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Published in:
International Journal of Electrical Power & Energy Systems

DOI (link to publication from Publisher):
10.1016/j.ijepes.2019.02.033

Publication date:
2019

Document Version
Accepted author manuscript, peer reviewed version

A Hierarchical Energy Management Strategy for Interconnected Microgrids Considering Uncertainty

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Abstract

Coordinating the operation of neighboring microgrids is a promising solution for the problem of growing penetration of renewable-based microgrids into the power system. In this paper, a hierarchical stochastic energy management system is proposed for operation management of interconnected microgrids. At the upper-level, a central entity is responsible for coordinating the operation of microgrids. Based on the energy scheduling made at this level, the power reference values to be exchanged within the microgrids network and between the microgrids and the main grid are calculated and communicated with the local energy management systems. At the lower-level, a decision making approach based on chance-constrained model predictive control is adopted for local operation management of each microgrid taking into account different sources of uncertainties. The results show that the proposed strategy provides the microgrids with the opportunity of exploiting maximum available capacity in the network. Consequently, the microgrids dependency on the main grid will be reduced and some important performance indices such as multi-microgrid system cost and real-time power deviations will be improved.

Keywords: Energy management, multi-microgrid system, chance-constrained model predictive control, uncertainty management, Monte-Carlo algorithm.

1. Introduction

Microgrids which are considered as subsystems of distribution systems have been introduced as a promising solution for scalability and flexibility requirements of next generation power systems [1]. During the last decade, a large body of research has been carried out in order to investigate technical and economical characteristics of microgrids and develop new methodologies for their efficient operation management [2]-[10]. Studies show that aggregating renewable energy sources (RESs) and loads in the framework of microgrid under the control of an autonomous entity is an efficient solution to deal with scalability and complexity problems of conventional power systems. However, significant number of renewable-based microgrids might result in new problems similar to those they are supposed to solve. Intermittent nature of power produced by RESs and variability of loads in a small-scale microgrid may increase its dependency on the upstream network in order to smooth out power fluctuations.

Microgrids were initially introduced as a solution for large penetration problem of dynamic distributed resources through clustering them with local loads in a small geographical area. By reusing this solution strategy at a higher level, operation of neighboring microgrids can be coordinated locally for benefiting from existing production and demand diversity, utilizing maximum available capacity and reducing microgrids dependency on the main grid.

Considering these potential advantages, a growing body of research is emerging in this area [11]-[16]. Model predictive control (MPC) is one of the most appealing control strategies in developing energy management systems (EMSs) of interconnected microgrids. MPC-based EMSs can be found in centralized [17], decentralized [18]-[19] and hierarchical forms [20]-[22]. In [23], a comprehensive review on interconnected microgrids architecture is presented and potential advantages and disadvantageous of different schemes are discussed. A common approach in MPC-based strategies is that relying on the intrinsic robustness of the receding horizon strategy of decision-making, the problem is formulated in deterministic framework and uncertainty is not directly taken into account (Certainty equivalence principle).

Mitigating the uncertainty resulting from RESs production and variability of loads, different techniques have been adopted in multi-microgrid EMS strategies. In [24]-[27], robust techniques are used for energy management of interconnected microgrids. Despite effectiveness of the proposed robust approaches, the required computational time for designing uncertainty bounds and solving the problem as well as conservativeness of the solution strategy, make it inapplicable in many applications. Scenario-based approaches have been also considered in designing EMS strategies taking into account system uncertainty [28]-[30]. However, the computational effort which is required for deriving the solution strategy under different probable scenarios, is the main drawback of this optimization approach. In [31]-[33], chance-constrained MPC (CCMPC) is adopted to manage the uncertainty of RESs production and loads in EMS of interconnected microgrids. CCMPC, in contrast to the robust approaches in which uncertainty bounds are predetermined based on the worst case predicted scenario of uncertainty, will result in less conservative solutions. Moreover, knowledge of uncertain parameters can be incorporated to adjust conservativeness of the solution. The added advantage is that through adjusting confidence level, a satisfactory compromise between reliability and profitability of the solution can be achieved. In addition, CCMPC requires less computational effort compared to scenario-based approaches.

In the reviewed literature, despite above mentioned advantages of CCMPC compared to other stochastic optimization approaches and its good performance in other applications [34]-[36], very few studies are available in operation management of interconnected microgrids using CCMPC. Moreover, although there are valuable studies in distributed and hierarchical control of multi-microgrid systems, there are few models in stochastic hierarchical control of interconnected microgrids. Furthermore, the only sources of uncertainty which have been considered in energy management of interconnected microgrids, are related to the uncertainties in RESs production and consumer demand in local models. In this study, it is shown that in a multi-microgrid system, if these local sources of uncertainty are not managed efficiently inside each microgrid, they can be easily propagated throughout the network and degrade performance of the whole system.

In order to fill these gaps, this paper aims to develop a novel hierarchical stochastic energy management strategy based on CCMPC for operation management of interconnected microgrids. Local sources of uncertainty are related to the imperfect forecasting of RESs generation and consumers demand. Another source of uncertainty which is studied for the first time in this paper, is related to the uncertainty in exchanged power between microgrids that can be considered as an external source of uncertainty for each microgrid originating from outside of the subsystem. In other words, it is shown that presence of uncertainty in local operation of each microgrid will definitely affect its capability to cooperate with other microgrids. In addition, proposed strategy benefits from communication within microgrids network in order to make power scheduling based on the most recent available information of uncertain parameters. The main contributions of this paper can be summarized as follows:

1. Developing a hierarchical stochastic EMS for interconnected microgrids in the framework of CCMPC,
2. Modeling and studying the effects of uncertainty in exchanged power among the neighboring subsystems in the integrated operation management problem of multi-microgrid systems,
3. Proposing a communication-based control strategy to benefit from the most recent information of uncertain parameters.

Moreover, in order to evaluate the robustness characteristics of the proposed strategy against other conventional MPC approaches, a comparative statistical analysis is conducted. The rest of paper is organized as follows. Section 2 represents the energy management problem of interconnected microgrids while the proposed strategy is introduced in Section 3. Different case studies are evaluated in Section 4. Finally, conclusion remarks are given in Section 5.

2. Energy Management of Interconnected Microgrids

Different microgrids located in a neighborhood area, can be considered as interacting subsystems of a larger system. In this structure, each microgrid can benefit from taking power from neighboring subsystems in case of power shortage or delivering unused power in situations with power surplus. In case there is not enough power in the regional network to cover the demand, the main grid (upstream network) can be considered as a highly available source. From the perspective of the main grid, this higher level of abstraction will result in less complex control strategies since the set of interconnected microgrids are modeled through the net positive or negative demand disregarding further details and complexities.

Configuration of an illustrative multi-microgrid system along with power and information flows are illustrated in Figure 1. In the examined multi-microgrid network, all microgrids are interconnected to each other and also connected to the main grid. It should be mentioned that, power and communication links failures are not taken into account in this paper.

In order to give a quantitative point of view, consider the following dynamical equations for each microgrid. In Equation (1), $x_i(t)$ denotes the amount of stored energy in the i^{th} microgrid that can be represented as a state-of-charge (SOC) update function of a battery-based energy storage system with a charging/discharging power $P_{batt,i}(t)$ and self-discharging coefficient A_i. Positive values of $P_{batt,i}(t)$ are related to charging process while negative values represent discharging of the battery. In Equation (2), $P_{ij}(t)$ and $P_{ig}(t)$ refer to the exchanged power with neighboring subsystems and the main grid, respectively. Positive values for these variable show the power is transmitted from the i^{th} microgrid to the j^{th} microgrid and the main grid. Furthermore, N_i is the neighboring

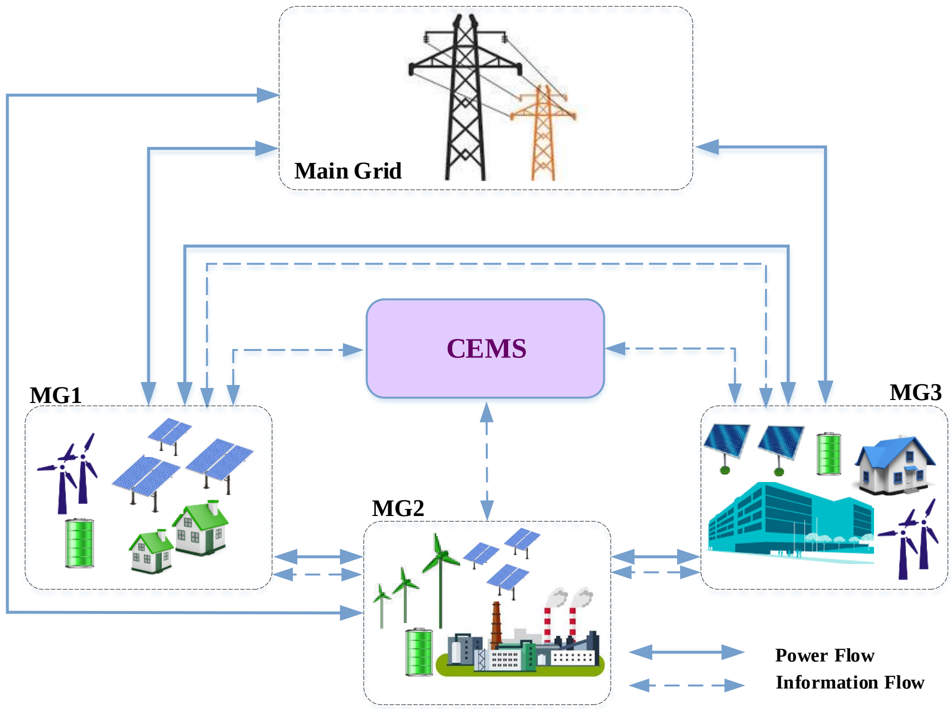

Figure 1: Illustration of the multi-microgrid system

set of the i^{th} microgrid and $P_i(t)$ denotes the local power adjustment made by controlling the output power of on-site generators. In addition, B_i is a $n \times m$ matrix containing 1 and -1 with respect to the corresponding decision parameter, while n is the number of storage devices and m shows the number of on-site generators. Moreover, $\mu_i(t)$ which is defined as the predicted power balance is calculated through Equation (3) in which M is the number of microgrids and P^i_{WT}, P^i_{PV} and L_i represent estimated values of wind turbines (WTs) and photovoltaic systsms (PVs) generation and local consumption of the i^{th} microgrid, respectively. Furthermore, $N_{WT,i}$ and $N_{PV,i}$ denote the number of wind turbines and photovoltaic systems in the i^{th} microgrid, respectively.

$$x_i(t+1) = A_i x_i(t) + P_{batt,i}(t) \tag{1}$$

$$P_{batt,i}(t) = -\sum_{j \in N_i} P_{ij}(t) - P_{ig}(t) + B_i P_i(t) + \mu_i(t) \tag{2}$$

$$\mu_i(t) = \sum_{j=1}^{N_{WT,i}} P^i_{WT,j}(t) + \sum_{z=1}^{N_{PV,i}} P^i_{PV,z}(t) - L_i(t) \qquad i = 1, 2, ..., M \tag{3}$$

Taking into account intermittent nature of RESs production and inherent variability of loads, $\mu_i(t)$ cannot be perfectly forecasted. Accordingly, adopting dynamical system approach, this abstracted variable can be defined as an endogenous source of uncertainty originating from internal behavior of related subsystem. However, in a dynamical system with interacting parts, if the uncertainty cannot be managed properly inside a subsystem, it will be easily propagated to other parts of the system. In the examined energy management problem, interacting parts refer to the power exchange within the microgrids network and also with the main grid. A microgrid with positive energy content (i.e., energy surplus), is supposed to deliver specific amount of power to the neighboring microgrids with power shortage or the main grid. The amount of power to be exchanged is required to be determined before the realization of uncertain parameters based on the microgrids estimation of surplus energy. Accordingly, in case the realized production and consumption values do not match with the estimated quantities, the microgrid would not be able to comply with the committed values.

From the perspective of the neighboring microgrids with negative energy content (i.e., energy shortage), in addition to the endogenous source of uncertainty ($\mu_i(t)$), fluctuation of $P_{ij}(t)$ could be also considered as an exogenous source of uncertainty which is originated from the outside environment. Accounting for these endogenous and exogenous sources of uncertainties, microgrids are required to adopt efficient stochastic energy management strategies to mitigate undesirable effects of real-time power imbalances. Possible actions to ensure supply-demand balance include management of the batteries as well as on-site generators in case of any probable power deviation. In case a microgrid could not manage this issue internally, the power deviation could be compensated through the main grid but at higher cost values with respect to pre-scheduling power transactions and local production cost in order to make local EMSs (LEMSs) to minimize their unscheduled power transactions with the upstream network.

From the main grid viewpoint, these power fluctuations can be seen as undesirable disturbances. More importantly, with the growing number of RES-based microgrids in the next generation power systems, compensating unscheduled real-time power deviations of all grid-connected microgrids will complicate energy management problem of utilities.

In this paper, it is assumed that the final goal of interconnected microgrids is to cooperatively manage uncertainty inside the microgrids network and represent the multi-microgrid system as a predictable entity to the main grid. In the next section, the aforementioned sources of uncertainties are appropriately modeled and adopting CCMPC, stochastic control strategies are proposed to efficiently handle the problem and manage the uncertainty.

3. Proposed Methodology

A multi-microgrid system is composed of a number of interacting heterogeneous microgrids with different specifications and requirements. Accordingly, a central energy management system (CEMS) will face a complex decision-making process for the integrated system considering internal dynamics of individual microgrids as well as interacting parts. Using a hierarchical architecture, decisions could be made at different levels which considerably reduce the complexity and computational burden of decision-making process. In this section, a two-level stochastic EMS is proposed for optimal operation management of interconnected microgrids.

3.1. Level 1: Central energy management system

At first, day-ahead prediction of energy shortage/surplus in individual microgrids is made by LEMSs during the adopted optimization horizon T using Equation (3). This information is then communicated with the CEMS which is responsible for coordinating the operation of neighboring microgrids considering predicted values of power shortage and surplus. After receiving microgrids information, a power flow analysis is required to determine the optimal values of power to be transferred within the microgrids network and between the microgrids and the main grid. At this level, the CEMS's objective is to estimate the net amount of power that microgrids will be committed to exchange with the main grid. Accordingly, from the upstream network's point of view, the multi-microgrid system can be seen as an aggregated load or power source in each time interval. To this end, the energy surplus of interconnected microgrids is primarily exchanged with the neighboring microgrids suffering from power shortage and the remaining unmet or surplus power is exchanged with the main grid.

Equations (4)-(8) introduce the operational constraints of power dispatching process which are considered by the CEMS. Equations (4) and (5) are related to the power lines capacity constraints while nodal balance constraint is guaranteed using Equation (6). According to Equations (7) and (8) receiving and delivering power at the same time is not allowed. These constraints are applied to the problem through adjusting lower and upper bounds of decision variables based on the sign of $\mu_i(t)$ at each time interval. The power scheduling is then communicated with the LEMSs to be considered as power exchange reference trajectories. This procedure is summarized in $Algorithm$ 1.

As the original idea is to manage uncertainty within the network of microgrids and prevent from passing it to the main grid, microgrids seek an efficient operating strategy to cooperatively comply with the committed values of $P_{ij}(t)$ and $P_{ig}(t)$ which are considered as power exchange reference trajectories at lower level.

$$P_{ij}^{min} \leq P_{ij}(t) \leq P_{ij}^{max} \qquad i, j = 1, 2, ..., M \tag{4}$$

$$P_{ig}^{min} \leq P_{ig}(t) \leq P_{ig}^{max} \qquad i = 1, 2, ..., M \tag{5}$$

$$\sum_{j \in N_i} P_{ij}(t) + P_{ig}(t) - \mu_i(t) = 0 \qquad i = 1, 2, ..., M \tag{6}$$

$$if \quad (\mu_i(t) \leq 0): \qquad P_{ij}(t) \leq 0, \qquad P_{ig}(t) \leq 0 \tag{7}$$

$$if \quad (\mu_i(t) \geq 0): \qquad P_{ij}(t) \geq 0, \qquad P_{ig}(t) \geq 0 \tag{8}$$

Algorithm 1 Day-ahead power scheduling problem

1: *LEMSs calculate day-ahead energy surplus/shortage of microgrids based on the forecasted RESs production and consumer demand during adopted optimization horizon,*
2: *LEMSs transmit predicted values of microgrids power balance to the CEMS,*
3: *CEMS determines power flows within multi-microgrid system and between microgrids network and the main grid considering system technical and operational requirements according to Equations (4)-(8),*
4: *CEMS transmits time-varying power reference trajectories to LEMSs.*

3.2. Level 2: Local energy management system

At the second control level, LEMSs have the responsibility of optimizing microgrids operation according to the power references received from the top level. In this paper, the LEMSs are categorized in two groups; LEMSs for microgrids with power shortage and LEMSs for microgrids with power surplus.

3.2.1. LEMSs with power shortage

Microgrids with negative energy content, could compensate their power shortage through neighboring microgrids and the main grid. Microgrids can also benefit from on-site controllable resources considering related generation cost. We assume that there is no uncertainty in the power to be delivered by the main grid. However, since the power scheduling of CEMS has been accomplished based on the predicted power surplus values of microgrids, there is uncertainty in the power to be delivered by the neighboring subsystems as well as amount of actual required power. As a result, microgrids in power shortage state, face two sources of uncertainties; an endogenous source $\mu_i(t)$ and some exogenous sources including $P_{ij}(t)$. Therefore, microgrids require efficient operation strategies to ensure supply-demand power balance. The dynamical equation of microgrids in this category can be considered as Equations (1)-(3). In Equation (2), $P_i(t)$ denotes decision vector of the i^{th} microgrid containing $P^i_{CG,r}(t)$ and $P^i_R(t)$ in which $P^i_{CG,r}(t)$ denotes power generation of the r^{th} conventional generator which its corresponding element in matrix B_i is equal to 1. It is assumed that in case of expected power surplus, RESs output power could be also reduced. Accordingly, $P^i_R(t)$ illustrates a reduction term for RESs output power which the corresponding element in matrix B_i is equal to -1.

Considering different sources of uncertainties, satisfying power balance constraint of Equation (2) might not be fully guaranteed. Imbalances between supply and demand may lead to unexpected real-time power surplus (Δ^+) or shortage (Δ^-). Any real-time power imbalances will be compensated through the main grid but at large penalty costs to penalize any unscheduled power transactions with the upstream network. Accordingly, LEMSs desire an operating strategy which minimizes operation cost of related microgrid while probable penalty cost resulted from real-time power deviations will also be reduced. This way, each microgrid through optimal management of its local resources not only minimizes its local cost but also contributes in improving overall performance of the network by minimizing real-time power deviations through accounting for its own and other subsystems uncertainties.
Considering growing penetration of RES-based microgrids, these cooperative strategies result in more predictable behaviors of multi-microgrid systems from the distribution system perspective. Moreover, it also enables the microgrids in a neighborhood area to benefit from maximum available capacities and flexibilities in the network. In the following, we propose a CCMPC-based strategy for energy management problem of microgrids with power shortage.

- **Problem statement of microgrids with power shortage**

Energy management problem of microgrids with power shortage can be formulated as represented in Equations (9)-(16). At each time step t, each microgrid measures the value of stored energy in the battery $x_i(t)$ and solves the following optimization problem. where, H_p and H_u show prediction and control horizons, respectively. The cost function includes conventional generators operating cost as well as cost resulted from cutting RESs available power with the factor of $\gamma_i(t)[\frac{M.U}{kW}]$ where $M.U$ stands for monetary unit. In Equations (13) and (14), uncertain parameters are decomposed into two parts including forecasted value ($\bar{\mu}_i(t)$ and $\bar{P}_{ij}(t)$) and forecasting error ($\tilde{\mu}_i(t)$ and $\tilde{P}_{ij}(t)$). In Equation (16), P_i^{max} and P_i^{min} denote $[P_{CG,r}^{i,max}, P_{R,i}^{max}(t)]$ and $[P_{CG,r}^{i,min}, P_{R,i}^{min}(t)]$, respectively in which $P_{CG,r}^{i,max}$ and $P_{CG,r}^{i,min}$ are determined based on the r^{th} generator specifications. The value of $P_{R,i}^{max}$ is considered to be the maximum available power of RESs at related hour while $P_{R,i}^{min}$ is set to zero.

$$\min_{P_i(t,\ldots,t+H_u-1)} \sum_{n=0}^{H_u-1} f(P_i(t+n)) \tag{9}$$

$$f(P_i(t)) = C(P_{CG,r}^i(t)) + \gamma_i(t)P_R^i(t) \tag{10}$$

$$s.t. \quad x_i(t+n+1) = A_i x_i(t+n) + P_{batt,i}(t+n) \tag{11}$$

$$P_{batt,i}(t+n) = -\sum_{j\in N_i} P_{ij}(t+n) - P_{ig}(t+n) + B_i P_i(t+n) + \mu_i(t+n) \tag{12}$$

$$\mu_i(t+n) = \bar{\mu}_i(t+n) + \tilde{\mu}_i(t+n) \tag{13}$$

$$P_{ij}(t+n) = \bar{P}_{ij}(t+n) + \tilde{P}_{ij}(t+n) \tag{14}$$

$$x_i^{min} \le x_i(t+n) \le x_i^{max} \quad n = 1,\ldots,H_p \tag{15}$$

$$P_i^{min} \le P_i(t+n) \le P_i^{max} \quad n = 0,\ldots,H_u-1 \tag{16}$$

- **Proposed CCMPC-based energy management strategy for microgrids with power shortage**

Considering uncertain behavior of $\tilde{\mu}_i(t)$ in each microgrid and its influence on power interaction ($P_{ij}(t)$) and taking into account the real-time power balance equations (11)-(12), $x_i(t)$ is also an uncertain parameter. As a result, holding the hard constraint in the form of Equation (15) cannot be fully guaranteed. Based on the chance-constrained optimization approach, this hard constraint can be replaced with a probabilistic constraint in the form of Equation (17) which ensures that the probability of not violating the constraint will be higher than a pre-specified confidence level $1-\rho_i^x$.

$$P(x_i^{min} \le x_i(t) \le x_i^{max}) \ge 1-\rho_i^x \tag{17}$$

Any real-time power deviation within the microgrid according to Equations (11) and (12) will directly influence energy storage level in the battery. Considering Equation (11), it is possible that power deviation cannot be fully compensated through storage system. In this case, the imbalance power will be compensated by the main grid which ensures feasibility of the solution.

Adopting the proposed approach in [37]-[38] to derive solution strategy, the following structure denoted in Equation (18) is considered for each microgrids control law, where $\bar{P}_i(t)$ and $\bar{x}_i(t)$ are related to the expected values of control and state variables, respectively. Moreover, k_i denotes correction vector which is required to ensure stability of $(A_i + B_i k_i)$. In the examined energy management problem, state variable refers to the SOC of the battery while decision variables are considered as control variables.

$$P_i(t) = \bar{P}_i(t) + k_i(x_i(t) - \bar{x}_i(t)) \tag{18}$$

Using expected values for state and control variables, system dynamics can be written as follows.

$$\bar{x}_i(t+1) = A_i\bar{x}_i(t) + \bar{P}_{batt,i}(t) \tag{19}$$

$$\bar{P}_{batt,i}(t) = -\sum_{j\in N_i} \bar{P}_{ij}(t) - \bar{P}_{ig}(t) + B_i\bar{P}_i(t) + \bar{\mu}_i(t) \tag{20}$$

Defining the state error as $\delta x_i(t) = x_i(t) - \bar{x}_i(t)$, the dynamic of state error for the i^{th} microgrid can be written as

$$\delta x_i(t+1) = (A_i + B_i k_i)\delta x_i(t) - \sum_{j\in N_i} (P_{ij}(t) - \bar{P}_{ij}(t)) + (\mu_i(t) - \bar{\mu}_i(t)) \tag{21}$$

Taking into account covariance matrix of state $P_{X,i}(t+1) = E[\delta x_i(t+1)\delta x_i(t+1)^T]$ and control variables $P_{P,i}(t+1) = E[\delta P_i(t+1)\delta P_i(t+1)^T]$, from Equations (18) and (21) we have:

$$P_{X,i}(t+1) = (A_i + B_i k_i)P_{X,i}(t)(A_i + B_i k_i)^T + \sum_{j\in N_i} W_{ij}(t) + W_i(t) \tag{22}$$

$$P_{P,i}(t+1) = k_i P_{X,i}(t+1)k_i^T \tag{23}$$

in which, $W_{ij}(t)$ represents input covariance matrix of subsystem j from subsystem i point of view at time instant t and $W_i(t)$ denotes covariance value for $\mu_i(t)$.

Considering Equation (20), expected values of neighboring subsystems inputs $(\bar{P}_{ij}(t+n))$ during the prediction horizon $n = 0, ..., H_p - 1$ are required to evaluate system dynamic [37]. In this paper, these variables are considered as power references which are received initially from CEMS and updated through the process using proposed strategy which will be introduced in section 3.2.3. Moreover, according to the recursive update formulation of state variable covariance matrix represented through Equation (22), the input covariance matrices of neighboring subsystems will be also needed. It is assumed that control agents have a good estimation of that after several rounds of power exchanging with each other.

Since solving an optimization problem with probabilistic constraints is a challenging task, chance constraints are required to be replaced with their deterministic counterparts in a suitable manner. With the assumption of normal probability distribution for uncertain parameters, i.e., $\tilde{\mu}_i(t) \sim \mathcal{N}(0, W_i(t))$ and $\tilde{P}_{ij}(t) \sim \mathcal{N}(0, W_{ij}(t))$, and linear properties of dynamic equations, deterministic counterparts of the probabilistic constraints can be derived according to Equations (24)-(27) at the price of suitable tightening of feasible region. In these equations, erf^{-1} denotes the inverse of error function and $1-\rho_i^x$ and $1-\rho_i^p$ show the confidence level of the battery state and control variables, respectively.

Without loss of generality of the paper, one can assume unknown distribution function for the uncertain parameters and rely on Chebyshev-Cantelli inequality to extract deterministic counter parts of chance constraints according to [37]-[38].

$$\bar{x}_i(t+n) \le x_i^{max} - \sqrt{2P_{X,i}(t+n)}erf^{-1}(1-2\rho_i^x) \quad n = 1, ..., H_p \tag{24}$$

$$\bar{x}_i(t+n) \ge x_i^{min} + \sqrt{2P_{X,i}(t+n)}erf^{-1}(1-2\rho_i^x) \quad n = 1, ..., H_p \tag{25}$$

$$\bar{P}_i(t+n) \le P_i^{max} - \sqrt{2P_{P,i}(t+n)}erf^{-1}(1-2\rho_i^p) \quad n = 0, ..., H_u - 1 \tag{26}$$

$$\bar{P}_i(t+n) \ge P_i^{min} + \sqrt{2P_{P,i}(t+n)}erf^{-1}(1-2\rho_i^p) \quad n = 0, ..., H_u - 1 \tag{27}$$

In conclusion, the proposed stochastic energy management problem of microgrids with power shortage could be reformulated as follows:

$$\min_{\bar{P}_i(t,\dots,t+H_u-1)} \sum_{n=0}^{H_u-1} f(\bar{P}_i(t+n)) \tag{28}$$

$$f(\bar{P}_i(t)) = C(\bar{P}^i_{CG,r}(t)) + \gamma_i(t)\bar{P}^i_R(t) \tag{29}$$

s.t (19), (20), and (22)-(27)

Solving the optimization problem at each sampling time, the expected optimal control sequence $\bar{P}_i(t),\dots,\bar{P}_i(t+H_u-1)$ for each subsystem will be computed and thanks to Equation (18) the optimal control law for the actual system will be achieved. Following receding horizon control strategy, only the first sample of the optimal sequence is implemented and state variables are updated using Equations (11) and (12) considering realized values of neighboring subsystems transferring power as well as actual power generation of RESs and consumer demand. This procedure is summarized in *Algorithm* 2.

Algorithm 2 Operating strategy for LEMSs dealing with power shortage

1: *Measure the level of stored energy in the battery* $x_i(t)$*,*
2: *Solve the chance-constrained model predictive control problem of Equations (28)-(29) with respect to Equations* (19)-(20) *and* (22)-(27) *and compute control sequence using Equation* (18),
3: *Implement first sample of the optimal control sequence,*
4: *Update system state according to the actual load consumption and RESs generation using Equations* (11) *and* (12),
5: *Calculate total cost including operation cost according to Equation (10) and penalty cost resulted from real-time power imbalances using (*$\Delta^+\lambda^+ + \Delta^-\lambda^-$*),*
6: *Update power references for the following prediction horizon based on the received information from neighboring LEMSs,*
7: *Shift prediction and control horizons one step and repeat the procedure for the next time interval.*

3.2.2. LEMSs for microgrids with power surplus

Microgrids in this group are committed to deliver specific amounts of power to the microgrids with power shortage and also to the main grid based on their power surplus estimation. However, considering intrinsic uncertainty of RESs production and variability of loads, the realized surplus power might deviate from predicted values. Accordingly, LEMSs are responsible for developing efficient strategies to compensate possible power deviations.

- **Problem statement of microgrids with power surplus**

The energy management for these microgrids can be formulated as a tracking control problem in presence of uncertainty. Problem formulation is represented through Equations (30)-(36); In Equation (31), the first term penalizes the deviation of transferred power from associated reference values ($\hat{P}_i(t)$), while the last term represents the penalty cost related to any deviation of SOC of batteries with respect to the desired value ($\hat{x}_i(t)$). The control vector $P_i(t) = [P_{ij}(t); P_{ig}(t)]$ includes power to be transferred to the neighboring microgrids as well as to the main grid and $B_i = [-1 \ -1]$. In these equations, $R_i \in R^{|N_i|+1 \times |N_i|+1}$ and $Q_i \in R^{n \times n}$ represent relative weighting factors while $|N_i|$ shows the number of neighboring subsystems of the i^{th} microgrid. As the final goal is to manage the uncertainty within the multi-microgrid system and to reduce unscheduled power exchange between the microgrids network and the main grid, related weight coefficient of exchanged power with upstream network in the matrix R_i is set relatively much higher than coefficients related to the power transactions with neighboring subsystems as well as Q_i elements.

$$\min_{P_i(t,\ldots,t+H_u-1)} \sum_{n=0}^{H_u-1} J(P_i(t+n)) \tag{30}$$

$$\begin{aligned} J(P_i(t+n)) = [&(P_i(t+n) - \hat{P}_i(t+n))R_i(P_i(t+n) - \hat{P}_i(t+n))^T \\ &+ (x_i(t+n) - \hat{x}_i(t+n))Q_i(x_i(t+n) - \hat{x}_i(t+n))^T] \end{aligned} \tag{31}$$

$$s.t \qquad x_i(t+n+1) = A_i x_i(t+n) + P_{batt,i}(t+n) \tag{32}$$

$$P_{batt,i}(t+n) = B_i P_i(t+n) + \mu_i(t+n) \tag{33}$$

$$\mu_i(t+n) = \bar{\mu}_i(t+n) + \tilde{\mu}_i(t+n) \tag{34}$$

$$x_i^{min} \le x_i(t+n) \le x_i^{max} \quad n = 1,\ldots,H_p \tag{35}$$

$$P_i^{min} \le P_i(t+n) \le P_i^{max} \quad n = 0,\ldots,H_u-1 \tag{36}$$

- **Proposed CCMPC-based energy management strategy for microgrids with power surplus**

Taking into account the uncertainty in RESs production and local demand, the state constraint of Equation (35) might not be fully guaranteed. Accordingly, this constraint should be replaced with a probabilistic constraint in the form of Equation (17). Finally, adopting the same approach described in the previous sections, the proposed CCMPC-based energy management strategy is formulated as follows. At each time step t, each microgrid measures the value of stored energy in the battery $x_i(t)$ and solves optimization problem according to Equations (37)-(45). The optimal control sequence $\bar{P}_i(t),\ldots,\bar{P}_i(t+H_u-1)$ is then utilized in order to determine optimal control inputs to be implemented in actual system using the control law introduced in Equation (18). This procedure is summarized in *Algorithm* 3.

$$\min_{\bar{P}_i(t,\ldots,t+H_u-1)} \sum_{n=0}^{H_u-1} J(\bar{P}_i(t+n)) \tag{37}$$

$$s.t \qquad \bar{x}_i(t+n+1) = A_i\bar{x}_i(t+n) + \bar{P}_{batt,i}(t+n) \tag{38}$$

$$\bar{P}_{batt,i}(t+n) = B_i\bar{P}_i(t+n) + \bar{\mu}_i(t+n) \quad (\bar{P}_i(t) = [\bar{P}_{ij}(t); \bar{P}_{ig}(t)]) \tag{39}$$

$$\bar{x}_i(t) \leq x_i^{max} - \sqrt{2P_{X,i}(t)}erf^{-1}(1-2\rho_i^x) \quad n = 1,\ldots,H_p \tag{40}$$

$$\bar{x}_i(t) \geq x_i^{min} + \sqrt{2P_{X,i}(t)}erf^{-1}(1-2\rho_i^x) \quad n = 1,\ldots,H_p \tag{41}$$

$$\bar{P}_i(t) \leq P_i^{max} - \sqrt{2P_{P,i}(t)}erf^{-1}(1-2\rho_i^p) \quad n = 0,\ldots,H_u-1 \tag{42}$$

$$\bar{P}_i(t) \geq P_i^{min} + \sqrt{2P_{P,i}(t)}erf^{-1}(1-2\rho_i^p) \quad n = 0,\ldots,H_u-1 \tag{43}$$

$$P_{X,i}(t+1) = (A_i+B_ik_i)P_{X,i}(t)(A_i+B_ik_i)^T + W_i(t) \tag{44}$$

$$P_{P,i}(t+1) = k_iP_{X,i}(t+1)k_i^T \tag{45}$$

3.2.3. Proposed updating process of power reference trajectories

Utilizing recent information of uncertain variables, subsystems with power surplus could achieve more accurate estimations for the power to be transferred to the neighboring subsystems through the process. LEMSs can benefit from communication technologies in microgrids network in order to exchange updated information and improve multi-microgrid system performance. Accordingly, in this paper it is proposed that in microgrids with power surplus, after implementing the first sample of optimal control sequence, the remaining samples $(\bar{P}_{ij}(t+1),\ldots,\bar{P}_{ij}(t+H_u-1))$ can be used to update the trajectory of power references for the following prediction horizon. It is worth noticing that according to Equation (31), new references will not deviate considerably from the day-ahead scheduled trajectory. The proposed hierarchical energy management strategy is illustrated in Figure 2.

Algorithm 3 Operating strategy for LEMSs dealing with power surplus

1: *Measure the level of stored energy in the battery* $x_i(t)$*,*
2: *Solve the chance-constrained model predictive control problem of Equation (37) with respect to Equations (38)-(45) and compute control sequence using Equation* (18)*,*
3: *Implement first sample of the optimal control sequence,*
4: *Update system state according to the actual load consumption and RESs generation using Equations* (32) *and* (33)*,*
5: *Evaluate cost function considering penalty cost resulted from real-time power imbalances,*
6: *Find new power references utilizing optimal control sequence,*
7: *Communicate new references for the power to be transferred to neighboring microgrids during the next prediction horizon,*
8: *Shift prediction and control horizons one step and repeat the procedure for the next time interval.*

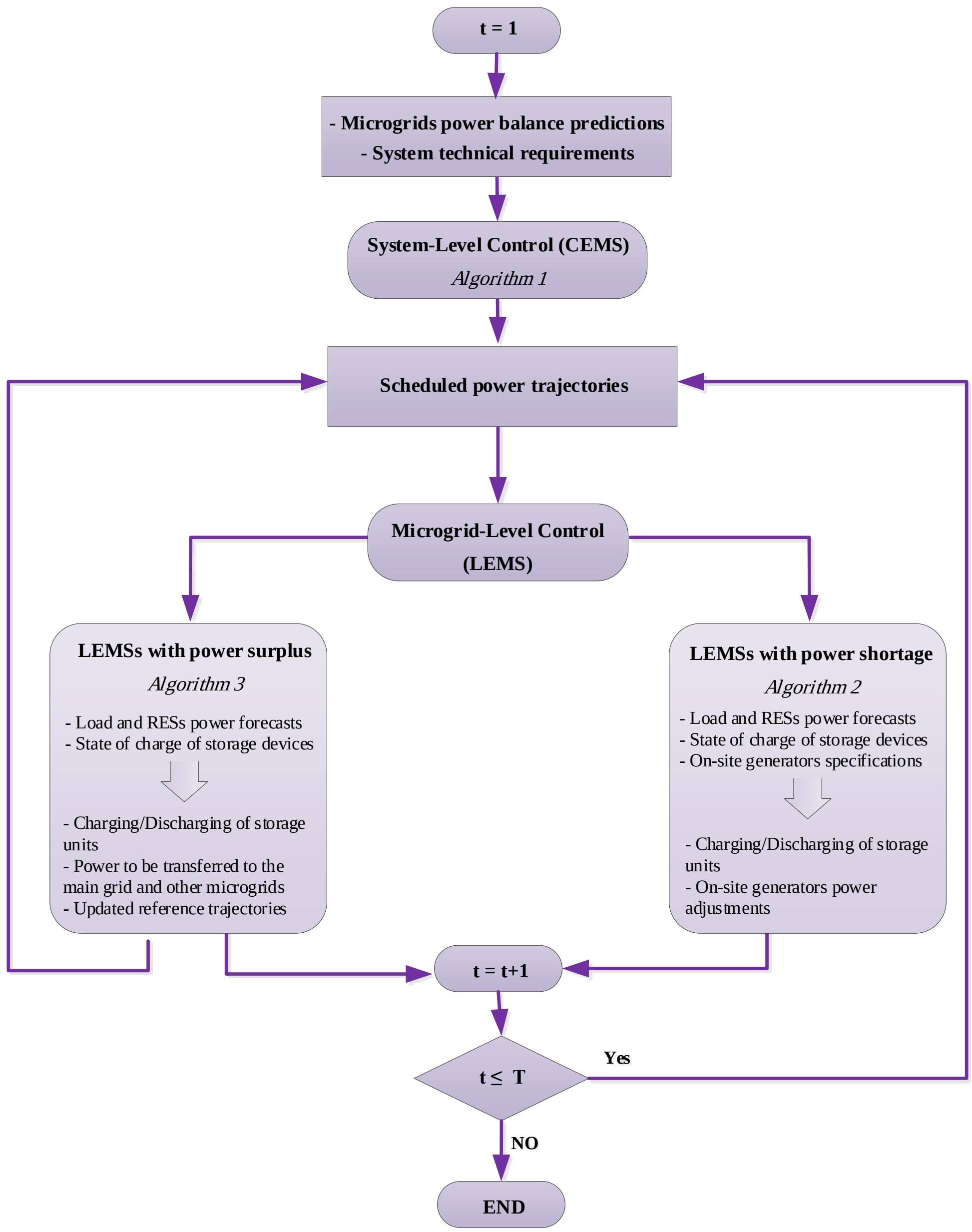

Figure 2: Proposed hierarchical EMS structure

4. Simulation Results

In this section, performance of the proposed strategy is evaluated for a multi-microgrid system as illustrated in Figure 1. It is assumed that the system contains three modified CIGRE medium voltage microgrids with total installed capacity of 3790 kW, 3700 kW and 4150 kW for microgrids 1, 2 and 3, respectively. CIGRE benchmark is based upon an European medium-voltage distribution network [39]-[41]. Sitting and sizing of the distributed energy resources (DERs) within each microgrid are presented in Table 1. In order to further clarify the system setup, single-line diagram of the modified benchmark for microgrid 1 is shown in Figure 3. The peak load of microgrids 1, 2 and 3 in the modified system is assumed to be 2600 kW, 2700 kW and 2750 kW, respectively. Diesel generators operational cost parameters are represented in Table 2 [42]. Other required simulation data is given in Table 3 in which λ^- and λ^+ refer to penalty coefficients related to the real-time power shortage and surplus, respectively. As it can be seen the penalty coefficients are assumed to be higher with respect to the cost of on-site generators to show the importance of pre-scheduling for power exchange with the main grid. The initial value of SOC for all of the microgrids is assumed to be 50% of the nominal capacity. Moreover, minimum and maximum SOC values are set to 20% and 80% of battery nominal capacity of each microgrid, respectively.

Day-ahead predicted values of power balance variables for three microgrids which are calculated based on the forecasted data of RESs generation and consumer demand, are represented by solid lines in Figure 4. CEMS collects this information from LEMSs and determines the optimal power scheduling. Day-ahead power scheduling results for three microgrids during adopted optimization horizon are also shown in Figure 4. This information is sent back to the LEMSs in the lower level to be considered as reference values for future power exchanges. Positive values for P_{ij} represent power is transferred from microgrid i to microgrid j and vice versa. Based on the assumed power balance profile of microgrids, the entire optimization horizon can be divided into four 6-hour intervals in which role of microgrids changes according to their net energy contents.

Table 1: DERs sitting and sizing specifications

Microgrid 1			Microgrid 2			Microgrid 3		
Node	Type	$P_{Max}[kW]$	Node	Type	$P_{Max}[kW]$	Node	Type	$P_{Max}[kW]$
3	PV	80	2	PV	40	3	PV	80
4	PV	80	4	PV	120	4	PV	80
5	PV	120	5	PV	160	5	PV	80
5	BSS*	900	5	DG	300	6	WT	1000
6	PV	120	6	WT	1000	6	WT	300
7	WT	1000	6	WT	150	6	WT	150
7	WT	150	6	WT	150	6	WT	150
7	WT	150	7	PV	120	7	PV	80
7	WT	150	8	PV	160	7	PV	40
8	PV	120	9	PV	120	8	PV	160
9	PV	120	10	PV	160	8	DG	400
9	DG	300	10	PV	20	9	PV	120
10	PV	160	10	BSS	800	10	PV	160
11	PV	40	13	DG	400	12	DG	400
13	DG	300				13	BSS	950

* BSS: Battery Storage System

Table 2: Cost coefficients of diesel generator units ($C(P) = aP^2 + bP + c$)

Unit	Capacity (kW)	$a_j(M.U^*/kWh^2)$	$b_j(M.U/kWh)$	$c_j(M.U)$
1	300	0.0061	0.091	0.184
2	400	0.0056	0.142	0.221

* M.U: monetary unit

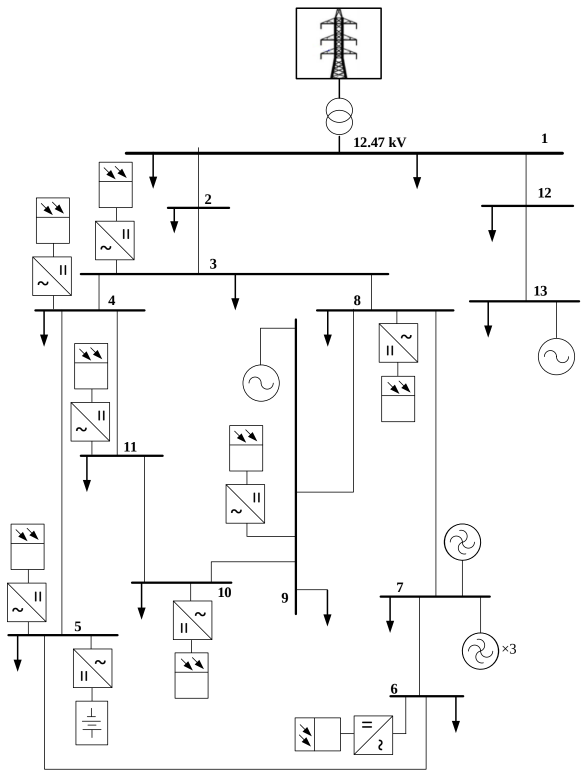

Figure 3: Single-line diagram of microgrid 1 based on modified CIGRE benchmark

Table 3: Simulation data

Parameter	Value	Unit	Parameter	Value	Unit
$\lambda^- = \lambda^+$	20	[M.U]	$P_{12}^{max}, P_{21}^{max}$	1000	kW
$\gamma_i \quad i = 1,2,3$	10	[M.U]	$P_{13}^{max}, P_{31}^{max}$	1100	kW
R	$\begin{bmatrix} r_{ij} & 0 \\ 0 & r_g^i \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 5 \end{bmatrix}$	[M.U]	$P_{23}^{max}, P_{32}^{max}$	1200	kW
Q	0.2	[M.U]	$P_{ig}^{max} \quad i = 1,2,3$	1500	kW
H_P, H_U	4	Hour	$\rho_i^p = \rho_i^x \quad i = 1,2,3$	20	%
T	24	Hour	$A_i \quad i = 1,2,3$	1	

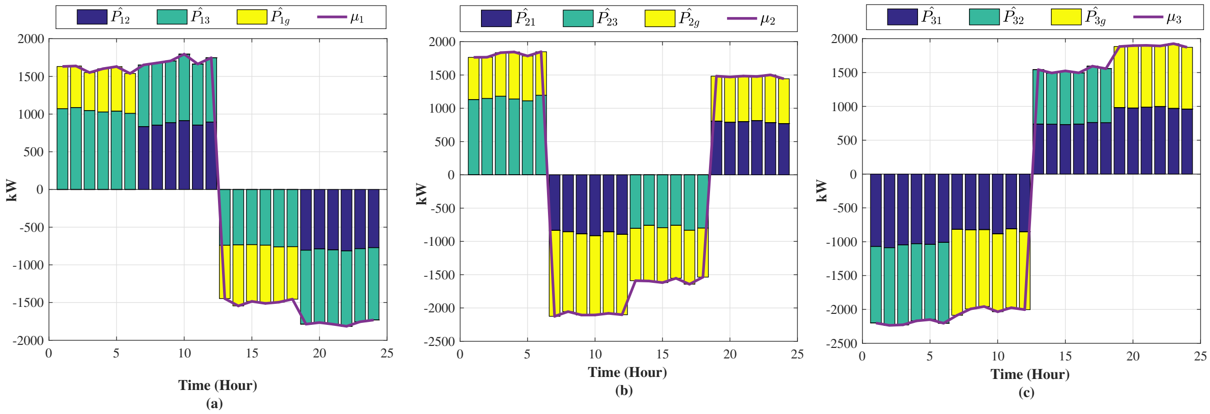

Figure 4: Predicted power balance and energy exchange references of (a) microgrid 1, (b) microgrid 2 and (c) microgrid 3

As it can be seen in Figure 4, microgrid 3 suffers from power shortage during the the first two intervals (i.e., 01:00-12:00), while microgrid 1 has power surplus during this time. Accordingly, microgrid 1 is committed to deliver specific amounts of power to microgrid 3 and the main grid during 1:00-6:00 and to microgrid 2 and microgrid 3 during 7:00-12:00, (see Figure 4-(a)). During 13:00-24:00, microgrid 1 suffers from power shortage and receives power from neighboring subsystems and the main grid.

Implementing *Algorithm* 3 by the microgrids with power surplus, associated tracking performance is represented in Figure 5 in which tracking intervals of each microgrid are specified. These results show the importance of taking into account the uncertainty of neighboring subsystems behavior. As an example, in the time interval between 13:00-18:00 in which microgrid 3 is committed to transfer power to other two microgrids, in case microgrids 1 and 2 do not account for the uncertainty of P_{31} and P_{32}, their operation could be affected by local uncertainty of microgrid 3 which might result in real-time supply-demand imbalance and consequently large penalty costs. Adopting *Algorithm* 2, microgrids with power shortage manage energy level of their batteries and control the output power of on-site generators taking into account this source of uncertainty. Table 4 represents hourly generation profiles of microgrid 1 and 2 during the third time interval for two different cases. Case 1 is related to the proposed CCMPC-based strategy while case 2 refers to the MPC-based EMS approach where no uncertainty is assumed in predicted values. Accordingly, in case 2 the energy management problem for microgrids with power shortage is considered according to Equations (9)-(16) and for microgrids with power surplus, as represented in Equations (30)-(36). However, the proposed updating mechanism for power exchange references is adopted in both cases. As it can be seen in the table, hourly generation of both microgrids in the first case is higher than those related to the second case. Although this conservative strategy results in high operating cost, it is an uncertainty management tool to improve the reliability of the microgrid and to prevent from higher penalties resulted from possible real-time power deviations.

According to Figure 5, a good tracking performance has been achieved for power exchange between multi-microgrid system and the main grid during the entire optimization horizon which

complies with our original goal to confine uncertainty within the microgrids network and to minimize unscheduled power transactions with the main grid. For more clarifying the issue, the total transferred power between the microgrids network and the main grid including real-time power imbalances are depicted in Figure 6.
Furthermore, Figures 7 and 8 represent normalized SOC of energy storage devices in each microgrid in cases 1 and 2, respectively. It is worth mentioning that, adopting the proposed approach for microgrids with power shortage, the SOC will be kept at higher levels with respect to deterministic case in order to prevent from real-time power shortage.

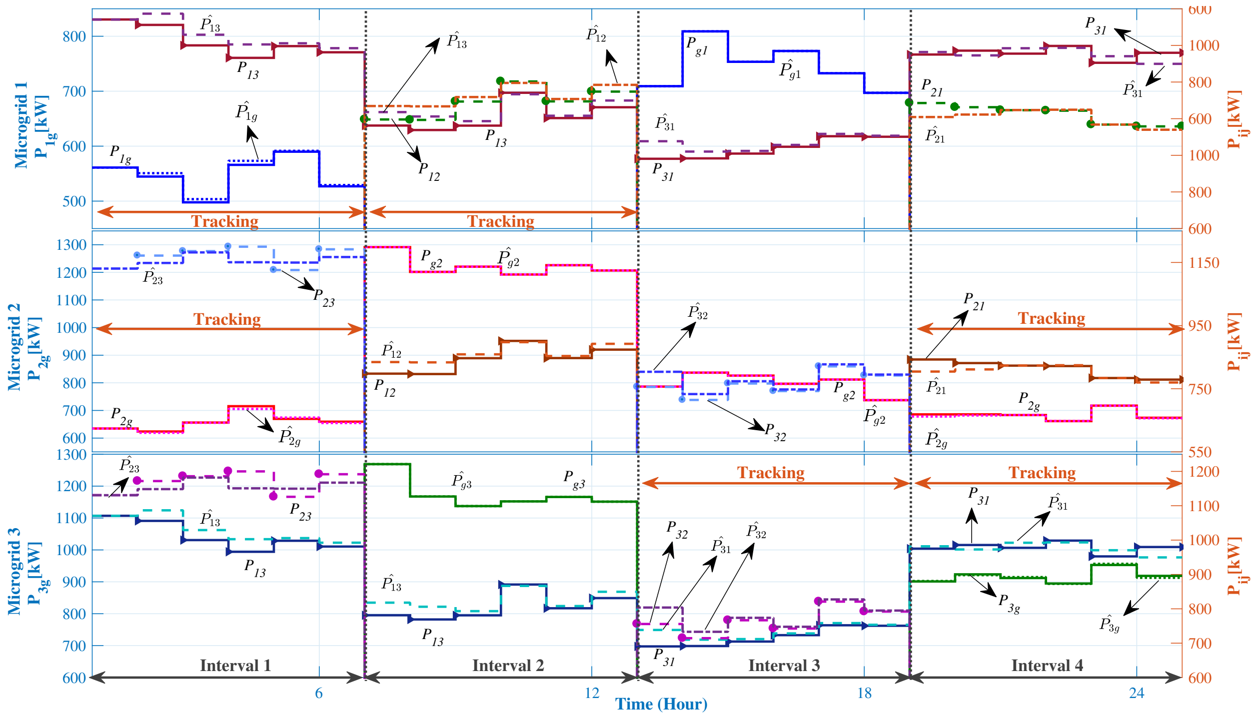

Figure 5: Tracking performance of the examined microgrids using proposed approach (Case 1)

Table 4: Hourly generation profiles of Microgrid 1 and Microgrid 2 during the third interval [kW]

Hour	Case 1		Case 2	
	Microgrid 1	Microgrid 2	Microgrid 1	Microgrid 2
13:00	0.00	0.00	0.00	0.00
14:00	37.10	48.34	5.14	39.90
15:00	5.51	44.58	0.00	38.02
16:00	30.15	0.00	12.48	0.00
17:00	0.00	0.00	0.00	0.00
18:00	0.00	0.00	0.00	0.00
Total	72.75	92.92	17.62	67.92

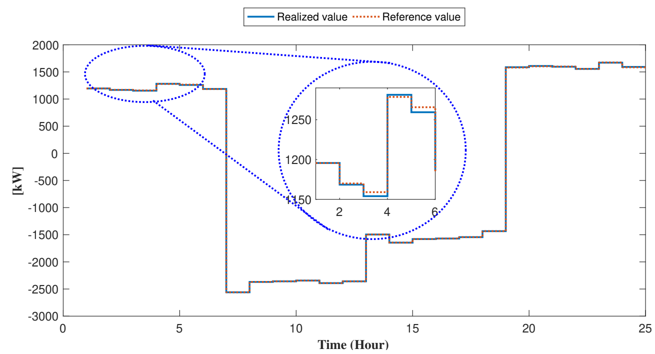

Figure 6: Daily power exchange between microgrids network and the main grid (Case 1)

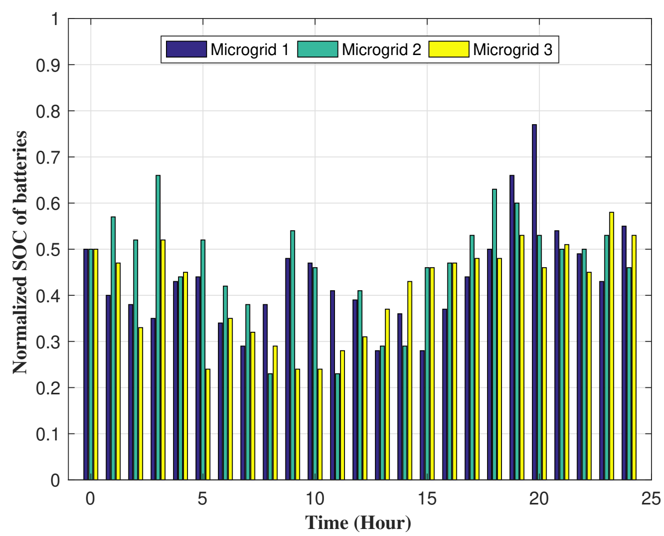

Figure 7: Normalized SOC of energy storage devices (Case 1)

4.1. Robustness Analysis

In order to show effectiveness of the proposed approach in considering different sources of uncertainties and benefiting from communication strategies to update power references, two other test cases named Case 3 and Case 4 are considered. Case 3 adopts proposed CCMPC-based strategy while Case 4 relies on the MPC-based approach. The difference between these cases and Cases 1 and 2, is that LEMSs only rely on the day-ahead power scheduling received form the CEMS and the proposed method for updating power references is not implemented in the system.

Monte Carlo algorithm has been used to generate discrete random scenarios representing the uncertain nature of RESs production and consumer demand. Random scenarios have been generated from normal distributions where forecasted quantities were considered as mean values and standard deviations were set to 5% of the forecasted values for all microgrids.

The average of total real-time power deviations for all 4 cases are given in Table 5 in which, Δ^{+} shows the power surplus while Δ^{-} represents power shortage. These parameters are informative

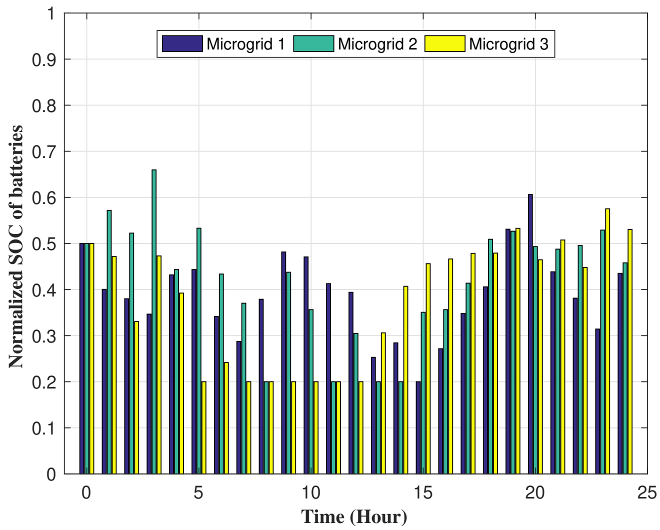

Figure 8: Normalized SOC of energy storage devices (Case 2)

indices to evaluate uncertainty management capabilities of different strategies. The lower the values of Δ^+ and Δ^-, the more robust strategy and consequently the lower penalty costs.

Table 6 demonstrates the daily average cost of microgrids including operational cost and penalty cost which is resulted from real-time power imbalances. According to Table 5 and Table 6, the minimum cost and real-time power imbalances are related to the proposed CCMPC-based approach with communication which approves its superiority in comparison with other strategies. Comparing total cost and power deviation values in the proposed approach with the obtained result from deterministic MPC-based strategies, it can be concluded that in a multi-microgrid network, neglecting effects of uncertainty in exchanged power among the neighboring subsystems and relying on the intrinsic robustness of the receding horizon strategy of decision-making, will result in performance degradation of the whole system.

Moreover, as it can be seen from simulation results in different cases, strategies with communication among LEMSs to update power references based on the most recent information of RESs production and loads, result in better performance in terms of cost and real-time power balances with respect to those strategies without communication and updating mechanism (i.e., case 1 with respect to case 3 and case 2 with respect to case 4). Breakdown of average daily cost of multi-microgrid system by operational and penalty costs are denoted in Figure 9. According to this figure, stochastic methods result in more operating cost in comparison with the deterministic counterpart strategies (i.e., case 1 with respect to case 2 and case 3 with respect to case 4). Obviously, the extra cost of stochastic methodologies is related to improving system robustness and avoiding real-time power imbalances. Robustness could be approved through penalty cost represented in the same figure. As it can be seen, penalty cost has substantially increased in deterministic cases as a result of more real-time power imbalances.

Table 5: Total average real-time power imbalances in 100 random scenarios [kW]

Case No.	Strategy	Δ^+	Δ^-
1	Proposed CCMPC-based strategy with communication	51.59	29.31
2	MPC-based strategy with communication	107.37	110.37
3	Proposed CCMPC-based strategy without communication	53.28	33.57
4	MPC-based strategy without communication	111.19	113.55

Table 6: Average daily cost of microgrids network in 100 random scenarios [M. U]

Case No.	Microgrid1	Microgrid2	Microgrid3	Total cost
1	30411.75	33158.65	31899.98	95470.38
2	30450.74	33019.24	32609.58	96079.57
3	33246.21	37065.14	34469.96	104781.31
4	33393.47	36807.73	35054.25	105255.46

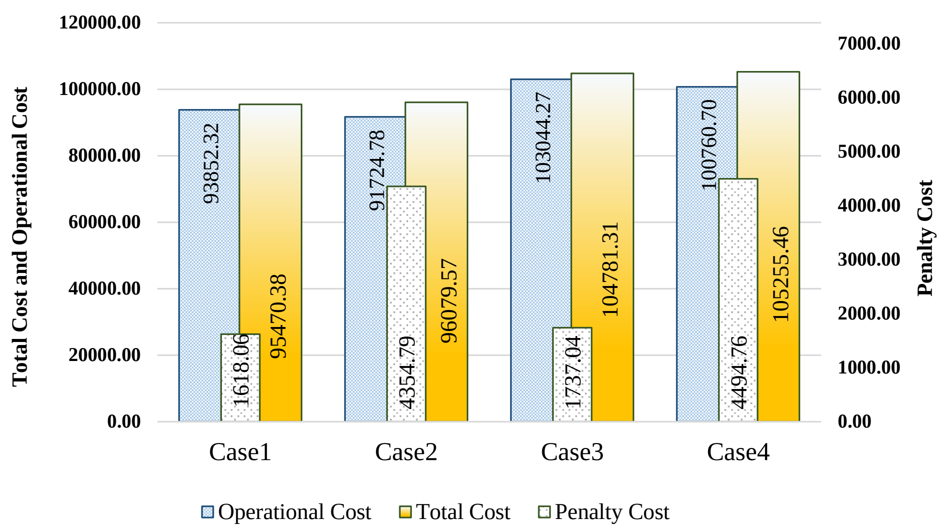

Figure 9: Breakdown of multi-microgrid system daily cost to operational and penalty costs [M. U]

5. Conclusion

In this paper, a hierarchical stochastic energy management strategy was proposed for a multi-microgrid system. It was shown in our studies that interconnected microgrids are imposed to different endogenous and exogenous sources of uncertainties that need to be accurately modeled in problem formulation. The goal of interconnected microgrids in this paper was to confine uncertainty inside the microgrids network and to minimize the unscheduled power exchange with the main grid considering system cost. Adopting receding horizon control approach, the problem was formulated in the framework of chance-constrained model predictive control. Moreover, it was proposed that in order to benefit from the most recent information of the uncertain parameters, local energy management systems could communicate with each other to update reference trajectories for power transactions. In order to evaluate effectiveness of the proposed methodology, simulation studies were carried out in different test cases. According to simulation results, through implementing the proposed methodology, considerable reduction in multi-microgrid system costs was achieved. Moreover, results demonstrated that although accounting for different sources of uncertainties results in more operating cost, it prevents from large penalty values. Furthermore, it was shown that by exploiting most recent information of uncertain parameters through inter-microgrids communication, real-time power imbalances and consequent penalty costs could be decreased.

The main drawback of MPC-based approaches is related to the computational time which depends on many factors including prediction and control horizons and the number of control parameters which obviously increases with the number of microgrids. This was one of the most important motivations of the authors to move from centralized approaches to hierarchical and distributed methodologies. Since every microgrid only solves a local optimization problem, flexibility and scalability of this approach is much better than centralized techniques. However, even in decentralized approaches, increasing the number of subsystems will result in more computational and communicational time which should be handled by appropriate solutions such as event-based or learning-based mechanisms.

Finally, during the paper communication and power line failures were not taken into account. Future work will focus on isolated mode of operation for interconnected microgrids as well as considering possibility of communication links failure.

References

[1] R. H. Lasseter, “Smart distribution: Coupled microgrids,” Proceedings of the IEEE, 99: 1074-1082, 2011.

[2] N. Bazmohammadi, A. Karimpour, and S. Bazmohammadi, “Optimal operation management of a microgrid based on MOPSO and Differential Evolution algorithms,” In Smart Grids (ICSG), 2nd Iranian Conference on 2012 May 24 (pp. 1-6), IEEE.

[3] A. Parisio, E. Rikos, and L. Glielmo,“A model predictive control approach to microgrid operation optimization,” IEEE Transactins on Control System Technology, 22(5): 1813-1827, 2014.

[4] R. Palma-Behnke et al., “A microgrid energy management system based on the rolling horizon strategy,” IEEE Transactions on Smart Grid, 4(2): 996-1006, 2013.

[5] J. Silvente, LG. Papageorgiou, V. Dua, “Optimal management of microgrids under uncertainty using scenario reduction,” In Computer Aided Chemical Engineering, 40: 2257-2262, 2017, Elsevier.

[6] P. Kou, Y. Feng, D. Liang, L. Gao, “A model predictive control approach for matching uncertain wind generation with PEV charging demand in a microgrid,” International Journal of Electrical Power and Energy Systems, 105: 488-99, 2019.

[7] A. Anvari-Moghaddam, A. Rahimi-Kian, M.S. Mirian, J.M. Guerrero, "A Multi-Agent Based Energy Management Solution for Integrated Buildings and Microgrid System," Applied Energy, 203: 41-56, 2017.

[8] J. Silvente, GM. Kopanos, V. Dua, LG. Papageorgiou, "A rolling horizon approach for optimal management of microgrids under stochastic uncertainty," Chemical Engineering Research and Design, 131: 293-317, 2018.

[9] Y. Zhang, R. Wang, T. Zhang, Y. Liu, B. Guo, "Model predictive control-based operation management for a residential microgrid with considering forecast uncertainties and demand response strategies," IET Generation Transmission and Distribution, 10: 2367-2378, 2016.

[10] M. Vahedipour-Dahraie, H. Rashidizaheh-Kermani, H.R. Najafi, A. Anvari-Moghaddam, J.M. Guerrero, "Stochastic Security and Risk-Constrained Scheduling for Microgrid with Demand Response and Renewable Energy Resources," IET Renewable Power Generation, 11(14): 1812-1821, 2017.

[11] M. Mao, Y. Wang, L. Chang, and Y. Du, "Operation optimization for multi-microgrids based on centralized-decentralized hybrid hierarchical energy management," In Energy Conversion Congress and Exposition (ECCE), IEEE 2017 Oct 1 (pp. 4813-4820), IEEE.

[12] X. Zhou, L. Zhou, Y. Chen, J.M. Guerrero, A. Luo, W. Wu, L. Yang, "A microgrid cluster structure and its autonomous coordination control strategy," International Journal of Electrical Power and Energy Systems, 100: 69-80, 2018.

[13] V.-H. Bui, A. Hussain, and H.-M. Kim, "A Multiagent-Based Hierarchical Energy Management Strategy for Multi-Microgrids Considering Adjustable Power and Demand Response," IEEE Transactions on Smart Grid, 9(2): 1323-1333, 2018.

[14] Y. Wang, S. Mao, RM. Nelms, "On hierarchical power scheduling for the macrogrid and cooperative microgrids," IEEE Transactions on Industrial Informatics, 11(6): 1574-1584, 2015.

[15] T. Lu, Z. Wang, Q. Ai, WJ. Lee, "Interactive model for energy management of clustered microgrids," IEEE Transactions on Industry Applications, 53(3): 1739-1750, 2017.

[16] S. Baldi, A. Karagevrekis, IT. Michailidis, EB. Kosmatopoulos, "Joint energy demand and thermal comfort optimization in photovoltaic-equipped interconnected microgrids," Energy Conversion and Management, 101: 352-63, 2015.

[17] A. Ouammi, H. Dagdougui, L. Dessaint, and R. Sacile, "Coordinated model predictive-based power flows control in a cooperative network of smart microgrids," IEEE Transactions on Smart grid, 6: 2233-2244, 2015.

[18] H. Dagdougui, and R. Sacile, "Decentralized control of the power flows in a network of smart microgrids modelled as a team of cooperative agents," IEEE Transactions on Control Systems Technology, 22 (2): 510-519, 2014.

[19] A. Parisio, C. Wiezorek, T. Kyntäjä, J. Elo, K. Strunz, and K. H. Johansson, "Cooperative MPC-based energy management for networked Microgrids," IEEE Transactions on Smart Grid, 8: 3066-3074, 2017.

[20] CA. Hans, P. Braun, J. Raisch, L. Grune, C. Reincke-Collon, "Hierarchical distributed model predictive control of interconnected microgrids," IEEE Transactions on Sustainable Energy, 2018.

[21] DI. Hidalgo-Rodríguez, J. Myrzik, "Optimal Operation of Interconnected Home-Microgrids with Flexible Thermal Loads: A Comparison of Decentralized, Centralized, and Hierarchical-Distributed Model Predictive Control," In 2018 Power Systems Computation Conference (PSCC), 2018 Jun 11 (pp. 1-7), IEEE.

[22] H. Farzin, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, "A hierarchical scheme for outage management in multi-microgrids," International Transactions on Electrical Energy Systems, 26(9): 2023-2037, 2016.

[23] E. Bullich-Massagué, F. Díaz-González, M. Aragüés-Peñalba, et al., "Microgrid clustering architectures," Applied Energy, 212: 340-361, 2018.

[24] A. Hussain, V.-H. Bui, and H.-M. Kim, "Robust optimization-based scheduling of multi-microgrids considering uncertainties," Energies, 9(4): 278, 2016.

[25] B. Zhang, Q. Li, L. Wang, and W. Feng, "Robust optimization for energy transactions in multi-microgrids under uncertainty," Applied Energy, 217: 346-360, 2018.

[26] J. Xu, Y. Zou, Y. Niu, "Distributed Predictive Control for Energy Management of Multi-Microgrids Systems," IFAC Proceedings Volumes, 46(13): 551-556, 2013.

[27] C. Bersani, H. Dagdougui, A. Ouammi, R. Sacile, "Distributed Robust Control of the Power Flows in a Team of Cooperating Microgrids," IEEE Transactions on Control Systems Technology, 25(4): 1473-1479, 2017.

[28] N. Nikmehr, S. Najafi-Ravadanegh, A. Khodaei, "Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty," Applied energy, 198: 267-279, 2017.

[29] A. Hooshmand, M. H. Poursaeidi, J. Mohammadpour, et al.: "Stochastic model predictive control method for microgrid management," In Innovative Smart Grid Technologies (ISGT), IEEE PES 2012 Jan 16 (pp. 1-7). IEEE.

[30] DT. Nguyen, LB. Le, "Optimal energy management for cooperative microgrids with renewable energy resources," In Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on (pp. 678-683), IEEE.

[31] N. Bazmohammadi, A.R. Tahsiri, A. Anvari-Moghaddam, J.M. Guerrero, “Optimal Operation Management of a Regional Network of Microgrids Based on Chance-Constrained Model Predictive Control,” IET Generation, Transmission and Distribution, 12 (15): 3772 – 3779, 2018.

[32] N. Bazmohammadi, A.R. Tahsiri, A. Anvari-Moghaddam, J.M. Guerrero, “Stochastic Predictive Control of Multi-Microgrid Systems,” In IEEE 18th International Conference on Environment and Electrical Engineering and 2nd Industrial and Commercial Power Systems Europe 2018 (pp. 1-6), IEEE Press.

[33] P. Kou, D. Liang, L. Gao, “Distributed EMPC of multiple microgrids for coordinated stochastic energy management,” Applied energy, 185:939-52, 2017.

[34] JD. Vergara-Dietrich, MM. Morato, PR. Mendes, et al., “Advanced chance-constrained predictive control for the efficient energy management of renewable power systems,” Journal of Process Control, 2017.

[35] F. Oldewurtel, A. Parisio, C. Jones, et al., “Energy efficient building climate control using stochastic model predictive control and weather predictions,” In Proceedings of the 2010 American control conference (ACC), 2010 (pp. 5100-5105).

[36] M. Amini, M. Almassalkhi, “Trading off robustness and performance in receding horizon control with uncertain energy resources,” In Power Systems Computation Conference (PSCC), 2018 Jun 11 (pp. 1-7), IEEE.

[37] M. Farina, L. Giulioni,and R. Scattolini, “Distributed Predictive Control of stochastic linear systems with chance constraints,” In American Control Conference (ACC), 2016 Jul 6 (pp. 20-25), IEEE.

[38] M. Farina, L. Giulioni, L. Magni, et al., “An approach to output-feedback MPC of stochastic linear discrete-time systems,” Automatica, 55: 140-149, 2015.

[39] K. Rudion, A. Orths, Z.A. Styczynski, et al., “Design of benchmark of medium voltage distribution network for investigation of DG integration,” In Power Engineering Society General Meeting, IEEE 2006 Oct 16, IEEE.

[40] D.E. Olivares, C.A. Cañizares, and M. Kazerani, “A centralized energy management system for isolated microgrids,” IEEE Transactions on smart grid, 5(4): 1864-1875, 2014.

[41] T.K. Alharbi, “Energy Management and Smart Charging of PEVs in Isolated Microgrids,” Master’s thesis, University of Waterloo, 2015.

[42] M. Mazidi, A. Zakariazadeh, S. Jadid, and P. Siano, “Integrated scheduling of renewable generation and demand response programs in a microgrid,” Energy Conversion and Management, 86: 1118-1127, 2014.