A Stochastic MPC based Approach to Integrated Energy Management in Microgrids

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Abstract: In this paper, a stochastic model predictive control (SMPC) approach to integrated energy (load and generation) management is proposed for a microgrid with the penetration of renewable energy sources (RES). The considered microgrid consists of RES, controllable generators (CGs), energy storages and various loads (e.g., curtailable loads, shiftable loads). Firstly, the forecasting uncertainties of load demand, wind and photovoltaic generation in the microgrid as well as the electricity prices are represented by typical scenarios reduced from a large number of primary scenarios via a two-stage scenario reduction technique. Secondly, a finite horizon stochastic mixed integer quadratic programming model is developed to minimize the microgrid operation cost and to reduce the spinning reserve based on the selected typical scenarios. Finally, A SMPC based control framework is proposed to take into account newly updated information to reduce the negative impacts introduced by forecast uncertainties. Through a comprehensive comparison study, simulation results show that our proposed SMPC method outperforms other state of the art approaches that it could achieve the lowest operation cost.

Keywords: Microgrid; model predictive control; stochastic programming; energy storage; distributed generators.

Nomenclature

Indices	
t	*time index*
$\mathcal{S}_{po}$, $\mathcal{S}_{pr}$	*Set of net load and electricity price scenarios respectively*
s_{po}, s_{pr}	*net load and electricity price scenario index*
s	*index of* $\mathcal{S}_{po} \times \mathcal{S}_{pr}$, *in the form of (*$s_{po}$, s_{pr}*)*
sh	*shiftable load index*
Forecast values	
$P_{solar}^{pre}(t)$ $P_{wind}^{pre}(t)$	*forecasted PV/ wind power production at time* t *(kW)*
$P^{pre}(t)$	*forecasted net load at time* t *(kW)*
$P_{crit}^{pre}(t)$ $P_{curt}^{pre}(t)$	*forecasted critical/ curtailable load demand at time* t *(kW)*
$Pr^{pre}(t)$	*forecasted electricity prices at time* t *(€)*
Parameters	
S_{po} S_{pr}	*Total number of selected net load and electricity price scenarios*
N_{sh}	*number of shiftable loads*
T	*Control time horizon*
$\pi^{s_{po}}, \pi^{s_{pr}}$	*probability of net load scenario* s_{po} *and electricity price scenario* s_{pr}
a_1, a_2, a_3	*cost coefficients of the diesel generator (€/(kWh)², €/kWh, €)*
b_1, b_2	*cost coefficients of the fuel cell (€/kWh, €)*
Δt	*duration of each time interval*
$Pr^s(t)$	*the base electricity price in time* t *of scenario* s *(€)*
$\rho_{in}(t)$ $\rho_{out}(t)$	*the purchasing and selling coefficients at time* t
$Pr_{in}^s(t)$ $Pr_{out}^s(t)$	*Purchasing/selling electricity price of the microgrid in time* t *of scenario* s *(€/kWh, €/kWh)*
P_{gridin}^{max} P_{gridin}^{min}	*Minimum/ maximum power can be purchased from the external grid (kW)*
$P_{gridout}^{max}$ $P_{gridout}^{min}$	*Minimum/ maximum power can be sold back to the external grid (kW)*
$Resu(t)$ $Resd(t)$	*Up/down spinning reserve ratio in time interval* t *(%)*
C_E C_E^{ctd} C_E^{dtc}	*maintenance cost, charge-to-discharge, and discharge-to-charge switch cost of energy storage device (€/kWh, €, €)*
C_D^{start} C_D^{down} C_D^{OM}	*start-up cost, shut-down cost, maintenance cost of diesel generator (€, €, €/kWh)*
C_{FC}^{start} C_{FC}^{down} C_{FC}^{OM}	*start-up cost, shut-down cost, maintenance cost of fuel cell (€, €, €/kWh)*
P_D^{max} P_D^{min}	*minimum, maximum power output of the diesel generator (kW)*
P_{FC}^{max} P_{FC}^{min}	*minimum, maximum power level of the fuel cell (kW)*
T_D^{minup} T_D^{mindn}	*minimum up and down time of the diesel generator unit (h)*
T_{FC}^{minup} T_{FC}^{mindn}	*minimum up and down time of the fuel cell generator (h)*
$P_{wind}^s(t)$ $P_{solar}^s(t)$	*Actual output of wind, PV generators in time interval* t *of scenario* s *(kW, kW)*
P_{wind}^{max} P_{solar}^{max}	*capacity of the wind, PV generators (kW)*
$P_{curt}^s(t)$ $P_{crit}^s(t)$	*Power demand of the curtailable, critical load in time interval* t *of scenario* s *(kW)*
P_{curt}^{max} P_{crit}^{max}	*maximum power of the curtailable load, the critical load (kW)*
β_{curt}^{max}	*Maximum curtailment ratio of the curtailable load (%)*
P_{sh}	*rated power level of the sh-th shiftable load (kW)*
T_{sh}	*time periods required to complete tasks of sh -th shiftable load*
E_{ESS}^{min} E_{ESS}^{max}	*Minimum/ maximum energy level of the energy storage (kWh)*
P_{Ed}^{min} P_{Ed}^{max}	*Minimum/ maximum discharging power level of the energy storage (kW)*
P_{Ec}^{min} P_{Ec}^{max}	*Minimum/ maximum charging power level of the energy storage (kW)*
η_{Ec} η_{Ed}	*Charging/ discharging efficiencies of the energy storage (%)*
φ_{ESS}	*self-loss of energy storage (kW)*
Decision variables	
$p_{gridin}^s(t)$ $p_{gridout}^s(t)$	*power purchased from, sold back to the external grid at time* t *in scenario* s *(kW)*
$p_{Ec}^s(t)$ $p_{Ed}^s(t)$ $e_{ESS}^s(t)$	*charging power, discharging power and energy level of the energy storage at time* t *in scenario* s *(kW, kW, kWh)*

p_D^s, p_{FC}^s	*power output of the diesel generator and the fuel cell at time* t *in scenario* s *respectively (kW)*
$\beta_{curt}^s(t)$	*curtailment ratio of the* $curt$*-th curtailable load at time* t *in scenario* s
t_{sh}^{st}	*start time of the* sh*-th shiftable load (h)*
$\delta_{Ec}^s(t)$ $\delta_{Ed}^s(t)$	*charging status, discharging status of the energy storage at time* t *in scenario* s *(binary)*
$\delta_{Ectd}^s(t)$ $\delta_{Edtc}^s(t)$	*charge-to-discharge switch status and discharge-to-charge switch status of the energy storage at time* t *in scenario* s *(binary)*
$\delta_D^s(t)$	*running status of the diesel generator at time* t *in scenario* s *(binary)*
$\delta_{Dst}^s(t)$ $\delta_{Dsh}^s(t)$	*Start-up and shut-down status of diesel generator at time* t *in scenario* s *(binary)*
$\delta_{FC}^s(t)$	*running status of the fuel cell at time* t *in scenario* s *(binary)*
$\delta_{Fst}^s(t)$ $\delta_{Fsh}^s(t)$	*Start-up and shut down status of the fuel cell at time* t *in scenario* s *(binary)*
$\delta_{gridin}^s(t)$ $\delta_{gridout}^s(t)$	*power purchasing, selling status of the microgrid at time* t *in scenario* s *(binary)*
$\delta_{sh}^s(t)$	*operation status of the* sh*-th shiftable load at time* t *in scenario* s *(binary)*

1. Introduction

With the increasing electricity demand (e.g. it has risen by more than 3% per year since 1980 (Luderer et al., 2017) and the significant increase is expected in the coming years due to the electrical vehicles), the requirements to mitigate global climate change, and the needs to reduce transmission losses, distributed energy resources (DERs) have attracted growing attentions recently (Maleki, Rosen, & Pourfayaz, 2017). Typically, DERs include non-dispatchable renewable energy sources (RES) (e.g., wind, solar), energy storages (e.g., battery energy storage, super capacitor), and controllable generators (CGs) (Lasseter, 2002). Due to its intermittent and variable nature, the integration of RES will increase the uncertainties in power systems. As indicated in (Atwa & El-Saadany, 2010), when RES penetration reaches sufficiently high levels (that is, about 20%–30% of total generation), it can begin to cause noticeable, negative effects on the entire grid.

Microgrids, which are low voltage intelligent distribution networks, have attracted enormous attentions from both academia and industry as an effective method to accommodate DERs and to reduce the negative effects of RES on the entire grid via various optimal energy management schemes (D. Zhang, Shah, & Papageorgiou, 2013). Although there are many different studies on optimal energy management in microgrids and buildings, they can be approximately categorized into deterministic and stochastic methods (Reynolds, Rezgui, & Hippolyte, 2017).

For deterministic methods, RES generation and load demands as well as electricity prices are assumed to be either perfectly forecasted or represented by their point forecasts and are treated as known parameters in the energy management model. For instance, an open-loop based smart energy management system is proposed in (Chen, Duan, Cai, Liu, & Hu, 2011) to optimize the operation of a microgrid. A closed-loop based model predictive control (MPC) approach with feedback mechanism to efficiently operate a microgrid is proposed in (Parisio, Rikos, & Glielmo, 2014) and (Kriett & Salani, 2012) where the microgrid optimal operation problem is modelled as a mixed integer linear programming (MILP) problem. In (Khakimova et al., 2017), a hybrid MPC scheme is proposed to optimally manage the thermal and electrical subsystems of a small-size residential building. In (Sharma et al., 2016), a centralized energy management system (CEMS) framework based on MPC is proposed for optimal off-grid operations of a residential building. In (Y. Zhang, Meng, & Wang, 2017), a comprehensive MPC based energy management system is proposed for optimal operations in islanded microgrids. It is worth mentioning that the above closed-loop MPC based approaches, which always utilise the most recent updated forecast and system information, can help reduce the negative impacts caused by RES to some extent. However, such type of methods essentially operates based on an expected point forecast value, which still possess great uncertainties. As a result, dedicated methods that could directly deal with forecast uncertainties are needed to manage the uncertainties more efficiently.

On the other hand, stochastic approaches have been adopted to consider the forecasting uncertainties explicitly. For instance, a scenario-based stochastic approach is proposed in (Mohammadi, Soleymani, & Mozafari, 2014) for operation management of a microgrid including DERs. In (Su, Wang, & Roh, 2014), a two-stage stochastic microgrid energy scheduling model is developed which consists of a day-ahead microgrid energy scheduling stage and a real-time microgrid operation stage. In (Soares, Fotouhi Ghazvini, Borges, & Vale, 2017), a stochastic model is proposed for energy resources management by considering demand response in the context of smart grids. In (Maurovich-Horvat, Rocha, & Siddiqui, 2016), a multi-stage stochastic optimisation model is proposed to the optimal operations of a combined heat and power under uncertainty and risk aversion. In (Marzband, Alavi, Ghazimirsaeid, Uppal, & Fernando, 2017), an optimal energy management system based on stochastic approach for a home microgrid with responsive load and energy storage is proposed whereas the uncertainties of the load demand and renewable energy outputs are accounted for by a stochastic approach. In (Schulze & McKinnon, 2016), a stochastic programming method to stochastic unit commitment problem is proposed and evaluated on the British 2020 power system. In (Roustai, Rayati, Sheikhi, & Ranjbar, 2018), a stochastic model for scenario-based optimization of smart energy hub operations is proposed with considering conditional-value-at-risk. The above stochastic approaches provide a systemic way to capture the stochastic processes in the system and represent forecast uncertainties using scenarios. However, it should be noted that the above stochastic methods are operated based on the open-loop control approach and therefore do not exhibit the same capability of utilising the most recent updated system and forecast information as the closed-loop MPC based control approach.

More recently, stochastic model predictive control (SMPC), which combines advantages of both stochastic programming and model predictive control (MPC) with the aim to reduce negative impacts of forecasting uncertainties and to improve the system control performance, has been applied to power system operations and microgrids energy management. For instance, a stochastic model predictive control approach is proposed in (Parisio, Rikos, & Glielmo, 2016) for economic/environmental operation management of microgrids. An economic dispatch problem of a hybrid energy system which consists of CGs and energy storages is tackled via a decomposed SMPC approach in (Zhu & Hug, 2014). In (Olivares, Lara, Canizares, & Kazerani, 2015), a stochastic-predictive energy management system is proposed for isolated microgrids energy management. A SMPC based energy management model for a domestic microgrid is proposed in (Bruni, Cordiner, Mulone, Sinisi, & Spagnolo, 2016). In (Yoshida, Yoshikawa, Fujimoto, Amano, & Hayashi, 2018), a stochastic receding horizon control scheme is proposed for a home EMS with demand forecasting uncertainties. In

(Vasilj, Gros, Jakus, & Zanon, 2017), a combined day-ahead scheduling and real-time economic operation model based on stochastic programming and MPC is proposed to control the CHP-based Microgrid with smart buildings.

Motivated by the above literature search and comparative analysis, in this paper we propose a stochastic model predictive control (SMPC) based two-stage optimal scheduling strategy to integrated energy management in microgrids. Different from the above listed studies, in this paper we propose an *integrated demand-side and supply-side energy management* scheme in the microgrid by considering demand-side and generation-side uncertainties simultaneously. At the demand-side, we categorize the demands into different load types based on their characteristics. For controllable and shiftable loads, an optimal deterministic demand response strategy is applied. For critical and curtailable loads, the demand uncertainties are captured by the proposed scenario based stochastic model. The RES generation, load demand and electricity price forecasts are considered as uncertain parameters in the optimization model and represented by primary scenarios generated by Monte Carlo simulation methods (Wu, Shahidehpour, & Li, 2007). Furthermore, a two-stage scenario reduction method is proposed in this paper to select typical scenarios from the primary scenarios to alleviate the model computational burden. The control inputs of the model at each time period are obtained by solving a stochastic energy management problem using mixed integer quadratic programming (MIQP) method. The main contributions of this study are summarized as follow:

- Firstly, a two-stage scenario reduction method based on simultaneous backward scenario reduction (Dupačová, J., Gröwe-Kuska, N., Römisch, 2003) is proposed to select typical scenarios from primary scenarios to reduce the model computational burden. Furthermore, an integrated stochastic energy management model, which simultaneously considers unit commitment for generators and demand side management for demand loads / energy storage systems, is proposed to minimize the microgrid operation cost and is formulated as a scenario-based mixed integer quadratic programming problem (MIQP).

- A SMPC based two-stage microgrid control framework, which includes a power prescheduling stage and a real-time control stage, is proposed. The two stages are implemented within a receding horizon control framework to take into account the newly updated system and forecast information.
- A comprehensive simulation study is implemented in this paper to compare the proposed SMPC approach with various state-of-the-art approaches to evaluate its performance thoroughly.

The rest of this paper is organized as follows. Section II presents the system model of our proposed SMPC method. Simulation results are presented in Section III and the paper is concluded in Section IV.

2. System Modelling

In this paper, a grid-connected microgrid which consists of components such as DERs (e.g., micro-turbines, fuel cells, wind generators, PV generators and battery energy storage system), and various loads (e.g., curtailable loads such as heating, shiftable loads such as washing machine and critical loads such as lighting) is considered, which is illustrated in Fig. 1. The energy management system (EMS) controls various components in the microgrid and power interactions with the external grid.

The main difficulty in solving the microgrid energy management problem is how to deal with the forecast uncertainties of RES, load demand and electricity price such that the problem could be numerically tractable. A practical way to describe the stochastic features and the forecast uncertainties is to approximate their stochastic processes using scenarios. In the following, we firstly discuss how to represent forecast uncertainties using scenarios and then propose a two-stage scenarios reduction method to select representative scenarios from the primary scenarios pool. Secondly, we formulate the stochastic microgrid energy management problem as a mixed integer quadratic programming based on selected typical scenarios. Finally, the proposed SMPC microgrid control framework is presented.

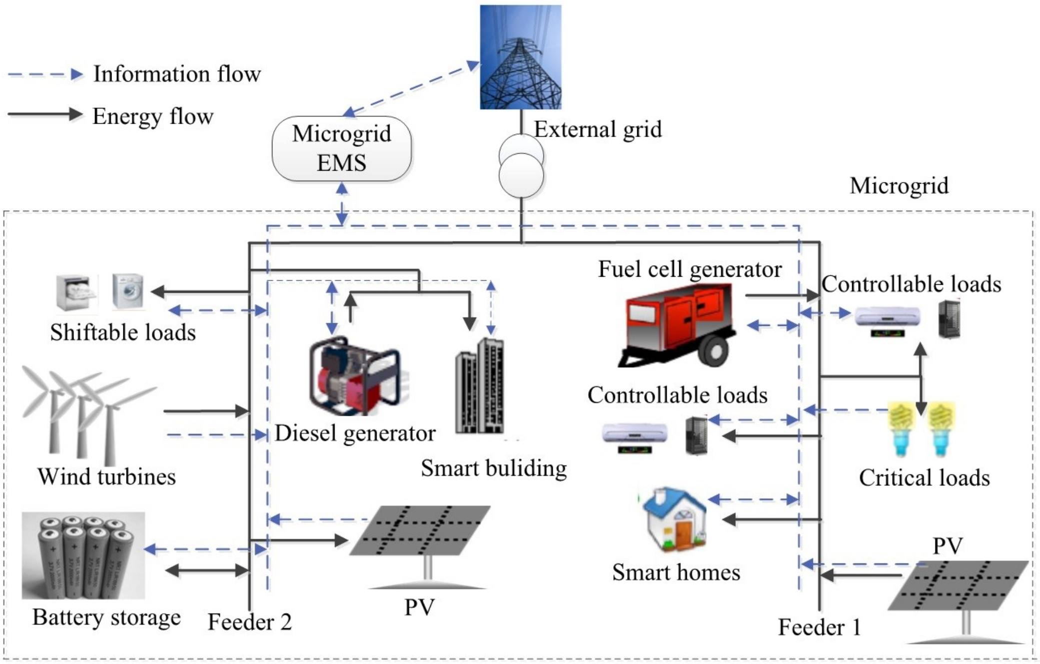


Fig.1 The microgrid configuration considered in this paper.

2.1 Scenarios Generation and Reduction

In this paper, we consider forecasting uncertainties of load, wind, PV and electricity prices and the forecast errors of load demand, wind production, PV generation and electricity price in each time period t follow independent Gaussian distribution with a mean of zero and a standard deviation of $\sigma_{load}^{pre}(t)$, $\sigma_{wind}^{pre}(t)$, $\sigma_{solar}^{pre}(t)$, and $\sigma^{S_{pr}}(t)$ respectively. By following (Doherty & O'Malley, 2005), we define the net load of the microgrid as the difference between the load and wind/PV generation. As a result, the net load follows the Gaussian distribution with a mean of zero and the standard deviation of $\sigma^{S_{po}}(t) = \sqrt{\left(\sigma_{load}^{pre}(t)\right)^2 + \left(\sigma_{wind}^{pre}(t)\right)^2 + \left(\sigma_{solar}^{pre}(t)\right)^2}$. In order to approximate the forecast uncertainties, a large number of primary scenarios are usually needing to be generated from the forecasting error distributions. In this paper, the Lattice Monte Carlo Simulation method (LMCS) (Wu et al., 2007) is adopted to generate primary scenarios for the net load and electricity price independently.

Due to the number of primary scenarios is huge, it is very computational expensive to solve the stochastic problem in the current form. On the other hand, by using too few or unrepresentative scenarios, it could not approximate the uncertainties well. As a result, a scenario reduction technique is usually used to improve the computational tractability while preserving key characteristics of the original scenario set. However, traditional scenario reduction methods such as the simultaneous backward scenario reduction (SBSR) method (Dupačová, J., Gröwe-Kuska, N., Römisch, 2003) have a computation time growing rapidly with the number of scenarios, and therefore not computational efficient in dealing with a large number of primary scenarios. In this paper, we propose a two-stage scenario reduction framework where the simultaneous backward scenario reduction method is applied separately at each stage to improve the scenario reduction time efficiency. The main idea of the two-stage scenario reduction approach adopts the divide and conquer concept. At the first stage, we divide the set of primary scenarios into a number of smaller disjoint sets (the union of these smaller sets equals to the original primary scenarios set) randomly, and then apply the simultaneous backward scenario reduction separately to each of such smaller set, where the selected scenarios from each smaller set are saved. At the second stage, we gather the selected scenarios from each smaller set together, and then apply the simultaneous backward scenario reduction to get the final targeted scenarios, which will then be used in the microgrid energy management model.

The proposed two-stage scenario reduction method is summarized in Algorithm 1 where the number of targeted typical scenarios mentioned in Steps 1 and 2 are determined using stopping rules proposed in (Siahkali & Vakilian, 2010).

Algorithm 1 Two-stage Scenario Reduction Framework

Input: The number of N_{sce} primary scenarios

Output: The number of N_{SE} targeted scenarios

1. Generate an initial scenario set containing the number of N_{sce} primary scenarios using LMCS; denote the targeted typical scenarios as N_{SE}.

2. Divide N_{sce} primary scenarios into N_S subsets randomly; denote the number of selected typical scenarios from each subset as $N_{SE_n}; n = 1, \ldots, N_S$. In addition, the following constraint $N_{SE} \leq N_{SE_n} \leq N_{sce}/N_S$ should be imposed to improve the diversity of solution candidates from each subset and to prevent premature convergence. To be more specific, the number of selected scenarios from each subset N_{SE_n} should be no less than N_{SE} (to guarantee that there is a sufficiently large number of scenarios for the second stage operation). The upper bound constraint indicates that the number of selected scenarios from each subset is constrained by the number of total scenarios in that subset.
3. **First stage scenario reduction**: apply the SBSR by removing the most similar scenarios in each subset until N_{SE_n} scenarios are selected/ left in each subset.
4. **Second stage scenario reduction:** group the selected scenarios from each smaller set in the first stage together, and apply SBSR to these scenarios (with an amount of $N_{SE_n} \times N_S$ scenarios) by removing the most similar scenarios till the final targeted N_{SE} scenarios are selected/left.

2.2 Stochastic Integrated Microgrid Energy Management

The objective of the microgrid EMS is to minimize the expected microgrid operation cost over the control horizon based on selected typical scenarios, which is formulated as a MIQP problem. The key decision variables include unit commitment variables such as power output/operation status of CGs, demand side management variables such as energy storage charging/discharging schedules, power curtailment ratio of curtailable loads and start running time of shiftable loads, and power interaction variables such as power purchased from/sold back to the external grid.

2.2.1 *Objective function*

The objective function is formulated as Eq. (1) where the forecasting errors of net load demand and price are represented by S_{po} and S_{pr} typical scenarios respectively.

$$\min \sum_{Spr=1}^{Spr} \sum_{Spo=1}^{Spo} \pi^{Spo}\, \pi^{Spr} \sum_{t=1}^{T} \Big\{ \; p_{gridin}^{Spo,Spr}(t) Pr_{in}^{Spr}(t)\Delta t - p_{gridout}^{Spo,Spr}(t) Pr_{out}^{Spr}(t)\Delta t \; + \Big[\Big(p_{Ec}^{Spo,Spr}(t) + p_{Ed}^{Spo,Spr}(t)\Big) C_E \Delta t + C_E^{ctd}\delta_{Ectd}^{Spo,Spr}(t) + C_E^{dtc}\delta_{Edtc}^{Spo,Spr}(t)\Big] + \rho_{curt}(t)\beta_{curt}^{Spo,Spr}(t) P_{curt}^{Spo}(t)\Delta t \; + \Big[\Big(a_1\big(P_D^{Spo,Spr}\big)^2 + a_2 P_D^{Spo,Spr} + a_3\delta_D^{Spo,Spr}(t)\Big)\Delta t \; + C_D^{start}\delta_{Dst}^{Spo,Spr} + C_D^{down}\delta_{Dsh}^{Spo,Spr} + C_D^{OM}\delta_D^{Spo,Spr}(t)\Delta t\Big] + \Big[\Big(b_1 P_{FC}^{Spo,Spr} + b_2\delta_{FC}^{Spo,Spr}(t)\Big)\Delta t \; C_{FC}^{start}\delta_{FCst}^{Spo,Spr} + \; C_{FC}^{down}\delta_{FCsh}^{Spo,Spr} + C_{FC}^{OM}\delta_{FC}^{Spo,Spr}(t)\Delta t\Big]\Big\} \qquad (1)$$

In Eq. (1), the first term is the electricity purchasing cost from the external grid while the second term is the electricity selling revenue to the external grid. The third term is the energy storage system running cost, which consists of the maintenance cost, the charge-to-discharge, and discharge-to-charge switch cost while the fourth term is the curtailment penalty cost of curtailable loads to reflect discomforts caused to customers. The fifth term represents the operation cost of diesel generator, which consists of fuel cost, the start-up and shutdown costs, while the last term is the fuel cell operation cost including fuel cost, the start-up and the shutdown costs. Δt represents the length of each time interval.

To ensure an effective and robust operations of the microgrid, the following equality and inequality constraints must be met, which can be categorized into system level constraints, generation side constraints, demand side constraints, and spinning reserve constraints.

2.2.2 *System Level Constraints*

Power balance constraints

The supplied power must satisfy the total load demand in each time period at each scenario so as to ensure a reliability and safety operation of microgrid, which is represented as Eq. (2).

$$p_D^{Spo,Spr}(t) + p_{FC}^{Spo,Spr}(t) + p_{Ed}^{Spo,Spr}(t) + p_{gridin}^{Spo,Spr}(t) + P_{wind}^{Spo}(t) + P_{solar}^{Spo}(t) = \Big(1 - \beta_{curt}^{Spo,Spr}(t)\Big) P_{curt}^{Spo}(t) + P_{crit}^{Spo}(t) + p_{Ec}^{Spo,Spr}(t) + p_{gridout}^{Spo,Spr}(t) + \sum_{sh=1}^{N_{sh}} \delta_{sh}^{Spo,Spr}(t) P_{sh}(t) \qquad (2)$$

The left-hand side of Eq. (2) represents the power supplied in the microgrid in period t, and the right-hand side of Eq. (2) is the power demanded in the microgrid during period t.

Power interaction constraints

The power exchange between the microgrid and external grid is modelled as (3).

$$P_{gridin}^{min}\delta_{gridin}^{s_{po},s_{pr}}(t) \le p_{gridin}^{s_{po},s_{pr}}(t) \le P_{gridin}^{max}\delta_{gridin}^{s_{po},s_{pr}}(t) \quad (3a)$$

$$P_{gridout}^{min}\delta_{gridout}^{s_{po},s_{pr}}(t) \le p_{gridout}^{s_{po},s_{pr}}(t) \le P_{gridout}^{max}\delta_{gridout}^{s_{po},s_{pr}}(t) \quad (3b)$$

$$\delta_{gridout}^{s_{po},s_{pr}}(t) + \delta_{gridin}^{s_{po},s_{pr}}(t) \le 1 \quad (3c)$$

In the above, (3a) and (3b) represent the power purchasing and selling limit. Eq. (3c) is adopted to avoid simultaneous power sell/purchasing behaviours. Note that different from the model method adopted in existing literatures (e.g., (Liu, Guo, Zhang, Wang, & Zhang, 2016)) that uses only one decision variable to represent the power exchange decision with the sign indicating the direction of power exchanges, we adopt two separate variables to model the power selling/purchasing actions separately. This modelling method can avoid introducing many extra variables and mixed integer constraints as experienced in (Liu et al., 2016), which is more straightforward and has a lower model complexity. For a grid-connected microgrid, it usually determines the amounts of energy exchanged with the external grid according to electricity prices and net load situations. Furthermore, in order to encourage the use of local RES in the microgrid and reduce external interferences to the microgrid [8], purchasing and selling prices for the microgrid at each time period are set to be different as below.

$$Pr_{in}^{s_{po},s_{pr}}(t) = \rho_{buy}(t)Pr^{s_{po},s_{pr}}(t) \quad t \in [1,2,\cdots,T]$$

$$Pr_{out}^{s_{po},s_{pr}}(t) = \rho_{sell}(t)Pr^{s_{po},s_{pr}} \quad t \in [1,2,\cdots,T]$$

where $\rho_{buy}(t) \ge 1$ and $0 \le \rho_{sell}(t) \le 1$.

2.2.3 Generation-side constraints

RES generation constraints

RES generation constraints are imposed on wind and PV generators to ensure that RES power outputs are not greater than their rated power capacity at each time period for each scenario, which are shown as Eqs. (4a) and (4b).

$$0 \leq P_{wind}^{S_{po}}(t) \leq P_{wind}^{max} \quad (4a)$$

$$0 \leq P_{solar}^{S_{po}}(t) \leq P_{solar}^{max} \quad (4b)$$

Controllable generators operation limits

The power output from CGs (i.e. diesel generator and fuel cell) should not exceed its designed capacity, and the power varying in two consecutive time periods should not exceed its designed ramp up/down limits. In addition, minimum up/down time limits should be considered. In this paper, we propose a generic model for CGs, which applies to both diesel generator and fuel cell (i.e. the subscript 'CG' in Eq. (5) can be replaced with 'D' and 'FC' respectively).

$$P_{CG}^{min}\delta_{CG}^{S_{po},S_{pr}}(t) \leq p_{CG}^{S_{po},S_{pr}}(t) \leq P_{CG}^{max}\delta_{CG}^{S_{po},S_{pr}}(t) \quad (5a)$$

$$-\Delta P_{CG} \leq p_{CG}^{S_{po},S_{pr}}(t) - p_{CG}^{S_{po},S_{pr}}(t-1) \leq \Delta P_{CG};\ t \in [2,T] \quad (5b)$$

$$\begin{aligned}&\delta_{CG}^{S_{po},S_{pr}}(t) - \delta_{CG}^{S_{po},S_{pr}}(t-1) \leq \delta_{CG}^{S}\left(\tau_{CG_1}^{S_{po},S_{pr}}\right);\\ &\tau_{CG_1}^{S_{po},S_{pr}} \in \left[t, min\left(t + T_{CG}^{minup} - 1, T\right)\right],\ t \geq 2\end{aligned} \quad (5c)$$

$$\begin{aligned}&\delta_{CG}^{S_{po},S_{pr}}(t-1) - \delta_{CG}^{S_{po},S_{pr}}(t) \leq 1 - \delta_{CG}^{S_{po},S_{pr}}\left(\tau_{CG_2}^{S_{po},S_{pr}}\right);\\ &t \in [2,T],\ \tau_{CG_2}^{S_{po},S_{pr}} \in \left[t, min\left(t + T_{CG}^{mindn} - 1, T\right)\right]\end{aligned} \quad (5d)$$

$$\delta_{CGst}^{S_{po},S_{pr}}(t) \geq \delta_{CG}^{S_{po},S_{pr}}(t) - \delta_{CG}^{S_{po},S_{pr}}(t-1)\ \ t \in [2,T] \quad (5e)$$

$$\delta_{CGsd}^{S_{po},S_{pr}}(t) \leq \delta_{CG}^{S_{po},S_{pr}}(t-1) - \delta_{CG}^{S_{po},S_{pr}}(t);\ t \in [2,T] \quad (5f)$$

$$\delta_{CGsd}^{S_{po},S_{pr}}(t) + \delta_{CGst}^{S_{po},S_{pr}}(t) \leq 1;\ t \in [2,T] \quad (5g)$$

where $\tau_{CG_1}^{S_{po},S_{pr}}$ and $\tau_{CG_2}^{S_{po},S_{pr}}$ are auxiliary time indexes used to represent the minimum up and down time constraints of CGs whereas $\delta_{CGst}^{S_{po},S_{pr}}(t)$ and $\delta_{CGsd}^{S_{po},S_{pr}}(t)$ are auxiliary variables to represent the start-up and shut-down actions of the controllable generators.

In the above (5a)-(5d) represent the power output limit, ramping up/down limit, minimum up time and minimum down time constraints of CGs (Carrion & Arroyo, 2006). In addition, the start-up and shut-down behaviours are modelled as (5e) - (5f). Further, Eq. (5g) is enforced to ensure that the generator cannot start-up and shut down simultaneously. It is worth highlighting that the above model not only considers operation limits such as ramp up/down rates and minimum up/down time, the introduction of auxiliary variables such as $\delta_{CGst}^{S_{po},S_{pr}}(t)$ and $\delta_{CGsd}^{S_{po},S_{pr}}(t)$ can also be used to constrain the number of generator start-up/shut-down cycles.

2.2.4 Demand-side constraints

Battery energy storage operation limits

The battery energy storage model mainly consists of a system dynamic model, an energy capacity model, a power charge/discharge model and an operation status model, which is given below.

$$e_E^{S_{po},S_{pr}}(t+1) = e_E^{S_{po},S_{pr}}(t) + \eta_{Ec} p_{Ec}^{S_{po},S_{pr}}(t)\Delta t - {}^{1}/_{\eta_{ED}}\, p_{Ed}^{S_{po},S_{pr}}(t)\Delta t - \varphi_E \Delta t; \qquad (6a)$$

$$E_E^{min} \le e_E^{S_{po},S_{pr}}(t) \le E_E^{max} \qquad (6b)$$

$$P_{Ec}^{min} \delta_{Ec}^{S_{po},S_{pr}}(t) \le p_{Ec}^{S_{po},S_{pr}}(t) \le P_{Ec}^{max} \delta_{Ec}^{S_{po},S_{pr}}(t) \qquad (6c)$$

$$P_{Ed}^{min} \delta_{Ed}^{S_{po},S_{pr}}(t) \le p_{Ed}^{S_{po},S_{pr}}(t) \le P_{Ed}^{max} \delta_{Ed}^{S_{po},S_{pr}}(t) \qquad (6d)$$

$$\delta_{Ed}^{S_{po},S_{pr}}(t) + \delta_{Ec}^{S_{po},S_{pr}}(t) \le 1 \qquad (6e)$$

$$\delta_{Ectd}^{S_{po},S_{pr}}(t) - \delta_{Edtc}^{S_{po},S_{pr}}(t) = \delta_{Ed}^{S_{po},S_{pr}}(t+1) - \delta_{Ed}^{S_{po},S_{pr}}(t) \qquad (6f)$$

$$\delta_{Ectd}^{S_{po},S_{pr}}(t) + \delta_{Edtc}^{S_{po},S_{pr}}(t) \le 1 \qquad (6g)$$

where $\delta_{Ectd}^{S_{po},S_{pr}}(t)$ and $\delta_{Edtc}^{S_{po},S_{pr}}(t)$ are auxiliary variables used to represent charge-to-discharge and discharge-to-charge switch actions respectively.

The energy storage dynamic model is shown in (6a), which indicates that energy level of the battery in period $t+1$ equals to the energy level in period t plus the charged power in period t minus the discharged power in period t as well as the self-discharged power. To avoid simultaneous charge/discharge operations, Eq. (6e) is imposed. In addition, (6b) -(6d) represent the energy capacity constraints, charging power limit and discharging power limit respectively. Finally, (6f) - (6g) capture the charge-to-discharge and discharge-to-charge behaviours of the energy storage system. Note that the above proposed battery energy storage model can not only model regular operation behaviours (e.g., energy level, charge/discharge limits) but could also be used to constrain the number of energy storage charge-to-discharge cycles through the introduced auxiliary variables $\delta_{Ectd}^{Spo,Spr}(t)$ and $\delta_{Edtc}^{Spo,Spr}(t)$. Such a feature is particularly useful in modelling battery energy storage system which suffers seriously from short cycle life.

Load demand constraints

The residential loads can be approximately categorized into critical loads, curtailable loads, and shiftable loads (Meng & Zeng, 2013), which are modelled as (7). The demand uncertainties of critical/curtailable loads are captured by the scenario based stochastic model.

$$0 \leq P_{crit}^{Spo}(t) \leq P_{crit}^{max} \tag{7a}$$

$$\sum_{t=\gamma_{sh}^{st}}^{\gamma_{sh}^{sd}} \delta_{sh}^{Spo,Spr}(t) = T_{sh};\ sh \in [1, N_{sh}] \tag{7b}$$

$$\sum_{t=t_{sh}^{st}}^{t_{sh}^{st}+T_{sh}-1} \delta_{sh}^{Spo,Spr}(t) = T_{sh};\ sh \in [1, N_{sh}] \tag{7c}$$

$$0 \leq P_{curt}^{Spo}(t) \leq P_{curt}^{max} \tag{7d}$$

$$0 \leq \beta_{curt}^{Spo,Spr}(t) \leq \beta_{curt}^{max} \tag{7e}$$

where $\gamma_{sh}^{st} \leq t_{sh}^{st} \leq \gamma_{sh}^{sd} - T_{sh}$ represents the start running time of sh-th shiftable load.

In the above, Eq. (7a) represents the power rate limits for critical loads. Eqs. (7b)-(7c) represent the operation time limits of the sh-th shiftable load in which (7b) indicates that the task of sh-th shiftable load will take T_{sh} time periods to finish and must be completed within a predetermined time window

$[\gamma_{sh}^{st}, \gamma_{sh}^{sd}]$ whereas (7c) means that once started, the shiftable load needs to run continuously till the task is completed. Further, (7d) - (7e) model the power demand limit and power curtailment ratio limit of curtailable loads.

2.2.5 *Spinning reserve constraints*

The spinning reserve is required to maintain system frequency stability in emergency operating conditions and to accommodate sudden load increase or the renewable generation increase. When the penetration level of RES (such as wind energy) is high, there are two spinning reserve schemes need to be considered in the generation scheduling problem in order to reduce negative impacts caused by fluctuant power outputs of RES and to increase the power supply quality: the up spinning reserve (USR) and the down spinning reserve (DSR) (Lee, 2007).

USR:

$$\begin{aligned}
&P_D^{max}\delta_D^{Spo,Spr}(t) + P_{FC}^{max}\delta_{FC}^{Spo,Spr}(t) + P_{solar}^{Spo}(t) + P_{wind}^{Spo}(t) + P_{gridin}^{max}\delta_{gridin}^{Spo,Spr}(t) \\
&-P_{gridout}^{min}\delta_{gridout}^{Spo,Spr}(t) + p_{Ed}^{Spo,Spr}(t) - p_{Ec}^{Spo,Spr}(t) \\
&\geq (1 + Resu(t))\left[P_{crit}^{Spo}(t) + P_{curt}^{Spo}(t) + \sum_{sh=1}^{N_{sh}} \delta_{sh}^{Spo,Spr}(t) P_{sh}(t)\right] \qquad t \in [1,2,\cdots,T]
\end{aligned} \tag{8a}$$

DSR:

$$\begin{aligned}
&P_D^{min}\delta_D^{Spo,Spr}(t) + P_{FC}^{min}\delta_{FC}^{Spo,Spr}(t) + P_{solar}^{Spo}(t) + P_{wind}^{Spo}(t) + P_{gridin}^{min}\delta_{gridin}^{Spo,Spr}(t) \\
&-P_{gridout}^{max}\delta_{gridout}^{Spo,Spr}(t) + p_{Ed}^{Spo,Spr}(t) - p_{Ec}^{Spo,Spr}(t) \\
&\leq (1 - Resd(t))\left[P_{crit}^{Spo}(t) + P_{curt}^{Spo}(t) + \sum_{sh=1}^{N_{sh}} \delta_{sh}^{Spo,Spr}(t) P_{sh}(t)\right] \qquad t \in [1,2,\cdots,T]
\end{aligned} \tag{8b}$$

In the above, Eq. (8a) is the up-spinning reserve constraint which is used to keep the system reliability to accommodate situations such as a sudden load increase or unpredictable fall in wind turbine generator power. Eq. (8b) is the down-spinning reserve constraint, which is designed for sudden load decreases and unpredictable increases in wind turbine generator power output.

2.3 SMPC Control Framework

The performance of the traditional open-loop based energy management strategy deteriorates rapidly when the penetration level of the RES in the microgrid becomes high. Although traditional MPC based energy control strategy with rolling up and feedback mechanisms can reduce the negative impacts caused by RES to some extent, it essentially operates based on an expected point forecast value and does not provide a systematic way to deal with forecast uncertainties. SMPC based energy management model, which combines advantages of both stochastic programming and MPC, is more suitable to our considered problem and therefore adopted in this study.

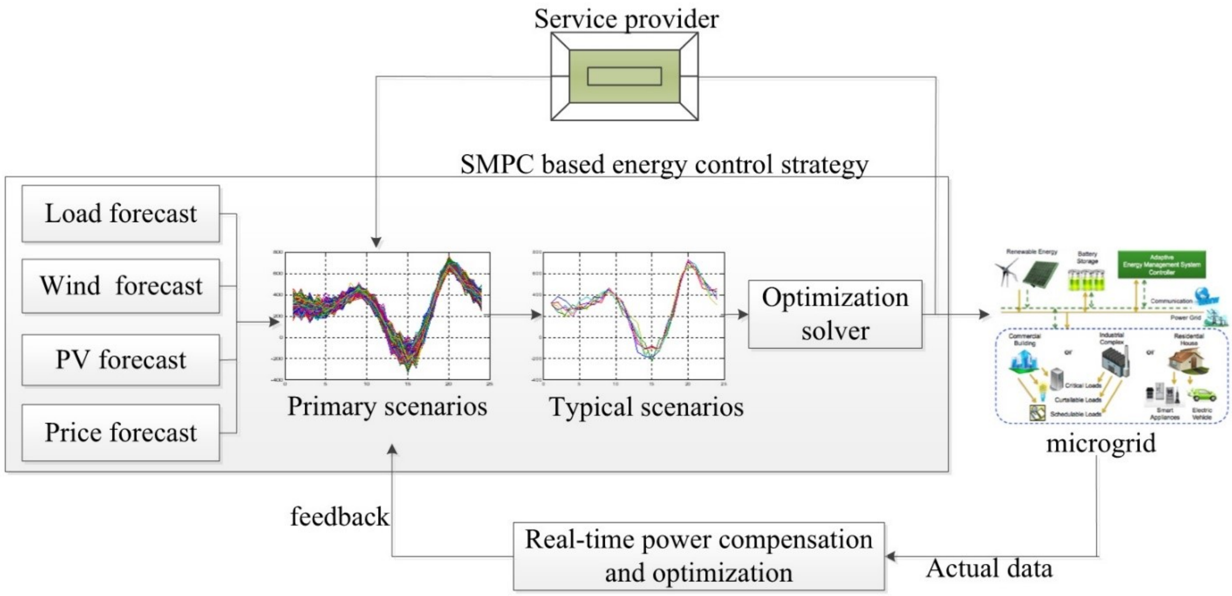


Fig.2 Framework of SMPC based microgrid energy control strategy.

The proposed SMPC based two-stage microgrid control framework consists of a power prescheduling stage and a real-time control stage, which is illustrated in Fig. 2. The first-stage (i.e. prescheduling stage) operation is implemented before actual observations/measurements of stochastic variables (i.e. actual wind/PV/load/price data) become available. An optimal control sequence over the control horizon T is obtained by solving the microgrid stochastic energy management model Eq. (1) but only the control action for the immediate next time period will be applied to the system. Further, in order for the control action to be applied in real applications, additional non-anticipation constraints (Zhu & Hug, 2014) need to be included when solving Eq. (1) to ensure that control actions under different scenarios will be the same. The second-stage (i.e. real-time control stage) operation is implemented when actual observations/measurements become available by determining optimal corrective actions to satisfy the real-time power balance at a minimum cost to compensate any infeasibility of the control sequence obtained in the first-stage operation (i.e., a compensation cost minimization problem).

At the next time step, the time horizon is shifted one-step forward and the optimization problem over another T time periods for the first-stage operation and the compensation cost minimum problem for the second-stage operation are solved again. The above process is repeated until the end of the simulation horizon. The proposed SMPC microgrid control procedure is presented in Algorithm 2.

Algorithm 2 SMPC microgrid control procedure

1. Simulation initialization: $t \leftarrow 0$.

2. By the end of time period t, in the prescheduling stage, a control sequence between time period $t+1$ and $t+T$ is obtained by solving optimizations problem Eq. (1) subject to additional non-anticipation constraints where only the control action for $t+1$ will be applied to the system.

3. At the beginning of time period $t+1$, in the real-time control stage, optimal adjustments of dispatchable units are obtained which aims to compensate the forecast errors at a minimum cost based on actual load demand, electricity price and RES data. Finally, the resulted control action after adjustment is applied to the system in time period $t+1$.

4. The final microgrid operation state, actual load demand, electricity price and RES data in time period $t+1$ are sent back to the microgrid EMS to update the forecast model and energy management optimization model.

5. $t \leftarrow t+1$, go to Step (2).

3. Simulation Results

3.1 Simulation Setup

In order to demonstrate the effectiveness of our proposed approach, a low voltage grid-connected microgrid as shown in Fig. 1 is considered. The time interval of each time period is set to 1 hour for both the prescheduling stage and the real-time control stage. The receding control horizon is set to 24 hours (24 intervals) and the whole simulation horizon is set to 4 days.

The shiftable load data are modified from [1] where the load model parameters are given in Table 1. For the battery energy storage, maximum and minimum charging (discharging) rates are 60 kW and 2 kW respectively while the maximum and minimum energy levels are set to 150 kWh and 30 kWh respectively. Both the charging and discharging efficiencies are set to 0.95 while the self-discharge rate is 0.002 kWh per hour. The initial energy level of the battery storage is 70 kWh. Further, to ensure the energy storage system has enough energy stored to deal with emergency conditions, the energy level at the beginning of each day during the simulation window is required to be same as the initial energy level.

Table 1 Model parameters of shiftable loads

Task	Power (kW)	Earliest starting time (h)	Latest finishing time (h)	Duration (h)
A1	22	5	21	2
A2	18	14	23	4

The wind and PV generation data are collected and modified from Elia, the Belgium's electricity transmission system operator (Elia, 2016). The PV capacity is 235 kW and wind capacity is 170 kW. The spot electricity price is adopted from (Mohammadi et al., 2014). In addition, to reduce the effects of the RES on the external grid and to encourage the local utilization of RES in microgrids, we set the electricity-buying price to be the same as spot market price ($\rho_{buy} = 1$) and the selling price to be 0.8 times of the spot price in the prescheduling stage ($\rho_{sell} = 0.8$). In the real-time control stage, the buying prices are set to be 1.2 times of the spot price ($\rho_{buy} = 1.2$) while the selling prices are set to be 0.7 times of the spot prices ($\rho_{sell} = 0.7$).

Due to the lack of historic data of curtailable loads and to take into account customers' comforts in our considered grid-connected microgrid, we set the curtailable load level in each period under each scenario as 20% of the corresponding critical load with the maximum curtailment ratio as 0.2. Finally, the 4-day history data of wind and PV generation, load demand and market electricity price (spot price) are illustrated in Fig. 3.

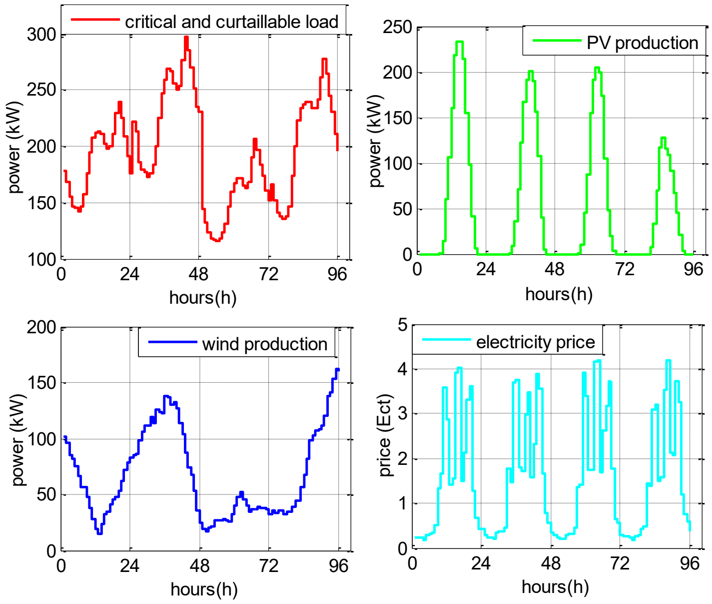


Fig. 3 History data of the critical/curtailable load, electricity price and PV/wind generation

The model parameters of diesel generator and fuel cell are given in Table 2 while the ramp power of the diesel generator and fuel cell is set to 80 kW and 40 kW respectively. Note that due to the unavailability of directly usable parameter settings of diesel generator/fuel cell in the literature, we select the above parameters by referring to exemplar parameter settings in (Maleki et al., 2017) through a trial and error manner. The remaining parameters of generators, loads and energy storage used in this simulation are adopted and scaled from (Zhang, Tao and Zhang, Fuxing and Zhang, 2016), which is a real multi-microgrids demonstration system to be deployed in Shanxi Province, China. The details of those remaining parameters are given follows: the curtailment penalty weight ρ_{curt} is set to 5 euro-cents per kWh. The maintenance cost of energy storage is set to €$0.6 \times 10^{-3}/kWh$, the charge-to-discharge, and discharge-to-charge switch costs are set to €1.1×10^{-3}. The cost coefficients of diesel generator (a_1, a_2, a_3) are set to $0.01, 2.66,$ and 0 respectively (€$0.01 \times 10^{-3}/(kWh)^2$, €$2.66 \times 10^{-3}/kWh$, and €$0$) while the cost coefficients of the fuel cell (b_1, b_2) are set to 2.84 and 0 respectively ($€2.84 \times 10^{-3}/kWh$ and €0). The start-up and shut down costs of diesel generator are both set to $€\,3.48 \times 10^{-3}$ while those of fuel cell are set to $€\,2.02 \times 10^{-3}$. The maintenance costs of diesel and fuel cell generators are set to $€\,0.4 \times 10^{-3}/\,kWh$ and $€\,0.6 \times 10^{-3}/\,kWh$ respectively.

Table 2 Model parameters of controllable generators

Type	Min power output (kW)	Max power output (kW)	Min up/down time (h)
Diesel	10	150	3
Fuel cell	5	55	2

By applying the two-stage scenario reduction method presented in Section II-A, we finally obtain six net load scenarios and five electricity price scenarios.

Our proposed SMPC approach is compared with three state-of-the-art approaches: 1) day-ahead programming (D-DA) (Erdinc, 2014); 2) stochastic day-ahead programming (S-DA) (Soares et al., 2017); and 3) standard MPC (D-MPC) (Liu et al., 2016), which are briefly described below. Further details can be found in the above cited works.

D-DA: It is a traditional two-stage open-loop energy management strategy where the wind productions, PV generation, load demand and electricity price take the expected values of corresponding forecasts.

S-DA: It is an improved two-stage open-loop energy management strategy by introducing the stochastic programming method into the D-DA strategy where the net load and electricity price scenarios are generated and selected by using methods proposed in Section II-A. Different from other strategies, for S-DA only operation statuses (on/off) of dispatchable units are determined in the prescheduling stage whereas the power outputs are determined in the real-time control stage.

D-MPC: It is a two-stage closed-loop energy control strategy by considering expected forecast values within a MPC framework.

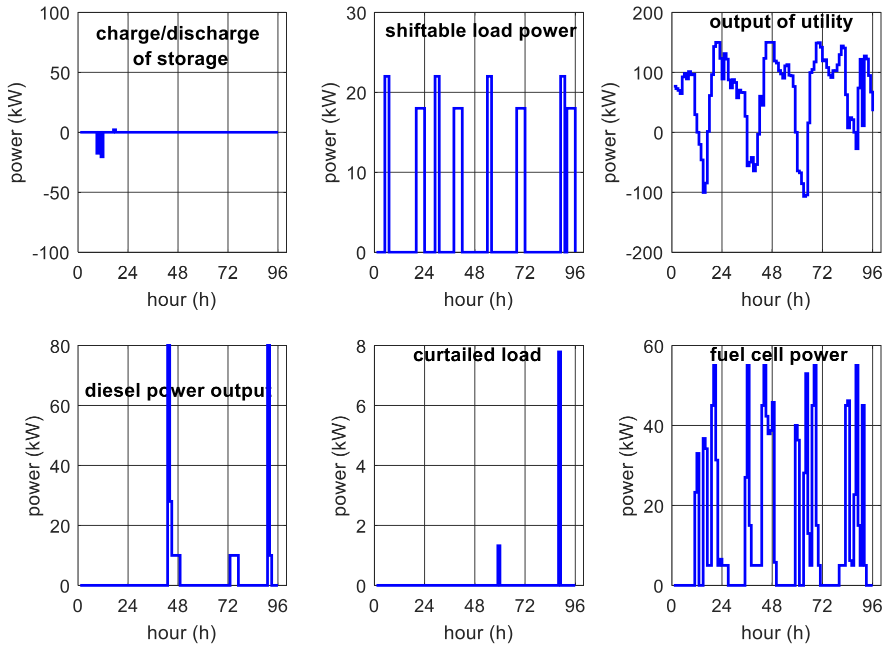
It is worth mentioning that the prescheduling stage optimization under open-loop based strategies is only implemented once at the beginning of each control horizon whereas for closed-loop based strategies it will be implemented once for every time period.

3.2 Results and Analysis

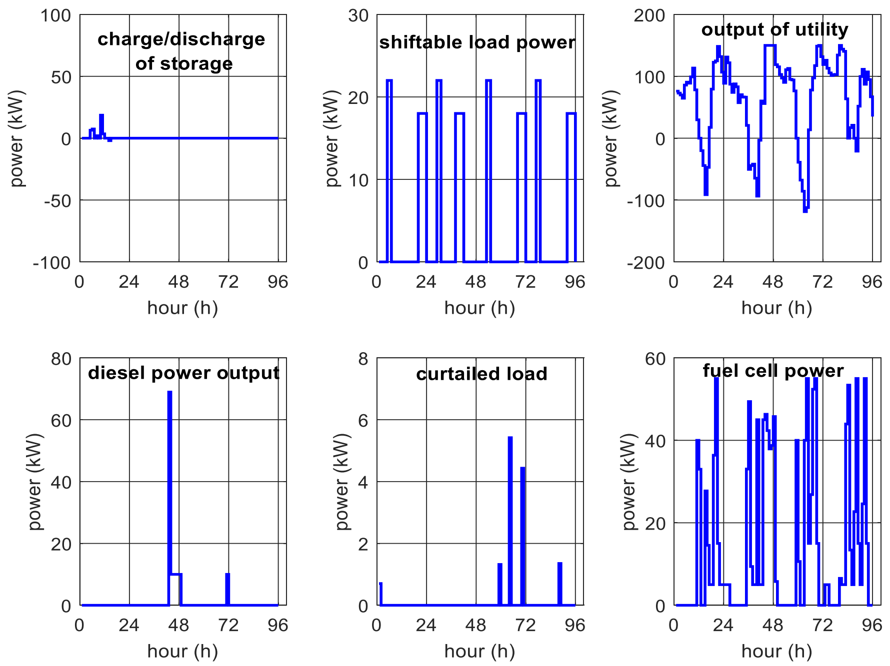
The evaluations are conducted from the following aspects: 1) comparison between deterministic strategies (i.e. D-DA and D-MPC) and stochastic strategies (i.e. S-DA and SMPC); 2) comparison between open-loop strategies (i.e. D-DA and S-DA) and closed-loop strategies (i.e. SMPC and D-MPC); 3) comparison of spinning reserve requirements under each strategy; and 4) comparison of microgrid operation cost under each strategy.

Firstly, operation schedules of dispatchable units under S-DA/ D-DA and SMPC/ D-MPC are illustrated in Figs. 4-5. From Fig.4, we could find out that service time of fuel cell under S-DA and D-DA are similar (54 vs. 53 hours). The diesel generator is in service for 10 hours under S-SA, which is higher than the 7 hours under D-DA. In addition, curtailable loads are only curtailed twice in the 59th and 88th hour under S-DA whereas the same loads are curtailed for 5 times under D-DA. The above difference indicates that a deterministic model using expected forecast values (e.g., D-DA) is usually less accurate in scheduling of CGs (e.g., diesel generators) than the stochastic model (e.g., S-DA) but incur more high-cost load curtailments.

The above findings could be further confirmed by the simulation results under SMPC and D-MPC as shown in Fig.5. For instance, the diesel generator under SMPC is in service from 43rd to 48th hour at the time of higher load demand while the fuel cell under SMPC is in service for 41 hours (i.e. almost 42.7% of the whole simulation time horizon). In addition, there is no power curtailment for curtailable loads under SMPC. In comparison, under D-MPC the diesel generator only operates from 43rd to the 45th hour and the fuel cell is only in service for only 32 hours, which is unable to cover high power demands in 47th and 48th hour. As a result, high-cost load curtailments in these two hours are implemented under D-MPC.

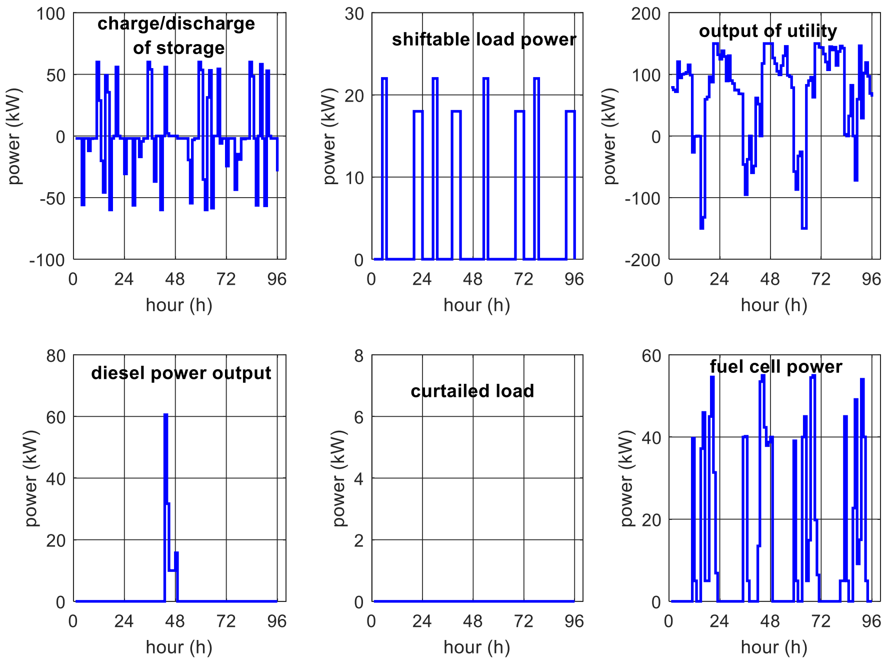


(a)



(b)

Fig. 4 Power levels of different units under S-DA strategy (a) and D-DA strategy (b).



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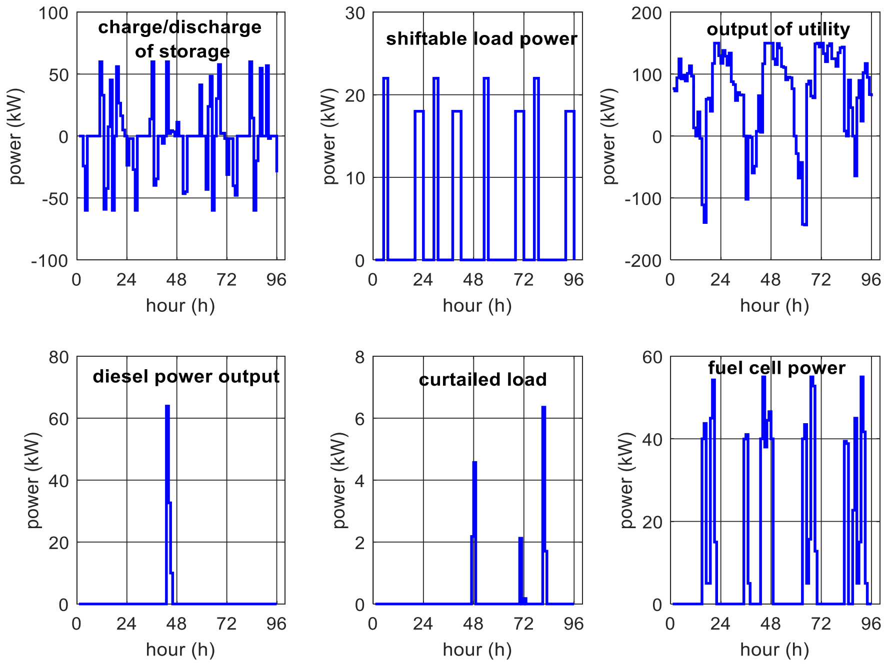
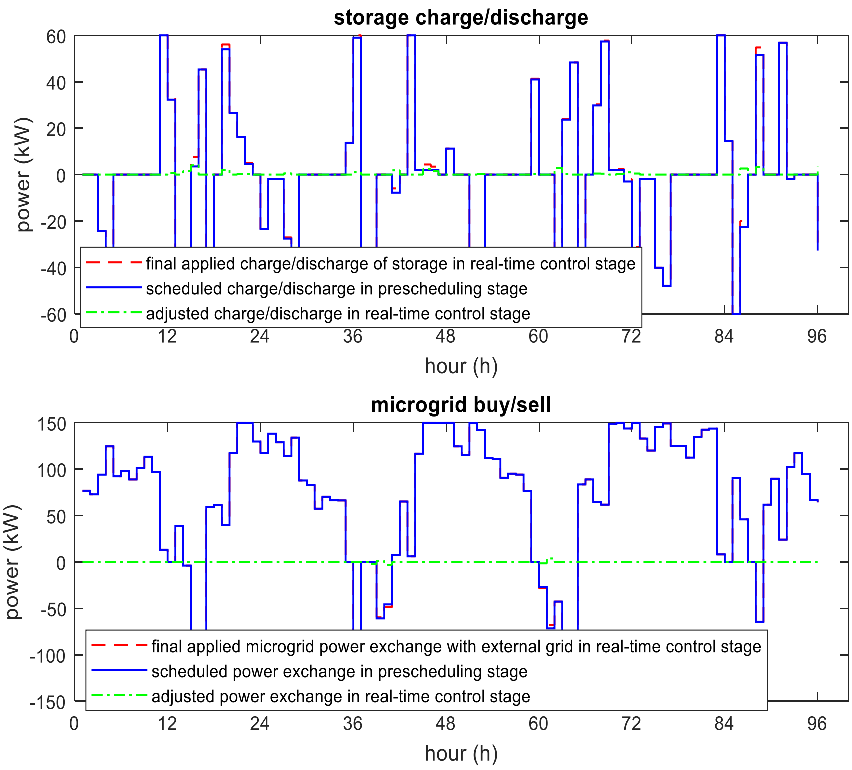


(b)

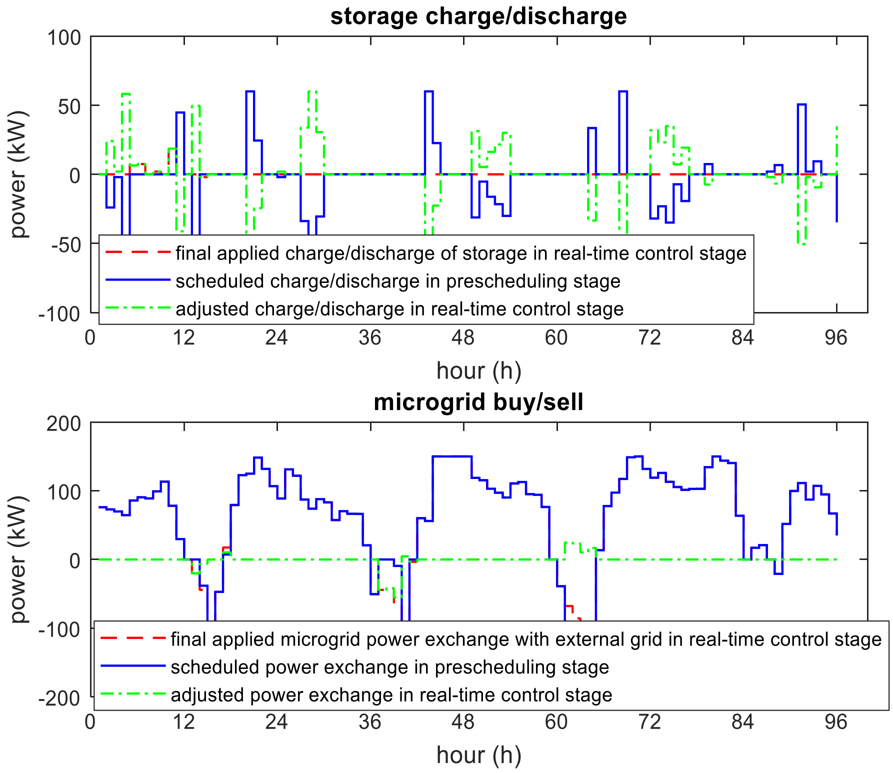
Fig. 5 Power levels of different units under SMPC strategy (a) and D-MPC strategy (b).

Secondly, in order to compare the control performances of open-loop and closed-loop strategies, the scheduled power exchange schedules and charge/discharge schedules of energy storage in the prescheduling stage (the blue curves), the optimal power adjustments in the real-time control stage (the green curves), and the final applied control actions to the system in the real-time control stage (the red curves) for each control strategy are illustrated in Figs. 6-7. It should be noted that the power adjustments shown in Figs. 6-7 are the differences between the actual power outputs (final applied control actions) in real-time control stage and the scheduled power outputs in the prescheduling stage. We can easily find out that the energy storage system is rarely operated (as shown by the red curves in the figures) under open-loop based strategies (i.e. S-DA and D-DA) and mainly acts as a power backup for the microgrid. The reason for the above lies in that the real-time control stage optimization model for open-loop based strategies is implemented separately from its prescheduling stage optimization model and therefore is only a 'short-sighted' optimization problem whose main objective is to satisfy the power balance constraint in that particular time-step. In comparison, the real-time control stage model under closed-loop based strategies is implemented based on the prescheduling stage optimization model within a receding horizon control framework and therefore is a 'long-sighted' optimization problem. Unsurprisingly, the superiority of energy storage system is fully utilized and demonstrated in closed-loop based strategies (i.e. D-MPC and SMPC), which can be seen from Figs. 6-7.

In addition, as the closed-loop strategies such as D-MPC and SMPC include a receding horizon mechanism, the control decisions made in the prescheduling stage are updated at each simulation time step by considering newly updated forecast and system information. However, the decision-makings for open-loop based strategies in the prescheduling stage are only made once at the beginning of each control horizon T based on the forecast/system information available at the time, which is likely to be outdated/ less accurate. As a result, the power mismatch between the prescheduling stage and the real-time control stage under closed-loop based strategies will be smaller than those under the open-loop based strategies, which incurs less power adjustments/lower cost in the real-time control stage. The above are confirmed in Figs. 6 and 7 that the power adjustments required under the closed-loop based strategies are much smaller than those required by the open-loop based strategies. More specifically, when looking at power interactions between microgrid and the external grid under each strategy, SMPC introduces lowest mismatch between the power schedules made in the prescheduling stage (blue curves) and final applied power schedules to the system after the power adjustments in the real-time control stage (red curves). In other words, there are minimum power adjustments in real-time control stage for SMPC among all strategies. It is well recognized that such power mismatches are inevitable due to inherent forecast errors, however, if not properly handled, such mismatch will not only cause additional operation costs to the microgrid but also negative impacts on the external grid. Our proposed SMPC, which combines advantages of both stochastic programming and MPC, performs best among all the above control strategies.

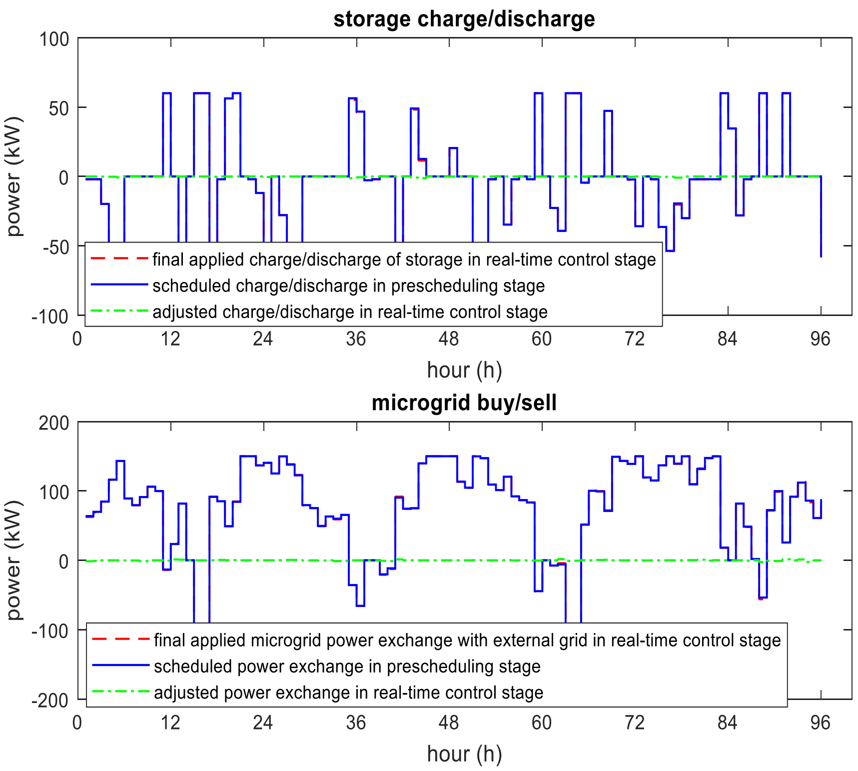


(a)

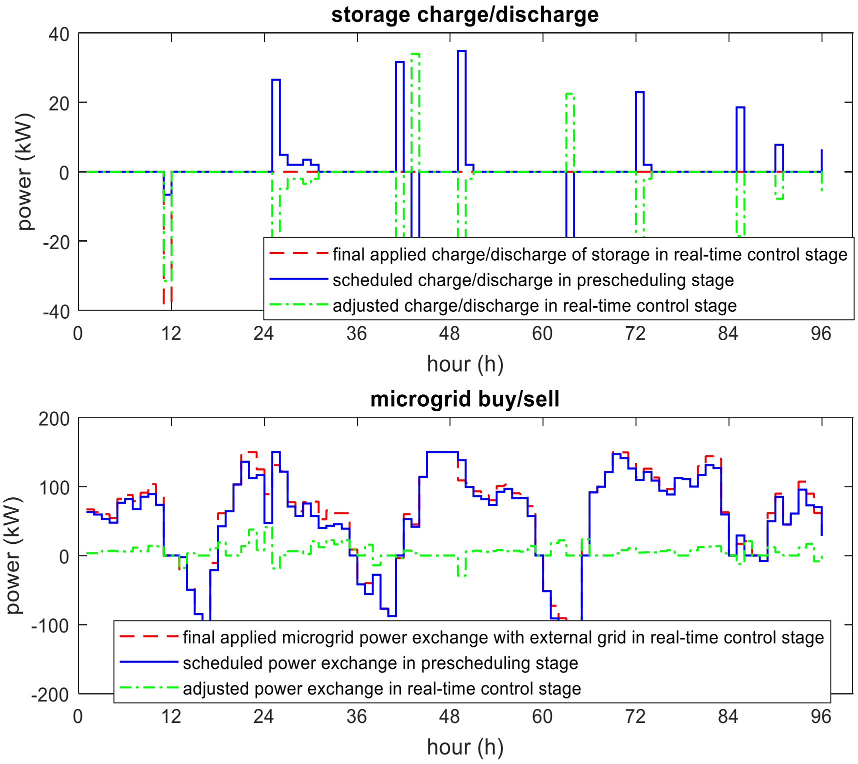


(b)

Fig. 6 Energy storage schedules/ power exchange with external grid under D-MPC strategy (a) and D-DA strategy (b).



(a)



(b)

Fig.7 Energy storage schedules/ power exchange with external grid under SMPC (a) and S-DA strategy (b).

Thirdly, for microgrid operator, the spinning reserve ratio is another important factor to reflect the system operation cost and reliability. In general, the more spinning reserve required, the more operation cost and lower system reliability. In this study, the up and down spinning reserve ratios under D-DA are about 12%. That is, when the spinning reserve ratio is less than 12%, the probability of blackouts in the microgrid will become very high. In addition, the up and down spinning reserve ratios under S-DA and D-MPC are both about 8%, which is less than D-DA strategy. Finally, the up and down spinning reserve ratios under SMPC are only 5%, which indicates that our proposed SMPC needs the lowest spinning reserve.

Fourthly, the operation costs of microgrid under all four strategies are investigated and listed in Table 3 where one can easily find out that SMPC is the most economic strategy. More precisely, the total cost under SMPC is 6.1% less than that of D-MPC strategy, 20% less than that of S-DA strategy and 21% less than that of D-DA. As aforementioned, only operation statuses of dispatchable units are determined in prescheduling stage of S-DA, it is not necessary to differentiate the cost between prescheduling stage and real-time control stage. As a result, only the total cost is available for S-DA.

Table 3. Operation cost of the microgrid under each control strategy

Strategies	Compensation cost (€)	Total cost (€)
SMPC strategy	-1.32	86.07
D-MPC strategy	2.41	91.66
S-DA strategy	----	107.5
D-DA strategy	12.6	109.06

4. Conclusion

In this paper, we propose a stochastic model predictive control (SMPC) based energy management strategy to minimize the operation cost of a microgrid with the penetration of RES by considering both generation-side and demand-side costs and constraints. The considered microgrid consists of wind turbines, PV generators, energy storage units, diesel generators, fuel cell generators, critical loads, curtailable loads, and shiftable loads. A large number of primary scenarios are firstly generated by Monte Carlo simulation method to represent the forecast uncertainties of the net load and electricity price. A two-stage scenario reduction method is firstly proposed to select typical net load and electricity price scenarios from primary scenarios with the aim to alleviate the computation burden. The stochastic microgrid energy management model based on selected scenarios is cast as a mixed integer quadratic programming (MIQP) problem, which is further applied within a SMPC framework. The control performance of our proposed SMPC is compared with the state of the art approaches (D-MPC, D-DA and S-DA) and simulation results demonstrate that our SMPC could achieve the lowest operation cost. We will then focus on distributed SMPC to coordinated operations of interconnected microgrids in our future work.

Although the stochastic programming provides more accurate/robust schedules for microgrid operations, it should be noted that the computation time is higher than that of deterministic model (e.g., by a factor of around 10 in our considered simulations). Since the computation time of stochastic model increases with the number of scenarios and that of its equivalent mixed integer model increases exponentially with the number of integer variables, the scalability could be a problem when dealing with large-scale optimization problems with many scenarios. To overcome such issues, decomposition based stochastic programming solutions such as (Schulze, Grothey, & McKinnon, 2017) will be developed by taking advantage the parallel computing facilities in our future work.

In addition, our considered microgrid model could be also extended in several aspects. Firstly, we could consider different types of generation technologies such as the combined heat and power (CHP) unit in the microgrid, which could provide both electrical and thermal energy. The above could be taken further by considering the multi-vector energy systems to consider the heat/gas/electricity network at the same time. It is also worth mentioning that our proposed stochastic MPC approach is generic and independent of any specific problem settings, therefore it will be readily applicable to the multi-vector energy systems management. Secondly, a more detailed demand side modelling, which consists of refined shiftable load models considering power variations across different time periods and operation constraints between different sub-tasks and a dedicated electric vehicle (EV) model considering different operation modes (e.g. vehicle to grid/ vehicle to home) and users' probabilistic driving schedules will be developed in our future work.

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