to erase non-expected electrical system unbalancing. Problems arise because the operational cost increases as well as emissions since they are higher during transients. Hence, a general energy management strategy is to plan conventional generators with slow dynamic response (called "slow generators") such that they could be used for a certain range of (possible) uncertainties and keep fast generators for less probable unbalancing. This paper proposes a framework for a separated commitment of slow and fast generators for economical and emissions minimization, according to the uncertainty modelling and considering the use of PV power curtailment (as PV generators have fast response time). Thus, a novelty in this study is:

Following the quantification of the required reserve at each time step under RES uncertainty, the reserve provision is optimized by checking the availability of PV generators (for possible power curtailment) and fast conventional generators, and searching for the optimal solution for reserve provision to minimize the costs and emissions.

Previously, a two-stage organization of a unit commitment process has been formulated with wind uncertainty by considering various locations of wind generators and transmission line failures and so for transmission applications [23]. A two-stage stochastic programming method is implemented in [24] for power generation scheduling to deal with unpredictable wind power and load demand. In [25], under wind uncertainty, a two-stage stochastic programming problem is discussed for optimizing both energy and OR one day ahead. In the studies all above, once the commitment decisions of slow generators are made in the first stage, they are unalterable in the second stage. Whereas for each fast generator, the commitment and the set point are adjustable in the second stage. However, the common feature of these approaches and methods is that curtailments of PV generators are not considered in OR provision while this process is inducing cost and emissions reduction for some operating range of the considered electrical system. In addition, they cannot be adapted for urban networks or microgrids, because transmission constraints complicate the building of scenarios. Furthermore, specificities of small power systems are not taken into account (as for example, fast dynamic variations since electrical systems with many power electronicconnected generators has a low inertia). In our study, a co-optimization framework will be presented for a local energy community with PV generation and Combined Heat and Power (CHP) generation comprising slow/fast generators that can be used for electrical energy compensation and emergency generation. Moreover, PV generators are considered as fast generators and can be regarded as an OR source under a security-constrained manner.

The literature review shows that probabilistic-based DUC and scenario-based SUC have certain advantages regarding reserve allocation onto controllable generators. They should be properly adapted and combined. The uncertainty handling by a proper reserve scheduling is a challenging and urgent task in UC problem. However, very few publications in the literature take into account the availability of RES, e.g. PV generators, for optimal reserve provision under uncertainty.

In this study, a stochastic optimization framework for day-ahead unit commitment is proposed to take into account the PV production uncertainty. The proposed operational planning scheme is organized in two stages, but with different tasks regarding the uncertainty handling. The first stage calculates ad hoc requirements on reserve supply from a probabilistic-based uncertainty analysis on past forecasting PV errors, and then, performs an optimal DUC with a Mixed-Integer Programming (MIP) method. The second stage is a stochastic operational planning. With an uncertainty prediction by considering various future scenarios and their corresponding probabilities, a SUC is formulated and applied to bring enough flexibility through the decided power scheduling of fast generators (including PV active generators) in case of possible deviations from forecasting values.

The contributions of this paper are:

1) A risk constraint-based method is detailed to determine the OR after a probabilistic analysis of past forecasting errors;

2) In a first stage, forecasted data and the required OR are considered and a DUC method is applied to optimize the generation planning one day-ahead;

3) In a second stage, occurrences of probable uncertainties are considered and the strategy is to use flexible generators to compensate them. Therefore, the commitment of slow generators is not changed. By considering probable PV production scenarios, a SUC method optimally recalculates the dispatching of the power reserve and the optimal generation planning of fast generators in order to adapt the OR capacity;

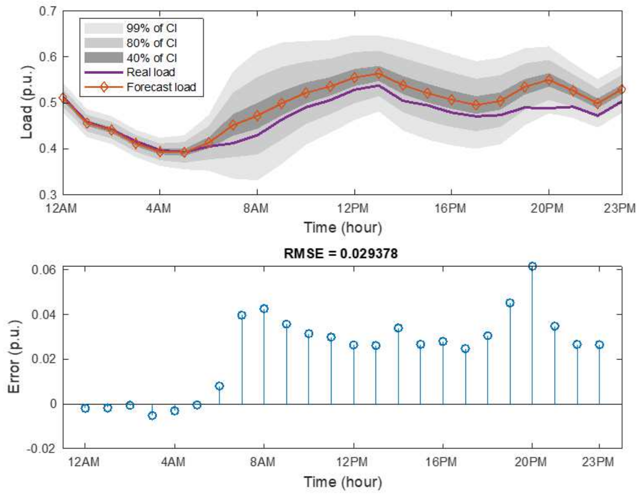
4) Mono-objective and multi-objective optimization are compared by considering operating economic costs and/or the CO2 equivalent emission environmental costs.

The paper is organized as follows: Section 2 explains the reserve determination, which is based on a risk assessment method; Section 3 describes the mathematical formulation of the Unit Commitment. Section 4 details the scheme of the two-stage optimization algorithm for the deterministic and stochastic operational planning. Section 5 presents the obtained results in a local energy community with distributed energy resource, as well as the impact analysis of the uncertainty propagation on the cost, risk criteria and the self-production rate of electricity from RES. Perspectives and conclusions are given in section 6.

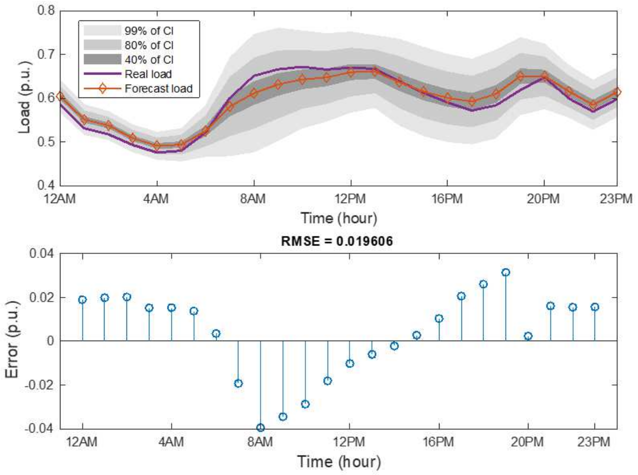
II. RISK CONSTRAINED PROBABILISTIC METHOD FOR RESERVE DETERMINATION

In recent decades, many techniques for forecasting have been developed and they all own two characteristics. Forecasting is a stochastic problem by nature and produces outputs in a probabilistic form, such as a probability density function, a prediction interval, some quantile of interest, a forecast under a scenario, etc. Current energy management systems cannot yet take probabilistic inputs, so the most commonly used forecasting output form is still the future expected value of a random variable. Moreover, forecast errors are inevitable due to the stochastic nature of forecasting. The motivation of our research work is not to focus on an improvement of forecasting techniques. It is first to analyze forecast error uncertainty regardless of applied forecasting technique and then to propose a method for planning generators in order to be able to balance possible errors.

To get forecasting errors, a homemade Back-propagation neural networks (BPNN) is used to generate PV power and load forecast data with their confidence intervals (CI) or prediction intervals (fig. 1 and fig. 2) [26]; but other forecasting techniques [27] could also be employed.

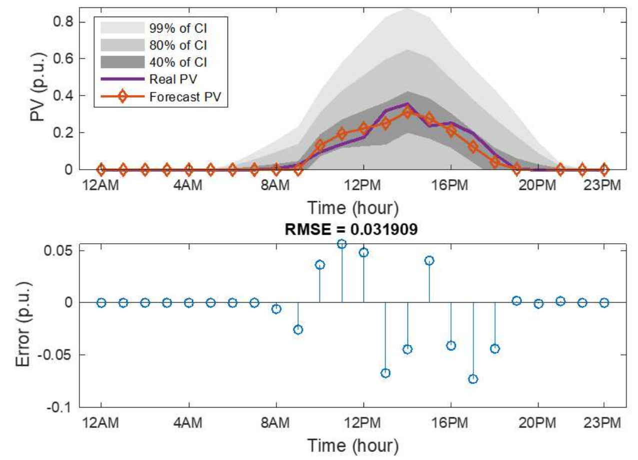


(a) On 29th August, 2020 (non-workday)

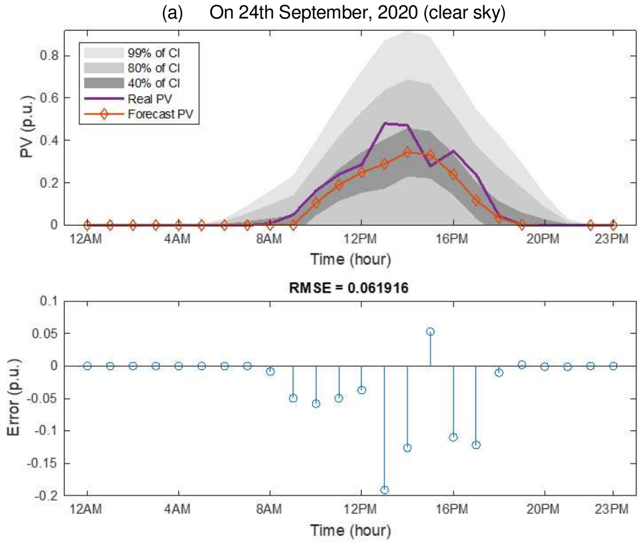


(b) On 31st August, 2020 (workday)

FIGURE 1. Load demand forecast results and forecast errors in a non-workday and a workday in Lille, France.



(a) On 24th September, 2020 (clear sky)



(b) On 23rd September, 2020 (cloudy sky)

FIGURE 2. PV power forecast results and forecast errors in a clear sky day and a cloudy day in Lille, France.

Forecast error uncertainty analysis is based on obtained forecasting errors. Operating reserve power is essential to ensure the power balance between intermittent RES generation and load demand in case of mismatch. To achieve an optimal generation planning with the consideration of reserve allocation, reserve requirements for all the electrical system must be quantified in advance. As uncertainties in energy forecasting vary in the day, an appropriate level of minimum power reserve must be determined for each considered time step. To set a desired level of system security, a risk index must be prescribed. Then the OR power is quantified in advance (one day-ahead) by carrying out a risk-constrained probabilistic method. According to the forecasted renewable energy generation uncertainty and load uncertainty at each time step, the probabilistic reliability is assessed by an index as the Loss of Load Probability (LOLP). LOLP is the probability that a power shortage may occur. It is a measure of the expectation that the load demand may exceed generating capacity of an electrical system during a given time step.

The positive net demand deviation represents the power losses, which may be caused by an unexpected increase in demand or an overestimation of PV generation capacity (Fig. 3).

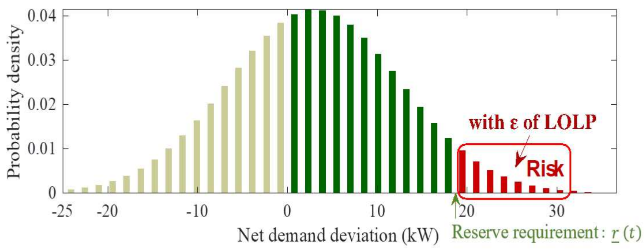


FIGURE 3. Distribution of the net demand deviations $\Delta D(t)$ with a risk index ε at the time step *t*.

An acceptable risk (ε) corresponds then to the area in red and the reserve power ($r(t)$) to cover this risk appears in green on the characteristic. The risk is assessed when the required reserve is enough to cover the net demand deviation $\Delta D(t)$:

$$\varepsilon = \mathbb{P}[\underline{r}(t) \le \Delta D(t)] = 1 - \int_{-\infty}^{\underline{r}(t)} pdf(x)\, dx \qquad (1)$$
$$= 1 - \phi\big(\underline{r}(t) \big| \mu(t), \sigma(t)\big) \;\; \forall t \in \mathcal{T}$$

pdf(x) is an approximated continuous function, representing the probability density function of the net demand error. As example, in [28], a Gaussian function is considered for *pdf(x)* and corresponding detailed calculations are given. $\phi(\underline{r}(t))$ is the cumulative distribution function at time step t, considering a reserve requirement $\underline{r}(t)$).

In order to assess the electrical system security level, the system operator can set a prescribed risk index; hence, the required reserve is obtained by the inverse cumulative distribution function (Fig. 4): $\underline{r}(t) = \phi^{-1}(1-\varepsilon)$. In this way, $\underline{r}(t)$ is the reserve requirement when $LOLP(t) \le \varepsilon$ is satisfied. i.e. $\underline{r}(t)$ is used to cover the loss of load and makes $LOLP(t)$ be equal or less than the given risk index.

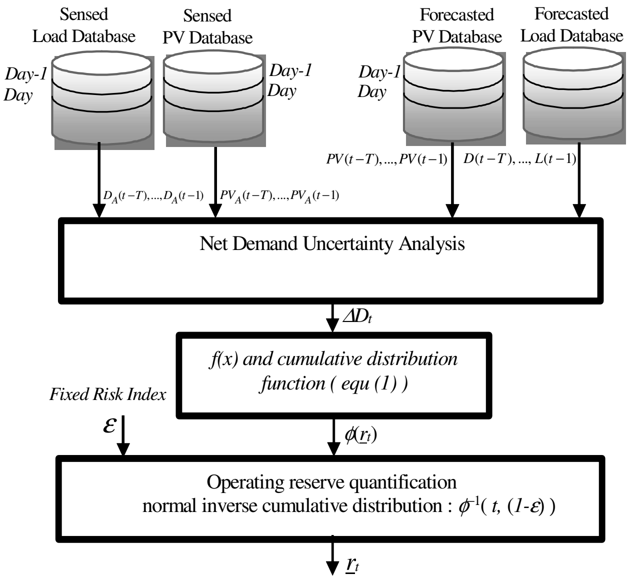


FIGURE 4. Scheme of the risk-constrained probabilistic method for reserve determination

For the ease of illustrations, consider normal distributions as Probability Density Function (*pdf*) approximations because they are simple to implement and well known to be used for easy fast testing:

$$pdf(x) = \int_{-\infty}^{\underline{r}(t)} \frac{1}{\sigma(t)\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu(t)}{\delta(t)}\right)^2}$$

From the historic database of PV and load demand forecasting errors, the mean value ($\mu(t)$) and the standard deviation ($\sigma(t)$) of the forecasted net demand errors are easily obtained at each time step and can be used to develop the normal *pdf* approximation. By calculating the reserve requirement under a risk level (ε), the LOLP curve can be obtained at each time step during the day. Meanwhile, the required power reserve varies under different risk level, e.g. if the risk level varies from 1% to 10% of LOLP, the required reserve will decrease gradually. Fig. 5 shows the obtained characteristic of the risk according to the power reserve at 11:00 time step. A ε=5% risk (LOLP index) requires a 21.5 kW reserve to obtain the wished security level.

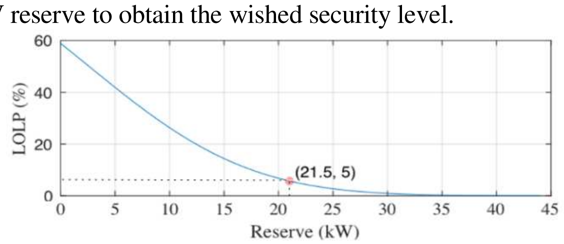


FIGURE 5. Risk characteristic regarding reserve at 11:00 in Villeneuve d'Ascq (Lille, France) the 23th of June, 2020.

III. GENERAL SCHEME AND FORMULATION OF THE UNIT COMMITMENT

A. TASK

The required OR ($\underline{r}(t)$) as well as the missed energy from passive renewables (net demand D(t)) must be provided by controllable generation units (Fig. 6).

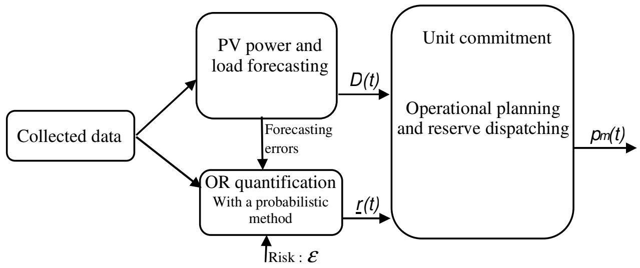


FIGURE 6. General scheme of inputs for the unit commitment.

Among a set of *M* controllable generation units, the unit commitment (UC) problem is a mathematical optimization that must decide whether a controllable generation unit is used to produce energy and how much power (p_m) each unit is producing at any time step to match the demand and the required reserve power while minimizing an objective function.

B. INTEGRATION OF UNCERTAINTIES IN THE OPTIMIZATION PROCESS

The main difficulty lies in the need of making decisions about the unit commitment before knowing how and when uncertainties will affect the electrical system balancing. The most used strategy is to consider two stages, thereby to solve this optimization problem and find optimal solution in expectation of uncertainty [29],[30] (Fig. 7).

The first stage is executed before the uncertain event realization and is based on the modelling of past forecasting errors with *pdf* to calculate the power reserve. The optimal dispatch and power scheduling of generation is determined with the expected consumption forecast, generation forecast and the required power reserve.

The second stage is based on a number of reasonable operating conditions that may arise in the future and so consider a probable uncertainty realization. Here, the uncertain PV production forecasting errors is represented in scenarios (rather than their distributions in the first stage). After the occurrence of forecasting uncertainties in each scenario ω, a second optimal dispatch is computed. The future uncertainties are taken into account with possible scenarios and the commitment of fast generators and the power scheduling of all generators are decided. The second stage is used to plan fast generators as flexible generators to erase future uncertainties. Hence at the end of second stage, fast generators are able to provide fast reserve and erase the future uncertainties, which are modeled by scenarios with corresponding probabilities.

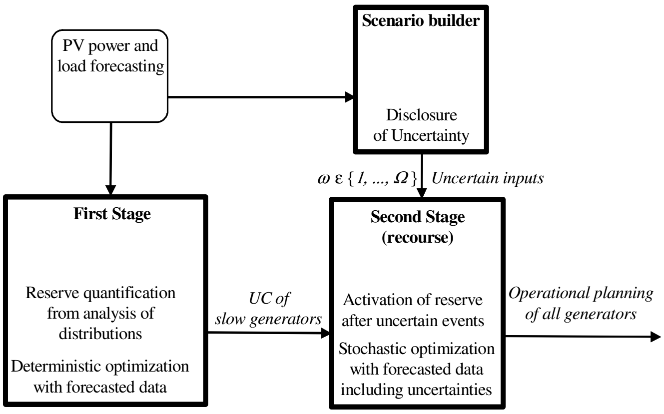


FIGURE 7. **Sequence of the two-stage stochastic programming for the reserve and energy optimization function.**

C. CONSTRAINTS

1) POWER BALANCING AND RESERVE PROVISION

The balance between generation and consumption is expressed as a first equality constraint. The total amount of conventional generation at time step t must meet the net demand forecast and the required reserve for all time steps:

$$\sum_{m=1}^{M} p_{m,\omega}(t) = D_{\omega}(t) + \underline{r}_{\omega}(t), \qquad \forall t \in \mathcal{T}, \forall \omega \in \mathcal{W} \tag{1}$$

The index ω indicates the considered scenario, as ω=0 is the forecasted scenario. For large power systems, losses in the distribution network must be added in the power balancing equation. The power reserve has a cost even when it is not used. Especially in small power systems, the cost of reserve is high. Hence it is important to have OR optimal dispatching techniques taking into consideration all conventional unit constraints.

2) GENERATOR LIMITS

The commitment orders of controllable generation units are modelled as binary decision variables (δ_m). The power generation limits between the minimum power ($\underline{p}_m$) and rated power ($\overline{p}_m$) of each generator m is expressed as:

$$\underline{p}_m \, \delta_{m,\omega}(t) \le p_{m,\omega}(t) \le \overline{p}_m \delta_{m,\omega}(t), \quad \forall m \in \mathcal{M}, \ \forall t \in \mathcal{T}, \forall \omega \in \mathcal{W} \tag{2}$$

Here $p_{m,\omega}(t)$, $r_{m,\omega}(t)$ and $\delta_{m,\omega}(t)$ are all scenario-dependent variables.

IV. TWO-STAGE OPTIMIZATION ALGORITHM

A. FIRST STAGE: DETERMINISTIC OPERATIONAL PLANNING WITH A MILP OPTIMIZATION

The operating costs and the CO_2 equivalent emission costs of each Micro Gas Turbine (MGT) m are modelled as linear functions $c_m(p_m)$ and $ce_m(p_m)$ respectively in order to describe objective functions [31]. Operating costs (in euros per kWh) are dependent on consumed gas and operating points of MGTs. CO_2 equivalent emission costs are estimated regarding the greenhouse gas emissions (CO_2, CO and NO_x). The emissions of CO and NO_x are converted to CO_2 equivalent emissions according to [32]: 1g of NOx is considered equivalent to 298g of CO2; 1g of CO equivalent to 3g of CO_2. $c_m^u u_m(t)$ and $c_m^d d_m(t)$ are the start-up and shutdown penalty on the operating costs, $ce_m^u u_m(t)$ and $ce_m^d d_m(t)$ are the start-up and shutdown penalty on the CO_2 equivalent emission costs. The start-up penalty is assumed equal to the operating costs / emission costs during a 5 minutes full load operation. The shut-down penalty is assumed equal to the costs of a full load operation during 2.5 minutes.

The economic cost-based mono-objective function for the operational planning in the first-stage is formulated as:

$$J_1 = \min_{\Delta,p,r} \sum_{t=1}^{T} \sum_{m=1}^{M} \{\delta_m(t) c_m(p_m(t)) + u_m(t) c_m^u + d_m(t) c_m^d\} \tag{3}$$

subject to (1),(2) $(\Delta, p, r) \epsilon \mathcal{F}$

$\mathcal{F}$ is the set of feasible solutions, i.e. set of feasible scheduling decision variables of commitment $\delta_m(t)$, and power generation $p_m(t)$ for MGT m at time step t. The notation ω=0 for the unique considered scenario is omitted for the ease of equation writing. Similarly, the emission-based mono-objective function for the operational planning in the first-stage is formulated by considering the CO_2 equivalent emission cost:

$$J_1 = \min_{\Delta,p,r} \sum_{t=1}^{T} \sum_{m=1}^{M} \{\delta_m(t) ce_m(p_m(t)) + u_m(t) ce_m^u + d_m(t) ce_m^d\} \tag{4}$$

The cost and emission-based multi-objective function is formulated as the sum of the two above functions:

$$J_1 = \min_{\Delta,p,r} \sum_{t=1}^{T} \sum_{m=1}^{M} \{\delta_m(t)[c_m(p_m(t)) + ce_m(p_m(t))] + u_m(t)[c_m^u + ce_m^u] + d_m(t)[c_m^d + ce_m^d]\} \tag{5}$$

B. BUILDING OF NET DEMAND SCENARIOS FOR THE REPRESENTATION OF FUTURE UNCERTAINTIES

The challenge of building scenarios for the SUC problem is to generate several representative operating points that will properly guide the SUC optimization of the second stage. Interest of the second optimization is to consider in advance a realizable unit commitment scheduling of fast generators and a power rescheduling of all generators in case of unexpected uncertainties at least cost. The set of scenarios $\mathcal{W}$ must take into account all the possible net demand events over the generation scheduling period (the following 24h) with the consideration of different PV generation scenarios.

Scenarios with different PV generation predictions are built according to probabilistic characteristics of forecasting errors. Based on the given large data set, the probability distribution of the PV forecast error at each time step t is approximated as a distribution function [33]. For a fixed standard deviation

(SD), an occurrence probability can be calculated [34] and so a corresponding future scenario can be considered.

As example, the set of available past PV forecast errors on 23th June at 11:00 has as mean value and standard deviation $\mu_{PV,t=11:00} = 0.03$ and $\sigma_{PV,t=11:00} = 0.2$, respectively.

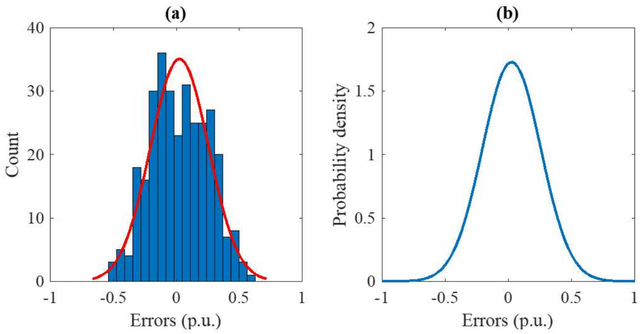


FIGURE 8. **(a) Frequency distribution histogram of the PV forecast errors at 11:00 (b) Normal distribution approximation.**

If the probability of errors is approximated by a normal distribution, then this simplified model can be exploited to consider and build possible future scenarios. As shown in Fig. 9, 68.2% of samples fall within an interval of ±1 SD from the mean, while 95.4% of samples are within an interval of ± 2 SD, and 99.7% of samples are within ±3 SD from the mean.

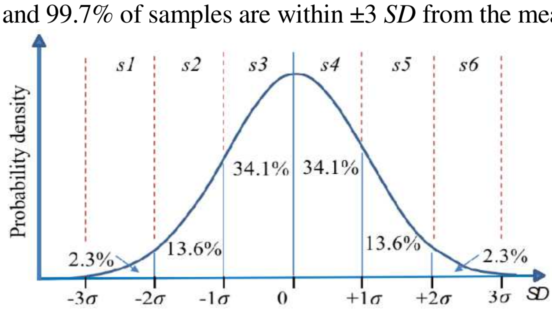


FIGURE 9. **Scenario generation based on pdf of PV forecast error at time step *t*.**

By considering three standard deviations around the mean, six scenarios can then be built with the PV forecasting time series ($\widehat{pv}(t)$). The occurrence probability of each scenario is deduced from the area of corresponding portion under the *pdf* curve. For example, the probability of scenario 3 ($s3$) is 34.1% regarding the area under *pdf* curve in the interval and so is obtained following:

$$\begin{aligned} s3: \widehat{pv}_3(t) &= \widehat{pv}(t) + \Delta pv_3(t) \\ &= \widehat{pv}(t) + \mu_{pv,\varepsilon}(t) - \frac{1}{2}\sigma_{pv,\varepsilon}(t) \end{aligned} \tag{6}$$

By doing so, for each scenario, the expected net demand $D_\omega(t)$ is calculated, and the operating cost is, hence, obtained by considering different deviations [35],[36]. These deviations are considered as constant all the day in order to estimate margins after propagation in the UC optimization algorithm. Hence, the dispatching adjusts the previous scheduled power in the first stage, according to the varying reserve requirement of each scenario in the second stage.

It must be pointed that other types of distributions for the approximation can be also considered as the aim is to generate future scenarios with their probabilities for consideration in the second optimization stage.

C. SECOND STAGE: STOCHASTIC OPERATIONAL PLANNING

1) RESERVE QUANTIFICATION FOR EACH SCENARIO

The considered uncertainty in each possible scenario is different. So, the operating reserve requirements for each considered scenario $\underline{r}_\omega(t)$ must be re-calculated. Hence, we implement an adjustment of previous scheduled power (in the first stage), according to the varying reserve requirement in each scenario. The reserve requirement for PV generation ($\Delta pv_\omega(t)$) is the difference between the predicted PV generation value, one day ahead, and the PV generation value in the current scenario. $\Delta pv_\omega(t)$ is equal to one value among six possibilities: $\{\mu_{pv,\varepsilon}(t) \pm 0.5\sigma_{pv,\varepsilon}(t), \mu_{pv,\varepsilon}(t) \pm 1.5\sigma_{pv,\varepsilon}(t), \mu_{pv,\varepsilon}(t) \pm 2.5\sigma_{pv,\varepsilon}(t)\}$. The average value regarding the upper and lower bound of PV generation is considered as the PV generation under scenario ω. Hence, the required reserve power $\underline{r}_\omega(t)$ is deduced:

$$\underline{r}_\omega(t) = \Delta pv_\omega(t) + \phi^{-1}\left(1 - \varepsilon \middle| \mu_{pv,\varepsilon}(t), \sigma_{pv,\varepsilon}(t)\right) \tag{7}$$

2) STOCHASTIC OPTIMIZATION

The optimization process must minimize the cost of the deterministic operational planning decisions of the first-stage (including the cost of the scheduled reserves) added with the expected cost of the second-stage decisions (including reserve provision called upon regarding each possible scenario). The trade-off that needs to be considered in the reserve dispatching is the flexibility of fast units versus their higher operating costs (due to their higher marginal fuel costs).

In this study case, fast generators can change commitment within one time step and have similar start up and turnoff costs to those of slow units. The unit commitment of slow generators $\forall m \in \mathcal{M}^{SLOW}$ in the first stage is kept in the second stage but their references may change. Only fast generators are committed in the second stage optimization ($\forall m \in \mathcal{M}^{FAST}$, Fig. 10).

$$\delta_{m,\omega}(t) = \delta_m(t), \forall m \in \mathcal{M}^{SLOW}, \forall t \in \mathcal{T}, \forall \omega \in \mathcal{W} \tag{9}$$

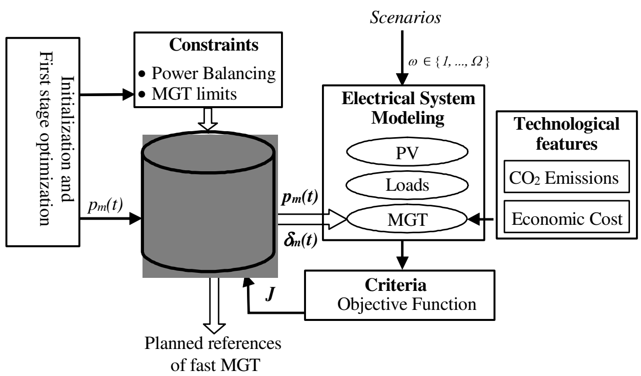


FIGURE 10. **Re-scheduling of fast generators in the second optimization stage.**

The purpose of the optimization function is to minimize the total costs of first and second stages, considering the recourse cost of the second-stage with a weighted probability. So, the cost-based mono-objective function of the operational planning in the second-stage is formulated to take into account the occurrence probability (π_ω) of each scenario ω:

$$J_2 = \min_{\Delta,p,r} \sum_{\omega=1}^{\Omega} \pi_\omega \sum_{t=1}^{T}\sum_{m=1}^{M} \{\delta_{m,\omega}(t) c_m(p_{m,\omega}(t)) + u_{m,\omega}(t) c_m^u + d_{m,\omega}(t) c_m^d\} \quad (10)$$

where $\sum_{\omega=1}^{\Omega} \pi_\omega = 1$. $\mathcal{F}$ is the set of scheduling decision variables $\delta_{m,\omega}(t)$ and $p_{m,\omega}(t)$.

Thus, this expected cost is directly affected by the uncertainty of the PV forecasting, which is modelled through scenarios and their probabilities.

Similarly, an emission-based mono-objective function for the operational planning in the second-stage is formulated by considering the CO_2 equivalent emission cost:

$$J_2 = \min_{\Delta,p,r} \sum_{\omega=1}^{\Omega} \pi_\omega \sum_{t=1}^{T}\sum_{m=1}^{M} \{\delta_{m,\omega}(t) ce_m(p_{m,\omega}(t)) + u_{m,\omega}(t) ce_m^u + d_{m,\omega}(t) ce_m^d\} \quad (8)$$

The cost & emission-based multi-objective function is formulated as the sum of the two above functions over the whole set of scenarios:

$$\begin{aligned} J_2 = \min_{\Delta,p,r} \sum_{\omega=1}^{\Omega} \pi_\omega \sum_{t=1}^{T}\sum_{m=1}^{M} \{&\delta_{m,\omega}(t)[c_m(p_{m,\omega}(t)) \\ &+ ce_m(p_{m,\omega}(t))] \\ &+ u_{m,\omega}(t)[c_m^u + ce_m^u] \\ &+ d_{m,\omega}(t)[c_m^d + ce_m^d]\} \end{aligned} \quad (12)$$

Mixed-Integer Linear Programming (MILP) is implemented for operation planning, and is solved by branch-and-cut algorithms, i.e. branch-and-bound algorithm combined with cutting planes [37].

V. APPLICATION FOR THE OPERATIONAL PLANNING OF AN URBAN ENERGY SYSTEM

A. PRESENTATION OF THE STUDIED ELECTRICAL SYSTEM

The studied local energy community includes 120kW residential rated loads, a set of 20 passive PV generators with 180kW rated power, and three CHP-based MGTs (*M*=3): 60kW (MGT 1) and two of 30 kW (MGT 2 ad MGT 3). All generators and electrical loads are connected locally in a residential district, thus voltage drops as well as line losses are ignored. Since PV generators are closely located in the current urban network, the received solar irradiation is assumed to be the same. CHP have constraints in response times and minimum electrical power generation, regarding heat power generation, because heat is in the form of hot water. In this study, with the largest rated power and more heat to consume, MGT 1 is a slow-start generator and its commitment cannot be rescheduled in the second stage. MGT 2 and MGT 3 are flexible generators (fast-start generators with a short time response) and their power reference can be rescheduled during the second stage.

The wish is to increase the self-consumption of the local generated electricity while decreasing power exchanges with the bulk power system. In this purpose, the presented methodology is implemented to make operate the local energy community autonomously. The profiles of the half-hourly electricity consumption forecast, and half-hourly forecasted daily PV generation for the corresponding day are given in Fig. 11. Under this situation, the forecasted daily PV energy is 539 kWh; the forecasted daily load demand energy is 1082 kWh. The operating cost functions of MGTs $c_m(p_m(t))$ and CO_2 equivalent emission cost functions are approximated as linear functions in their operating range.

The optimization application is using YALMIP [38] and IBM ILOG CPLEX Optimization Solver [39] with Matlab R2018b. The used computer has 8 GB of installed RAM and a 2.70 GHz processor.

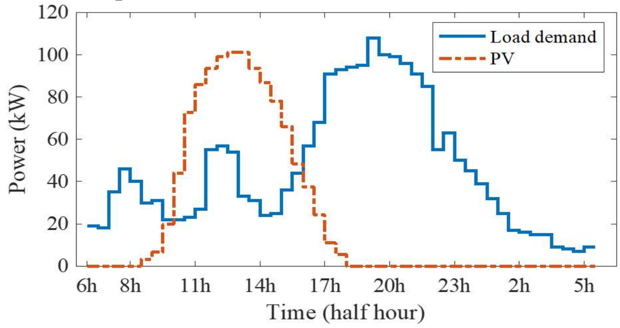


FIGURE 11. Load demand forecast and PV generation forecast.

B. RESULTS WITH A DETERMINISTIC OPTIMIZATION

1) QUANTIFICATION OF THE OR WITH THE *N-1* CRITERION

Traditionally, OR is scheduled by deterministic methods as a percentage of the load demand or generation, or by the *N-1* criterion as the capacity of the largest power generation unit. Under *N-1* criterion, in case of tripping of the largest generation unit, the scheduled OR must be capable of restoring the power. In this study, with the integration of a high penetration of RES, if PV generation is regarded as the tripping generation unit, the power reserve is then calculated according to the largest loss of PV production. The *N-1* criterion is implemented as following:

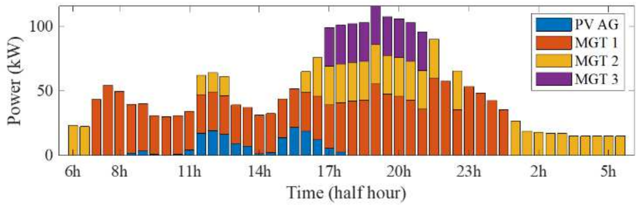
1) The UC and generation scheduling are calculated by considering only the load demand (no PV generation as the previous case).

2) According to the PV production forecast, the power set point of MGTs is reduced to satisfy the power balancing constraint.

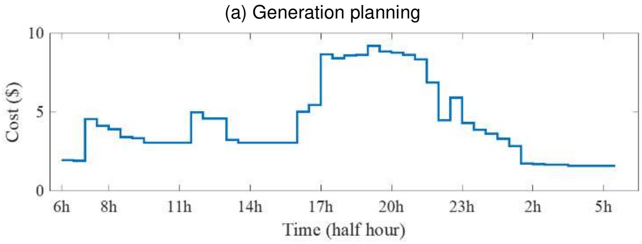
3) If one (or many) MGT power reference is under their minimum power, the MGT power reference is increased and forced to be equal to their minimum power. In consequence,

the PV production is reduced to satisfy the power balancing constraint and a part of PV generation is lost.

With this criterion, all MGTs are committed by considering no PV generation, their power set points are reduced (to the minimum value if necessary) and so they are always able to produce the power for the load demand in case of the loss of the entire PV power. Fig. 12 shows the generation planning results following the *N-1* criterion and the corresponding operating cost at each time step.



(a) Generation planning



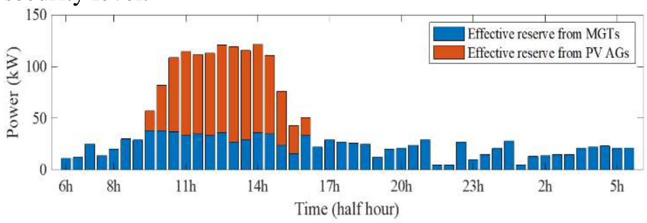
(b) Operating cost

FIGURE 12. Generation planning and operating cost under N-1 criterion.

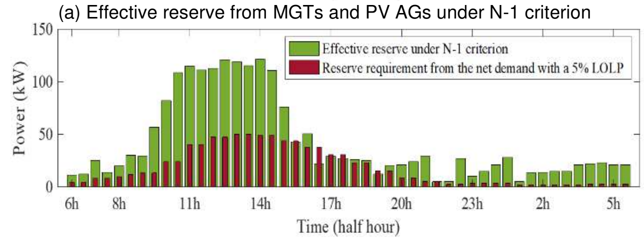
A large part of the PV power is lost when PV panels are operating under the Maximum power point (MPP) because:
- all committed MGTs must remain committed with their minimum power reference and
- the PV power exceeds the load demand during the day (Fig. 11).

With this N-1 strategy, the daily PV self-consumption rate of PV generation is 17% and the PV self-production is 9%. The effective OR is regarded as the difference between the total power ratings and the set point of committed generators at each time step. When the PV production is reduced, the lost PV power can be used as operating reserve because the PV production can be increased if necessary (more load demand as forecasted, faults on a MGT, …). So, the effective reserve is now the addition of the scheduled lost PV power and power margin of committed MGTs (Fig. 13 (a)). Such PV generators enabling a dispatched power limitation is called PV Active Generators (PV AGs).

Fig. 13 (b) demonstrates that effective (and available) reserve under *N-1* criterion is over scheduled, compared with the required reserve for obtaining a 5% LOLP. The gap between the effective daily reserve and the required daily reserve is large from 9:30 to 15:00, and indicates an oversized reserve quantification. While from 15:30 to 19:00, the obtained effective reserve is possibly less than the reserve requirement, which implies a possible risk of a power deficit. It is the reason why deterministic methods for OR calculation are gradually replaced by probabilistic methods with a desired security level.



(a) Effective reserve from MGTs and PV AGs under N-1 criterion



(b) Comparison of effective reserve and reserve requirement

FIGURE 13. Obtained effective reserve without reserve requirement under *N-1* criterion.

From these results, we can conclude that it is not rational to schedule OR by *N-1* criterion, since it is rare to lose all predicted PV power. In case of forecasting error, just a part of the predicted PV power is usually lost. Moreover, the *N-1* criterion leads to a sub-optimal decision as the PV production uncertainty is unknown and not quantified. The obtained reserve can be over scheduled during one period, while a deficit of reserve may occur during another period. It is the reason why determinist methods for OR calculation are gradually replaced by probabilistic methods with a desired security level.

2) QUANTIFICATION OF THE OR WITH A RISK ASSESSMENT

When the reserve requirement is quantified by the risk assessment, Fig. 14 shows obtained power set points of generators.

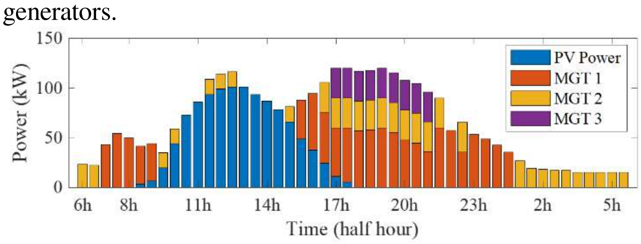


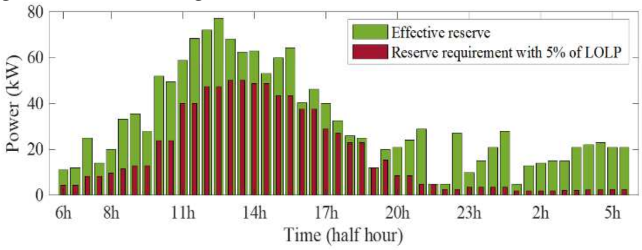
FIGURE 14. Generation planning under deterministic optimization and scheduled PV power.

All MGTs are switched off between 13:00 and 15:00. With this LOLP risk strategy, the PV self-consumption rate of PV generation is 67% and the PV self-production is 25%. The PV production must be limited (operating under the MPP) as it is sometimes more than the load. By this way, as the PV production can be increased if necessary, the shaded power constitutes an OR that is available. Then, the positive effective OR is provided both by the PV limitation ($r_{pv}(t)$) and by the difference between the maximum generation limits of committed MGTs and their output power at each time step. The available reserve power from the PV limitation is integrated in the optimization formulation, the general balancing constraint formulation (3-14) is adapted as:

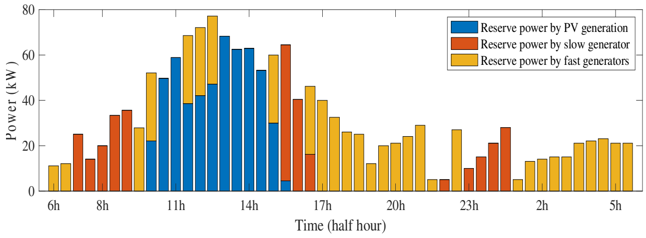
$$\sum_{m=1}^{M} p_m(t) = D(t) + \underline{r}(t) - r_{ag}(t), \qquad \forall t \in \mathcal{T} \tag{13}$$

$r_{ag}(t)$ is the reserve power from PV AGs.

It is observed that the obtained available effective reserve is equal or superior to the reserve requirement (Fig. 15 (a)). The pre-set security level is obtained. The required daily reserve is 426.5 kWh; the effective daily reserve is 762.5 kWh, which gives rise to a ratio of required reserve to effective reserve 56%. Compared with the *N-1* criterion, here the reserve scheduling is more reasonable with a higher reserve utilization rate. Fig. 15 (b) shows reserve power allocation in slow generator and fast generators.



(a) Obtained effective reserve with a LOLP ≤ 5% after the deterministic unit commitment



(b) Obtained effective reserve from slow and fast generators after the deterministic unit commitment

FIGURE 15. Reserve requirement and obtained effective reserve with a deterministic optimization.

C. RESULTS WITH THE STOCHASTIC-BASED METHOD

Based on the probabilistic distributions of the PV generation errors at each time step, six additional scenarios with their corresponding probabilities are considered for the next day to take into account the unexpected variation of PV generation, as explained in Section 4.3 (Fig. 17). Different levels of grey from dark to light indicate the possibility of occurrence from high to low, which imply 40% (dark grey), 80% (middle grey), 99% (light grey) of probability intervals. The load demand forecast is also shown in Fig. 16.

After the stochastic optimization with the different considered PV generation scenarios and the forecasted load demand is done, the generation scheduling is obtained (Fig. 17). The commitment of slow generator MGT 1 is kept whereas the planning of generators (MGT 2 and MGT 3) has changed (in comparison with the first stage, Fig. 16) in order to be able to compensate possible PV production uncertainties and according to nonlinear characteristics of generators.

The required reserve for each scenario is different and is calculated according to:

1) The deterministic load reserve, which is allocated at first-stage;

2) The stochastic PV reserve, which is re-scheduled based on the expected PV generation under each scenario. For example, the reserve requirement in the worst case regarding the net demand deviation (scenario 1), and effective reserve after stochastic optimization are shown in Fig. 18. Even in the worst-case situation (scenario 1), effective reserve is capable of covering all reserve requirement at each time step.

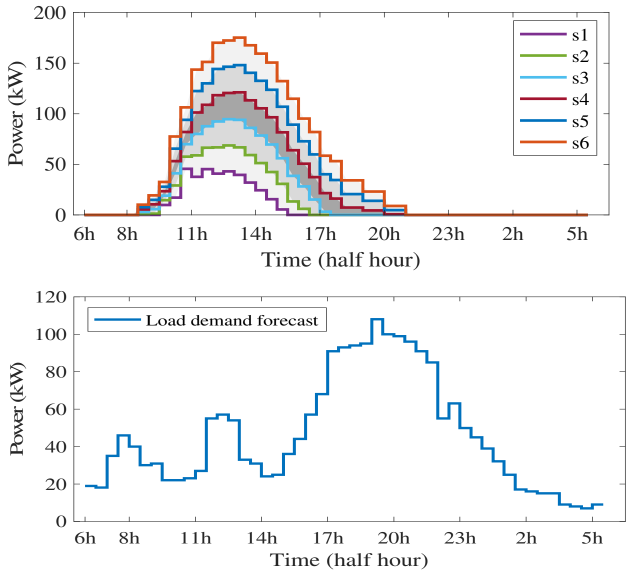


FIGURE 16. Expected PV generation under six probable scenarios and forecasted load demand.

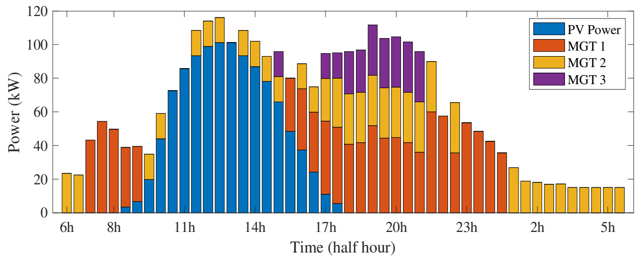
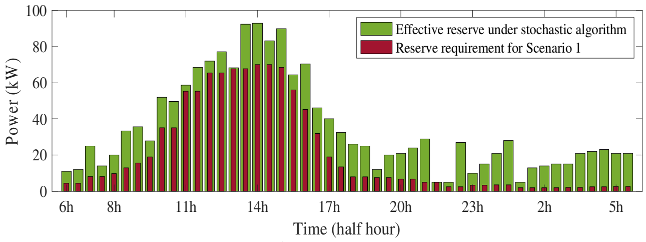
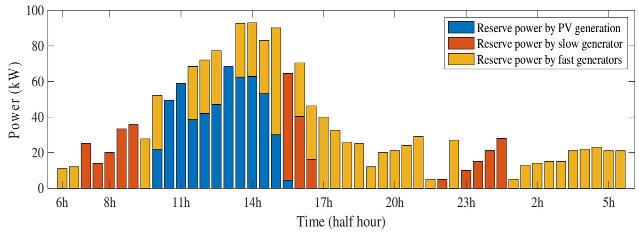


FIGURE 17. Generation scheduling under stochastic optimization.

By comparing the reserve under the stochastic optimization (Fig. 18 (a)) with the one under the deterministic optimization (Fig. 15), the reserve requirement has been more precisely calculated and re-scheduled regarding each scenario, as well as obtaining the wished high security level. Meanwhile, compared with Fig. 15 (c), Fig. 18 (b) illustrates that more reserve power is provided thanks to the commitment availability of fast generators. Daily reserve energy from slow generator is 208 kWh in both deterministic and stochastic unit commitment. As for reserve from fast generators, the daily reserve energy has increased to 450 kWh in the scenario-based stochastic optimization, compared with 390 kWh of reserve energy in the deterministic case, i.e. the daily reserve energy from fast generators has increased 15%.



(a) The reserve requirement for scenario 1 (worst case) and obtained effective reserve



(b) Obtained effective reserve from slow and fast generators

FIGURE 18. Reserve requirement for scenario 1(worst case) and the effective reserve under stochastic optimization.

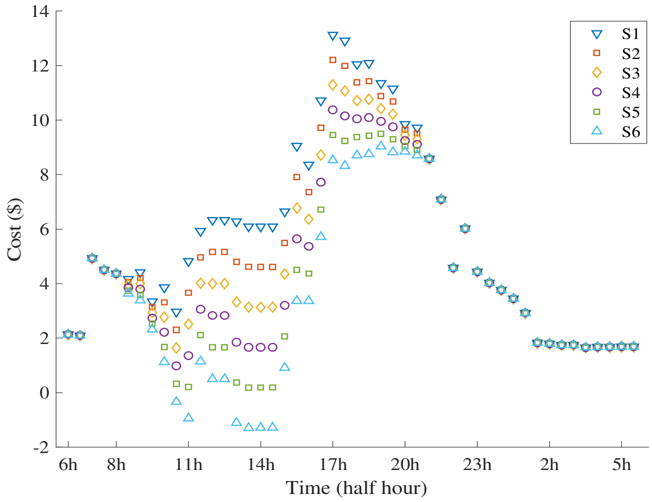
D. DISCUSSION

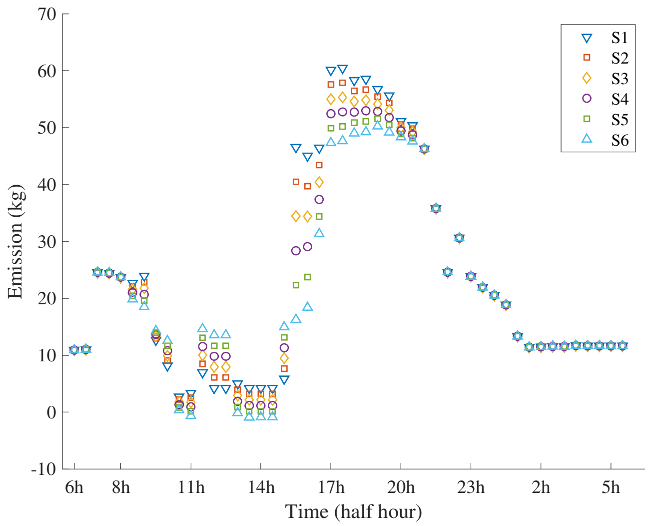
1) IMPACTS OF THE SCENARIO-BASED UNCERTAINTY MODELLING ON THE COST

The scenario-based optimization is implemented with three objective functions respectively: 1) cost-based mono-objective; 2) CO_2 equivalent emission-based mono-objective; and 3) multi-objective of cost and emission.

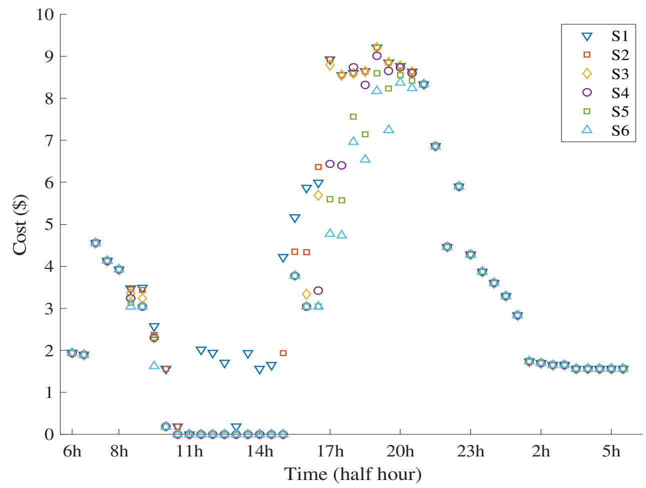
Here a multi-objective optimization is taken as an example to analyze the costs and emissions at each time step under six scenario S1-S6, and results are shown in Fig. 19. As illustrated in figures, at each time step, costs and emissions may fluctuate because of PV generation fluctuations around the forecast value. Fig. 19 (a) demonstrates impacts of PV uncertainties onto fuel costs and CO_2 equivalent emissions by considering only the 1st stage optimization. In this way, PV deviation $\Delta pv_{\omega}(t)$ must be compromised by effective reserve, which is considered as an additional cost for scenario ω. Fig. 19 (b) shows fuel costs and CO_2 equivalent emission after the 2nd stage optimization. Costs and emissions are optimized because reserve is properly scheduled during the 2nd stage optimization regarding uncertainties under each scenario.

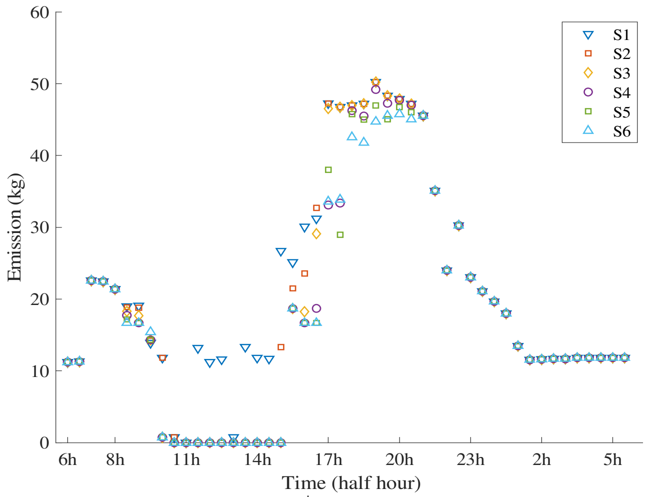
Table I compares fuel costs and CO_2 equivalent emissions before and after the 2nd stage optimization. The fuel cost and CO_2 equivalent emission cost vary according to the committed MGTs as well as considered PV generation. The fuel cost and CO_2-equivalent emission cost can be approximated by a normal distribution. For example, the *pdf* of the fuel cost at 17:00 is shown in Fig. 20 with a mean $\mu_{cost,t=17:00} = 8$ and a standard deviation $\sigma_{cost,t=17:00} = 0.1$, as well as the *pdf* of the CO_2-equivalent emission cost with $\mu_{emission,t=17:00} = 46, \sigma_{emission,t=17:00} = 0.4$. The fitted *pdf* curved is obtained for each time step according to the corresponding histogram.





(a) Before the 2nd stage optimization





(b) After the 2nd stage optimization

FIGURE 19. **Fuel costs and CO2 equivalent emission costs under 6 scenarios at each time step.**

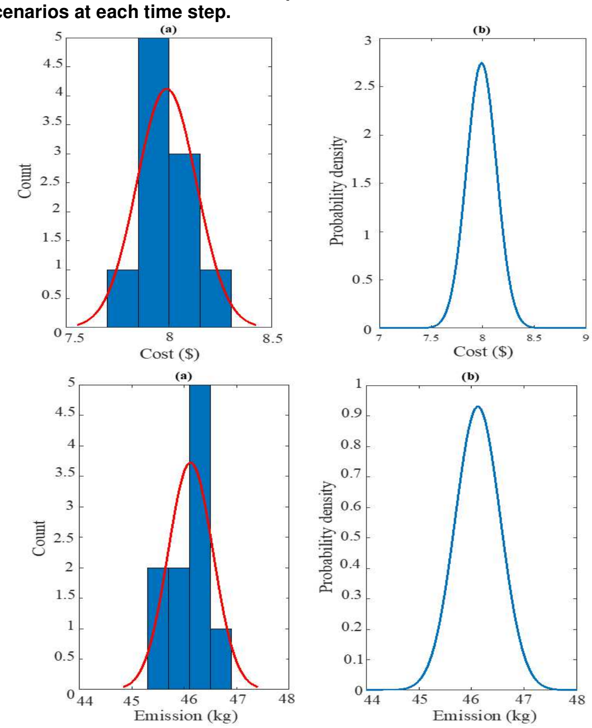


FIGURE 20. **Probabilistic modelling of fuel cost and CO2-equivalent emission cost at 17:00.**

TABLE I

Fuel costs and CO_2 equivalent emission costs results

		S1	S2	S3	S4	S5	S6
Before	Cost ($)	272	251	230	209	189	168
	Emission (ton)	1.14	1.11	1.09	1.06	1.03	1.01
After	Cost ($)	188	173	166	158	153	147
	Emission (kg)	1058	962	923	878	868	859

2) IMPACTS OF THE CHOSEN RISK CRITERIA

Criteria for the system security induce different costs. Meanwhile, when the LOLP assessment is considered in the reserve determination during operational planning, different outcomes are obtained under deterministic and scenario-based stochastic optimization algorithm. Table 2 shows the day-ahead operational planning results under different risk criterions. After the application of scenario-based stochastic multi-objective optimization, expected optimal operating cost / emission cost with LOLP in 1st Stage and 2nd Stage are reduced by up to around 15%, compared to the *N-1* criterion deterministic case. The total energy of the day-ahead reserve requirement and effective reserve are also compared.

3) IMPACTS OF THE RES SELF-PRODUCTION RATE

To study the impact of the RES penetration on operating cost and CO_2-equivalent emission cost, different RES self-production rates are considered. RES self-production rate is defined as the share of PV electricity over the total local electricity demand. The higher the PV self-production rate is, the more independent the power system is. Fig. 21 shows the cost and emissions under different PV self-production rates under multi-objective criterion. In the studied case, the maximum PV self-production rate is 28%. With the increase of PV self-production rate, the difference between costs of the deterministic *N-1* criterion and costs of the LOLP criterion (based on 1st stage and 2nd stage optimization) gradually increases. Similarly, CO_2-equivalent emissions have tendency to decrease under LOLP criterion, compared with the *N-1* criterion. As the self-production rate grows, comparing to 2nd stage emission, the 1st stage is more environmental-friendly. The operating costs are similar with a slightly difference. As for the risk level, 2nd stage planning results provide a higher level of power security because more effective reserve power is available in case of power losses. As shown in Table 3, more effective reserve (available reserve) is obtained under 2nd stage than in 1st stage.

Overall, with the presented scenario-based optimization approach, the 2nd stage optimization shows its advantages of more flexible operation planning regarding the reserve provision, giving rise to a higher security level.

TABLE II
Comparison of day-ahead operational planning results under different criterions

	Deterministic Optimization				Stochastic Optimization			
	Without Criterion		*N-1* Criterion		LOLP $\leq 5\%$ Criterion			
					1st Stage		2nd Stage	
	Cost ($)	CO_2 (kg)	Cost ($)	CO_2 (kg)	J_1-based Cost ($)	J_1-based CO_2 (kg)	J_2-based Cost ($)	J_2-based CO_2 (kg)
Multi-objective (cost & emission)	149	832	213	1174	181	1017	180	1047
Mono-objective (cost)	147	868	211	1221	180	1034	180	1079
Mono-objective (emission)	157	818	220	1164	191	1001	188	1035
Reserve requirement (kWh)	\		\		426		500	
Effective reserve (kWh)	403		554		763		838	

2) IMPACTS OF THE RES SELF-PRODUCTION RATE

To study the impact of the RES penetration on operating cost and CO_2-equivalent emission cost, different RES self-production rates are considered. RES self-production rate is defined as the share of PV electricity over the total local electricity demand. The higher the PV self-production rate is, the more independent the power system is. Fig. 21 shows the cost and emissions under different PV self-production rates under multi-objective criterion. In the studied case, the maximum PV self-production rate is 28%. With the increase of PV self-production rate, the difference between costs of the deterministic *N-1* criterion and costs of the LOLP criterion (based on 1st stage and 2nd stage optimization) gradually increases. Similarly, CO_2-equivalent emissions have tendency to decrease under LOLP criterion, compared with the *N-1* criterion.

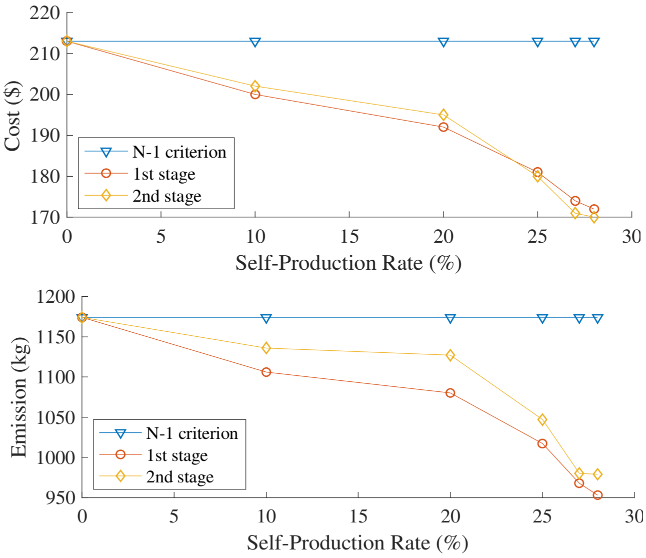


FIGURE 21. **Cost curves and emission curves regarding RES self-production rate.**

As the self-production rate grows, comparing to 2nd stage emission, the 1st stage is more environmental-friendly. The operating costs are similar with a slightly difference. As for the risk level, 2nd stage planning results provide a higher level of power security because more effective reserve power is available in case of power losses. As shown in Table 2, more effective reserve (available reserve) is obtained under 2nd stage than in 1st stage.

Overall, with the presented scenario-based optimization approach, the 2nd stage optimization shows its advantages of more flexible operation planning regarding the reserve provision, giving rise to a higher security level.

V. CONCLUSION

This work presents an optimization framework to address the problem of the optimal operational scheduling of micro grids. A two-stage optimization algorithm of generation scheduling is presented for an urban microgrid with optimal reserve dispatching. The proposed method deals with the uncertainty in forecast errors with the optimal operational planning of controllable generators, so that the minimum cost of the operation or/and CO_2 emissions one day ahead can be achieved.

In a first stage, the required half-hourly OR is decided with a prescribed LOLP-based risk level, applied on the *pdf* of the past net demand forecast errors. Then, a deterministic unit commitment gives the generation scheduling and includes PV and load forecasting in addition to OR that are calculated from past uncertainties realizations. Secondly, a stochastic day-ahead operational planning is implemented. The PV uncertainty is then considered according to different scenarios and their probabilities of occurrence at each half-hour. For each scenario, OR can be recalculated by considering the same level of security. Based on the presented PV scenario and by maintaining the commitment of slow generators, a stochastic operational planning considers possible commitment of additional fast generators if necessary and adapts power set-points of all generators to take into account future uncertainties.

Results are presented according to three different objective functions: 1) economic operating cost-based mono-objective; 2) CO_2 equivalent emission-based mono-objective; and 3) multi-objective of cost and emission. Three cases regarding reserve scheduling are compared: *N-1* criterion, optimization with probabilistic analysis (1st stage) and optimization with scenarios regarding probabilities of occurrence (2nd stage). Both economic operating costs environmental costs are saved while ensuring the targeted security level. Moreover, as shown, this framework enables the analysis of the impact of RES penetration ratio on costs and emissions.

Further works will be oriented to the integration of storage systems as an alternative for fast power reserve provision in replacement of fast generators and for CO_2 abatement.

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