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Stochastic Predictive Control of Multi-Microgrid Systems

Najmeh Bazmohammadi, Ahmadreza Tahsiri, Amjad Anvari-Moghaddam, *Senior Member, IEEE,* Josep M. Guerrero, *Fellow, IEEE*

***Abstract*—In this paper, integrated operation management of cooperative microgrids is formulated in the framework of stochastic predictive control. In the proposed scheme, a joint probabilistic constraint on the microgrids power exchange with the main grid couples operation of individual microgrids. In order to tackle the coupling constraint, a cooperative energy management strategy is proposed in which based on the statistical characteristics of uncertain parameters, the deterministic counterpart of the problem is derived and an efficient solution strategy is achieved. The proposed strategy is evaluated for an illustrative test case including two microgrids based on modified CIGRE benchmark. Moreover, statistical analysis is conducted to evaluate robustness characteristics of the solution strategy.**

***Index Terms*—Multi-microgrid systems, energy management system, model predictive control, chance constraints, Monte-Carlo algorithm.**

NOMENCLATURE

Constants

$\alpha_{DG_j^i}, \beta_{DG_j^i}, \gamma_{DG_j^i}$	Cost function coefficients of DG units
Δt	Time step (h)
λ_{ESS}	Operating cost of ESS
$\lambda_{pur}/\lambda_{sell}$	Power purchasing/selling price of the main grid
ρ	Risk factor of the multi-microgrid system
σ_i	Risk factor of the ith microgrid
$C_{ESS,i}$	ESS capacity of the ith microgrid (kWh)
H_p	Prediction horizon (h)
H_u	Control horizon (h)
$n_{DG,i}$	Number of DGs in the ith microgrid
$n_{p,i}$	Number of PVs in the ith microgrid
$n_{w,i}$	Number of WTs in the ith microgrid
M	Number of microgrids

Functions and variables

$\bar{\mu}_i$	Expected value of μ_i
μ_i	Power balance variable
$\phi(.)$	Cumulative distribution function of a standard normal variable with zero mean and unit variance
Σ_i	Variance of μ_i
$C^i_{DG,j}$	Cost function of the jth DG unit in the ith microgrid ($)
$P^i_{DG,j}$	Power production of the jth DG in the ith microgrid (kW)
$P_{ESS,i}$	Charging power ($P_{ESS,i} > 0$) / discharging power ($P_{ESS,i} < 0$) of ESS (kW)
$P_{L,i}$	Aggregated load of the ith microgrid (kW)
$P_{Pur,i}$	Power to be purchased from the utility (kW)
$P^i_{PV,j}$	Power production of the jth PV in the ith microgrid (kW)
$P_{sel,i}$	Power to be selled to the utility (kW)
$P^i_{WT,j}$	Power production of the jth WT in the ith microgrid (kW)
$W_{p,i}$	Variance of $P_{pur,i}$
$W_{s,i}$	Variance of $P_{sel,i}$
z_i	State of charge of ESS in the ith microgrid

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I. INTRODUCTION

LOCAL aggregation of distributed energy resources (DERs), energy storage systems (ESSs) and loads under the control of an autonomous entity is known as microgrid. Microgrids were initially introduced as a promising solution for large penetration of heterogeneous small-scale DERs into the power systems. From the perspective of the main grid, a microgrid can be seen as an aggregated load, a controllable power generator or a supporting unit for ancillary services [1]-[2]. Under the microgrid concept, utilities will be provided with a more abstracted form of information and consequently less complicated energy management problems.

The most important issue in operation management of a microgrid is related to the uncertain nature of renewable-based power resources such as wind turbines (WTs) and photo voltaic systems (PVs) as well as variability of loads which might result in real-time power deviations. Although the main grid can easily compensate for the small amounts of power mismatches, large values of power deviations caused by a large number of grid-connected microgrids might appear as grid disturbances and increase the complexity of energy management strategies.

Addressing this issue, a large body of research has been emerged in recent years in order to benefit from coordinated operation management of neighboring microgrids [3]-[5]. Adopting an efficient energy management system (EMS), a multi-microgrid system can exploit generation and consumption diversity of microgrids to smooth out power deviations and decrease its reliance on the main grid.

Model predictive control (MPC) is one of the most successful control strategies that has gained attention of power

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system society in this area. The capability of MPC to consider system technical and operational constraints and account for future predictions of the system behavior as well as its closed-loop control policy, make it an appealing control strategy for power system's applications. In [6]-[7], authors propose MPC-based cooperative energy management strategies for a network of interconnected microgrids. It is shown that microgrids can achieve considerable advantages through co-operation in comparison with single mode of operation. In [8], MPC is used to design a robust decentralized control strategy for multiple distributed generators in islanded mode of operation. In [9], a decentralized cooperative MPC-based EMS is developed for interconnected microgrids while tacking into account both electrical and thermal demand. Minimizing power exchange with the main grid and system cost are considered as common objectives of individual microgrids. In [10], chance-constrained MPC (CCMPC) is adopted to coordinate energy management of interconnected microgrids. The uncertainty resulted from imperfect prediction of renewable-based generations and consumers demand is modeled through a probabilistic constraint on battery state of charge (SOC). In [11], a CCMPC-based hierarchical approach is proposed for a multi-microgrid system. The goal of microgrids is to follow a predefined trajectory for power exchange with the main grid in a cooperative manner. In [12], a stochastic multi-objective optimization approach based on MPC is proposed for interconnected microgrids while considering power interchange capabilities of multi-microgrid system and distribution network. Authors in [13] propose a hierarchical energy management strategy taking into account different endogenous and exogenous sources of uncertainties.

Control of a multi-microgrid system differs from a single microgrid's control since in the former there is a sort of coupling between different subsystems which results in a complicated control problem for the integrated system. The coupling source might be a common objective function, a joint constraint or coupled dynamics [14]. In this paper which is the extension of the preliminary study presented in [15], energy management of microgrids is coupled through a joint constraint. It is assumed that power exchange between individual microgrids and the main grid is required to be bounded within a pre-specified range. Accommodating the uncertainty resulted from imperfect prediction of renewable energy sources (RESs) production and consumer demand, microgrids arrive in a cooperative strategy which guarantees that the probability of satisfying power exchange limitation of all microgrids will be higher than a pre-specified confidence level. In order to reduce computational complexity of the problem, the joint constraint is replaced with individual constraints using a decomposition approach. Finally, a statistical analysis is conducted to evaluate robustness characteristics of the proposed method. The main contributions of the paper can be summarized as follows:

- Modeling cooperative operation management of microgrids using a joint probabilistic constraint;
- Investigating the performance of the CCMPC-based EMS of microgrids in different situations with and without knowledge of uncertain parameters.
- Analyzing effects of uncertain parameter's statistical characteristics on the solution strategy;

The rest of paper is organized as follows. section II is related to the problem statement while CCMPC is introduced in section III. Proposed stochastic MPC-based strategy is presented in section IV and simulation results are illustrated in section V. Finally, section VI concludes the paper.

II. Problem Statement

In this paper, integrated operation management of cooperative microgrids is formulated in the framework of stochastic predictive control. It is assumed that the multi-microgrid system includes M heterogeneous microgrids. The dynamical equation of individual microgrids is considered as (1)-(2) where (2) represents power balance constraint of each microgrid. During the paper it is assumed that $\Delta t = 1h$.

$$z_i(t+1) = z_i(t) + \frac{P_{ESS,i}(t)}{C_{ESS,i}}\Delta t \tag{1}$$

$$\begin{aligned} &P_{sel,i}(t) + P_{ESS,i}(t) + P_{L,i}(t) = \\ &P_{pur,i}(t) + \sum_{j=1}^{n_{w,i}} P^i_{WT,j}(t) + \sum_{j=1}^{n_{p,i}} P^i_{PV,j}(t) + \sum_{j=1}^{n_{DG,i}} P^i_{DG,j}(t) \end{aligned} \tag{2}$$

According to (2), in case of power shortage, microgrids can purchase required power from the main grid and sell energy to the grid in power surplus situations. However, buying and selling power at the same time is not allowed. Referring to [11], since objective function which is represented in the following is a linear function of these variables and selling price is set to be lower than purchasing price, they cannot be both non-zero at the same time in optimal solution. Accordingly, no binary variable is required to apply this constraint. Moreover, there are available on-site dispatchable resources such as diesel generators which their output power can be controlled to meet microgrid demand.

Taking into account the microgrids cost function according to (3), each microgrid desires to control its operation in a cost-efficient manner. In (3), $C^i_{DG,j}$ illustrates the operation cost of dispatchable generators (DGs) which is generally approximated through a quadratic polynomial function according to (4).

$$\begin{aligned} Cost_i(t) = \lambda_{ESS,i}|P_{ESS,i}(t)| + \sum_{j=1}^{n_{DG,i}} C^i_{DG,j}(P^i_{DG,j}(t)) \\ +\lambda_{pur}P_{pur,i}(t) - \lambda_{sell}P_{sel,i}(t) \end{aligned} \tag{3}$$

$$C^i_{DG,j}(P^i_{DG,j}(t)) = \alpha_{DG^i_j}(P^i_{DG,j}(t))^2 + \beta_{DG^i_j}P^i_{DG,j}(t) + \gamma_{DG^i_j} \tag{4}$$

Moreover, there are a number of operational constraints as shown in (5)-(9) which should be satisfied for safe operation of the system. Equations (5)-(6) enforce technical limitations on ESS while (7) illustrates the operation limits of DG units.

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Moreover, (8) and (9) represent upper and lower bounds for power transactions with the main grid.

$$z_i^{min} \leq z_i(t) \leq z_i^{max} \tag{5}$$

$$P_{ESS,i}^{min} \leq P_{ESS,i}(t) \leq P_{ESS,i}^{max} \tag{6}$$

$$P_{DG,j}^{i,min} \leq P_{DG,j}^{i}(t) \leq P_{DG,j}^{i,max} \tag{7}$$

$$0 \leq P_{pur,i}(t) \leq P_{pur,i}^{max} \tag{8}$$

$$0 \leq P_{sel,i}(t) \leq P_{sel,i}^{max} \tag{9}$$

Although employing RESs can bring considerable economic and environmental benefits, imperfect forecasting of their output power could also represent new challenges to the EMS of microgrids. Moreover, the power consumption behavior of the end-use consumers can be uncertain. Considering the uncertainty of RESs production and variability of loads, the power balance equality denoted in (2) might not be fully satisfied. In other words, realized values of renewable-based power and system demand may result in power shortage or surplus. Accordingly, the estimated power to be exchanged between microgrids and the main grid will be affected by the real-time power deviations. In order to ensure stability of the system, it is assumed that any real-time power deviation of microgrids will be technically compensated by the upstream network. However, large amounts of power flow deviations might appear as grid disturbances and increase the complexity of energy management problem of the main grid.

In this paper, it is proposed that in a cooperative network of microgrids, in order to manage uncertainties internally within the local network, microgrids cooperate with each other to keep the power flow between the utility and each microgrid within the pre-scheduled interval. Accordingly, taking into account the uncertain nature of the power transactions of microgrids, a joint probabilistic constraint in the form of (10) is applied to the multi-microgrid system where P is the probability operator and $1-\rho$ denotes a pre-specified confidence level. It should be noted that since selling and purchasing power at the same time are not allowed, one of these constraints would be activated for each microgrid at each time instant.

$$P\left\{ \begin{array}{l} P_{pur,i}(t) \leq P_{pur,i}^{max} \\ P_{sel,i}(t) \leq P_{sel,i}^{max} \end{array} \; for \;\; i=1,...,M \right\} \geq 1-\rho \tag{10}$$

According to the joint constraint (10), the probability of satisfying power exchange constraint for all microgrids in the system will be higher than $1-\rho$. However, as a result of applying this constraint to the multi-microgrid system, the operation of individual microgrids will be coupled to each other.

Solving an optimization problem with a joint chance constraint in the form of (10) is a challenging task since the evaluation of an integral of multi-variable probability distribution function will be required [16]. Utilizing the decomposition approach introduced in [16], the problem can be approximated with replacing the stochastic constraint with M individual chance constraints in the form of (11) and a new coupling constraint represented in (12) where σ_i is interpreted as the risk factor of each microgrid. In a cooperative multi-microgrid system, the central EMS is responsible for allocating risk parameters to individual microgrids through minimizing the total cost of the system. Interested readers are referred to [16] for more details and mathematical proof.

$$P\left\{ \begin{array}{l} P_{pur,i}(t) \leq P_{pur,i}^{max} \\ P_{sel,i}(t) \leq P_{sel,i}^{max} \end{array} \right\} \geq 1-\sigma_i(t), \quad for \;\; i=1,...,M \tag{11}$$

$$\sum_{i=1}^{M} \sigma_i(t) \leq \rho \tag{12}$$

III. Chance-constrained predictive control

In MPC, tacking into account dynamical prediction model of the system, a constrained optimization problem is solved during the adopted control horizon and a sequence of optimal control actions is derived. However, only the first sample of the obtained optimal control sequence is implemented in the system and the remaining samples are neglected. At the next time step, the control system goes through the whole optimization procedure while taking into account the most recent information of system states and parameters. This inherent feedback mechanism brings robustness capability to the algorithm which makes it an appropriate tool for making decisions under uncertainty.

In CCMPC, beside deterministic constraints, some probabilistic (chance) constraints in the form of (13) could also be included in the optimization problem. In this situation, the most common solution strategy is to reformulate the chance constraints with their deterministic counterparts taking into account statistical characteristics of the uncertain parameters.

$$P\{x^{min} \leq x(t) \leq x^{max}\} \geq 1-\rho \tag{13}$$

Assuming a Gaussian probability distribution function (PDF) for the uncertain parameter $x(t) \sim \mathcal{N}(m, a^2)$, constraint (13) can be reformulated as (14)-(15).

$$P\{\frac{x(t)-m}{a} \leq \frac{x^{max}-m}{a}\} \geq 1-\rho \tag{14}$$

$$P\{\frac{x^{min}-m}{a} \leq \frac{x(t)-m}{a}\} \geq 1-\rho \tag{15}$$

Using cumulative distribution function (CDF) properties, the deterministic counterparts of (13) can be derived as follows:

$$m \leq x^{max} - a\phi^{-1}(1-\rho) \tag{16}$$

$$m \geq x^{min} + a\phi^{-1}(1-\rho) \tag{17}$$

In case the PDF of uncertain parameter is unknown, Chebyshev-Cantelli inequality can be used to derive deterministic constraints according to (18)-(19) [17]. However, as a result of more tightening of feasible region, more conservative solutions will be achieved [18]-[19]. In order to more clarifying the issue, the two functions $f_1 = \phi^{-1}(1-\rho)$ and $f_2 = \sqrt{\frac{1-\rho}{\rho}}$ for $0.05 \leq \rho \leq 0.5$ are plotted in Fig.1.

$$m \leq x^{max} - a\sqrt{\frac{1-\rho}{\rho}} \tag{18}$$

$$m \geq x^{min} + a\sqrt{\frac{1-\rho}{\rho}} \tag{19}$$

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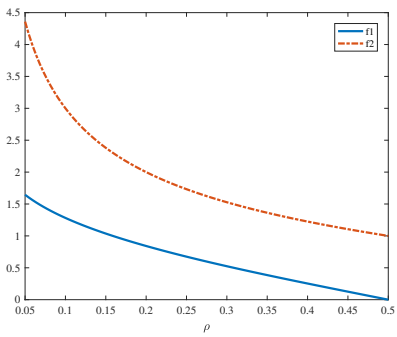

Fig. 1. Constraint tightening illustration

IV. Proposed Strategy

In this section, the operation management problem of cooperative microgrids with joint constraint, will be formulated in the framework of CCMPC. Considering intermittent generation of WTs and PVs and variability of loads as different sources of uncertainty, a new variable $\mu_i(t)$ is defined according to (20). It is assumed that $\mu_i(t)$ follows a normal PDF, i.e., $\mu_i(t) \sim \mathcal{N}(\bar{\mu}_i(t), \Sigma_i)$.

$$\mu_i(t) = \sum_{j=1}^{n_{w,i}} P^i_{WT,j}(t) + \sum_{j=1}^{n_{p,i}} P^i_{PV,j}(t) - P_{L,i}(t) \tag{20}$$

Taking into account linearity of (2), the expected and covariance values of selling and purchasing powers can be derived as follows:

$$\bar{P}_{pur,i}(t) = -\sum_{j=1}^{n_{DG,i}} P^i_{DG,j}(t) + P_{ESS,i}(t) - \bar{\mu}_i(t) \tag{21}$$

$$\bar{P}_{sel,i}(t) = \sum_{j=1}^{n_{DG,i}} P^i_{DG,j}(t) - P_{ESS,i}(t) + \bar{\mu}_i(t) \tag{22}$$

$$W_{s,i}(t) = W_{p,i}(t) = \Sigma_i(t) \tag{23}$$

Finally, the proposed CCMPC-based energy management problem of cooperative microgrids with coupling probabilistic constraint can be formulated as follows:

$$\min_{\substack{P_{ESS,i}, P^i_{DG,j}, P_{pur,i}, P_{sel,i}(t,\ldots,t+H_p-1),\\ \sigma_i(t,\ldots,t+H_p-1)}} \sum_{k=0}^{H_p-1} \sum_{i=1}^{M} [\lambda_{ESS,i}|P_{ESS,i}(t+k)| + \sum_{j=1}^{n_{DG,i}} C^i_{DG,j}(P^i_{DG,j}(t+k)) + \lambda_{pur}\bar{P}_{pur,i}(t+k) - \lambda_{sell}\bar{P}_{sel,i}(t+k)] \tag{24}$$

$$s.t. \quad (1), (5)-(7), (12), (21)-(23) \tag{25}$$

$$\bar{P}_{pur,i}(t) \le P^{max}_{pur,i} - \sqrt{W_{p,i}}\phi^{-1}(1-\sigma_i(t)) \tag{26}$$

$$\bar{P}_{sel,i}(t) \le P^{max}_{sel,i} - \sqrt{W_{s,i}}\phi^{-1}(1-\sigma_i(t)) \tag{27}$$

At the beginning of each sampling time interval, the central energy management unit of the multi-microgrid system collects required information from individual microgrids and solves the above optimization problem with respect to linear and non-linear constraints. The obtained control sequence is then communicated with the microgrids local controllers to be implemented in associated subsystem. In the examined energy management system, control sequence includes amount of charging/discharging of the battery ($P_{ESS,i}(t)$), the energy to be produced by controllable energy resources ($P^i_{DG,j}$) as well as the power to be sold ($P_{sel,i}(t)$) (purchased($P_{pur,i}(t)$)) to (from) the main grid. Fig. 2 illustrates flowchart of the proposed EMS strategy. It should be noted that in this system-level study, it is assumed that bus voltages within each microgrid are regulated locally (if needed) and lines/feeders are well sized not to reach their thermal limits on different operating conditions.

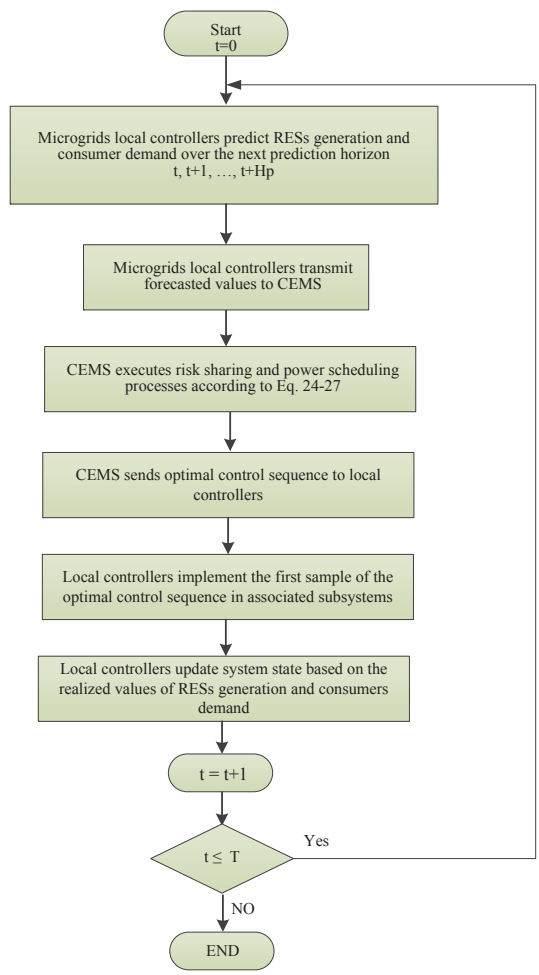

Fig. 2. Proposed EMS structure

V. Simulation Results

In this section, in order to investigate effectiveness of the proposed methodology, simulation analysis are conducted on a representative test case illustrated in Fig. 3. The proposed method is applied to a multi-microgrid system which consists of two heterogeneous microgrids based on the modified CIGRE benchmarks [21]-[23]. Table I represents siting and sizing of distributed energy resources (DERs) in two microgrids.

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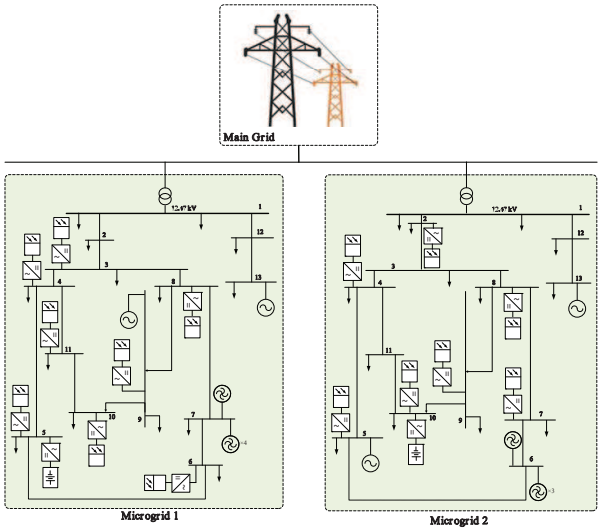

Fig. 3. Illustration of the multi-microgrid system

Technical and economical characteristics of DG units are also tabulated in Table II [24]. The minimum and maximum SOC of ESSs are assumed to be 20% and 80% of the nominal capacity for each microgrid. Moreover, the initial values of SOC are set to 20% of the ESS nominal capacity. Table III represents the estimated values for power balance variables. Other simulation data are given in Table IV.

Implementing the proposed stochastic strategy, daily scheduling of microgrids and ESSs profiles are illustrated in Figs. (4)-(5), respectively. Moreover, Fig. (6) represents risk factor sharing between two microgrids.

TABLE I
DERS SITTING AND SIZING SPECIFICATIONS

Microgrid 1			Microgrid 2		
Node	Type	$P^{max}[kW]$	Node	Type	$P^{max}[kW]$
3	PV	80	2	PV	40
4	PV	80	4	PV	120
5	PV	120	5	PV	160
5	ESS	900	5	DG	300
6	PV	120	6	WT	1200
7	WT	1100	6	WT	150
7	WT	150	6	WT	150
7	WT	150	6	WT	150
7	WT	150	7	PV	120
7	WT	150	8	PV	160
8	PV	120	9	PV	120
9	PV	120	10	PV	160
9	DG	300	10	PV	120
10	PV	160	10	ESS	800
11	PV	40	13	DG	400
13	DG	300			

TABLE II
TECHNICAL AND ECONOMICAL CHARACTERISTICS OF DG UNITS

Unit	$\alpha_{DG}(\$/kWh^2)$	$\beta_{DG}(\$/kWh)$	$\gamma_{DG}(\$)$	$P^{min}(kW)$	$P^{max}(kW)$
1	0.0061	0.091	0.184	30	300
2	0.0056	0.142	0.221	40	400

According to the figure, microgrids try to minimize the total system operation cost through iterative sharing of risk factor parameter while the summation of individual risk parameters is upper bounded.

A. Stochastic analysis

In this section, in order to investigate robustness characteristics of the proposed strategy, operation of the multi-microgrid system will be analyzed in different cases. Two operating cases have been assumed based on the PDF knowledge of the uncertain parameters. In the first case, it is assumed that the uncertain parameter follows a normal PDF while case 2 is conducted based on the assumption of unknown PDF for uncertain parameter. Accordingly, constraints (16) and (17) are replaced with equations (18) and (19) in case 2.

TABLE III
ESTIMATED POWER BALANCE (μ $[kW]$)

Hour	MG 1	MG 2	Hour	MG 1	MG 2
1	1453.46	1204.77	13	-1876.28	1786.68
2	1374.84	1226.97	14	-1881.28	1836.28
3	1375.95	1228.00	15	-1826.6	1700.77
4	1268.82	1224.99	16	-1875.48	1554.89
5	1317.72	1171.13	17	-1860.80	1399.32
6	1219.93	985.94	18	-1837.08	1323.90
7	-1667.12	-1842.60	19	1437.06	-1672.40
8	-1596.88	-1877.95	20	1441.69	-1561.85
9	-1529.90	-1805.50	21	1449.93	-1587.05
10	-1594.50	-1686.55	22	1474.74	-1634.75
11	-1509.40	-1672.65	23	1415.30	-1558.65
12	-1558.38	-1355.60	24	1448.90	-1599.05

TABLE IV
SIMULATION DATA

Parameter	Value	Unit	Parameter	Value	Unit
$\lambda_{ESS,i}$ $i=1,2$	0.02	$[\frac{\$}{kWh}]$	$P^{max}_{pur,1}$, $P^{max}_{sel,1}$	1650	$[kW]$
λ_{pur}	1	$[\frac{\$}{kWh}]$	$P^{max}_{pur,2}$, $P^{max}_{sel,2}$	1750	$[kW]$
λ_{sell}	0.6	$[\frac{\$}{kWh}]$	ρ	40	%
H_P, H_U	4	Hour	T	24	Hour

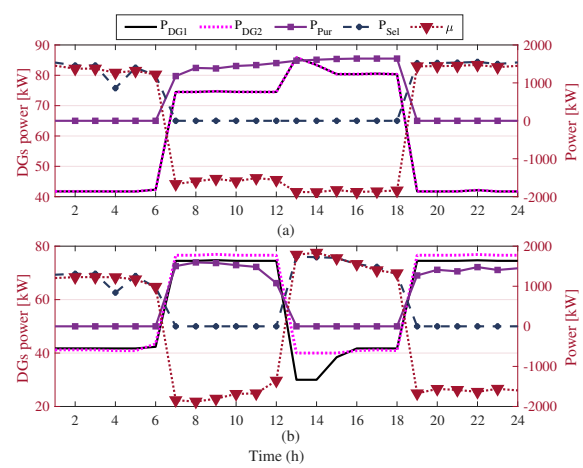

Fig. 4. Daily scheduling (a) Microgrid 1 (b) Microgrid 2

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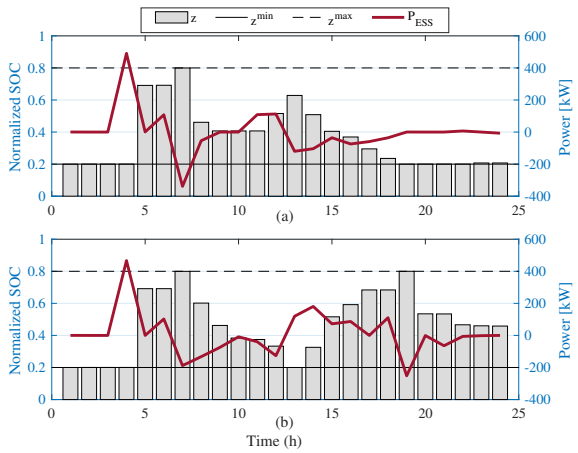

Fig. 5. ESS daily profile (a) Microgrid 1 (b) Microgrid 2

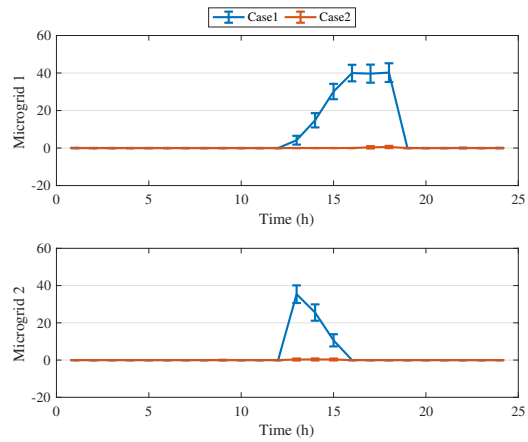

Fig. 7. Average percentage of constraint violation

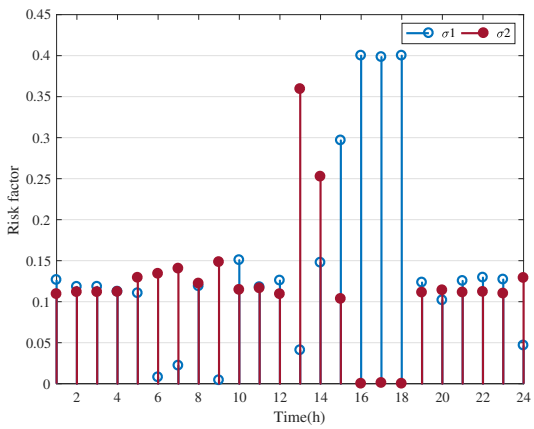

Fig. 6. Risk factor sharing, Case 1

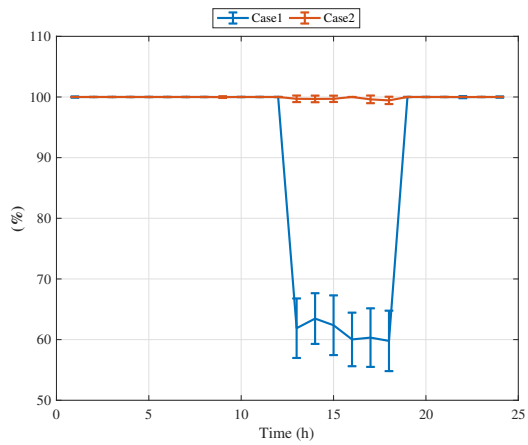

Fig. 8. Average percentage of the joint constraint satisfaction

- **Case 1:** Proposed CCMPC-based EMS strategy with known PDF assumption;
- **Case 2:** Proposed CCMPC-based EMS strategy with unknown PDF assumption;

Monte-Carlo algorithm has been utilized in order to generate discrete random scenarios for representing RESs generation and load uncertainty. Scenarios are extracted from a normal distribution which the mean values are assumed to be equal to the forecasted values and the standard deviations are set to α percent of forecasted quantities. Fig.7 and Fig.8 represent the average probability of constraint violation for each microgrid and the joint chance constraint satisfaction probability over 100 different random scenarios, respectively for $\alpha = 2$.

As it can be seen in the figures, performance of the proposed strategy in both cases complies with the expected behavior since the average constraint violation probabilities of both microgrids are less than $\sigma_i(t)$ and average percentage of the joint constraint satisfaction is higher than $(1-\rho)$ as required.

In case 2, EMS adopts the proposed CCMPC-based strategy with the assumption of unknown PDF for the uncertain parameter. Accordingly, this case results in more conservative solutions since all constraints are satisfied in all probable scenarios during the adopted scheduling horizon. The advantage of exploiting available knowledge of uncertain parameters is that microgrids can benefit from maximum allowable power deviation to minimize operating cost of the multi-microgrid system.

In order to have a more comprehensive analysis, total estimated operation cost of the microgrids in different cases are tabulated in Table V. Moreover, Fig.9 illustrates the hourly costs of microgrids. As it can be seen in case 2 that knowledge of the uncertain parameter is not exploited, operational cost has been increased in comparison with the first case. It should be noted that these values represent expected cost of microgrids. The actual cost which is calculated after realization of the uncertain parameters might deviate from these values based on microgrids real-time power deviations. Fig. 10 illustrates the risk factor sharing process of microgrids in case 2.

TABLE V
TOTAL OPERATION COST OF MICROGRIDS IN DIFFERENT CASES [$]

Microgrid	Microgrid 1	Microgrid 2	Total
Case 1	9345.77	8670.00	18015.77
Case 2	9664.20	8650.31	18314.51

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B. Sensitivity analysis to PDFs specifications

In this section, sensitivity of the proposed CCMPC-based strategy to the estimation accuracy of PDF specifications is analyzed. Underestimation and overestimation cases are related to the situations where standard deviation (std) of the uncertainty PDF is estimated lower and higher than the actual value. Table VI represents the average mean and std values of the joint constraint satisfaction percentage of both cases in 100 random scenarios.

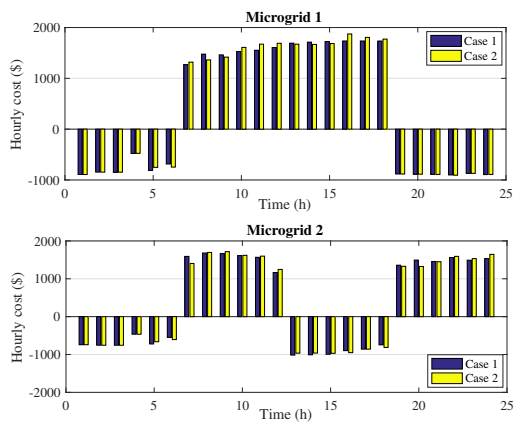

Fig. 9. Hourly cost of microgrids in different cases

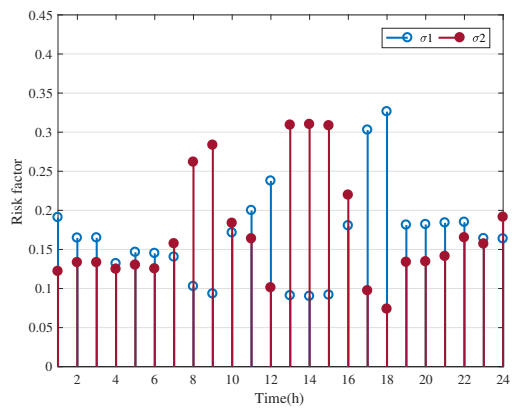

Fig. 10. Risk factor sharing, Case 2

As it can be seen in the table, CCMPC-based strategy with the assumption of known PDF is sensitive to accurate estimation of the uncertainty specifications. Specifically, in situations where standard deviation is under-estimated, the performance will be degraded. The minimum sensitivity is related to case 2 in which it is assumed that the probability distribution of uncertain parameter is not known. However, this solution strategy which has the maximum conservativeness might result in higher operating cost with respect to the other case.

C. Sensitivity analysis to PDF of the uncertain parameter

In this section, sensitivity of the proposed approach with respect to PDF knowledge of the uncertain parameter is analyzed. In contrast to the previous section that a normal PDF has been assumed for the power balance variable (μ_i), random scenarios for each of uncertain parameters, i.e., aggregated WTs and PVs generation and consumer demand, have been generated separately from different PDFs. After generating scenarios for the random parameters, equation (20) has been used to calculate the power balance variable.

TABLE VI
AVERAGE VALUES FOR MEAN AND STD OF JOINT CONSTRAINT SATISFACTION PROBABILITY IN 100 RANDOM SCENARIOS

Case	Under-estimation		Accurate estimation		Over-estimation	
	Mean	std	Mean	std	Mean	std
Case 1	88.3297	1.4211	90.3258	1.1919	94.1333	0.9917
Case 2	99.1204	0.5263	99.9213	0.1248	100	0

Figs. (11)-(12) illustrate error-bars related to the real-time power deviation of individual microgrids and joint constraint satisfaction probabilities, respectively. As it can be seen in these figures, the CCMPC-based strategy with the assumption of unknown PDF represents better performance with respect to the other case. Since no specific assumption has been made on PDFs of the uncertain parameter while deriving operating strategy, it has capability of handling uncertain behavior of the random parameter.

Simulation results emphasize the significance of applying the right approach based on the available knowledge of uncertain parameters. In this part, the random scenarios were generated for aggregated production of PVs and WTs as well as total consumption of the microgrids. In a more realistic case, the random scenarios should be generated separately for individual RESs power production and consumer demand. According to the central limit theorem, in case a number of independent random variables are added, PDF of the resulting summation will be close to a normal PDF. Accordingly, in a microgrid where the power balance variable is influenced by different random parameters (power generation of some PVs and WTs as well as power demand of a number of consumers) the resulting PDF tends toward a normal PDF and benefiting from this knowledge less conservative strategy will be reached.

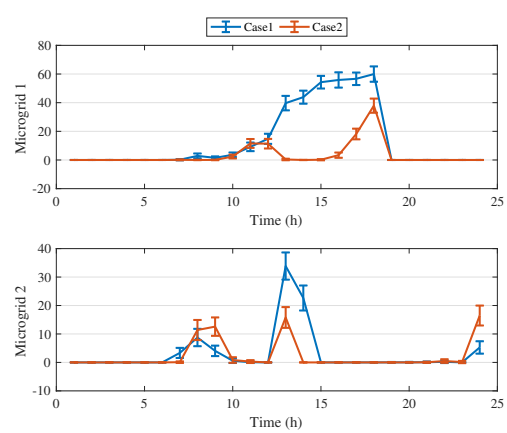

Fig. 11. Average percentage of constraint violation

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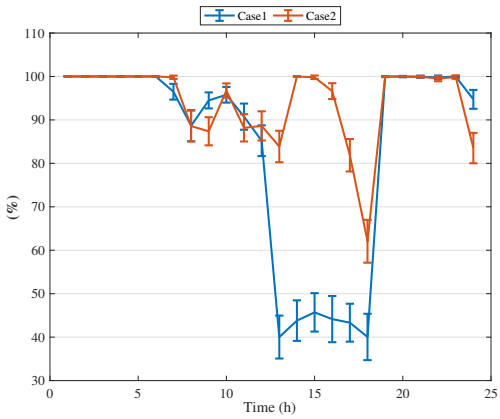

Fig. 12. Average percentage of the joint constraint satisfaction

VI. Conclusion

In this paper, operation management of cooperative microgrids was formulated in the framework of CCMPC. A joint probabilistic constraint was introduced which guaranteed that the real-time power exchange of microgrids with the main grid would not violate the desired operating range with a pre-specified confidence level. Considering growing penetration of renewable-based microgrids into the power system, the proposed strategy could result in more predictable behavior of grid-connected microgrids and consequently less complex energy management systems from the main grid point of view. Simulation studies were conducted in different scenarios to investigate operating performance of the proposed approach. Simulation results represented importance of relying on accurate estimation methods in deriving statistical models of uncertain variables while adopting the proposed CCMPC-based strategy. Microgrids controllers can be equipped with appropriate identification tools to extract statistical characteristics of uncertain parameters. Although including forecasting strategies in EMS will increase the complexity of decision making process, the available knowledge in the system will be efficiently exploited and less conservative solutions can be achieved at lower operating costs.

Furthermore, the proposed strategy in this paper is a centralized approach which although relying on general knowledge of the system will result in more optimal solutions, it suffers from scalability issues. Accordingly, in case the number of subsystems in a multi-microgrid system increases, decentralized approaches will be much more preferred.

Future plan is to develop adaptive forecasting methods for stochastic MPC-based control of multi-microgrid systems. Furthermore, the authors are interested in expanding the proposed method in their future studies to the situations where microgrids are interconnected and power exchange can take place directly within microgrids network in addition to selling/purchasing power to/from the main grid.

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