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Development of a tool for urban microgrid optimal energy planning and management

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ABSTRACT

Small-sized variable renewable energy sources (RES) live a large-scale development in urban electrical systems. They increase local high dynamic unbalancing and then can create instabilities on the inertia response. Thus, setting an adequate operating reserve (OR) power to compensate the unpredicted imbalance between RES generation and consumption is essential for power system security. Indeed, effective calculation and dispatching of OR considering inaccurate forecast of both RES and load demand can provide substantial cost reductions. Thus, to facilitate the energy management and system optimization in an urban microgrid (MG), a user-friendly tool for Energy Management System and Operational Planning has been developed. The tool provides a complete set of user-friendly graphical interfaces to study the details of photovoltaic (PV) and batteries, load demand, as well as micro gas turbines (MGTs). Furthermore, this energy management system allows system operators to properly model RES uncertainty. In addition, it could assist operators for the day-ahead energy management with an efficient information system and an intelligent management.

Nomenclature

AG	Active Generator
DP	Dynamic Programming
EENS	Expected Energy Not Served
EMS	Energy Management System
LC	Local Controller
LOLP	Loss of Load Probability
MCEMS	Microgrid Central Energy Management System
MG	Microgrid
MGT	Micro Gas Turbine
ND	Net Demand
OR	Operating Reserve
PV	Photovoltaic
RES	Renewable Energy Sources
SoC	State of Charge

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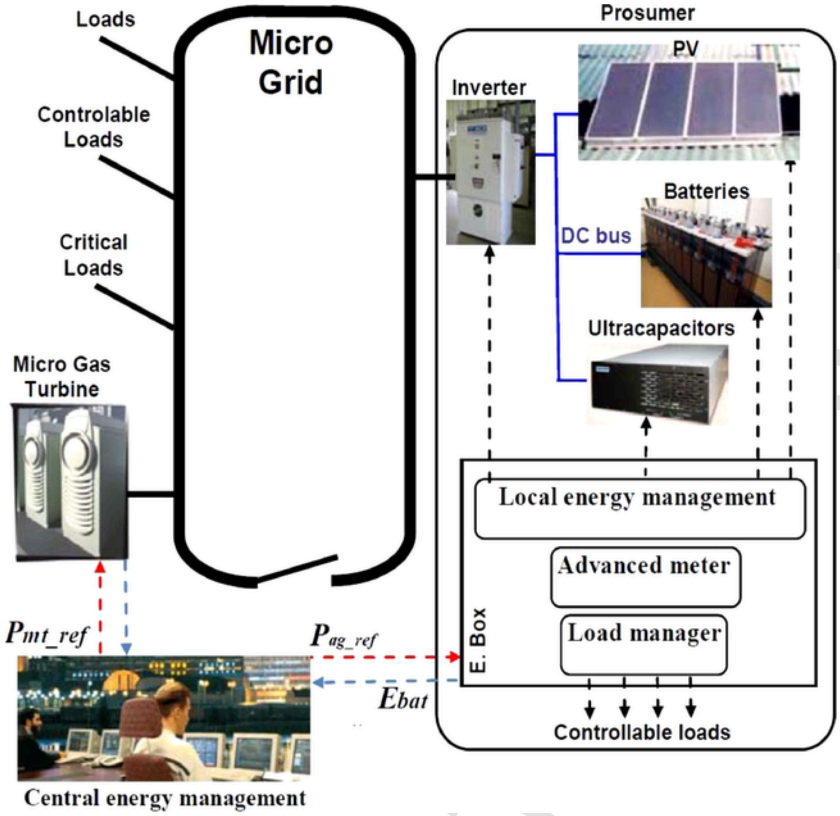

Fig. 1. Description of the studied MG.

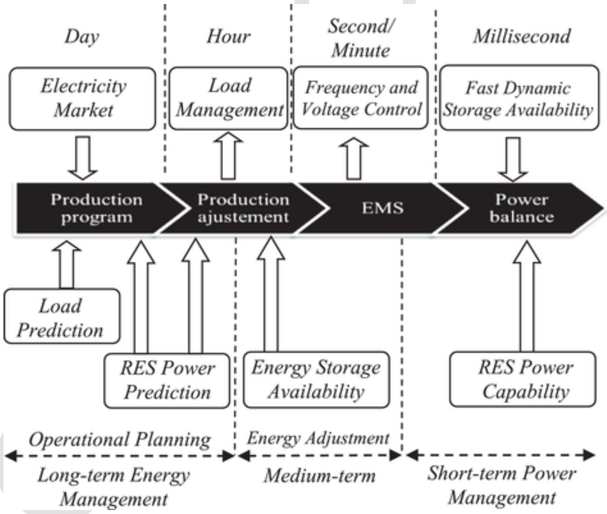

Fig. 2. Timing classification of control functions in the context of MG.

SCADA	Supervisory Control and Data Acquisition
UCP	Unit Commitment Problem

Indices and Parameters

t	Index of the scheduling time step: from 1 to T
x	Index of LOLP, from 1 to 100
n	Index of active PV generator, from 1 to N
m	Index of micro gas turbine, from 1 to M

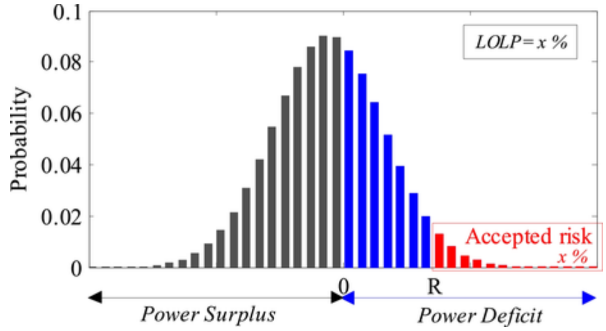

Fig. 3. Calculation of OR based on forecast ND uncertainty (ε_N^t) with x% of LOLP, at time step t. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

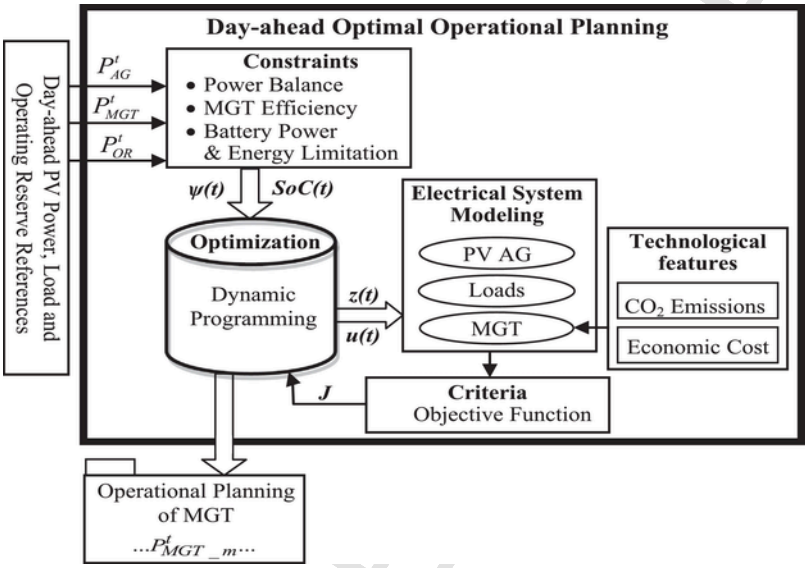

Fig. 4. Day-ahead optimal operational planning scheme.

$z(t)$	MGT power reference vector
$u(t)$	MGT state vector
J	Optimization objective function
Variables	
E_{bat}	State of charge for energy storage
L_A^t	Load demand at time step t
L_F^t	Forecasted load demand at time step t
PV_A^t	PV power at time step t
PV_F^t	Forecasted PV power at time step t
N_A^t	Actual net demand at time step t
N_F^t	Forecasted net demand at time step t
ε_l^t	Forecasted load error at time step t
ε_{PV}^t	Forecasted PV error at time step t
ε_N^t	Forecasted net demand error at time step t
μ_N^t	Mean value of forecasted net demand error at time step t
σ_N^t	Standard deviation of forecasted net demand error at time step t
$P_{PV\_n}^t$	Active PV power reference at time step t
$P_{MGT\_m}^t$	MGT power reference at time step t
P_{OR}^t	Operating reserve reference at time step t

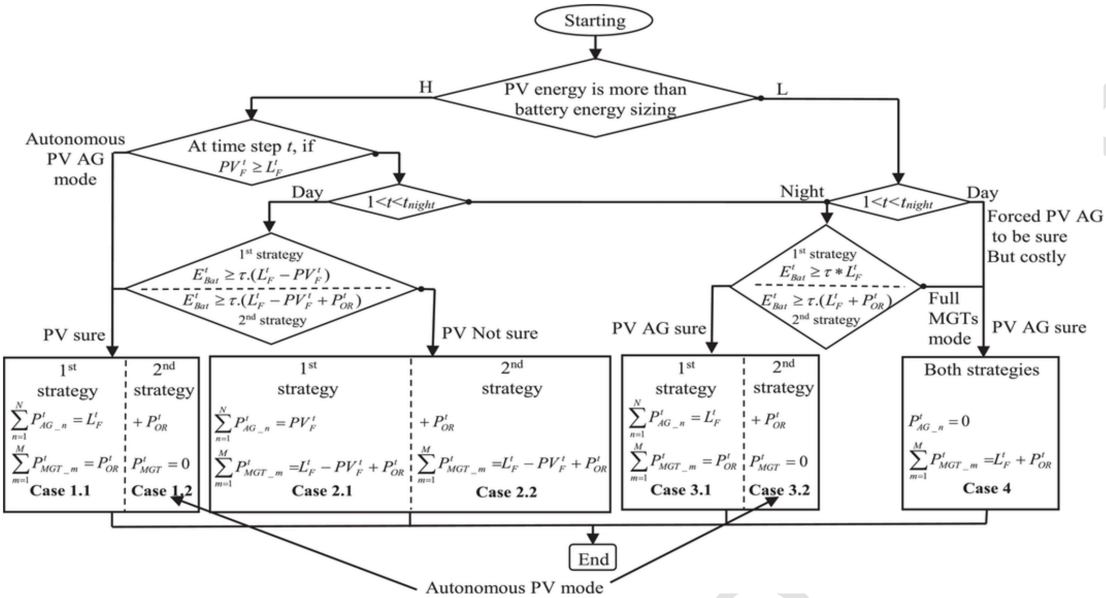

Fig. 5. Operating power reserve dispatching strategies with different scenarios.

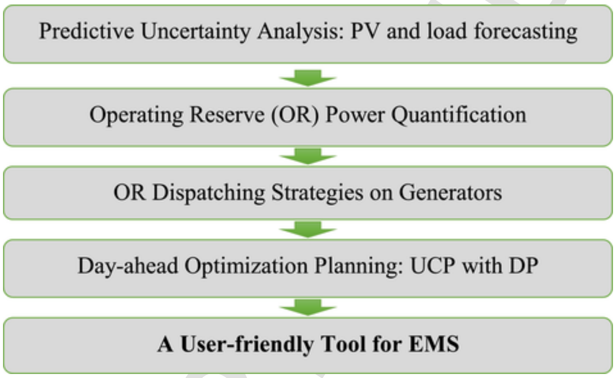

Fig. 6. Work trajectory and planning.

Table 1
Main and individual interfaces.

Main Interfaces	Individual Modules
Data Collection and System Uncertainty Analysis	• Historical Data Collect • Day-ahead Data Download: Weather Information, Load, and PV Power • PV Power and Load Demand Forecast
System Uncertainties Assessment and OR Power Quantification	• PV Power Uncertainty • Load Demand Uncertainty • Net Demand Uncertainty • OR Quantification
Operational and OR Dispatching	• Dispatching Strategies • PV AGs and MGTs Power References

1. Introduction

Microgrid (MG) coupled with RES can yield significant economic and environmental benefits. It must be self-sustainable, fault tolerant, reliable, secure and with good power quality. However, taking into account uncertainty is vital to ensure the proper functioning of restructured electrical grid especially with higher integration of variable RES, such as PV power and wind power. Therefore, there are growing concerns on renewable portfolio standards and CO2 emissions allowance. Also, the importance of developing tools to help electrical system planning under uncertainty has been recognized [1].

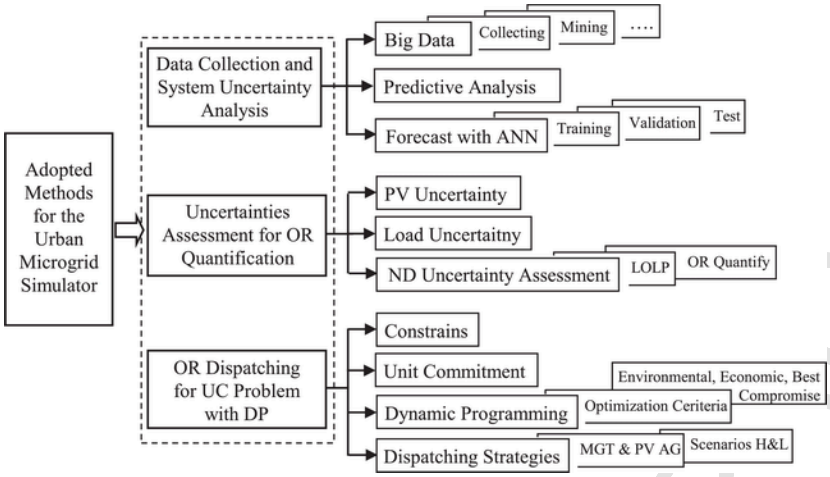

Fig. 7. System block diagram of adopted methodologies for the MCEMS.

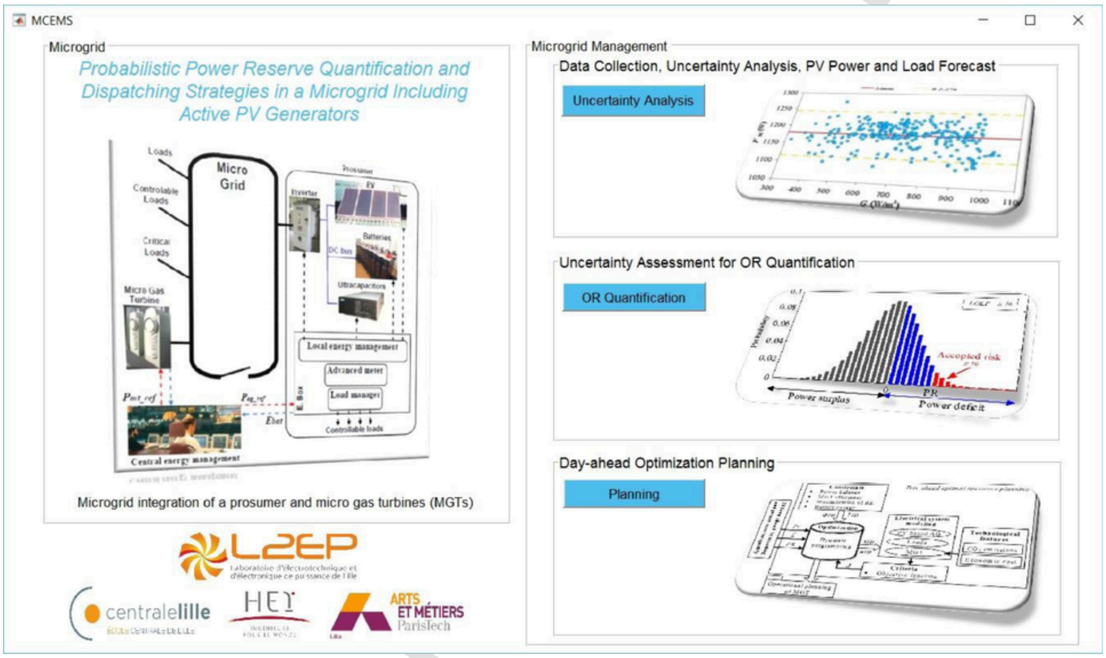

Fig. 8. Graphical interface of the MCEMS.

Several studies have been reported in the literature regarding smart grid and MG simulation [2–8]. For instance, an algorithm for a smart grid simulator is presented in [7]. Features and decision algorithms of the simulator are explained with detail in the paper and test results are illustrated for system validation. In [3], an intelligent energy management system (EMS) has been proposed for power controlling when a large amount of hybrid vehicles penetrates the market. As an integral part of the supervisory control and data acquisition (SCADA) system, a Graphical User Interface (GUI) was developed for real time data monitoring and control. Also, a Matlab GUI simulator for the generation of distribution grid models is proposed in [8]. It enables distribution grids generation by focusing on the peculiar features of distribute networks. In [4], a multi-agent system for real-time MG operation is presented. Considering the system and distributed energy resources constraints, the purposes of the proposed simulator are to maximize the power production of local generators, to minimize the operational cost, and to optimize the power exchange between the main power grid and the MG. Nonetheless, authors did not take into consideration RES uncertainties in the system. A smart residential load simulator with several user-friendly graphical interfaces is developed in [6]. The proposed freeware is based on Matlab-Simulink-Guide toolboxes and aims to model residential energy consumption and local generation resources. The disadvantages of this study are that wind and photovoltaic (PV) power generation are considered as local power sources and are not dispatchable. Moreover, many researches on MG energy management have been done [9–14]. However, none of the existing studies and simulation tools takes into accounts uncertainties and distribution of the reserve power in an urban MG.

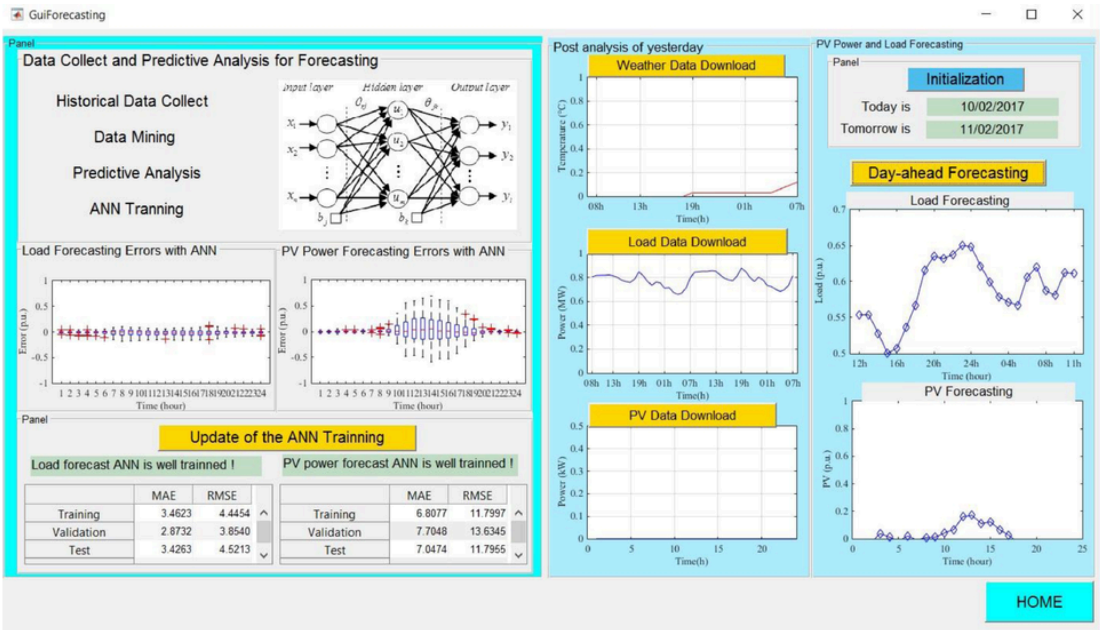

Fig. 9. Data collect for system uncertainty analysis interface.

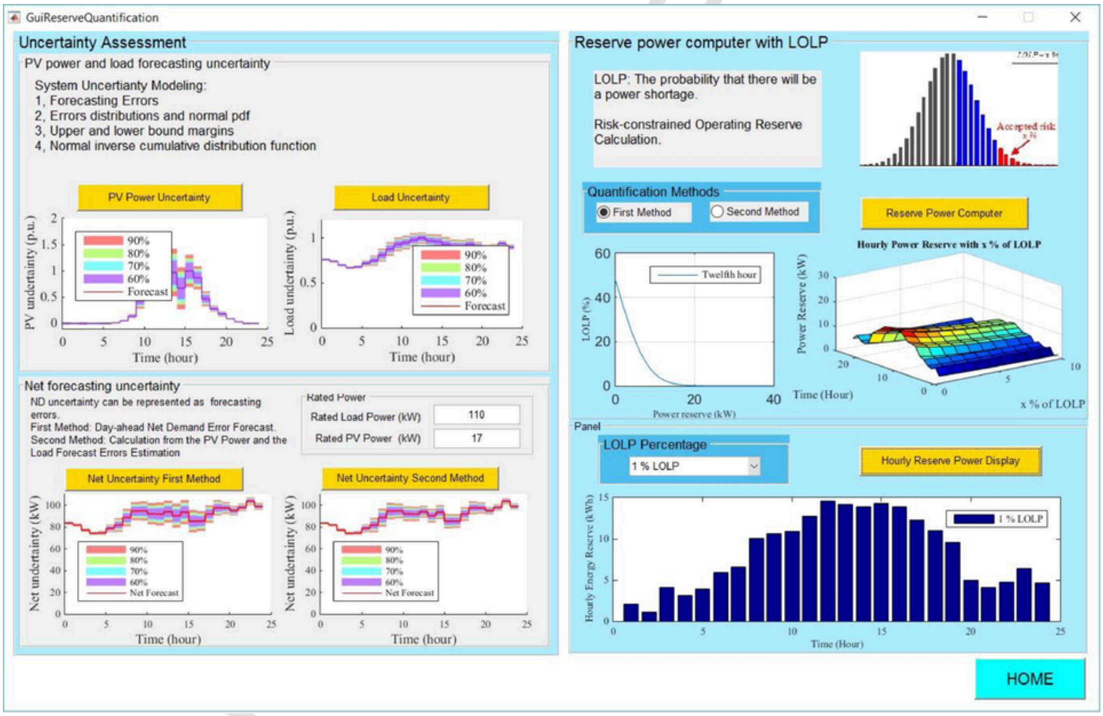

Fig. 10. System uncertainties assessment and OR quantification interface.

Some previous experiences in developing additional control functions in RES generators for provision of ancillary services and participation to the energy management of electrical networks are presented [15]. According to French regulatory policy, aggregation of OR capacity in distribution networks will be a new obligation to create reserve market for power systems reliability. In this specific context, several proposed papers tackle the theoretical problem of the coordination of Micro Gas Turbine (MGT) and PV Active Generator (PV AG). Proposed methods deal with the optimal dispatching of power references and OR into all power generators including RES. They aim to satisfy a risk index in order to balance the power system following load demand and RES production forecasting [16,17].

Fig. 11. OR dispatching interface.

Fig. 12. PV panels installed ot the roof of the student residence of Ecole Centrale de Lille and three solar PV inverters.

To going further, in this paper, a complete set of user-friendly graphical interfaces of an urban MG EMS is developed to conceptualize the overall system operation. The designed simulator is based on the Matlab GUI. It helps users to properly model and study the details of different power generators and load demand. Also, the proposed simulator helps to model power flows from production to consumption. It enables a better understanding of uncertainties in terms of energy dispatching in the different power generators, as well as to facilitate the visualization of the energy management in MG.

The remainder of this paper is organized as follows: Firstly, an urban MG is presented in part II. To better understand the MG management system, different data sources and data managing methods are studied. Then, in part III, an urban MG simulator with three main window interfaces and several individual modules is designed. Finally, this paper is finished with results discussion and conclusions.

2. Work content and objectives

2.1. Urban MG with PV AGs

In [18], a MG integration of PV AGs and MGTs is briefly presented. PV AGs, which means PV panels combined with storage devices are considered as prior energy production sources. Storage device, especially battery is the key point of PV AG. Therefore, con-

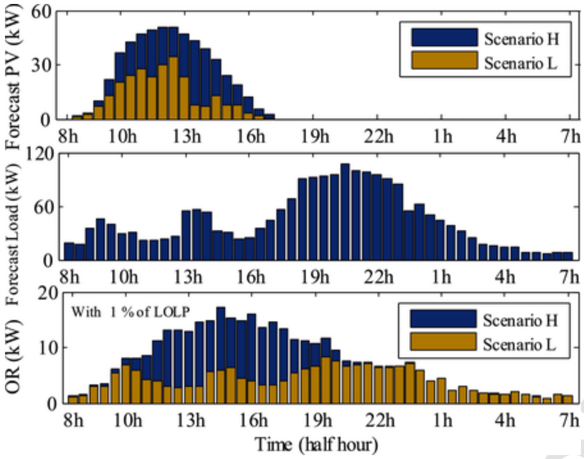

Fig. 13. Day-ahead PV power forecast, load forecast and reserve power with 1% of LOLP.

Table 2
Day-ahead operational planning results.

Scenarios	Optimization strategies	Cost (€)	Pollution (kg)	OR on AG (%)	Ebat_Max (kWh)	MGT Power Ratio		
						MGT_1	MGT_2	MGT_3
H 1st strategy	None	173	1224	0	78.6	0.5166	0.7901	0.8032
	Environmental	169	1141	0	78.6	0.4871	0.8008	0.8480
	Economic	167	1167	0	78.6	0.5266	0.7342	0.9123
	Best compromise	171	1156	0	78.6	0.6684	0.8641	0.7843
H 2nd strategy	None	173	1027	35.4	52.7	0.7770	0.7901	0.8032
	Environmental	171	937	35.4	52.7	0.7851	0.8010	0.8390
	Economic	168	976	35.4	52.7	0.7511	0.7256	0.9054
	Best compromise	170	952	35.4	52.7	0.8243	0.8641	0.7855
L 1st strategy	None	185	1290	0	132.4	0.6679	0.7551	0.7702
	Environmental	182	1181	0	132.4	0.6619	0.7764	0.8068
	Economic	180	1245	0	132.4	0.6583	0.6881	0.8821
	Best compromise	183	1195	0	132.4	0.6941	0.8601	0.7664
L 2nd strategy	None	188	1119	11.8	132.4	0.7672	0.7464	0.7479
	Environmental	184	993	11.8	132.4	0.8178	0.7758	0.7930
	Economic	181	1063	11.8	132.4	0.7754	0.6826	0.8577
	Best compromise	185	1006	11.8	132.4	0.8739	0.8504	0.7543

trolling the PV AG can have an important impact on system energy management. Several previous research works on this topic have been published studying both system structure and energy managing framework [18–21]. In addition, MGTs are used as backup energy sources. Since gas turbines consume fossil fuel and discharge pollutant gases, it is necessary to study its characters for system operational optimization purpose to minimize gas emission and fuel cost. In order to design the MG simulator, an urban MG, previously introduced in [22], is shown in Fig. 1.

According to different management objectives, a Microgrid Central Energy Management System (MCEMS) for the long term and medium term energy management and a local energy management in the E-box for real time balancing are implemented. A communication network is used to implement interconnection between central energy management system and Local Controller (LC), such as data acquisition and information exchange. The adopted EMS is based on PV power production, load prediction and optimized power planning for system operation in terms of technical, economical or ecological goals on the basis of available information (such as network state, availability of micro gas turbines).

2.2. Sources of data in utilities and its management

Compared to traditional fossil fuel power generation, RES are normally smaller units that are scattered throughout the electrical grids at distribution levels. Since weather conditions have a major influence on them, their accessible power production is uncertain. Nowadays, uncertainties in both generation side (especially RES) and load demand side are increasing and becoming the new normal in electrical power system. In order to have a better understanding of these uncertainties and to reduce their impact on electrical grid performance, many monitor technologies are invested in electrical power system operations. Therefore, those installed monitoring devices generate a huge amount of data and information. A SCADA system is a compulsory for electrical grid monitoring and operations. It collects numerous measurements, such as voltages, currents, power consumption, power injection at each grid node,

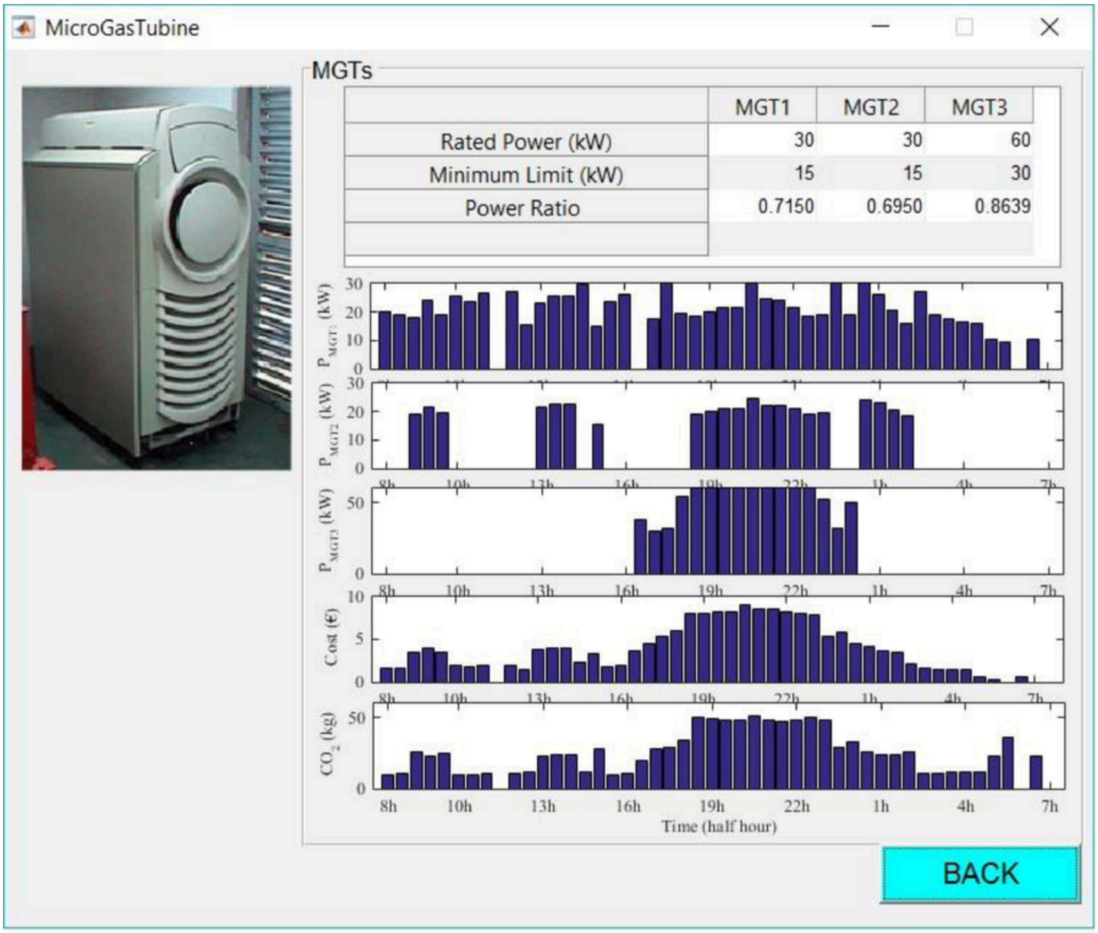

Fig. 14. Individual interface window of MGT.

and so forth. Combined with various computer software applications, system operators can have a precise real-time view of the current grid state. To try to overcome RES integrating challenges and to maintain the dynamic security of the power system, new monitoring systems (for instance, smart meters) have been installed. Consequently, many data are flooded into grid control centre, such as grid operation data, renewable production data, load metering data, simulation data, and market data. A well understand and smart management of those collected data will be a great help for RES integration into electrical power systems [23].

As more and more sensors are installed in electrical power system, large databases can be built. However, the value of collected data and information is limited if there is not enough valuable knowledge to be extracted from huge volumes of datasets. To release the potential high value in the data and put them into decision making, collected data need to be analysed and studied wisely. These increased data flows need to be clustered (chronologically and/or geographically) via statistical procedures, such as incremental and/or iterative approach, and so forth. The purpose is thus to provide to DSO a set of mathematical tools that help to reduce the data quantity and to improve their quality. To implement this, different data management tools and data mining techniques are necessary [24].

2.3. MG supervisor

The MG EMS can be analysed and classified in different timing scales and various functions (Fig. 2). The management functions are conventionally organized in three main groups according to their dynamics: long-term, medium-term, and short-term supervision. The short-term management functions correspond to the primary control and are executed by the local controller located within the generators. Long-term management corresponds to a secondary control and is carried out by a central controller located in a dispatch centre for large networks. In a MG, this management must be able to be carried out independently to enable an isolated operating by MCEMS.

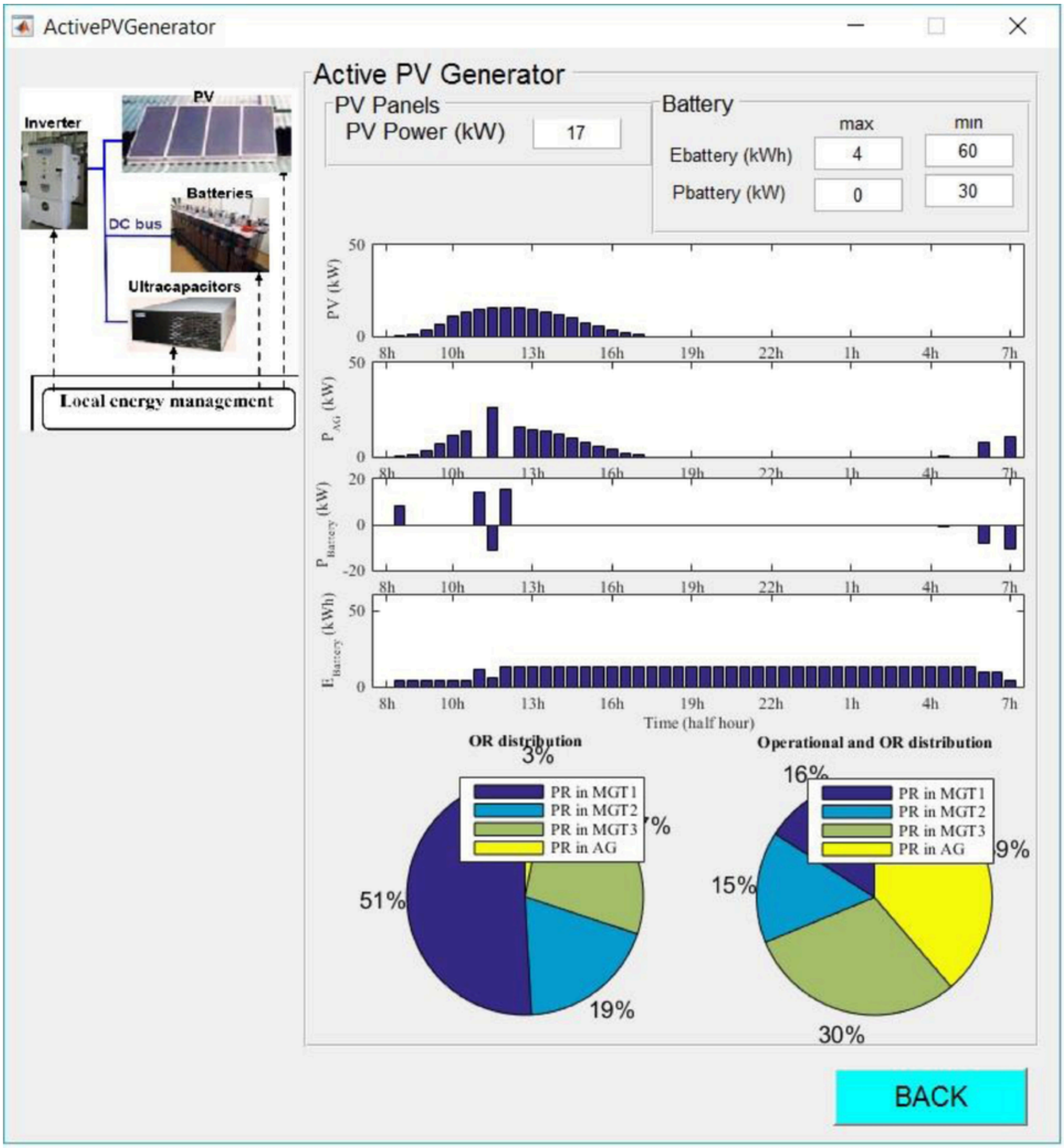

Fig. 15. Individual interface window of PV AG.

3. Reserve quantification with risk-constrained reliability

3.1. Urban MG management analysis

Integration of RES is a world wild demand in recent years. However, increased uncertainties in electrical system complicate the traditional paradigm of dynamic security assessment. Currently, with the help of collected big data in all aspects and data mining, deterministic methods are gradually replaced by probabilistic methods. In offline applications, big data information helps to identify uncertainties probability distribution and their correlations (e.g. the probability density distributions of PV power forecasting uncertainty and load forecasting uncertainty, and their relations). Based on the forecasting methods (and Monte Carlo methods) for realistic simulations, the security level of a particular state of the grid can be calculated by a dynamic security assessment method [25]. System energy dispatching and optimization procedures are implemented through a MCEMS and within an intelligent EMS and LC (for PV AGs, MGTs, and load demands), as shown in Fig. 1. Aggregator collect the requests and signals for prosumers from the DSO. They are the key mediators between producers and consumers to form grid services to the different power system participants via various markets [26]. The MG central controller measures the state variables and dispatches them to different sources via the communication bus. LC receives reference power points, in the same time, and sends real-time information back to the central controller.

As shown in Fig. 2, our previous work focused on the long-term energy management including:

- the hourly (or half-hourly) RES production and load demand forecast;
- the provision of an appropriate level of OR power capacity by considering the energy production and the load demand forecast uncertainty;
- the OR and operational power dispatching.

3.2. Uncertainty analysis and OR quantification

Deterministic calculation methods for the reserve settlement are gradually replaced by probabilistic methods that are more appropriate with the stochastic factors corresponding to system reliability. Moreover, the nonlinear interactions of the power system become more complicated when a large amount of variable RES is connected. As mentioned above, OR does not progress linearly with the RES increasing in an electrical system. It is impacted by different factors, such as power system size, schedule strategies, load and RES forecast accuracy, and so forth. Regardless of a sudden blackout of generators, OR is defined as the real power capacity that can be called at any instance of imbalance between power generation and load demand. Required OR is calculated with both load and PV power forecast uncertainties [17].

Before OR calculation, two assumptions are made:

- Assumption 1: The probability density functions (PDFs) of the forecast errors of PV plant and load demand are estimated from historical data. In this paper, a Gaussian distribution is used [29].
- Assumption 2: The probability distributions of forecasting errors from PV power and load demand are independent.

The load demand in a time step t (L_A^t) is assumed the sum of the day ahead forecasted load (L_F^t) and an error (ε_L^t), which represents the load forecasting uncertainty:

$$L_A^t = L_F^t + \varepsilon_L^t \tag{1}$$

The PV power output for the next day (day D + 1) is represented as the sum of a day ahead forecast PV power (PV_F^t) and a forecast error (ε_{PV}^t), which represents the PV power forecasting uncertainty:

$$PV_A^t = PV_F^t + \varepsilon_{PV}^t \tag{2}$$

Knowing PV power forecast and load demand forecast, the forecasted ND (N_F^t) is expressed as:

$$N_F^t = L_F^t - PV_F^t \tag{3}$$

The real ND (N_A^t) is composed of the forecasted day-ahead ND and a forecast error ($\varepsilon_{\mathrm{N}}^{\mathrm{t}}$), which represents the ND forecasting uncertainty:

$$N_A^t = L_A^t - PV_A^t = N_F^t + \varepsilon_N^t \tag{4}$$

By assuming that the forecasting errors of PV power and load demand are uncorrelated and that the uncertainties have a Gaussian distribution, the mean values and the standard deviation of the forecast error of the ND are respectively calculated by (5) and (6):

$$\mu_N^t = \mu_L^t + \mu_{PV}^t \tag{5}$$

$$\left(\sigma_N^t\right)^2 = \left(\sigma_L^t\right)^2 + \left(\sigma_{PV}^t\right)^2 \tag{6}$$

Following this uncertainty modelling, ND errors can be forecasted one day ahead in each time step and then considered for the OR computing [27].

3.3. Risk-constrained operating reserve calculation

To estimate the impact of forecasted ND uncertainty, loss of load probability (LOLP) is used as a common reliability assessment parameter. Here, LOLP represents the probability that the load demand exceeds the PV power:

$$LOLP^t = prob\left(L_A^t - PV_A^t > 0\right) = 1 - \int_{-\infty}^{R} pdf(\tau)\,\mathrm{d}\tau \tag{7}$$

$prob\left(L_A^t - PV_A^t > 0\right)$ is the probability that the OR (R) is enough to satisfy the ND in the time step t.

By setting a risk/reserve characteristic curve, the operator can easily quantify the OR [28]. At each time step t, a probability density distribution of ND forecasting errors can be obtained according to (μ_N^t, σ_N^t), as shown in Fig. 3. The red part represents the accepted risk of violation with x % of LOLP, and R is the needed OR power to compensate the remaining power unbalance.

This assessment has been made under the assumption of a positive forecasted ND. Otherwise, if the forecasted ND is negative, the OR for the same reliability level will be unnecessary (the power generation is more than the load demand). Since the ND forecasting uncertainty can be approximated by an exponential function for high power values, the accepted risk can be modelled as:

$$x = \frac{1}{\sigma_N^t\sqrt{2\pi}}\int_R^{\infty} e^{\frac{-\left(\tau-\mu_N^t\right)^2}{2\left(\sigma_N^t\right)^2}}\,d\tau = \mathrm{F}\left(R\middle|\mu_N^t, \sigma_N^t\right) \tag{8}$$

The reserve power covers the remaining probability that the load demand exceeds the PV power generation (blue part in Fig. 3). Hence, R can be extracted by a normal inverse cumulative distribution function for a desired risk x (Fig. 3):

$$R = F^{-1}\left(x\middle|\mu_N^t, \sigma_N^t\right) = \left\{R : F\left(R\middle|\mu_N^t, \sigma_N^t\right) = x\right\} \tag{9}$$

4. Joint operational and OR power dispatching

4.1. General introduction

As electricity industry moves to new restructured forms with renewable energy distributed generators in local electrical networks, the local energy management of these networks must be adapted or imagined. The objective is to satisfy the local load demand with local renewable resources. The general problem of a local Energy Management System can be: How to plan local controllable generators to achieve a local energy balancing and dispatch the total OR on them?

To solve this problem, a general case study is considered and consists in designing the one day-ahead energy management of a MG. It is powered by controllable generators: N active PV generators and M MGTs. MGTs are very interesting energy generators as they can produce both electricity and heat that can be stored in a hot water tank. As PV energy is considered as the prior energy source, MGTs are used to cover the power deficit.

Then, obtained OR is dispatched in a MG, which is powered by PV active generators (PV AGs) including storages, and MGTs. According to different PV power generation scenarios, two strategies are analysed to dispatch the OR: separately distributes OR only into MGTs, and simultaneously allocates it into MGTs and PV AGs. An equality constraint for PV AG (P^t_{AG}), MGT generation (P^t_{MGT}), reserve power (P^t_{OR}), and load demand (P^t_L) must be satisfied for the balancing between production and consumption, as shown in Fig. 4.

4.2. OR dispatching strategies considering the maximization of RES usage

4.2.1. Analysis of the uncertainty according to the power plant production and management

In the micro grid, PV AGs are managed as prior sources because of their low operating cost and absence of gas emissions. MGTs are set as backup sources for the missing energy. The use of a battery (included in the PV AG) reduces the uncertainty of the PV AG:

- During time steps of the night, the PV production is surely unavailable. Unless, PV AG can produce if the batteries are loaded,
- During time steps of the day, if the forecasted PV power is superior to the load demand, hence, enough output power of the PV AG can be used to cover the load demand and the exceeding PV power can be stored in batteries.

Thus, the OR dispatching procedure must be organized according to the battery energy capacity.

If the daily forecasted PV energy is smaller than the maximum battery capacity (scenario L), the PV power generation can be stored into the batteries during the daytime. In this situation, the PV power is not injected in the MG during the day, but stored in the batteries. As the MG operator uses only controllable generators (MGTs) PV power forecast errors have no influence during the day operating of the electrical system. The available stored PV energy will be used during the night. For the operation of the network during the day, only the uncertainty coming from the load demand forecasting must be taken into consideration.

While, if the daily forecasted PV energy is larger than the battery energy capacity (scenario H), the OR must cover both PV power and load forecast uncertainties. So two scenarios are considered:

- Scenario H: daily forecasted PV energy is much more than the maximum battery capacity;
- Scenario L: daily forecasted PV energy is less than the maximum battery capacity.

Regardless of those two situations, two different OR allocation strategies are proposed: into the MGTs or into MGTs and PV AGs. As no power is available from PV panels during the night, power references are calculated separately for the night and for the day-time.

4.2.2. Scenario h

4.2.2.1. First strategy: OR provision by MGTs For the first strategy, the OR is only provided by MGT, so at least one of them works all the time.

$$\sum_{m=1}^{M} P^t_{MGT\_m} = L^t_F - PV^t_F + P^t_{OR} \tag{10}$$

In this situation, if the power reference of MGT is less than its minimum power output, the MGT must operate at the minimum point (with a low efficiency). Hence, the power reserve will be more than needed.

Power balancing with PV in autonomous operating If the predicted PV power is more than the predicted load demand during the time step t ($PV^t_F \geq L^t_F$), an autonomous energy supply is possible and implemented (case 1.1 in Fig. 5). In case that actual PV power is not as much as the forecasted PV power, the batteries help to cover the difference. Since all PV panels are in the same location and they share the same environmental situation, this total power is dispatched to the *N* PV AGs according to their rated power ($P^t_{AG\_rated\_n}$):

$$P^t_{AG\_n} = L^t_F \cdot \frac{P^t_{AG\_rated\_n}}{\sum_{n=1}^{N} P^t_{AG\_rated\_n}} \tag{11}$$

While all the PV powers are used to feed the load demand, the remaining PV energy will be stored into batteries for a night use and the deficit power will be provided by additional MGTs. The PV energy surplus is automatically stored into batteries, which are controlled by the local EMS. The battery state of charge (SoC) is calculated by Local Controllers and sent to the central EMS:

$$E^{t+1}_{Bat} = E^t_{Bat} + \tau.\left(PV^t_F - L^t_F\right) \tag{12}$$

τ is the time step duration when powers are constant. For this operating mode, MGTs just provide the OR, which is required by the load demand uncertainty and $P^t_{MGT} = P^t_{OR}$.

Power balancing with MGTs If the predicted PV power is not enough for the predicted load demand at time step *t* ($PV^t_F < L^t_F$):

- During the day, the power references of PV AGs are set to the predicted values:

$$P^t_{AG\_n} = PV^t_F \cdot \frac{P^t_{AG\_rated\_n}}{\sum_{n=1}^{N} P^t_{AG\_rated\_n}} \tag{13}$$

Then, the uncertainty coming from the bad PV forecast is managed by batteries that produce the missing power or store the exceed power in case of errors during the day (case 2.1 in Fig. 5). MGTs must balance the remaining load demand and provide the OR, which is required by the load demand uncertainty (equ. 10).

- During the night, if the SoCs of batteries are enough to feed the predicted load demand, then MGTs are just working to provide the OR, which is required by the load demand uncertainty. The SoC is updated with Eq. (15). Otherwise, MGTs must balance the remaining load demand and provide the OR, which is required by the load demand uncertainty (equ. 10 with $P^t_{PV} = 0$) and we have a full MGTs mode.

4.2.2.2. Second strategy: OR provision by MGTs and PV AGs As PV AGs are managed as prior energy sources, if the available PV AG power is more than the load demand and the required OR ($PV^t_F \geq L^t_F + P^t_{OR}$), then the MGTs will be shut down and PV AG will provide alone the load demand and the OR, which is required by the load demand uncertainty (case 1.2 in Fig. 5):

$$P^t_{AG\_n} = \left(L^t_F + P^t_{OR}\right) \cdot \frac{P^t_{AG\_rated\_n}}{\sum_{n=1}^{N} P^t_{AG\_rated\_n}} \tag{14}$$

An autonomous PV supply is then implemented. The energy surplus is automatically saved in batteries by the local EMS controller:

$$E^{t+1}_{Bat} = E^t_{Bat} + \tau * \left(PV^t_F - \left(L^t_F + P^t_{OR}\right)\right) \tag{15}$$

If the predicted PV power is not enough for the predicted load and power reserve ($PV^t_F < L^t_F + P^t_{OR}$):

- During the day, if the battery energy is enough to cover the remaining load demand and OR, then the PV AG power reference is set as Eq. (13). In this circumstance, the load and OR are seen as the total load demand (case 1.2 in Fig. 5). Otherwise, the MGTs must balance the remaining load demand and provide the power reserve (Eq. (10)) and PV AG are set to the forecasted data (case 2.2 in Fig. 5). In fact, as OR is treated as a part of system load demand, it is dispatched in proportion to power generators.

- During the night, if the stored energy is enough to feed the predicted load and the OR, which is required by the load demand uncertainty, then MGTs are switched off and power references of PV AGs are set to satisfy the total load demand (case 3.2 in Fig. 5). The SoC is updated with Eq. (13). Otherwise, MGTs must balance the remaining load demand and provide the OR, which is required by the load demand uncertainty (Eq. (10) with $P^t_{PV} = 0$) (case 4 in Fig. 5).

4.2.3. Scenario l

4.2.3.1. First strategy: OR provision by MGTs If the PV energy is less than the battery energy sizing, all the PV power is stored into the batteries during the day. The PV AG power reference is set to 0 ($P^t_{AG\_n} = 0$) and the battery SoC is updated at each time step fol-low-ing Eq. (12) with ($L^t_F = 0$). The load demand and the OR (which is required by the load demand uncertainty) are provided by MGTs following Eq. (13) with ($PV^t_F = 0$).

During the night, the battery discharge strategy is the same as in scenario H.

4.2.3.2. Second strategy: OR provision by MGTs and PV AGs During all the day, the PV power is stored into the batteries. The PV power uncertainty is then erased. The only power sources are MGTs, which must cover the uncertainty from the load demand. Therefore, the strategy is the same as previously.

During the night, batteries are discharged and provide also the required power reserve to cover the uncertainty coming from the load. An autonomous PV AG operating mode is then implemented (case 3.2 in Fig. 5).

Finally, the flowcharts of overall OR power dispatching strategies with different scenarios are illustrated in the Fig. 5.

4.3. Day-ahead optimal UCP with DP

As described in [29], a day-ahead optimal dispatching with dynamic programming (DP) for unit commitment problem (UCP) is applied under certain constraints, as shown in Fig. 4. The computation procedure is described in the following steps.

Step 1. Formulation of the UCP. The 24-hour ahead operational planning is discretized with T periods for each $\tau = 24/T$ hour. Power references are considered constant during each time step. In fact, they are not, and this is handled by the short-term power balancing functions in the local EMS controller. The power references of the studied MGTs are represented as a vector *z(t)*:

$$z(\mathrm{t}) = \left[P^t_{MGT\_1}, P^t_{MGT\_2}, \ldots, P^t_{MGT\_M}\right] \tag{16}$$

Power references are considered remaining constant during each time step. And the states (δ) of each MGTs during time step t is set as a vector *u(t)*:

$$u(\mathrm{t}) = \left[\delta^t_1, \delta^t_2, \ldots, \delta^t_M\right] \tag{17}$$

Step 2. Optimizing objective functions with different optimization strategies. The solution of the optimal process comes to find an output vector *u(t)*. It will provide the generation set points of MGTs to guarantee the minimum fuel cost or CO_2 equivalent emissions while satisfying the load balance within the settled time interval (τ hour). Here, three optimizing objective strategies are defied:

- ***Economic criteria***: minimizing total fuel cost;
- ***Environmental criteria***: reducing equivalent CO_2 emissions;
- ***Best compromise criteria***: making a compromise between reduction of total fuel cost and reduction of CO_2 emissions.

Step 3. Multistage decision process formulation with backward recursion. During time step *t,* the power references of the studied MGTs are optimized with DP on minimizing equivalent CO_2 emissions and total fuel costs. The backward recursion method is applied for the serial multistage UCP. During the recursion optimization procedure, the final state is regarded as the input and previous state is regarded as output for the stage. The recursive analysis proceeds from the first stage to the last stage *T*. The objective is to find a vector of generator states (*u(t)*) and a vector of power references of MGTs (*z(t)*), which minimizes the total system cost. The optimal solution of the overall problem is obtained by selecting the optimal vector *u(t)* for all time steps recursively from $t = T$ to $t = 1$.

Step 4. DP for UCP. DP programming procedure consists of two typical parts:

- An evaluation of all possible configurations in each time step (***Stages and States***);
- A “back-track” operation from end back to beginning over the optimal path (***Recursive Optimization***).

This procedure builds a solution of the overall *T*-stage problem by first solving a one-stage problem. Then, the remaining stages are solved, sequentially, one-by-one until the overall optimum has been achieved.

Step 5. Solving the UCP with the chosen optimization criteria defined in Step 2. Finally, output the solution(s) results.

5. Urban MG management simulator frame design

5.1. GUI description

Continuing the work and going further in MG uncertainties study to facilitate energy management and system optimization in an urban MG, a freeware Urban MG Simulator is developed (Fig. 6). It conceptualizes the overall system operation. The designed simulator is based on Matlab GUI. It provides a complete set of user-friendly graphical interfaces to properly model and study the details of active PV generators (PV AGs), which includes PV panels and batteries, load demand, as well as micro gas turbines (MGTs). In addition, the proposed simulator helps to model the way appliances generate and consume power and energy. It assists users to better understand how those uncertainties based OR are distributed in the different power generators and their effects on system security with different dispatching scenarios and optimization criteria.

Instead of focusing on system controlling algorithms or real-time hardware-in-the-loop tests, an urban MG EMS is developed in this part so that its operation can be more convenient and user-friendly. The proposed EMS includes three main interfaces and several individual modules, as summarized in Table 1 and Fig. 7:

The interface window is shown in Fig. 8. For each different interface, numerous methods and strategies are applied. In addition, different criteria and scenarios are considered. For example, data collection, predictive data analysis, in addition to PV power and load forecasting with ANN are used for the first main interface "Data Collection and System Uncertainty Analysis".

The interface provides a complete graphical interface window with three major interfaces: "Data collection, uncertainty analysis, PV power and load forecast", "Uncertainty assessment for OR quantification", and "Day-ahead optimization planning" . User can access to these three interfaces by clicking the blue buttons, as "Uncertainty Analysis", "OR Quantification", and "Dispatching". Fig. 7 shows in details the system block diagram of adopted methodologies for the MCEMS.

5.2. Data collection and system uncertainty analysis

5.2.1. Layout design

As displayed in Fig. 8, three major modules are studied in this uncertainty analysis interface: data collection, predictive analysis, and forecasting. Firstly, historical data are collected, for example past few months or years of weather data (temperature, solar irradiation, humidity, air pressure, wind speed, and so on), PV power data (PV power output, AC voltage, AC voltage, and so on), and load demand data. The collected data are used for predictive analysis to identify correlated patterns and parameters, related to PV power output and load demand. Then, forecasting models are built for PV power and load forecast. As presented in [17], a three-layer BP ANN is developed for both PV power and load forecast. Before implementing this tool for PV power and load demand prediction, ANNs need to be well trained with collected past data.

Once the ANN is well trained, it can be used for day-ahead forecast. The first step is to download the data one day-ahead to update the ANNs. Then, with the well trained ANN, PV power production and load demand for the forecast day (day D + 1) can be obtained. ANN models and forecasting procedures are also detailed in [17].

5.2.2. Interface design

Fig. 9 shows the designed interface. The left part is the data collection and predictive analysis for PV power and load forecast ANN training. The right part is the downloaded data, the day-ahead PV power and load demand forecasting.

5.3. System uncertainties assessment and OR quantification

5.3.1. Layout design

Uncertainty assessment: First, PV power and load demand forecasting uncertainties are calculated, respectively. Then, ND uncertainty is computed according to those two independent variables. Two possible methods are proposed to calculate forecasted ND errors. As detailed in [17], the first method is day-ahead ND error forecast, and the second one is from PV power and load forecast errors estimation.

Risk-constrained OR Quantification: According to the probability distribution of ND uncertainty, a probabilistic risk-constrained method is proposed for OR quantification with the LOLP as a security factor. For a certain amount of OR, ND forecasting uncertainty *pdf* can be used to calculate the probability that power generation cannot cover the load demand. As a result, the risk/reserve characteristic curves with different quantity of OR can be obtained. If a constant LOLP is set, OR for each time interval can be obtained.

5.3.2. Interface design

Fig. 10 is the designed interface of OR quantification. The left part is the PV power, load, and ND uncertainty assessment, while in the right is the OR calculation.

5.4. Operational and OR dispatching

5.4.1. Layout design

Initialization: The system needs to be initialized (such as set the initial value of battery, set the rated power of MGTs, and so forth).

OR dispatching strategies: As presented in [29], different strategies are considered, with high or low PV power scenarios, and OR dispatching into MGTs or into MGTs and PV AGs.

Dynamic programming for UC problem: The UC problem concerns the minimization of equivalent CO_2 emissions and total fuel cost by DP. To solve the objective function, different operational power and OR distribution strategies are proposed with several non-linear constraints. DP is applied for UC problem with different objective functions and different optimization criteria.

5.4.2. Interface design

Designed interface window is illustrated in Fig. 11. In the right part, OR dispatching scenarios and DP for UC problem criteria are illustrated. In the left, there are two individual modules (PV AG and MGT), which will be demonstrated and discussed with details in the "Results and discussion" section.

6. Results and discussion

6.1. Data collection

ANNs are used here for both PV power and load forecasting. Before being applied for forecasting, they are trained with many data. To choose the inputs and outputs of each ANN, a predictive analysis is implemented. This part has been well explained in [17]. ANN training results are shown in the bottom-left tables of Fig. 9.

For PV power forecast, day-ahead predicted temperatures can be obtained from the weather forecasting website (www.wunderground.com), and last 24 hours PV power output data are collected from three PV inverters (3 kW each), which are installed on the roof of the student residence of the Ecole Centrale de Lille (Fig. 12). Load demand data are downloaded from the RTE website (www.rte-france.com). For load forecast, the last 48 hours French power consumption has been scaled as ANN input. With obtained inputs and well trained ANNs, day-ahead PV power and load demand can be forecasted. Plots of downloaded PV data, load data, and predicted temperature at 9/29/2016 are shown in Fig. 9.

Based on the forecasting database, uncertainties assessment results of PV power, load and ND can be found in Fig. 11. The results of OR calculation with a security factor LOLP are shown in the same interface window. Since the methods used in this part have been explained with details in [17], those results will not be explained again.

6.2. A case study application

In this case study, a system with 110 kW of rated load, 55 kW of rated PV power, three MGTs with rated power respectively 30 kW ($MGT_{\_1}$), 30 kW ($MGT_{\_2}$), 60 kW ($MGT_{\_3}$) and the OR with 1% of LOLP coming from the uncertainty assessment of load and PV power forecasting are taken into consideration. Two different scenarios, scenario H represents a sunny day and scenario L represents a cloudy day, are shown in Fig. 13.

Generally, thanks to the larger PV energy, the total cost and pollution for scenarios H1 and H2 are less than scenarios L1 and L2 (as shown in Table 2). Compared with scenario H1, scenario H2 has 38.9% of OR on PV AG (during a 24-hour of operation). Since there is no OR dispatched in PV AG with scenario H1, larger battery storage (78.6 kWh for scenario H1 vs. 52.7 kWh for scenario H2) is needed with the same fuel cost and pollution. While compared to scenario L1, scenario L2 has 11.8% of OR located on PV AG but with similar battery storage (132.4 kWh), knowing that all the PV energies are stored into the batteries during the day. Among each scenario, system cost and pollution are lower with optimization then there is no optimization at all.

To have a much clear visual representation of MGTs and PV AGs working conditions, two individual interface windows have been developed, as shown in Figs. 14 and15 (in H 2nd strategy).

As shown in Fig. 14, all MGTs are shut down in some periods (from 10 h to 13 h, 14:30 to 15 h, 15:30 to 16 h, and 4 h to 7 h). The load demand and OR are covered by PV AGs during these operation steps. The energy is from the PV panels in the daytime and batteries in the night. From the table in the top, the average power ratio of three MGTs is as high as 0.758 (0.7150, 0.6950, and 0.8639, respectively).

Fig. 15 shows the screen copy of the PV AG data. The PV power is used during the day time and the extra energy is stored into the battery. During the night, the battery is discharged. The two figures in the bottom presents the OR dispatching and the OR plus load demand dispatching into the different generators. The first OR dispatching pie chart shows that PV AGs provide 20% of OR, while the second pie chart shows that 39% of the load plus the OR are provided by PV AG.

7. Conclusion

In this paper, an EMS of an urban MG has been developed under Matlab. System uncertainties are analyzed with real data. After the operation of this tool in the day D, in the end, system operators can easily obtain:

- The forecasted PV power generation and the load demand in the day D + 1;
- The required OR with a desired system security level for the day D + 1;
- The percentage of OR covered by MGTs and PV AGs, under different dispatching strategies;
- The operating schedules of three MGTs by using UC with DP, which could lead to a minimum fuel cost or a minimum CO_2 emission, according to your choices.

Three main interfaces (Data collection for system uncertainty analysis, System uncertainty assessment, and OR dispatching) and several individual modules are designed to illustrate the details. This software platform can also be a useful tool to model and understand RES forecasting uncertainties and OR calculation in urban MGs. This EMS and GUI could facilitate the day-ahead energy management in micro/smart grids as it proposes:

- An efficient information system: real time data collection (from smart meters, sensors, and meteorological observatory), predictive data analysis, and day-ahead PV power and load demand forecasting with artificial intelligence;
- An intelligent management.

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