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Abstract: A regional network of microgrids includes a cluster of microgrids located in a neighbourhood area connecting together through power lines. In this study, the problem of operation management of networked-microgrids is considered. The main goal is to develop an efficient strategy to control local operation of each microgrid including the amount of energy to be requested from the main grid and the optimal charging/discharging patterns of batteries along with the transferred power among microgrids considering system's technical constraints. Accounting for system uncertainty due to the presence of renewable energy sources and variability of loads, the problem is formulated in the framework of chance-constrained model predictive control. Moreover, the Monte Carlo algorithm is adopted to generate discrete random scenarios to evaluate the solutions. Simulation studies have been exemplarily carried out in order to show the effectiveness of the proposed approach.

1 Introduction

Microgrids are defined as small-scale power systems including distributed generators, loads and storage devices. Microgrids can operate either isolated or connected to the utility grid and are commonly in a range from a few hundred kilowatts to a few megawatts. One of the most important issues in control of microgrids is the stochastic nature of renewable energy sources (RESs) and variability of loads [1, 2]. In grid-connected mode, the main grid can be considered as an additional highly reliable source compensating for the possible energy shortage the microgrids may face. However, this compensation may not be always desirable as it requires transferring power over long distances which results in more power dissipation. Moreover, requesting power from the upstream network which mainly relies on non-renewable sources is not compatible with the environmentally friendly objectives. Accordingly, there are some other alternative approaches to cope with this issue such as designing hybrid power systems in order to benefit from the diversity of different distributed generation technologies or utilising energy storage devices with a larger size that each one has its own limitations [3].

In recent years, cooperation among microgrids in a regional area has been raised as a promising solution to the economical and reliable operation of smart microgrids. In a regional network of microgrids, the existence of load profile diversity and different climate patterns resulting in different production behaviour of RESs, motivate the efficient cooperation of microgrids in order to utilise the maximum existing capacity in the network [3]. Based on this, the problem of operation management of networked-microgrids has been attracting the attention of researchers in recent years.

Different methodologies have been adopted to address this problem including centralised methods [3–6], decentralised [7–13], and hieratical schemes [14–18]. In a centralised control approach, the whole system is controlled through a central controller. It is theoretically expected that this architecture results in the most optimal performance. Specifically, in cooperative scenarios where different entities desire a common objective at the system level, centralised control schemes will be an effective decision approach. However, scalability is the most important issue. In decentralised and hierarchical decision approaches, since decisions are made by different agents or at different control levels, a considerable reduction in computational burden will be achieved. Moreover, in competitive situations or scenarios where different microgrids belong to different owners who desire to improve the individual performance, these strategies will be much preferred. However, optimality and convergence are critical issues.

In [3], a power-sharing problem in a cluster of microgrids is investigated under the assumptions of fully and partially cooperative microgrids. In [4, 5], an energy management problem in a cluster of microgrids is modelled as a linear quadratic Gaussian problem. The main limitation is due to the assumption of unconstrained decision variables. In [6], the isolated household prosumers (consumers with energy production capability) are considered as small-scale microgrids. In comparison with the isolated mode, it has been shown that cooperation of prosumers in a neighbourhood area will result in greater reliability and performance.

In [7, 9], a distributed Lagrange-based model predictive control (MPC) is adopted in order to devise optimal control strategies of a large-scale smart grid. Utilising this approach, different partitions of a large-scale system can be modelled as interacting subsystems and their operation could be analysed in parallel through local agents instead of a large central controller. In [10], the coordinated operation management problem of a cluster of microgrids is considered as a bi-level stochastic optimisation problem. In [12], the objective of microgrids is to maintain their storage level and power exchanged with the main grid around a reference value through cooperatively power sharing with each other. The main drawback is related to neglecting operational constraints. Moreover, the problem has been modelled as a deterministic problem. In [13], a power sharing methodology based on coalitional game theory is presented in which grid-connected microgrids based on their individual utility function decide to cooperate with each other.

In [14], a hierarchical algorithm for cooperative operation management of multi-microgrids is proposed. The common objective function of microgrids includes minimisation of operation cost and exchanged power with the mains. In [15], a three-level hierarchical optimisation approach is presented which adopts gossip algorithm to coordinate microgrids. A two-stage hierarchical methodology is also introduced in [16] in order to share the free capacity of storage and generation of different microgrids during the emergency condition. In [17], it is shown that sharing the amount of adjustable power along with power shortage/surplus information will result in considerable improvement in multi-microgrids performance.

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Despite the great effort made in recent years, the operation management problem of networked-microgrids is still in its infancy and more effort is required. According to the current literature, most of the existing studies are carried out in deterministic space or neglect important technical constraints.

The most important challenges in the operation management problem of RES-based microgrids are the intermittent nature of RESs' production and variability of loads. Prediction errors of production and consumption powers should be considered as sources of uncertainty and explicitly modelled in problem formulation. Those errors result from the forecasting methodology, quality of data and more importantly unpredictable behaviour of consumers. Moreover, neglecting the system constraints makes the solutions inapplicable in practical situations.

In power system studies, there are several approaches for analysis of system operation under uncertainty. However, most of them are based on scenario generation approaches [19]. For example, two-stage stochastic programming with recourse [20, 21] and stochastic MPC based on dynamic programming [22] which requires intensive computational efforts. Robust optimisation approaches also received much attention in power system applications [23]. However, since the problem is solved under a worst-case scenario, the results might be too conservative. Lyapunov optimisation approaches also have been used to handle random event processes [24, 25]. In which, the constraints are reformulated using virtual queues and a drift-plus-penalty objective function is minimised for each time step. Although only relying on real-time information of a single step a substantial reduction in system complexity and required computational effort will be achieved, the time average expected cost may not be the most optimal but within a bound of optimal value [25].

This study aims at optimising the operation of a regional network of microgrids based on a control oriented approach considering practical constraints. Accounting for system uncertainty, chance-constrained MPC (CCMPC) is adopted as a high-level controller to provide the local controllers with optimal set-points considering production and demand uncertainties. The most important contributions of this study can be summarised as follows:

- Implementing the operation management problem of a group of microgrids in a neighbourhood area considering systems' technical constraints, forecasting errors of RESs' production and microgrids' load and modelling the problem in an uncertain environment.
- Modelling the operation management problem of networked-microgrids in the framework of CCMPC.
- Analysing the effects of prediction horizon on the performance of the proposed method through investigating profitability and reliability indices while the Monte Carlo simulation is adopted to generate discrete random scenarios.

The rest of this paper is structured as follows. The problem statement is presented in section 2. Section 3 presents the problem formulation while section 4 introduces CCMPC. In sections 5 and 6 illustrative case studies and simulation results are provided, respectively. Finally, the conclusion remarks are given in section 7.

2 Problem statement

In a regional microgrid network, each microgrid can be considered as a subsystem in a dynamical network with its own operational characteristics and constraints. Microgrids with connecting links have the possibility of transferring power and exchanging information through associated links. In the context of dynamical systems and adopting control oriented approaches, each subsystem can be represented as a state variable whose evolution over time is affected by the inflows/outflows from/to other subsystems. The state of a microgrid is related to the state of charge (SOC) of energy storage devices and input variables represent exchanging power among microgrids and also between microgrids and the mains (upstream network).

In this structure, each microgrid in case of power shortage can either discharge its storage devices or request power from the utility or neighbouring microgrids considering network topology and system constraints. This decision-making process in each subsystem is accomplished in order to achieve some specific goals. In a situation with self-interested microgrids, the objectives of various subsystems may be totally different or even in contrast to each other while in a cooperative environment achieving a common goal in system-level is desired. Moreover, each microgrid may have local objectives in addition to system-level goals such as adjusting its storage state at a reliable level.

The main goal in controlling a regional network of microgrids is to develop an effective strategy to keep the system in balance. Therefore the local operation of each microgrid should be accurately determined while considering system technical and security constraints. In this study, the local operation includes the amount of energy to be requested from the main grid, optimal charging/discharging patterns of the batteries and the power to be exchanged with neighbouring microgrids. Moreover, system constraints are those related to the capacity of storage devices as well as distribution power lines limitation. One of the most important issues in microgrids control is the uncertainty introduced by forecasted consumption and generation which plays an important role in determining the optimal strategy. In such an uncertain environment, decisions should be made about the future scheduling of power transactions and management of energy storage units before the realisation of uncertain parameters. As a result, relying on deterministic approaches for decision making which do not consider the impacts of likely deviations of forecasted variables, will result in inappropriate solutions in case of large errors. Consequently, stochastic approaches which exploit an explicit model of uncertainty in their optimisation procedure will result in more reliable strategies.

3 Problem formulation

The networked-microgrids under consideration are a set of interconnected microgrids. It is assumed that microgrids production is based on RESs including wind turbines and solar panels, and their production can be forecasted during the future N-step prediction horizon. Moreover, the load profile predicted values are also available during the prediction horizon. It is assumed that each microgrid is equipped with an energy storage device with a limited capacity which is considered as a state variable in this study. Specifically, for the ith microgrid at step k, the evolution of the stored energy is described by the following discrete time state equation.

In (1), $x_i(k)$ denotes the normalised SOC of ith microgrid during the time interval k. The battery nominal capacity is represented by $C_{\mathrm{nom},i}$ and M shows the number of microgrids. Δ is related to the time duration between two consecutive steps. Throughout the study, it is assumed that $\Delta = 1$ and so it could be dropped from the equations. In this equation, control variables $u_{ij}(k)$ represent the amount of power to be transferred between subsystems i and j during time step k. Variables b_{ij} take their values from the set of $\{-1, 0, 1\}$ depending on the link directions.

According to [12], links are directed from lower to higher subsystem numbers while the highest number is assigned to the mains. As an example, for microgrids 1 and 2 in case there is a power link between them, we set $b_{12} = -1$ and $b_{21} = 1$. In case there is no direct link between two microgrids, the associated coefficient will be set to zero. Consequently, microgrid i is said to be a neighbour of microgrid j if and only if $b_{ij} \neq 0$. However, the parameter $u_{12}(k)$ could take both positive and negative values. The positive value of $u_{12}(k)$ represents transferring power from microgrid 1 to microgrid 2 and vice versa

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$$x_i(k+1) = x_i(k) + \frac{1}{C_{\text{nom},i}}\left(\sum_{\substack{j=1\\ j\neq i}}^{M} b_{ij}u_{ij}(k) + \tilde{u}_{\text{wt},i}(k) + \tilde{u}_{\text{pv},i}(k) - \tilde{d}_i(k)\right)\Delta,$$
$$\text{for all } i, \quad i = 1, 2, \ldots, M. \tag{1}$$

Moreover, $\tilde{u}_{\text{wt},i}(k)$, $\tilde{u}_{\text{pv},i}(k)$, and $\tilde{d}_i(k)$ represent the predicted values of wind turbine generation, photovoltaic unit production, and aggregated loads of microgrid i in time step k, respectively. According to (2), for computation simplicity, these parameters can be abstracted to a single parameter named power imbalance. Although many forecasting methods have been developed in recent years, there are considerable errors in their results. The main reason is the intrinsic uncertainty of consumption behaviour of consumers and exogenous factors like weather conditions including wind speed and solar radiation as well as ambient temperature

$$\tilde{\mu}_i(k) = \tilde{u}_{\text{wt},i}(k) + \tilde{u}_{\text{pv},i}(k) - \tilde{d}_i(k). \tag{2}$$

Utilising (2), the amount of expected power shortage ($\tilde{\mu}_i(k) < 0$) or surplus of power ($\tilde{\mu}_i(k) > 0$) in each time interval can be calculated which is then interpreted as unbalance behaviour of a related subsystem. Possible actions in order to compensate for this unbalance situation include trading power with the upstream network, charging/discharging energy storage devices or exchanging power with neighbouring subsystems. To preserve the stability of the system it is required that (1) be satisfied in each subsystem. Moreover, to guarantee system's safety and prevent equipment damaging, operational constraints must be met. These requirements are considered according to (3) and (4), where (3) is related to the battery SOC constraint and (4) represents line capacity limitation

$$x_{i,\min} \le x_i(k) \le x_{i,\max}, \tag{3}$$

$$u_{i,\min} \le u_i(k) \le u_{i,\max}. \tag{4}$$

The objective is to maintain the level of energy storage in each microgrid and the power exchange among them around a reference value. So, the amount of deviation will be penalised according to (5) at each time slot t

$$\begin{aligned} j_i^* &= \min\ j_i(x_i, u_i) \\ &= \min \left[\begin{array}{l} \sum_{k=t+1}^{t+N} \left(x_i(k) - \hat{x}_i(k)\right)^{\mathrm{T}} Q_i \left(x_i(k) - \hat{x}_i(k)\right) \\ + \sum_{k=t}^{t+H_u-1} (\boldsymbol{u}_i(k) - \hat{\boldsymbol{u}}_i(k))^{\mathrm{T}} R_i (\boldsymbol{u}_i(k) - \hat{\boldsymbol{u}}_i(k)) \end{array} \right], \end{aligned} \tag{5}$$

where $\hat{x}_i(k)$ is the reference value for energy stored in the battery. Moreover, $\boldsymbol{u}_i(k)$ is the control vector containing the amount of power to be exchanged between microgrid i and its neighbouring subsystems including utility in case there is a direct link between them. The reference vector is denoted by vector $\hat{\boldsymbol{u}}_i(k)$. Furthermore, $\boldsymbol{Q}_i \in R^{n\times n}$ and $\boldsymbol{R}_i \in R^{m\times m}$ are positive-definite, symmetric weighting matrices; representing the relative importance of state and input deviations in the cost function. Where, n and m show state and input dimensions, respectively, and Hu denotes control horizon.

4 Chance constrained MPC

In MPC, based on a dynamic model of the system under consideration and prediction of system's future behaviour, a sequence of control actions is determined. The first sample of the optimal input sequence is applied to the system which takes the system to a new state, where the whole procedure will be repeated with the most recent data for the next prediction horizon. This implied feedback mechanism of MPC along with its capability to account for system constraints makes it a promising strategy in power system applications [26–28].

To use MPC, the system should be described in a suitable dynamic prediction model which is used in order to predict future behaviour of the system. However, in practice due to the presence of uncertainty, such predictions are never exact. In most of the MPC-based approaches, according to the certainty equivalence principle, it is just relied on the intrinsic robustness of MPC resulted from the rolling horizon strategy and no further action is taken. However, if uncertainty is considerable this strategy may lead to infeasibility or undesirable degradation of system performance.

Uncertainty and variability are inherent characteristics of any system in real-world which may arise due to the unpredictable system's endogenous or exogenous variables. As a result, in order to have a robust design and safe operation of the system, it is necessary to consider different disturbances and uncertainties a system may experience during its operation [27]. This problem which is categorised in the field of robust optimisation and control has attracted much attention over the years. Designing robust deterministic MPC includes min–max optimisation problems [29] or designing invariant sets [30, 31] is a mature research area [32]. Although the effectiveness of these approaches in many applications, they suffer from some disadvantageous. First of all, these approaches are very time consuming, which make them inapplicable in power system applications. Secondly, they may result in too conservative solutions [32, 33].

CCMPC is an optimisation approach which incorporates probabilistic constraints in MPC formulation. In this strategy, instead of guaranteeing to hold constraints definitely, it is ensured that the probability of not violating the constraints is higher than a predefined confidence level [27, 34, 35]. For more clarifying the issue, consider MPC problem represented through (6)–(8) in each time slot t. In which, $\mu(k)$ is considered as an external disturbance. In the examined energy management problem, external disturbance refers to the uncertainty resulted from RESs production and load forecasting errors.

Accordingly, since the dynamical model of a state variable contains uncertainty, the state variable itself is an uncertain parameter. As a result, holding the state constraints of the form (8) cannot be fully guaranteed.

$$\min_{u[t:t+H_u-1]} \left[\sum_{k=t+1}^{t+N} x^{\mathrm{T}}(k) Q x(k) + \sum_{k=t}^{t+H_u-1} u^{\mathrm{T}}(k) R u(k) \right], \tag{6}$$

$$x(k+1) = Ax(k) + Bu(k) + C\mu(k), \tag{7}$$

$$x_{\min} \le x(k) \le x_{\max}. \tag{8}$$

The CCMPC approach is based on reformulating the constraints as chance constraints. Following this strategy, the constraint of (8) can be rewritten as (9) in which P denotes the probability operator and ρ is the confidence level. The advantageous of this representation known as an individual chance constraint is that different confidence levels can be assigned to different state variables considering their importance [35]. Based on the stochastic description of uncertain parameters, chance constraints could be reformulated as deterministic constraints at the price of tightening feasible region

$$P\{x_{\min} \le x(k) \le x_{\max}\} \ge \rho. \tag{9}$$

In linear dynamical systems, the distribution function of "the" uncertain parameter which may be approximated through historical data. With the assumption of a normal distribution for $\mu(k)$, the state variable in (7) will also have normal density in which its mean and standard deviation could be derived as (10) and (11), where $\bar{x}(k)$ and $\bar{\mu}(k)$ represent expected values and $\boldsymbol{P}_x(k)$ and $\boldsymbol{P}_\mu(k)$ stand for covariance matrices related to $x(k)$ and $\mu(k)$, respectively [36]

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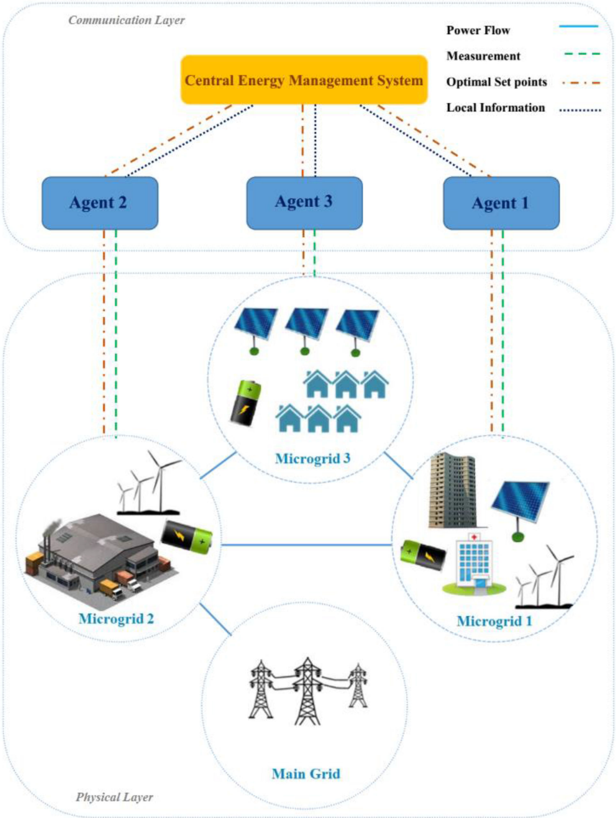

Fig. 1 *Typical regional network of microgrids*

$$\bar{x}(k+1) = A\bar{x}(k) + B\bar{u}(k) + C\bar{\mu}(k), \tag{10}$$

$$\boldsymbol{P}_x(k+1) = A\boldsymbol{P}_x(k)A^{\mathrm{T}} + C\boldsymbol{P}_\mu(k)C^{\mathrm{T}}. \tag{11}$$

Using the expected values of state and input variables, the MPC problem can now be reformulated as (12)–(15). The constraint in (9) verified if the constraints denoted by (14) and (15) could be held. In this equation, $F(\rho)$ is the cumulative distribution function of a standard normal variable with zero mean and unity variance [32]. Equations (14) and (15) are known as the deterministic equivalence of chance constraint. It is worth mentioning that there is a trade-off between the feasible region and confidence level. In case of choosing a high value for the confidence level, an infeasible optimisation problem may be reached

$$\min_{u[t:t+H_u-1]} \sum_{k=t+1}^{t+N} \bar{x}^{\mathrm{T}}(k)Q\bar{x}(k) + \sum_{k=t}^{t+H_u-1} \bar{u}^{\mathrm{T}}(k)R\bar{u}(k), \tag{12}$$

$$\bar{x}(k+1) = A\bar{x}(k) + B\bar{u}(k) + C\bar{\mu}(k), \tag{13}$$

$$\bar{x}(k) \geq x_{\min} - F^{-1}(1-\rho)\sqrt{\boldsymbol{P}_x(k)}, \tag{14}$$

$$\bar{x}(k) \leq x_{\max} + F^{-1}(1-\rho)\sqrt{\boldsymbol{P}_x(k)}. \tag{15}$$

With the assumption that $x(k)$ is an uncertain variable with unknown distribution function, using Chebyshev–Cantelli inequality, the term $F^{-1}(1-\rho)$ will be replaced by $F(\rho)$ which is calculated according to the following equation [32, 33]:

$$F(\rho) = \sqrt{(1-\rho)/\rho}. \tag{16}$$

5 Illustrative example

In this section, the operation management problem of networked-microgrids is modelled in the framework of CCMPC. The effectiveness of the proposed algorithm will be tested in a benchmark presented in Fig. 1 according to [12]. It is assumed that the test distribution system is partitioned into different microgrids, where each microgrid is an aggregation of local distributed resources, storage devices and loads under the control of a local control entity, i.e. in this network clustering approach, each single generation/consumption unit belongs to a microgrid and would be controlled by a dedicated local controller. The only constraint considered in [12] for the system is system's dynamical equation represented in (1) in which $\tilde{\mu}_i(k)$ models power imbalance in the ith microgrid and it is assumed that its value is definitely known during the optimisation horizon.

In this study, considering operational constraints the amount of SOC should comply with permissible range [$\mathrm{SOC}_{\min}$, $\mathrm{SOC}_{\max}$] according to (19). Furthermore, considering line capacities there should be some limitations on power transmitted through the network (20). Accordingly, the problem is considered in its centralised form as shown in (17) with constraints represented in (18)–(20)

$$J^* = \min J(x,u) = \min \left(\begin{array}{l} \displaystyle\sum_{k=t+1}^{t+N} \left(x(k)-\hat{x}(k)\right)^{\mathrm{T}} Q\left(x(k)-\hat{x}(k)\right) \\ + \displaystyle\sum_{k=t}^{t+H_u-1} \left(\left(u(k)-\hat{u}(k)\right)^{T} R\left(u(k)-\hat{u}(k)\right)\right) \end{array} \right). \tag{17}$$

Subject to

$$x(k+1) = Ax(k) + \frac{1}{C_{\mathrm{nom}}}(Bu(k) + \tilde{\mu}(k)), \quad x(t) \text{ is given} \quad k = t,\dots,t+N-1, \tag{18}$$

$$x_{\min} \leq x(k) \leq x_{\max}, \tag{19}$$

$$u_{\min} \leq u(k) \leq u_{\max}, \tag{20}$$

where $\boldsymbol{x}(k) = [x_1(k), x_2(k), x_3(k)]$ and $\boldsymbol{u}(k) = [u_{12}(k), u_{13}(k), u_{23}(k), u_{24}(k)]$. Moreover, $\tilde{\boldsymbol{\mu}}(k) = [\tilde{\mu}_1(k), \tilde{\mu}_2(k), \tilde{\mu}_3(k)]$ represents the stochastic imbalance power vector containing independent and identically distributed random variables.

In (18), $\tilde{\boldsymbol{\mu}}(k)$ is characterised by normal probability distribution in this study, i.e. $\tilde{\boldsymbol{\mu}}(k) \sim N(\bar{\boldsymbol{\mu}}(k), \boldsymbol{P}_\mu(k))$ in which, $\boldsymbol{P}_\mu(k)$ is the block diagonal covariance matrix of $\tilde{\boldsymbol{\mu}}(k)$.

Due to the linear dynamical equation, state variable $\boldsymbol{x}(k)$ will have a normal distribution as well. Adopting CCMPC strategy, the optimisation problem takes a new form as represented in (21)–(25). In (22), the forecasted power imbalance vector is considered as expected values of $\tilde{\boldsymbol{\mu}}(k)$. Covariance matrix $\boldsymbol{P}_x(k)$ in (23) and (24) is also calculated using (11)

$$J^* = \min [J(\bar{x},\bar{u})] = \min \left[\begin{array}{l} \displaystyle\sum_{k=t+1}^{t+N} \left(\left(\bar{x}(k)-\hat{x}(k)\right)^{\mathrm{T}} Q\left(\bar{x}(k)-\hat{x}(k)\right)\right) \\ + \displaystyle\sum_{k=t}^{t+H_u-1} \left(\left(\bar{u}(k)-\hat{u}(k)\right)^{\mathrm{T}} R\left(\bar{u}(k)-\hat{u}(k)\right)\right) \end{array} \right]. \tag{21}$$

Subject to

$$\bar{x}(k+1) = A\bar{x}(k) + \frac{1}{C_{\mathrm{nom}}}(B\bar{u}(k) + \bar{\mu}(k)), \quad x(t) \text{ is given}, \quad k = t,\dots,t+N-1, \tag{22}$$

$$\bar{x}(k) \geq x_{\min} - F^{-1}(1-\rho)\sqrt{P_x(k)}, \tag{23}$$

$$\bar{x}(k) \leq x_{\max} + F^{-1}(1-\rho)\sqrt{P_x(k)}, \tag{24}$$

$$u_{\min} \leq \bar{u}(k) \leq u_{\max}. \tag{25}$$

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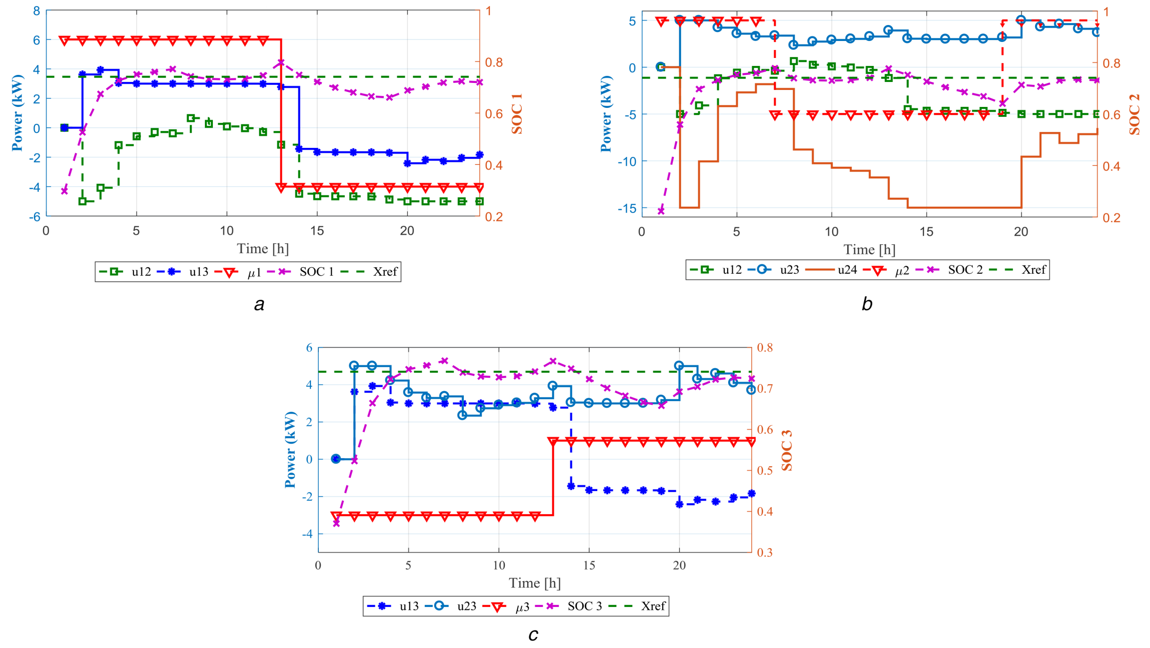

Fig. 2 *MPC-based optimal operation strategy:*
(a) Microgrid 1; ***(b)*** Microgrid 2; ***(c)*** Microgrid 3

In this study, it is assumed that the developed methodology provides the system with optimal set-points. It is also assumed that there are local controllers with fast enough responses which guarantee voltage and frequency stability while tracking operational set-points provided by higher control levels.

6 Simulation results

In this section, simulation results will be presented and discussed. Simulation data according to [12] are represented in Table 1. The battery nominal capacity in each microgrid is assumed to be equal to $C_{\text{nom}} = 27$ kWh and the reference values for the SOC is set to $\hat{x} = 20$ kWh in all three microgrids. The input constraints are shown in Table 2. The values of $x_{\min}$ and $x_{\max}$ are assumed to be equal to 20 and 80% of the battery nominal capacity, respectively. Moreover, the predicted values of imbalance power vector of microgrids 1, 2 and 3 are modelled through (26)–(28), respectively. Values of weighting matrices are set to $\boldsymbol{Q} = 5 \times I^{3\times3}$ and $\boldsymbol{R} = I^{4\times4}$ [12]. The term M.U. throughout this section stands for monetary unit. The simulations are implemented using MATLAB 2016b software

$$5\text{sign}\left(\sin\left(\frac{\pi}{12}(k+0)\right)\right) + 1, \tag{26}$$

$$5\text{sign}\left(\sin\left(\frac{\pi}{12}(k+6)\right)\right), \tag{27}$$

$$2\text{sign}\left(\sin\left(\frac{\pi}{12}(k+12)\right)\right) - 1. \tag{28}$$

Table 1 System parameters

Subsystem	a_m	b_m	x_0, kWh
microgrid 1	0.85	[−1 −1 0 0]	8
microgrid 2	0.85	[1 0 −1 −1]	6
microgrid 3	0.85	[0 1 1 0]	10

Table 2 Line data

u_{ij}	u_{12}	u_{13}	u_{23}	u_{24}
$u_{\min}$	−5	−5	−5	−15
$u_{\max}$	5	5	5	15

6.1 Case A: deterministic operation management of a regional network of microgrids

In this case, in accordance with [12], it is assumed that the predicted values of imbalance power of microgrids are accurate and there is no prediction error. The MPC approach based on certainty equivalence principle represented through (17)–(20) has been applied to the problem. By setting the length of simulation period to $T = 24$ h, following results have been achieved. The total cost in this case according to (17) is equal to $J^* = 4.423 \times 10^3$ M.U.

The optimal operation strategy of microgrids is depicted in Fig. 2. As it can be seen, those microgrids with negative imbalance power values are supplied through their neighbours with surplus power. For instance, positive values for u_{13} and u_{23} during time interval 1–6 show the power is transferred from microgrids 1 and 2 to microgrid 3. Considering power lines capacity, microgrid 2 also transmits power to microgrid 3 through microgrid 1 which is consistent with the negative sign of u_{12} during this interval. This compensation results in lower cost and accordingly higher performance throughout the system.

The negative values for u_{24} represent transferring power from the mains to microgrid 2. The normalised state of the charge of storage devices in all three microgrids are also represented in Fig. 2. As it can be seen during the simulation period, a good tracking performance has been achieved in all subsystems. Moreover, according to the results, all control variables comply with their permissible operating range.

6.2 Case B: stochastic operation management of a regional network of microgrids

In this case, the operation management problem of networked-microgrids is modelled as a stochastic optimisation problem in the framework of CCMPC (21)–(25). The electric power supply–demand imbalance in each subsystem is considered as a stochastic variable with normal density distribution function [4, 5], where forecasted values are considered as its mean value and the standard deviation is set to 15% of the expected value. Although standard deviation in most studies is set to a fixed and independent value, in this study, according to [10], it has been set as a percentage of the predicted values which has more consistency with reality. Simulation results are depicted in Fig. 3. As it can be seen, the proposed strategy results in desirable tracking performance. Moreover, power flow limitations are satisfied during the examined

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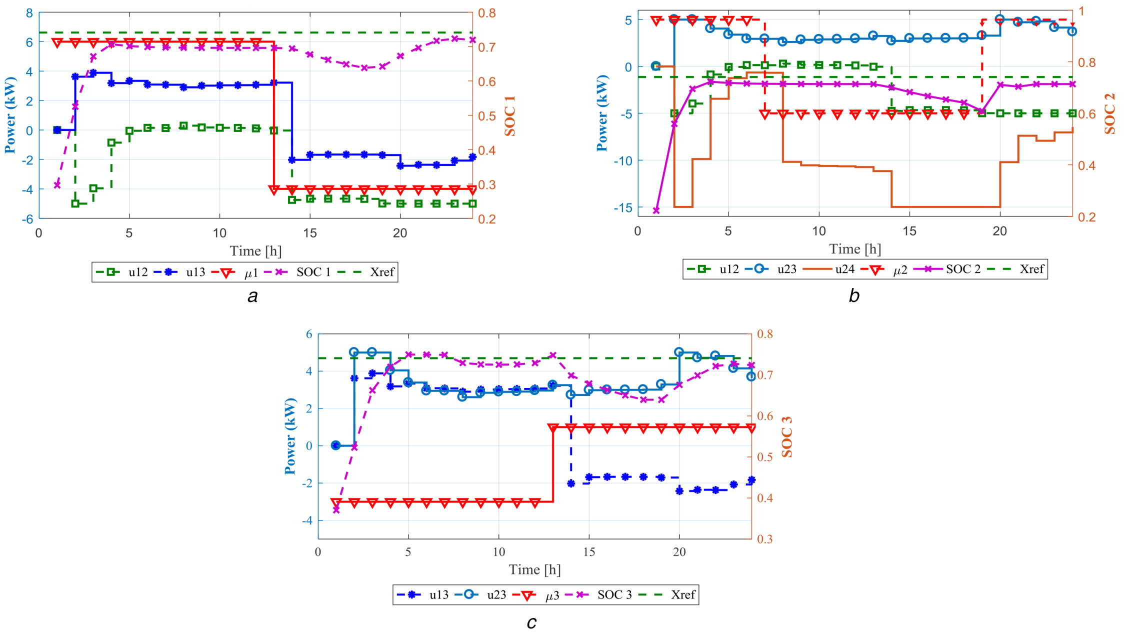

Fig. 3 *CCMPC-based optimal operation strategy:*
(a) Microgrid 1; ***(b)*** Microgrid 2; ***(c)*** Microgrid 3

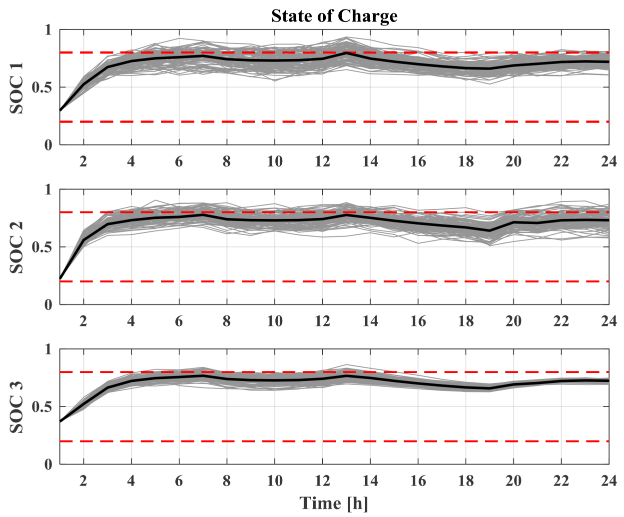

Fig. 4 *Normalised state of the charge in 100 scenarios with random profiles (case A)*

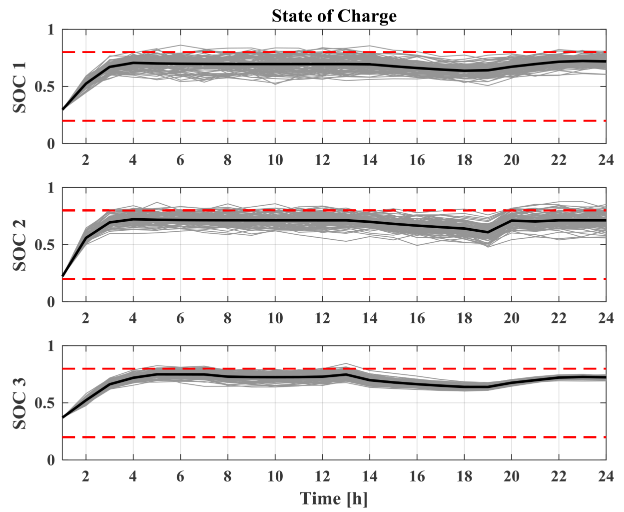

Fig. 5 *Normalised state of the charge in 100 scenarios with random profiles (case B)*

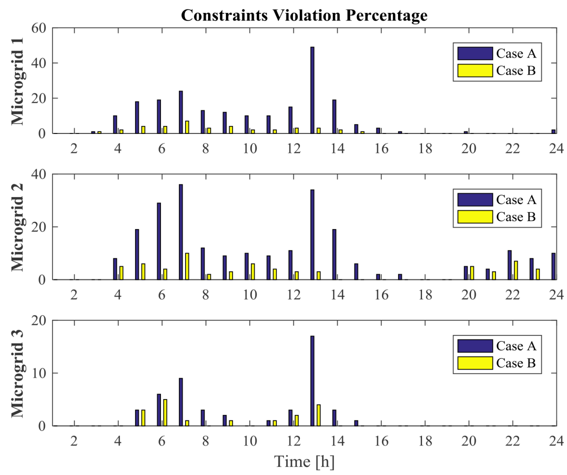

Fig. 6 *Comparison of constraint violation percentage for cases A and B*

horizon. However, the amount of optimal cost, in this case, is equal to $J^* = 4.708 \times 10^3$ M.U. which is relatively larger than the operation cost obtained in case A.

6.3 Robustness analysis

In this section, the robustness characteristics of both deterministic and stochastic strategies are verified. To model uncertain behaviour of RESs output power and variability of load, 100 random power mismatch profiles are generated through Monte Carlo algorithm. The obtained results of the deterministic case are depicted in Fig. 4 whereas Fig. 5 shows the results of the stochastic case. The black thick line in both figures is related to the solution obtained in cases A and B. As was expected, the control strategy obtained under the deterministic strategy is highly sensitive to the accuracy of predicted data and slight changes in power mismatch vector would result in state's constraint violation which makes the strategy inefficient. In contrast, when applying the control strategy obtained in the stochastic case to the same 100 random imbalance power profiles, only a few number of variables violate their constraints. So, the strategy obtained under the chance-constrained strategy shows better performance in the presence of uncertainty. Fig. 6 depicts the percentage of constraint violation in each time step under two strategies. As can be seen, for the solution based on the deterministic strategy the violation percentage is substantially higher than the robust solution obtained in case B which again

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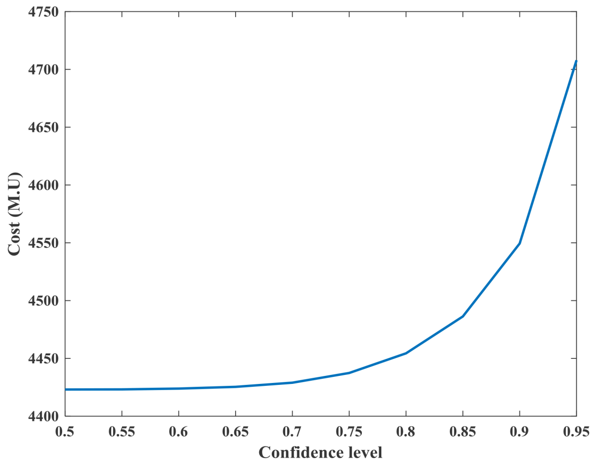

Fig. 7 *Cost versus confidence level*

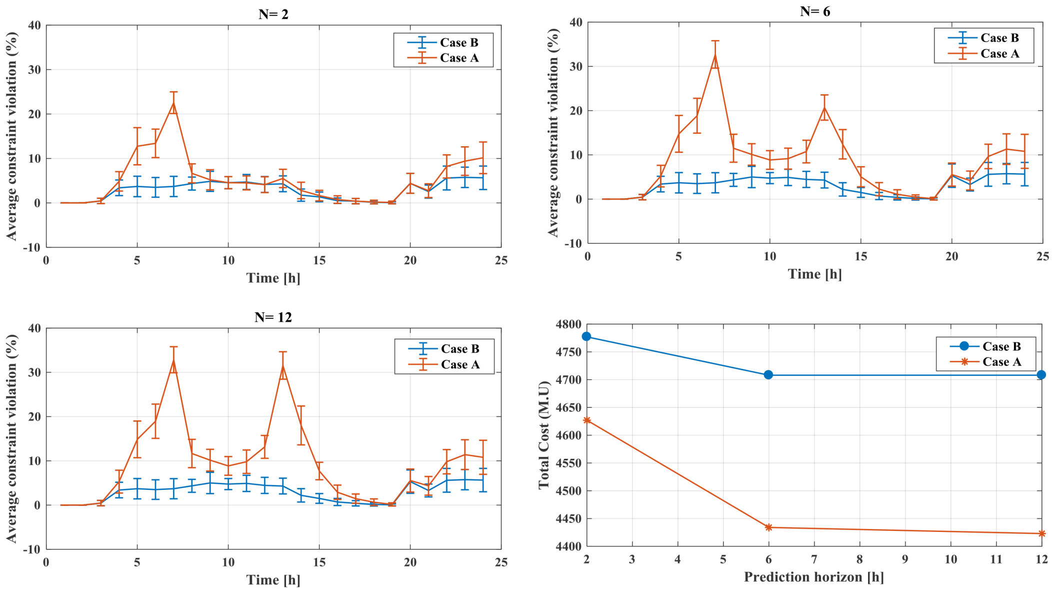

Fig. 8 *Prediction horizon effects on constraints' violation percentage and cost*

confirms the superiority of the stochastic approach. However, it should be noted that this robustness has been achieved at a higher operating cost. It is worth mentioning that this is an advantage of this approach which provides the decision maker with the opportunity of making a satisfactory compromise between reliability and profitability of the solution. For more clarifying the issue, the variation of cost function versus the confidence level has been depicted in Fig. 7. The results clearly highlight the trade-off between reliability and profitability of the stochastic solution. As the confidence level increases, higher values of operating cost are imposed.

6.4 Varying prediction horizon

In general, a longer prediction horizon is preferred as it provides the decision maker with the opportunity to better see the consequences of its decisions and hence results in better performance. However, a larger prediction horizon requires more computational time and in case there is uncertainty in prediction model may result in unacceptable errors [37].

In this section, in order to analyse the effects of prediction horizon on the performance of the proposed methodology, several simulations with different prediction horizons are performed. For $N \in \{2, 6, 12\}$, the average percentage values of constraints violations as well as related standard deviations for microgrid 2 are shown through error bars plotted in Fig. 8. Since further increasing of prediction horizon has a minor impact on system performance, it is not considered in our study. From the results, it can be seen that the average number of constraint violations in case A is substantially higher than case B. Moreover, in both cases total cost decreases as prediction horizon increases while constraints' violation percentage has an ascending trend. In conclusion, if controller parameters are not well tuned, microgrid's performance may be considerably affected by the costs incurred by constraints' violation because of uncertainty in the prediction model.

7 Conclusion

In this study, in order to optimise the operation of a regional network of microgrids based on a control oriented approach, CCMPC is adopted as a high-level controller to provide the local controllers with optimal set-points considering system operational constraints. Accounting for RESs production and demand uncertainty, this approach includes stochastic constraints in its formulation. Based on the stochastic characteristics of uncertainty, the deterministic equivalence of constraints has been derived. The results show through adopting CCMPC strategy due to the explicitly modelling of uncertainty, the reliability of the system operation will be considerably improved. Moreover, this approach provides the operator with the opportunity of arriving at a satisfactory compromise between reliability and profitability. The results of this study highlight the idea that utilising CCMPC in optimal operation management problem of multi-microgrids may be a promising approach to be implemented in the next generation of smart grids. Investigating performance of distributed CCMPC and implementing it in a large-scale multi-microgrid operation management problem is under investigation by the authors as a future work.

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