Coordinated Chance-constrained Optimization of Multi-energy Microgrid System for Balancing Operation Efficiency and Quality-of-service

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Abstract—To enhance the flexible interactions among multiple energy carriers, i.e., electricity, thermal power and gas, a coordinated programming method for multi-energy microgrid (MEMG) system is proposed. Various energy requirements for both residential and parking loads are managed simultaneously, i.e., electric and thermal loads for residence, and charging power and gas filling requirements for parking vehicles. The proposed model is formulated as a two-stage joint chance-constrained programming, where the first stage is a day-ahead operation problem that provides the hourly generation, conversion, and storage towards the minimization of operation cost considering the forecasting error of photovoltaic output and load demand. Meanwhile, the second stage is an on-line scheduling which adjusts the energy scheme in hourly time-scale for the uncertainty realizations. Simulations have demonstrated the validity of the proposed method, i.e., collecting the flexibilities of thermal system, gas system, and parking vehicles to facilitate the operation of electrical networks. Sensitivity analysis shows that the proposed scheme can achieve a compromise between the operation efficiency and service quality.

Index Terms—Multi-energy microgrid system, operation efficiency, quality-of-service, joint chance-constrained programming.

I. INTRODUCTION

With the deployment of microgrid-scale distributed energy resources (DERs), e.g., building photovoltaics (PVs) and combined heat and power generators (CHPs)[1]-[3], multiple energy carriers, e.g., electricity, gas, and thermal flows, are all coupled with each other in both stationary and mobile applications [4]. By coordinately managing the local DERs, the multi-energy microgrid (MEMG) [5]-[8] is regarded as a powerful platform in many applications [9], and becomes the key facility for interconnected multiple energy systems [9]-[11]. In this manner, the optimal planning and operation of MEMGs will play an important role in the future reliable and efficient multiple energy systems. Various studies have been investigated for the planning and operation of different types of MEMGs, e.g., residential, commercial, industrial, agricultural MEMGs [12]. The optimal planning of MEMGs has been addressed from the perspectives of reliability, efficiency and emission [13], [14]. In [13] and [15], an optimal expansion planning model for generators, transmission networks, natural gas furnaces, and CHPs within the MEMG is proposed. In [14], a stochastic planning model is proposed for wind power integrated MEMG. In [16], 29 kinds of MEMG configurations have been reviewed.

In current research, the optimal operation of MEMGs has been formulated as deterministic optimization problems [17]-[22] or robust/stochastic optimization problems [23]-[28] depending on whether the uncertainties are considered. Without considering the uncertainties during the scheduling horizon, the deterministic optimization problems are to minimize the cost and emission level and maximize the efficiency, through the supply side management and demand-side management. In [17], a static optimal energy flow is formulated for the supply-side management to minimize the fuel cost, and solved by an evolutionary algorithm. In [20], a game theoretic approach for integrated demand-side management in MEMGs is proposed. In [21], a standardized matrix modeling technique is proposed for the joint operation of supply-side and demand-side resources, where a dynamic optimal energy flow problem is formulated accordingly to maximize the profit. In [22], the customer preferences and comfort level are formulated as constraint sets. For more information on the deterministic operation of various types of MEMGs, an outstanding review is referred to [12].

Recently, to properly address the uncertainties, the optimal operation of MEMGs can be formulated as robust [23], [24] or stochastic optimization problems [25]-[28]. In the robust optimization, the uncertainties are generally modeled as intervals and the operation scheme is obtained based on the worst case. In [23], a day-ahead operation method is proposed for MEMGs to manage data uncertainties. In [24], the bounded uncertainties of efficiency parameters are managed by robust optimization. As for the stochastic optimization, the uncertainties are modeled by probability distributions. In [25], a medium-term timescale optimal operation model is proposed to manage the uncertainties of wind power and electricity prices. The uncertainties are modeled as scenarios, and measured by conditional value at risk. In a demand re-
response and thermal energy market, [26] proposes a stochastic day-ahead optimization for the MEMG operation. In [27], a price-based bi-level stochastic management method is proposed against the market price uncertainties. In [28], a risk-averse and a risk-seeking day-ahead marketing strategies using information gap decision-making theory are proposed to address the uncertainties of wind power and load demand. Generally, to manage the uncertainty of MEMG, the supply side scheduling aims to mitigate the uncertainties [24]-[28] and demand-side scheduling is used to improve the efficiency [26], [27]. More relative literatures can be referred to [9].

Some other literatures propose novel frameworks to facilitate the coordination between the supply-side and demand-side resources. In [29] and [30], an integrated coordinated model is proposed for MEMG. In [31], a decomposition framework is proposed to handle the coupling between the electrical and thermal systems. In [32], a three-time-scale control framework is proposed for the operation of MEMGs, i.e., fast control of the electrical system, medium-speed control of the gas system, and slow control of the thermal system. However, these works [29]-[32] are all deterministic optimization, and the uncertainties during operation are not considered.

Nowadays, to accommodate the integration of various direct current (DC) equipments, i.e., PV, battery and DC loads, hybrid alternating current (AC)/DC microgrid becomes a useful tool [33], which makes the future MEMGs become hybrid AC/DC ones. Additionally, with the maturity of power-to-gas equipment [34], the electrical side and gas side of MEMG are connected in both ways, which may further bring flexibilities to the operation of MEMG. To coordinate the thermal, electrical and gas energy in hybrid AC/DC MEMG, a two-stage joint chance-constrained programming problem is formulated, where the first stage is to balance the operation efficiency of the supply side and service quality of the demand-side in the day-ahead time-scale. The second stage is proposed to address the uncertainty realizations. The contributions of this paper can be summarized as follows: ① a hybrid AC/DC MEMG dispatch framework is proposed with interactions between electricity, thermal power and gas; ② an exact relaxation of bi-directional converter-linked MEMG operation problem is given; ③ a two-time-scale optimal operation of MEMG is formulated as a joint chance-constrained programming problem, which can balance the operation efficiency and the quality of energy service.

This remainder of this paper is shown as follows. The hybrid AC/DC MEMG is introduced in Section II. The two-stage stochastic programming model is formulated in Section III. The mathematical model and solving method are shown in Section IV. The case study is performed and the simulation results are analyzed in Section V. Conclusions are drawn in Section VI.

II. MEMG System

The MEMG is generally an energy system with multiple energy carriers [9], e.g., electrical and thermal flows. A typical topology of MEMG is shown in Fig. 1. There are three energy resources in the MEMG, i.e., PVs, electrical substation, and gas pressure house. The PVs and substation inject electricity into the MEMG via DC and AC buses, respectively. The gas pressure house injects gas into the MEMG to the gas storage. Additionally, to improve the system flexibility, a battery energy storage system (ESS) and two thermal storages are incorporated.

![Fig. 1. Hybrid AC/DC MEMG.](image)

In this paper, the scheduling horizon is divided into equal time step $\Delta t$, denoted by set $T = \{1, 2, \ldots, T\}$. The proposed operation method is formulated as a two-stage framework, where the first stage is for the day-ahead time-scale, and the second stage is for real-time scheduling, i.e., hourly scheduling. In the day-ahead operation (first stage), the hourly energy scheme is provided considering the uncertainties, and then in the second stage, the MEMG adjusts its scheduling plan responding to the uncertainty of realizations in hourly time-scale.

III. DAY-AHEAD SCHEDULING MODEL OF MEMGS

In this section, the day-ahead operation of MEMGs is formulated as a two-stage stochastic optimization problem, considering the uncertainties of PV outputs, loads, prices, and ambient temperatures. These uncertainties are modeled as scenarios based on historical data or the forecasting results. The problem is to balance the energy costs in the day-ahead market and risks in the real-time operation, considering the various constraints in both day-ahead operation and real-time operation.

A. Objective Function

The objective is to minimize the excepted operation cost $f(x, \omega)$ and the weight conditional value at risk (CVaR) of operation cost:

$$\min_{x, \omega} E(f(x, \omega)) + \rho \cdot CVaR_{\alpha}(f(x, \omega))$$

(1)

where $x$ is the day-ahead scheduling of upstream utility grid (UG) and CHP, i.e., $x = \{P_{UG}(t), S_{i}(t), S_{g}(t), I_{cop}(t)\}$, $\forall t$, where $S_{i}(t)$, $S_{g}(t)$ and $I_{cop}(t)$ are the start-up, shut down and operation status of CHP, respectively; $X$ is the set of constraints; $\omega$ belongs to a finite probability space $\Omega$, and $\Omega$ is the uncertainty factor set with corresponding probabilities $\pi_{k}, k \in \Omega$; $\rho$ is the weight factor between the excepted operation cost and CVaR; and $\alpha$ is the risk level, which means the
probability  $\Pr(f(x, \omega) \geq CVaR_x(f(x, \omega))) = \alpha$. The operation cost is depicted as:

$$f(x, \omega) = \sum_{t=1}^{T} \left[ \lambda_{DA}(t) P_{UG}(t) + c_c S_U(t) + c_d S_D(t) \right] +$$

$$\pi_t \sum_{t=1}^{T} \left[ c_v(t) V_{CHP}(t) + CVaR_x(\lambda_{RT}(t) p_{UG}(t)) \right] +$$

$$c_{ESS}, p_{ESS, a}(t) + c_{ESS, p_{ESS, a}(t)}$$

where $c_v$ and $c_d$ are the start-up and shut-down costs of CHP, respectively; $V_{CHP}$ is the gas consumption of CHP; $\lambda_{DA}(t)$ and $\lambda_{RT}(t)$ are day-ahead and real-time prices in the electricity market, respectively; $c_v(t)$ is the price of gas from utility; $\gamma$ is the confidence level; $P_{UG}(t)$ and $p_{UG}(t)$ are the day-ahead and real-time energy trading plans between the MEMG and UG, respectively; $c_{ESS}$ and $c_{ESS, p}$ are the charging and discharging costs of BESSs, respectively, which represent the battery degradation cost; $p_{ESS}(t)$ and $p_{ESS, a}(t)$ are the charging and discharging rates of BESSs, respectively.

In (2), $CVaR_x(\lambda_{RT}(t) p_{UG}(t))$ represents the CVaR of energy trading in the real-time market with a confidence level $\gamma$. In this paper, the real-time market prices are assumed to follow normal distribution, i.e., $\lambda_{RT}(t) \sim \mathcal{N}(\bar{\lambda}_{RT}(t), \sigma_{RT}(t))$, where $\bar{\lambda}_{RT}(t)$ and $\sigma_{RT}(t)$ are the expectation and standard deviation of $\lambda_{RT}(t)$, respectively. Without considering the correlation among real-time prices, the CVaR in the real-time market can be depicted as:

$$CVaR_x(\lambda_{RT}(t) p_{UG}(t)) = \bar{\lambda}_{RT}(t) p_{UG}(t) +$$

$$\frac{\phi(VaR_x)}{1 - \gamma} \sigma_{RT}(t) \left| p_{UG}(t) \right|$$

where $\phi(x)$ is the standard normal distribution function; and $VaR_x$ is the value at risk of the standard normal distribution function with the quantile-level $\alpha$. As shown in (3), the selling prices may be increased by $\sigma_{RT}(t)$, and vice versa.

The constraints of the day-ahead operation and real-time operation are given in the following subsections.

**B. Constraints of Day-ahead Operation**

In the day-ahead operation, the constraints for $P_{UG}(t)$, $\forall t$ and $S_U(t)$, $S_D(t)$, $I_{CHP}(t)$, $\forall t$ are given as:

$$P_{\text{min}}^{\text{UG}} \leq P_{UG}(t) \leq P_{\text{max}}^{\text{UG}} \quad \forall t$$

$$S_U(t) - S_D(t) = I_{CHP}(t) - I_{CHP}(t-1) \quad \forall t$$

$$\sum_{t=1}^{T} S_U(t) \leq I_{CHP}(t) \quad \forall t \in \{UT, \ldots, T\}$$

$$\sum_{t=1}^{T} S_D(t) \leq 1 - I_{CHP}(t) \quad \forall t \in \{UT, \ldots, T\}$$

where $P_{\text{min}}^{\text{UG}}$ and $P_{\text{max}}^{\text{UG}}$ are the minimal and maximal energy exchanges between MEMG and UG, respectively; and $UT$ and $DT$ are the minimal up and down durations of CHP, respectively. The energy exchange between the MEMG and UG is given in (4). The up and down limitations of CHP together with the minimal up and down durations of CHP are illustrated in (5)-(7).

**C. Constraints of Real-time Optimization**

The constraints of the real-time operation include constraints in the electrical system, constraints in the thermal system, and constraints in the gas system, which are described as follows.

1) **Constraints of Electrical System**

Coupled by the AC/DC converters, the power balance at the AC bus and DC bus are depicted as follows, considering the conversion losses from AC bus to DC bus and from DC bus to AC bus.

$$P_{UG}(t) + p_{UG}(t) + \eta_{CHP} V_{CHP}(t) + \eta_{D2A} P_{D2A}(t) = P_{AC}(t) +$$

$$p_{D2A}(t) + p_{DC}(t) + p_{PV}(t) \quad \forall k, t$$

$$P_{ESS, a}(t) - P_{ESS, c}(t) + \eta_{D2A} P_{D2A}(t) + p_{PV}(t) =$$

$$P_{DC}(t) + p_{DC}(t) + p_{EV}(t) \quad \forall k, t$$

where $V_{CHP}$ is the gas consumption of CHP; $\eta_{CHP}$ is the electrical conversion efficiency of CHP; $\eta_{D2A}$ and $\eta_{D2A}$ are the conversion efficiencies from AC bus to DC bus and from DC bus to AC bus, respectively; $P_{D2A}(t)$ and $p_{D2A}(t)$ are the energy transferred from AC bus to DC bus and DC bus to AC bus during time slot $t$, respectively; $p_{PV}(t)$ and $p_{DC}(t)$ are the energy consumptions of the power-to-gas facility and the heating, ventilation and air conditioning (HVAC), respectively; $p_{PV}(t)$ is the PV output during time slot $t$; $P_{DC}(t)$ is the power-to-gas rate; $p_{DC}(t)$ and $p_{PV}(t)$ are electrical demand on the AC bus and DC bus during time slot $t$, respectively; and $p_{DC}(t)$ is the charging rate of electric vehicles (EVs). The power balance equations of AC bus and DC bus are shown in (8) and (9), respectively.

The constraints for the bi-directional energy conversion between AC and DC are shown as follows.

$$0 \leq p_{D2A}(t) \leq I_{D2A}(t) P_{\text{max}}^{\text{D2A}} \quad \forall k, t$$

$$0 \leq p_{D2A}(t) \leq (1 - I_{D2A}(t)) P_{\text{max}}^{\text{D2A}} \quad \forall k, t$$

where $P_{\text{max}}^{\text{D2A}}$ and $P_{\text{max}}^{\text{D2A}}$ are the maximal energy conversions form DC bus to AC bus and from DC bus to AC bus, respectively; and $I_{D2A}$ is a binary variable. Constraints (10) and (11) indicate that the MEMG can only convert electricity either from AC bus to DC bus or from DC bus to AC bus within each time slot.

The constraints for BESS are given as:

$$0 \leq P_{ESS, c}(t) \leq I_{ESS, c}(t) P_{\text{max}}^{\text{ESS, c}} \quad \forall k, t$$

$$0 \leq P_{ESS, a}(t) \leq (1 - I_{ESS, a}(t)) P_{\text{max}}^{\text{ESS, a}} \quad \forall k, t$$

$$e_{ESS}(t) = \eta_{ESS} e_{ESS}(t-1) +$$

$$P_{ESS, c}(t) \eta_{ESS, c} = \frac{P_{ESS, a}(t) \Delta t}{\eta_{ESS, a}} \quad \forall k, t$$

$$E_{\text{min}} \leq e_{ESS}(t) \leq E_{\text{max}} \quad \forall k, t$$

$$e_{ESS}(t) = E_{ESS}(0) \quad \forall k$$

where $P_{\text{max}}^{\text{ESS, c}}$ and $P_{\text{max}}^{\text{ESS, a}}$ are the maximal discharging and
charging rates of BESS, respectively; \( \eta_{ESS, c} \) and \( \eta_{ESS, d} \) are the charging, discharging and self-discharging efficiencies of ESS, respectively; \( E_{ESS, min} \) and \( E_{ESS, max} \) are the minimal and maximal energy status of BESS, respectively; \( E_{ESS}(0) \) is the initial energy stored in BESS; and \( I_{ESS, c,d,t} \) is a binary decision variable, indicating whether BESS is discharging or not. Constraints (12) and (13) limit the BESS to only discharge or charge within the given range in each time slot. (14)-(16) depict the energy limitations of BESS.

The constraints for HVAC, power-to-gas facility, and EVs are given as:

\[
0 \leq p_{HVAC}(t) \leq P_{max, HVAC} \quad \forall k, t \tag{17}
\]

\[
0 \leq p_{PG}(t) \leq P_{max, PG} \quad \forall k, t \tag{18}
\]

\[
\sum_{i \in EV} D_{EV, i}^{max}(t) \leq \sum_{i \in EV} p_{EV, i}(h) \leq \sum_{i \in EV} A_{EV, i}(t) \quad \forall k, t \tag{19}
\]

\[
0 \leq p_{EV, i}(t) \leq N_{EV}(t) P_{max, EV} \quad \forall k, t \tag{20}
\]

where \( P_{max, HVAC} \) and \( P_{max, PG} \) are the maximal electricity consumptions of HVAC and power-to-gas facility, respectively; \( A_{EV, i}(t) \) and \( D_{EV, i}^{max}(t) \) are the arrival curve and minimal departure curve of electricity demand of EV in scenario \( k \), respectively; \( EV \) is the set of EVs; \( N_{EV}(t) \) is the number of charging EVs; and \( P_{max, EV} \) is the maximal charging rate of EV. Constraints (17) and (18) limit the electricity consumption of HVAC and power-to-gas facility, respectively. Constraint (19) guarantees the quality of charging service for each EV.

2) Constraints of Thermal System

The MEMG can manage both the heating and cooling balances within the service area. The heating and cooling balances during the scheduling horizon are given as follows.

\[
\eta_{CHP} v_{CHP}(t) + q_{CHP, c,t} + q_{CHP, d,t} = q_{BD, c,t} + q_{BD, d,t} + q_{AC, c,t} + q_{AC, d,t} \quad \forall k, t \tag{21}
\]

\[
\eta_{CHP, c} p_{CHP}(t) + \eta_{CHP, d} q_{CHP, c,t} + \eta_{CHP, d} q_{CHP, d,t} = q_{BD, c,t} + q_{BD, d,t} + q_{AC, c,t} + q_{AC, d,t} \quad \forall k, t \tag{22}
\]

where \( q_{BD, c,t} \) and \( q_{BD, d,t} \) are the heating and cooling demands to control the indoor room temperature of residential blocks, respectively; \( q_{BD, c,t} \) and \( q_{AC, c,t} \) are the heating and cooling demands, respectively; \( q_{AC, c,t} \) is the heating consumption of absorption chiller with efficiency \( \eta_{AC, c} \); \( q_{CHP, c,t} \) is the heating efficiency of CHP; \( q_{BD, d,t} \), \( q_{AC, d,t} \), \( q_{BD, c,t} \), \( q_{BD, d,t} \), \( q_{AC, c,t} \), and \( q_{AC, d,t} \) are the charging and discharging power of heating storage and thermal storage, respectively; and \( v_{CHP} \) is the gas consumption of gas boiler with efficiency \( \eta_{CHP} \). Equations (21) and (22) depict the heating and cooling balances, respectively.

The indoor room temperature of a cluster of residential buildings is managed via \( q_{BD, c,t} \) and \( q_{BD, d,t} \). Considering the heat conduction effect, the indoor room temperature model can be approximated by the Fourier’s law as:

\[
\frac{q_{BD, c,t} - q_{BD, d,t}}{\Delta t} = c_{w} \Theta_{m,t} - \Theta_{m,t-1} \frac{\Theta_{m,t} - \Theta_{m,t-1}}{R_{f}} \quad \forall k, t \tag{23}
\]

where \( \Theta_{m,t} \) and \( \Theta_{m,t-1} \) are the indoor temperature and ambient temperature, respectively; \( c_{w} \) is the air heating capacity; and \( R_{f} \) is the thermal resistance of building envelope. To guarantee the thermal service quality, the indoor room temperature should be guaranteed within the given range as:

\[
\Theta_{m, min} \leq \Theta_{m,t} \leq \Theta_{m, max} \quad \forall k, t \tag{24}
\]

where \( \Theta_{m, min} \) and \( \Theta_{m, max} \) are the minimal and maximal limitations for the indoor room temperature, respectively.

The heating storage and cooling storage follow the same dynamics compared to BESS as shown in (12)-(15) regarding the charging, discharging and energy storage.

3) Constraints of Gas System

Using power-to-gas facilities and gas storage, the gas balance within MEMG can be depicted as:

\[
v_{c,t} + \eta_{PG} P_{PG}(t) + v_{CHP, c,t} = v_{CHP, d,t} + v_{CHP, d,t} + v_{G, c,t} + v_{G, d,t} \quad \forall k, t \tag{25}
\]

where \( \eta_{PG} \) is the power-to-gas efficiency; \( v_{G, c,t} \) and \( v_{G, d,t} \) are the charging and discharging rates of gas storage, respectively; and \( v_{G, c,t} \) is the gas consumption of gas vehicles (GVs).

The constraints for the GV and CHP unit is depicted as:

\[
0 \leq v_{GV, c,t} \leq v_{max, GV, c,t} \quad \forall k, t \tag{26}
\]

\[
\sum_{i \in GV} D_{GV, i}^{max}(t) \leq \sum_{i \in GV} v_{GV, i}(h) \leq \sum_{i \in GV} A_{GV, i}(t) \quad \forall k, t \tag{27}
\]

\[
I_{CHP}(t) v_{CHP} = v_{CHP, c,t} \leq I_{max, CHP} v_{CHP} \quad \forall k, t \tag{28}
\]

where \( v_{GV, c,t} \) is the maximal gas filling rate; \( N_{GV}(t) \) is the number of GVs; \( A_{GV, i}(t) \) and \( D_{GV, i}^{max}(t) \) are the arrival curve and minimal departure curve of gas demand from GV in scenario \( k \), respectively, which can be interpreted similarly as (19); and \( v_{max, CHP} \) and \( v_{max, GV} \) are the minimal and maximal gas consumptions of CHP, respectively.

The gas storage system follows the same power and energy constraints to BESS, as shown in (12)-(15).

D. Problem Formulation of Two-stage Stochastic Programming

The proposed problem in (1)-(28) can be rewritten in the following standard format:

\[
\min_{x} c^{T} x + E \left[ Q(x, \omega) \right] + \rho \cdot CVaR_{\alpha} \left[ c^{T} x + E \left[ Q(x, \omega) \right] \right] \tag{29}
\]

where \( x \), in a more detailed description, is the first-stage decision variable; \( X \) is the constraints for the first-stage decision variables, i.e., (4)-(7); \( Q(x, \omega) \) is the recourse of the second problem, i.e., \( X \times \omega = \min_{y} \left[ Q^{T} y \mid y \geq h - T x \right] \); \( Y \) is the second-stage decision variables in each scenario, i.e., \( Y = \{ y_{i} \} \); \( Q(x, \omega) \) is the set of GVs. \( Y(\omega) \) is the scenario dependent constraint set for the second-stage decision variables, i.e., (9)-(27). \( Y \geq h - T x \) represents the coupling constraints between the first-stage decision vari-
ables and second-stage decision variables, i.e., (8) and (28); \( \omega \) is the possible realization of the uncertain factors, i.e., \( \omega = \{ P_{\text{AC}1}(t), P_{\text{DC}1}(t), P_{\text{PV}1}(t), D_{\text{EV},\text{min}}(t), A_{\text{EV},1}(t), P_{\text{H},1}(t), \theta_{\text{m},1}, D_{\text{FU},1}(t), A_{\text{FU},1}(t), N_{\text{FU},1}(t), N_{\text{GV},1}(t), \forall t \in T \} \).

Problem (29) indicates that the MEMG operator aims to minimize the operation cost of the MEMG, while satisfying the constraints in both the day-ahead operation and real-time operation. The quality of thermal service, charging service and gas filling service can always be guaranteed when \( \omega \in \Omega \), as shown in (19), (24) and (27).

IV. QUALITY-OF-SERVICE RELAXED SCHEDULING

In this section, the quality of thermal service, charging service and gas filling service are relaxed to balance the operation efficiency and quality of services. The relaxations are formulated as joint chance constraints, extending (29) to a two-stage joint chance constrained programming problem.

A. Relaxation of Quality of Services

To relax the specific quality of services, the indicator decision variables \( h_{\text{Th},t}, h_{\text{EV},t}, h_{\text{GV},t} \) are introduced for each scenario, resulting in different relaxed constraint sets \( Y_{\text{Th}}(\omega), Y_{\text{EV}}(\omega), Y_{\text{GV}}(\omega) \), respectively, e.g., \( h_{\text{Th},t} = 1 \Rightarrow y \in Y_{\text{Th}}(\omega) \).

The detailed expressions of relaxed sets are depicted as:

\[
Y_{\text{Th}}(\omega) = \left\{ \begin{array}{l}
(9) - (23) \\
(25) - (27)
\end{array} \right.
\]

\[
\left( \theta_{\text{in},t} - \theta_{\text{in},t}^\text{min} \leq \theta_{\text{in},t}^\text{max} + h_{\text{Th},t} M \quad \forall \omega, t \right)
\]

\[
Y_{\text{EV}}(\omega) = \left\{ \begin{array}{l}
(9) - (18) \\
(21) - (27)
\end{array} \right.
\]

\[
\left( \sum_{i=1}^{I} p_{\text{EV},i}(h) \leq \sum_{i \in I} A_{\text{EV},i}(t) \quad \forall \omega, t \right)
\]

\[
\sum_{i=1}^{I} p_{\text{EV},i}(h) \geq \sum_{i \in I} D_{\text{EV},i}(t) - \bar{I}_{\text{EV},t} M \quad \forall \omega, t \in T \{ T \}
\]

\[
\sum_{i=1}^{I} p_{\text{EV},i}(h) \geq \sum_{i \in I} D_{\text{EV},i}^\text{min}(T) \quad \forall \omega
\]

\[
0 \leq p_{\text{EV},i}(t) \leq N_{\text{EV},i}(t) P_{\text{EV}}^{\text{max}} + \bar{I}_{\text{EV},t} M \quad \forall \omega, t
\]

\[
Y_{\text{GV}}(\omega) = \left\{ \begin{array}{l}
(9) - (25), (28)
\end{array} \right.
\]

\[
\left( \sum_{i=1}^{I} v_{\text{GV},i}(h) \leq \sum_{i \in I} A_{\text{GV},i}(t) \quad \forall \omega, t \right)
\]

\[
\sum_{i=1}^{I} v_{\text{GV},i}(h) \geq \sum_{i \in I} D_{\text{GV},i}^\text{min}(t) - \bar{I}_{\text{GV},t} M \quad \forall \omega, t \in T \{ T \}
\]

\[
\sum_{i=1}^{I} v_{\text{GV},i}(h) \geq \sum_{i \in I} D_{\text{GV},i}(t) \quad \forall \omega
\]

\[
0 \leq v_{\text{GV},i}(t) \leq N_{\text{GV},i}(t) v_{\text{GV}}^{\text{max}} + \bar{I}_{\text{GV},t} M \quad \forall \omega, t
\]

where \( M \) is a big scalar.

In (30), the indoor room temperature constraint is relaxed. In (31), the charging service can be postponed to the end the scheduling period, i.e., \( T \), (32) can be interpreted in the same way. The indicator variables \( h_{\text{Th},t}, h_{\text{EV},t}, h_{\text{GV},t} \) enable the relaxation of different service constraints to recover some infeasible second-stage problems. As shown in (29) - (32), it is clear that \( Y(\omega) \cap Y_{\text{Th}}(\omega) \cap Y_{\text{EV}}(\omega) \cap Y_{\text{GV}}(\omega) = \emptyset \) if \( h_{\text{Th},t} + h_{\text{EV},t} + h_{\text{GV},t} \leq 1 \), indicating that the relaxations of thermal service, charging service and gas filling service have no overlaps.

B. Two-stage Joint Chance-constrained Programming

By introducing the relaxation sets in (30)-(32), the following two-stage joint chance-constrained programming is formulated to realize the original constraint set \( Y(\omega) \):

\[
\begin{align*}
\min_{\omega \in \Omega} & \quad c^T x + \sum_{\omega \in D} \pi_\omega q^\omega y(\omega) + \rho \left[ \eta + \sum_{\omega \in \Omega} \pi_\omega y(\omega) \right] \\
\text{s.t.} & \quad \sum_{\omega \in D} h_{\text{Th},t} \geq 1 \\
& \quad \sum_{\omega \in D} h_{\text{EV},t} \geq 1 \\
& \quad \sum_{\omega \in D} h_{\text{GV},t} \geq 1 \\
& \quad \sum_{\omega \in D} \left( h_{\text{Th},t} + h_{\text{EV},t} + h_{\text{GV},t} \right) \pi_\omega = \beta \\
& \quad h_{\text{Th},t} + h_{\text{EV},t} + h_{\text{GV},t} \leq 1
\end{align*}
\]

(33)

As shown in (33), the decision variables can guarantee the quality-of-service with 1−\( \beta \) confidence level. As the uncertainty set \( \Omega \) is approximated by finite samples, i.e., scenario tree in this paper, problem (34) can be written as the following traditional two-stage stochastic model [35].

\[
\begin{align*}
\min_{x \in X} & \quad c^T x + \sum_{\omega \in D} \pi_\omega q^\omega y(\omega) + \rho \left[ \eta + \sum_{\omega \in \Omega} \pi_\omega y(\omega) \right] \\
\text{s.t.} & \quad v(\omega) \geq c^T x + q^\omega y(\omega) - \eta \\
& \quad y \in Y(\omega) \cup Y_{\text{Th}}(\omega) \cup Y_{\text{EV}}(\omega) \cup Y_{\text{GV}}(\omega) \\
& \quad \sum_{\omega \in D} \left( h_{\text{Th},t} + h_{\text{EV},t} + h_{\text{GV},t} \right) \pi_\omega = \beta \\
& \quad h_{\text{Th},t} + h_{\text{EV},t} + h_{\text{GV},t} \leq 1
\end{align*}
\]

(34)

Problem (34) is a mixed-integer linear programming problem, which can be solved efficiently using commercial solvers. In this paper, problem (34) is programmed by Python and solved by Gurobi.

V. CASE STUDY

A. Case Description

To realize the coordination among multiple energy systems, a hybrid AC/DC MEMG is proposed as shown in Fig. 1. The electrical load profile, heating load profile, and cooling load profile are shown in Fig. 2, which are all given in 1000 scenarios. The parameter settings in this paper are shown as follows. \( P_{\text{EV}}^{\text{max}} \) and \( P_{\text{GV}}^{\text{max}} \) are set to be 400 kWh and 1800 kWh, respectively; \( P_{\text{EV}}^{\text{max},e} \) and \( P_{\text{GV}}^{\text{max},e} \) are set to be 800 kW and 1000 kW, respectively; \( \eta_{\text{SS},e} \) and \( \eta_{\text{ES},e} \) are both set to be 0.9; \( c_{\text{ESS},e} \) and \( c_{\text{ESS},d} \) are both set to be 0.01 $/kWh; \( \eta_{\text{CHP},e} \) and \( \eta_{\text{CHP},d} \) are set to be 0.4 and 0.35, respectively; \( P_{\text{EV}}^{\text{min}} \) is set to be 5000 kW; \( \eta_{\text{BC}} \) is set to be 0.95; \( P_{\text{CHP}}^{\text{min}} \) is 6000
kW; \( G_{\text{ boiler}} \) is 8000 kW; \( P_{\text{max}}^{\text{UG}} \) is 5000 kW; \( P_{\text{max}}^{\text{HVDC}} \) is 5000 kW; and the capacity of PV is 10000 kW. 1000 scenarios are generated for the second-stage optimization, i.e., \( N=1000 \). The tolerance value \( \text{tol} \) in algorithm is set to \( 10^{-3} \).

To verify the effectiveness of proposed method, different cases are formulated as follows.

1) Case 1: two-stage optimization is considered, meanwhile the joint constraints are considered.

2) Case 2: only the first-stage optimization is considered.

Numerical tests are carried out on a laptop with an Intel i7-4770 CPU and 16 GB of RAM. The optimization problems in algorithm 1 are solved using the Gurobi solver.

**B. Result Analysis**

1) **Bi-directional AC/DC Power Flow**

To show the coordination between AC and DC sides of MEMG, the power flow via the bi-directional AC/DC converter is shown in Fig. 3. The AC to DC power is shown as the curved surface above the zero plane, while the DC to AC power is shown as the curve surface below the zero plane. Then, to show the effects of ESS, the state of charge (SOC) of battery is shown in Fig. 4. From the above figure, at first, when the PV power is almost zero, i.e., \( t=0-5, 20-24 \) hour, the DC load is mainly met by AC to DC converter. When the DC load gradually increases, i.e., \( t=5, 6 \) hour, the AC to DC power is also increasing, and the battery discharges to further support DC load. After that, as the PV power increases, the power demands also become larger, i.e., both DC and AC loads increase during \( t=10-16 \) hour. In those time intervals, the PV output is beyond the maximal DC load, which leads the PV power to change to AC via AC/DC converter to support the AC load or battery charging, which is shown as the surface below zero in Fig. 3 and the charging event in Fig. 4.

From the above results, the integration of AC/DC converter can bring great flexibilities to meet both DC and AC loads. The DC power for PV and AC power from UG and CHP can coordinately operate to enhance the energy efficiency.
2) Multiple Energy Flows

In conventional residential area, different energy carriers, i.e., electricity, thermal power and gas, are working independently. In MEMG, various energy carriers work coordinately to enhance the operation flexibility. To show those coordinations in MEMG, the power of CHP is shown in Fig. 5, the power of heat storage is shown in Fig. 6, the power of cooling storage is shown in Fig. 7, and the power of power-to-gas facility is shown in Fig. 8.

From Fig. 2(d) and (e), there are two demand impulses of both heat and cooling demands in $t=6,7$ hour. The CHP responds to those demand impulses and consumes the gas to produce electricity and heat. The heat energy is stored and both the heat and cooling storages are discharging in this period to satisfy the demand, which are shown as the deep valleys in their energy curves in Figs. 6 and 7. After that, CHP is shut-down since the total electricity demand is limited. The thermal demands are then met by the coordination of thermal storage and the gas boiler.

It should be noted that when $t=10-15$ hour, the temperature increases, and high air-conditioning power demand is required. While in this time-period, the PV power is also in its peak-hours. Then the PV power is converted to gas for the gas boiler to meet the air-conditioning power demand, which is shown as in Fig. 8.

The above results show that different energy carriers can be coordinated flexibly in MEMG. The excess electricity can be converted to gas for thermal demand. With the interactions between different energy carriers, the electric and thermal demand can both be satisfied and the flexibility of MEMG can be enhanced.

3) EVs and GVs

The energy demand of vehicles is quite important in future MEMG. However, before complete electrification of vehicles, the GVs and EVs will co-exist in MEMG. To satisfy their energy demands, the electric and gas sides of MEMG should be operated in coordination, respectively. In this case, the equivalent energy of GVs are shown in Fig. 9, and the charging power of EVs are shown in Fig. 10.

From Fig. 9, the energy peaks of GVs are in $t=10-15$ hour and 20-24 hour. The first peak period corresponds to the working hours, and the second one occurs when the vehicles come back for residence. From the results of EVs in Fig. 10, the charging patterns are more periodic with three peak hours, i.e., $t=10-15$, 16-18, and 20-24 hour. From the
above results, both the gas and electricity demands of vehicles can be satisfied.

C. Comparisons of Methods

1) Two-stage and Single-stage Comparisons

In this paper, a two-stage operation framework is proposed, which aims at the day-ahead operation and real-time operation. To show the benefits of proposed two-stage operating framework compared with single-stage one, the day-ahead and real-time UG purchased electricity is shown in Fig. 11.

![Day-ahead and real-time purchased UG power](image)

**Fig. 11.** Day-ahead and real-time purchased UG power.

As illustrated in Fig. 11, in the day-ahead market (first stage), the MEMG purchases electricity from the upper UG, which is shown as the upper surface. However, there are many uncertainties during real-time operation of MEMG, such as PV power, the arrival and departure of vehicles, and the electric, heat and cooling power demand. To cope with those uncertainties, the equipment in MEMG, i.e., CHP, gas boiler, heat storage, and cooling storage, will adjust their power, which are different with scenarios shown as different cases in Figs. 3–10. Those adjustments may require extra energy. Then in the real-time market (second stage), MEMG will purchase more electricity, which is shown as the lower surface in Fig. 11. The benefits of two-stage operation framework can be shown by the indoor temperature comparison shown in Fig. 12.

![Indoor temperature comparison](image)

**Fig. 12.** Indoor temperature with/without proposed two-stage operation.

From Fig. 12, without the two-stage operation framework, the indoor temperature cannot be always held at 20 °C. Meanwhile, with the two-stage operation framework, the indoor temperature can be maintained at 20 °C. This result demonstrates that the proposed two-stage operation framework can better withstand the operation uncertainties.

2) Result Comparisons in Different Relaxation Levels

In this section, the results of proposed model are compared in different relaxation levels. Different relaxation levels β, the computation times, gaps and objectives are shown in Table I.

| Relaxation level | Time (s) | Gap | Objective ($) |
|-----------------|----------|-----|---------------|
| 0% relaxation   | 660.4    | Optimal, tol = 0.02% | 33398 |
| 10% relaxation  | 841.9    | Non-optimal, tol = 0.08% | 33384 |
| 20% relaxation  | 2661.4   | Non-optimal, tol = 0.1% | 33378 |

From the results, the proposed solution method can obtain satisfactory solutions, i.e., optimal solution or low-gap solutions. It should also be noted that the relaxation will bring extra computation burdens and lead to longer computation time. However, even in the worst case, i.e., 20% relaxation level, the proposed method can still get the solution in an acceptable time, i.e., less than one hour for the day-ahead operation. As the relaxation level increases, the objective of obtained scheme decreases.

3) Result Comparisons with and Without CVaR

In this section, the results with and without CVaR are compared. The proposed method uses the objective function defined in (29). The objective function without considering CVaR is defined as (35). The results are compared in Table II.

\[
\min \mathcal{E}^* x + \mathbb{E} [ Q(x, w) ] 
\]

The results show that the computation times with and without CVaR are similar. Considering the CVaR in the objective function, the operation risk is decreased since the CVaR is reduced. The phenomenon demonstrates that the proposed method can limit the operation risk of the obtained operation schemes.

| Method             | Time (s) | CVaR ($) |
|--------------------|----------|----------|
| Proposed method    | 660.4    | 7206     |
| Method without CVaR| 662.3    | 7794     |

VI. CONCLUSION

In this paper, a two-stage optimization scheme is proposed for a hybrid AC/DC MEMG. In the first stage, the day-ahead hourly electrical, heat and cooling scheduling plans are optimized to minimize the operation cost. In the second stage, the real-time electrical, heat and cooling scheduling plans are optimized to minimize the expected operation cost considering the uncertainty of forecasting errors.

The simulation results show that the operation efficiency of MEMG can be increased by the coordination of different energy carriers, i.e., excess electricity can be converted to gas or thermal power to meet the demand, which will bring about quite significant flexibilities for MEMG operation. In addition, by sacrificing the quality of heating and cooling
service, the operation cost can be further reduced. Practically, the operator of MEMG can choose a proper compromise between the quality of service and the economic benefits. With the above simulation results, the proposed method verifies that the thermal system and electrical system can collaborate via the MEMG.

REFERENCES

[1] X. Dong, G. Pi, Z. Ma et al., “The reform of the natural gas industry in the PR of China,” Renewable and Sustainable Energy Reviews, vol. 73, pp. 582-593, Jun. 2017.

[2] Z. Li and Y. Xu, “Optimal coordinated energy dispatch of a multi-energy microgrid in gridconnected and islanded modes,” Applied Energy, vol. 210, pp. 974-986, Jan. 2018.

[3] Y. Li, T. Zhao, P. Wang et al., “Optimal operation of multimegawatts via cooperative energy and reserve scheduling,” IEEE Transactions on Industrial Informatics, vol. 14, no. 8, pp. 3459-3468, Jan. 2018.

[4] Z. Li, Y. Xu, S. Fang et al., “Multi-objective coordinated energy dispatch and voyage scheduling for a multi-energy ship microgrid,” IEEE Transactions on Industry Applications, vol. 56, no. 2, pp. 989-999, Nov. 2019.

[5] C. Grédié, G. Keoppel, P. Favre-Pérodd et al., “Energy hubs for the future,” IEEE Power and Energy Magazine, vol. 5, no. 1, pp. 24-30, Dec. 2007.

[6] W. Liu, F. Wen, and Y. Xue, “Power-to-gas technology in energy systems: current status and prospects of potential operation strategies,” Journal of Modern Power Systems and Clean Energy, vol. 5, no. 3, pp. 439-450, May 2017.

[7] Y. Cao, C. Chen, M. McCulloch et al., “Optimal design and operation of a low carbon community based multi-energy systems considering EV integration,” IEEE Transactions on Sustainable Energy, vol. 10, no. 3, pp. 1217-1226, Jul. 2019.

[8] Y. Jiang, C. Wan, C. Chen et al., “A hybrid stochastic-interval operation strategy for multi-energy microgrids,” IEEE Transactions on Smart Grid, vol. 10, no. 1, pp. 440-456, Jun. 2020.

[9] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo et al., “Energy hub: from a model to a concept – a review,” Renewable and Sustainable Energy Reviews, vol. 80, pp. 1512-1527, Dec. 2017.

[10] C. Zhang, Y. Xu, Z. M. Li et al., “Robustly coordinated operation of a multi-energy microgrid with flexible electric and thermal loads,” IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 2765-2775, May 2019.

[11] Y. J. Cao, Q. Li, Y. Tan et al., “A comprehensive review of Energy Internet: basic concept, operation and planning methods, and research prospect,” Journal of Modern Power Systems and Clean Energy, vol. 6, no. 3, pp. 399-411, May 2018.

[12] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo et al., “Optimal management of energy hubs and smart energy hubs – a review,” Renewable and Sustainable Energy Reviews, vol. 89, pp. 33-55, Jun. 2018.

[13] X. Zhang, M. Shahidehpour, A. Alabdulwahab et al., “Optimal expansion planning of energy hub with multiple energy infrastructures,” IEEE Transactions on Smart Grid, vol. 6, no. 5, pp. 2302-2311, Jan. 2015.

[14] A. Dolatabadi, B. Mohammadi-ivatloo, and M. Ahabpour, “Optimal stochastic design of wind integrated energy hub,” IEEE Transactions on Industrial Informatics, vol. 13, no. 5, pp. 2379-2388, Feb. 2017.

[15] L. Ni, W. Liu, F. Wen et al., “Optimal operation of electricity, natural gas and heat systems considering integrated demand responses and diversified storage devices,” Journal of Modern Power Systems and Clean Energy, vol. 6, no. 3, pp. 423-437, May 2018.

[16] S. D. Beigvand, H. Abdi, M. La Scala et al., “A general model for energy hub economic dispatch,” Applied Energy, vol. 190, pp. 1090-1111, Mar. 2017.

[17] A. Shabanpour-Haghighi and A. R. Seifi, “Energy flow optimization in multicarrier systems,” IEEE Transactions on Industrial Informatics, vol. 11, no. 6, pp. 1107-1117, Jul. 2015.

[18] T. Lu, Z. Wang, J. Wang et al., “A data-driven Stackelberg market strategy for demand response-enabled distribution systems,” IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 2345-2357, Jan. 2019.

[19] T. Lu, Z. Wang, Q. Ai et al., “Interactive model for energy management of clustered microgrids,” IEEE Transactions on Industry Applications, vol. 56, no. 3, pp. 1755-1766, Oct. 2012.

[20] A. Sheikh, M. Rayati, S. Bahrami et al., “Integrated demand side management game in smart energy hubs,” IEEE Transactions on Smart Grid, vol. 6, no. 2, pp. 675-683, Jan. 2015.

[21] Y. Wang, N. Zhang, C. Kang et al., “Standardized matrix modeling of multiple energy systems,” IEEE Transactions on Smart Grid, vol. 8, no. 1, pp. 652-661, Aug. 2017.

[22] M. Bozhchali, S. A. Hashmi, H. Hassen et al., “Optimal operation of residential energy hubs in smart grids,” IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 1755-1766, Oct. 2012.

[23] A. Vaccaro, C. Pisani, A. F. Zobra et al., “Affine arithmetic-based methodology for energy hub operation-scheduling in the presence of data uncertainty,” IET Generation, Transmission & Distribution, vol. 9, no. 13, pp. 1544-1552, Sept. 2015.

[24] A. Parisio, V. D. Carmen, and A. Vaccaro, “A robust optimization approach to energy hub management,” International Journal of Electrical Power & Energy Systems, vol. 42, no. 1, pp. 98-104, Nov. 2012.

[25] A. Najafi, H. Falaghi, J. Contreras et al., “Medium-term energy hub management subject to electricity price and wind uncertainty,” Applied Energy, vol. 168, pp. 418-433, Apr. 2016.

[26] M. J. Vahid-Pakdel, S. Nojavan, B. Mohammadi-ivatloo et al., “Stochastic optimization of energy hub operation with consideration of thermal energy market and demand response,” Energy Conversion and Management, vol. 145, pp. 117-128, Aug. 2017.

[27] A. Najafi, H. Falaghi, J. Contreras et al., “A stochastic bilevel model for the energy hub manager problem,” IEEE Transactions on Smart Grid, vol. 8, no. 5, pp. 2394-2404, Oct. 2017.

[28] A. Dolatabadi, M. Jadiibonab, and B. Mohammadi-ivatloo, “Short-term scheduling strategy for wind-based energy hub: a hybrid stochastic/IGDT approach,” IEEE Transactions on Sustainable Energy, vol. 10, no. 1, pp. 438-448, Jan. 2019.

[29] T. Ma, J. Wu, L. Hao et al., “Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub,” Energy conversion and management, vol. 133, pp. 292-306, Feb. 2017.

[30] J. Wasilewski, “Integrated modeling of microgrid for steady-state analysis using modified concept of multi-carrier energy hub,” International Journal of Electrical Power & Energy Systems, vol. 73, pp. 891-898, Dec. 2015.

[31] C. Lin, W. Wu, B. Zhang et al., “Decentralized solution for combined heat and power dispatch through benders decomposition,” IEEE Transactions on Sustainable Energy, vol. 8, no. 4, pp. 1361-1372, Mar. 2017.

[32] X. Xu, H. Jia, D. Wang et al., “Hierarchical energy management system for multi-source multi-product microgrids,” Renewable Energy, vol. 78, pp. 621-630, Jun. 2015.

[33] A. Gupta, S. Doolla, and K. Chatterjee. “Hybrid AC/DC microgrid: systematic evaluation of control strategies,” IEEE Transactions on Smart Grid, vol. 9, no. 4, pp. 3830-3843, Jul. 2018.

[34] Karlsruhe Institute of Technology. (2018, Mar.). Power-to-gas facility with high efficiency. [Online]. Available: https://phys.org/news/2018-03-power-to-gas-facility-high-efficiency.html

[35] X. Liu, S. Kyavuz, and J. Luedtke, “Decomposition algorithms for two-stage chance-constrained programs,” Mathematical Programming, vol. 157, no. 1, pp. 219-243, Oct. 2016.

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