Two-stage Stochastic Programming Based Model Predictive Control Strategy for Microgrid Energy Management under Uncertainties

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Abstract—Microgrids (MGs) are presented as a cornerstone of smart grid, which can integrate intermittent renewable energy sources (RES), storage system, and local loads environmentally and reliably. Due to the randomness in RES and load, a great challenge lies in the optimal operation of MGs. Two-stage stochastic programming (SP) can involve the forecast uncertainties of load demand, photovoltaic (PV) and wind production in the optimization model. Thus, through two-stage SP, a more robust scheduling plan is derived, which minimizes the risk from the impact of uncertainties. The model predictive control (MPC) can effectively avoid short sighting and further compensate the uncertainty within the MG through a feedback mechanism. In this paper, a two-stage SP based MPC strategy is proposed for microgrid energy management under uncertainties, which combines the advantages of both two-stage SP and MPC. The results of numerical experiments explicitly demonstrate the benefits of the proposed strategy.

Keywords—energy management; microgrid; model predictive control; stochastic programming; uncertainty.

NOMENCLATURE

Parameters and Variables

\( T \) number of time intervals; here equals 24
\( \Delta t \) time interval; here equals 1h
\( N_{DG} \) total number of controllable DGs
\( S \) total number of scenarios
\( t \) time interval index
\( e^P, e^W, e^L \) normalized forecast error of PV, wind, and load, respectively
\( \sigma^P, \sigma^W, \sigma^L \) normalized standard deviation of PV, wind, and load forecast error, respectively
\( P_{PV}^{t,s}, P_{Wind}^{t,s} \) aggregated power production of PV at time interval \( t \) in scenario \( s \) (kW)
\( P_{Load}^{t,s} \) aggregated power production of wind at time interval \( t \) in scenario \( s \) (kW)
\( Price_{import}^t \) price of imported power to the utility \( t \) ($/kWh)
\( Price_{export}^t \) price of exported power to the utility \( t \) ($/kWh)
\( Price_{renew}^t \) price of power exchange between MG and the utility for recourse at time interval \( t \) ($/kWh)
\( Price_{Deg}^t \) degradation cost of the battery system ($/kWh)
\( \rho_s \) probability of scenario \( s \)
\( P_{Load}^{t,s}, P_{DG}^{t,s} \) aggregated total load demand in MG at time interval \( t \) in scenario \( s \) (kW)
\( U_t, S_{DG} \) aggregated total DG consumption in MG at time interval \( t \) (kW)
\( SC_t, SD_t \) start-up, shut-down cost of the \( i \)th DG ($)
\( \eta^t, \eta^d \) variable to indicate start-up or shut-down state of the \( i \)th DG at time interval \( t \)
\( C_{i,DG}^{P^t} \) cost function of the \( i \)th DG ($/h)
\( P_{Char}^{t,s}, P_{DisChar}^{t,s} \) charging, discharging power of battery system at time interval \( t \) in scenario \( s \) (kW)
\( SOC_{min}, SOC_{max} \) minimum, maximum SoC of battery system (kWh)
\( SOC_{i} \) SoC of battery at time interval \( t \) (kWh)
\( SOC_{0} \) initial value of SoC, it is set to \( SOC_{min} \) (kWh)

Decision Variables

\( p_{import}^t \) imported power from the utility at time interval \( t \) (kW)
\( p_{export}^t \) exported power to the utility at time interval \( t \) (kW)
\( p_{renew}^t \) power exchange between MG and the utility for recourse at time interval \( t \) in scenario \( s \) (kW)
\( p_{Char}^{t,s}, p_{DisChar}^{t,s} \) charging, discharging power of battery system at time interval \( t \) in scenario \( s \) (kW)
\( SC_t, SD_t \) binary variable to indicate the charging state (1 for charging and 0 for not) of the
battery, at time interval $t$ in scenario $s$. A binary variable to indicate the discharging state ($1$ for discharging and $0$ for not) of the battery, at time interval $t$ in scenario $s$. The active power generation of the $i$th DG, at time interval $t$ (kW). A binary variable to indicate the on/off (1/0) state of the $i$th DG, at time interval $t$, set $on_{i,0} = 0$.

### I. INTRODUCTION

The microgrid (MG) is a micro power system integrating a number of intermittent renewable energy sources (RES), such as photovoltaic (PV), wind, storage system, and local loads. MGs have received great attention since they possess the potential to integrate intermittent RES in a flexible and decentralized way. Due to the randomness in RES and load, a great challenge lies in the optimal operation of MGs.

Recently, two-stage stochastic programming (SP) has been applied to MG energy management [1-3] and it is demonstrated to be a flexible and effective strategy to deal with the uncertainty in MG. For two-stage SP, stochastic variable scenarios are always generated through Monte Carlo Simulation (MCS). By considering all possible realizations of each scenario, the risk cost due to imprecise forecast of stochastic variable can be reduced. Zakariazadeh et al. [3] proposed a two-stage SP formulation for energy and reserve scheduling with demand response. Zhou et al. [1] proposed a two-stage SP method for the optimal design of distributed energy system. Niknam et al. [4] proposed a stochastic model for optimal energy management with the goal of cost and emission minimization. For solving the proposed model, a complex heuristic algorithm is used. However, the two-stage SP is an open loop strategy, which cannot effectively deal with forecast uncertainties in MG.

Model predictive control (MPC), also known as recording horizon control (RHC), is an advanced method for process control. Recently, MPC has also been used in the power system as it can incorporate both forecasted and newly updated information to make decisions [5, 6]. In [7], the effects of stochastic wind and load on the unit commitment and dispatch of power systems with high levels of wind power are examined by rolling planning strategy. The planning horizon is divided into multiple stages and generates scenarios with the scenario tree tool. However, the computing complexity will increase exponentially with the increase of stage numbers. Kriett et al. [8] proposed an MPC scheme to minimize the operating cost of a residential microgrid by iteratively producing a control sequence for the studied microgrid. However, the authors did not consider the uncertainties in MG. Zhang et al. [9] proposed an MPC-based strategy scheduling for microgrid operator to minimize the operation costs of a MG. However, as [8, 9], it did not consider the uncertainties related to load, PV and wind generation in the optimization model, which naturally affects the result accuracy and therefore the overall performances of MG.

In this paper, a two-stage stochastic programming based MPC strategy for microgrid energy management under uncertainties is proposed. Through the two-stage SP, the optimization model involves the forecast uncertainties of load demand, PV and wind production. In order to further compensate the uncertainty within the MG energy management, a feedback mechanism based on MPC is proposed to incorporate with two-stage SP. The results of numerical experiments explicitly demonstrate the benefits of the proposed strategy.

This paper is structured as follows. In Section II, two-stage SP formulation for MG energy management is proposed. In Section III, MPC is introduced. Section IV shows the numerical experiments. Finally, the conclusions are given in Section V.

### II. TWO-STAGE STOCHASTIC PROGRAMMING FORMULATION FOR MICROGRID ENERGY MANAGEMENT

A two-stage stochastic programming formulation is developed to model the load, PV and wind uncertainties within the MG energy management. In order to capture complete cycles of the load, solar, and wind profiles, the problem is investigated in a 24h time period and the time resolution is 1h. Thus, the programming horizon has 24 time intervals. In the stochastic programming method, all plausible states of load, PV and wind generation in 24h with 1h time resolution are modeled by generating different scenarios.

#### A. Scenario Generation and Reduction

In most literatures, the probability distribution of normalized forecast error of load demand, wind and PV power production are represented by normal distribution [10, 11], as shown by (1) to (3).

$$e^{PV} \sim N(0, \sigma^{PV^2})$$

$$e^{Wind} \sim N(0, \sigma^{Wind^2})$$

$$e^{Load} \sim N(0, \sigma^{Load^2})$$

(1) (2) (3)

To properly model the variations of load demand, PV and wind generation in a MG, the uncertainties corresponding to the forecast errors of them are modeled using the MCS [12]. Accoding to the generated forecast errors through MCS, a certain number (such as $N_0$) of scenarios are generated, and each scenario consists of a vector as shown by (4) and with the probability of $\sqrt{N_0}$.

$$X_s = \begin{bmatrix} P^{PV}_{s,1}, \ldots, P^{PV}_{s,T}, P^{Wind}_{s,1}, \ldots, P^{Wind}_{s,T}, P^{Load}_{s,1}, \ldots, P^{Load}_{s,T} \end{bmatrix}$$

(4)

Although a higher number of scenarios can result in a better modeling of the uncertainty in a MG, but it is at the expense of increasing the computational burden. Thus, scenario reduction method is needed to remove the similar scenarios and keep a good approximation of the uncertainty. The backward reduction algorithm (BRA), which has been proved to provide...
very good performances in the two-stage mixed integer stochastic programming [5], is adopted in this paper. The diagram of BRA [13] is shown in Fig. 1.

Let the distance between two scenarios is described as a 2-norm, as shown by (5).

$$d^{ij} = \|X_j - X_i\|$$

(5)

Initialization: Set \( n = 1, S_0 = N_i \),
\( \rho_s = \frac{1}{N_i} \) for \( s = 1, ..., N_i \),
calculate \( d^{s,j} \) for \( i, j = 1, ..., N_i \), according to (5),
Sort the records \( \{d^{s,j} : j = 1, ..., N_i\} \) for \( k = 1, ..., N_s \),
\( d^{j}(n) = \min_{s = 1, ..., N_s} d^{s,j} \), \( l = 1, ..., N_s \),
\( z_i(n) = \rho_i d^{j}(n), l = 1, ..., N_s \),
\( l(n) = \arg \min_{s = 1, ..., N_s} z_i(n), J = \{l(n)\} \).

\( n = n + 1, S_i = N_i - \text{numel}(J) \),
\( \text{numel}() \) means the number of array elements,
\( d^{j}(n) = \min_{s = 1, ..., N_s} d^{s,j}, J = J \cup \{l(n)\} \),
\( z_i(n) = \sum_{s = 1, ..., N_s} \rho_i d^{j}(n), l = J \),
\( l(n) = \arg \min_{s = 1, ..., N_s} z_i(n), J = J \cup \{l(n)\} \).

<table>
<thead>
<tr>
<th>Initialization</th>
<th>Yes</th>
<th>No</th>
<th>$S_i &lt; S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J$ is the index set of deleted scenarios. Computer probabilities for the preserved scenarios by (6) and output the preserved scenarios.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 1 Diagram of BRA algorithm.

Then, the BRA is implemented until \( S \) scenarios are remaining. The probabilities for the preserved scenarios can be calculated by (6).

$$\rho_j = \rho_j + \sum_{i \in J} \rho_i, \text{ for each } j \notin J,$$
where \( J = \{i \in J : j = f(i)\} \)
and \( j(i) = \arg \min_{j \in J} d^{j,i} \) for each \( i \in J \).

(6)

B. Objective Function

In grid-connected mode, the costs of MG consists of the start-up/shut-down cost and fuel cost of controllable DGs, degradation cost of battery, and power purchase cost from utility grid. Considering the uncertainty of load, PV and wind power generation, the costs of MG can be formulated as a two-stage objective function as shown by (7).

$$\text{Min } f = \sum_{i=1}^{T} \left( \sum_{s=1}^{N_i} u_{s}^{SU} \times U_{s}^{DG} + u_{s}^{SD} \times S_{s}^{DG} + C_{i} \left( P_{i}^{PV} \times P_{i}^{DG} \right) \times \Delta t \right)$$

(7)

In order to keep the model being a mixed integer convex quadratic programming (MICQP) model and without adding new variables, \( u_{s}^{SU} \) and \( u_{s}^{SD} \) can be defined as (8) and (9).

$$u_{s}^{SU} = \frac{1}{2} \left( o_{iou,s}^{DG} - o_{ion+1,s}^{DG} \right)^2 + \frac{1}{2} \left( o_{ion,s}^{DG} - o_{ion+1,s}^{DG} \right)$$

(8)

$$u_{s}^{SD} = \frac{1}{2} \left( o_{iou,s}^{DG} - o_{ion+1,s}^{DG} \right)^2 + \frac{1}{2} \left( o_{ion,s}^{DG} - o_{ion+1,s}^{DG} \right)$$

(9)

As shown by (7), the objective function contains two parts. In the first stage, it makes the decisions (i.e. commitment states of DGs and their scheduled energy, commitment power exchange between the utility and grid) before the actual realization of the uncertainty becomes available. In the second stage, it makes correction decisions (i.e. the charging/discharging power of battery and the recourse of power exchange between MG and the utility) to compensate any infeasibility from the first stage decisions, depending upon the particular realization of each scenario. The objective is to make proper decisions in the first stage in order to minimize the sum of first stage costs and the expected costs of second stage [5].

The cost function of the \( i \)th DG is approximated with a quadratic function [14], as shown in (10).

$$C_{i}(x) = a_{i}x^2 + b_{i}x + c_{i}, x > 0$$

(10)

where \( a_{i}, b_{i}, c_{i} \) are the cost coefficients of the \( i \)th DG.

C. First-stage Constrains

In grid-connected mode, the costs of MG consists of the start-up/shut-down cost and fuel cost of controllable DGs, degradation cost of battery, and power purchase cost from utility grid. Considering the uncertainty of load, PV and wind power generation, the costs of MG can be formulated as a two-stage objective function as shown by (7).

$$\text{Min } f = \sum_{i=1}^{T} \left( \sum_{s=1}^{N_i} u_{s}^{SU} \times U_{s}^{DG} + u_{s}^{SD} \times S_{s}^{DG} + C_{i} \left( P_{i}^{PV} \times P_{i}^{DG} \right) \times \Delta t \right)$$

(7)

In order to keep the model being a mixed integer convex quadratic programming (MICQP) model and without adding new variables, \( u_{s}^{SU} \) and \( u_{s}^{SD} \) can be defined as (8) and (9).

$$u_{s}^{SU} = \frac{1}{2} \left( o_{iou,s}^{DG} - o_{ion+1,s}^{DG} \right)^2 + \frac{1}{2} \left( o_{ion,s}^{DG} - o_{ion+1,s}^{DG} \right)$$

(8)

$$u_{s}^{SD} = \frac{1}{2} \left( o_{iou,s}^{DG} - o_{ion+1,s}^{DG} \right)^2 + \frac{1}{2} \left( o_{ion,s}^{DG} - o_{ion+1,s}^{DG} \right)$$

(9)

As shown by (7), the objective function contains two parts. In the first stage, it makes the decisions (i.e. commitment states of DGs and their scheduled energy, commitment power exchange between the utility and grid) before the actual realization of the uncertainty becomes available. In the second stage, it makes correction decisions (i.e. the charging/discharging power of battery and the recourse of power exchange between MG and the utility) to compensate any infeasibility from the first stage decisions, depending upon the particular realization of each scenario. The objective is to make proper decisions in the first stage in order to minimize the sum of first stage costs and the expected costs of second stage [5].

The cost function of the \( i \)th DG is approximated with a quadratic function [14], as shown in (10).

$$C_{i}(x) = a_{i}x^2 + b_{i}x + c_{i}, x > 0$$

(10)

where \( a_{i}, b_{i}, c_{i} \) are the cost coefficients of the \( i \)th DG.
D. Second-stage Constrains

The second-stage constraint helps to balance generation and load under different conditions of each scenario. The constraints of the battery are shown by (15) to (22).

\[ 0 \leq i_{t,s}^{\text{Char}} \leq \text{CharBat} \text{Max} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  
\[ 0 \leq i_{t,s}^{\text{DisChar}} \leq \text{CharBat} \text{Max} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  

\[ \text{Soc}_{t,s} = \text{Soc}_{t-1,s} + i_{t,s}^{\text{Char}} \times \Delta t \times \eta_{t,s}^{\text{eff}} - i_{t,s}^{\text{DisChar}} \times \Delta t / \eta_{t,s}^{\text{eff}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  

\[ \text{Soc}_{t,s}^{\text{min}} \leq \text{Soc}_{t,s} \leq \text{Soc}_{t,s}^{\text{max}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  

It should be note that the constant (19) is normally fulfilled even if not included in the model [6]. However, in some cases the second stage decisions might use simultaneous charging and discharging of battery units in order to absorb power from the system without affecting its state of charge (SoC) [15]. In order to avoid the simultaneous charging and discharging of battery system, as discussed in [15], the binary variables \( \text{St}_{t,s}^{\text{Char}} \) and \( \Delta t^{\text{DisChar}} \) are introduced and redefine the constant (19) as (20) to (22). In this way, It can guarantee a correct behavior while keeping the model as a MICQP model.

\[ \text{St}_{t,s}^{\text{Char}} \leq 1 \times \Delta t^{\text{DisChar}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  
\[ \text{St}_{t,s}^{\text{Char}} \times \text{CharBat} \text{Max} \geq i_{t,s}^{\text{Char}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  
\[ \text{St}_{t,s}^{\text{DisChar}} \times \text{CharBat} \text{Max} \geq i_{t,s}^{\text{DisChar}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  

\[ P_{t,s}^{\text{Load}} = P_{t,s}^{\text{Wind}} + P_{t,s}^{PV} + \sum_{i=1}^{N} P_{t,s}^{DG} + P_{t,s}^{\text{DisChar}} - P_{t,s}^{\text{Char}} \]  
\[ + P_{t,s}^{\text{Import}} - P_{t,s}^{\text{Export}} + P_{t,s}^{\text{PreV}} \quad \forall t = 1, \ldots, T \text{ and } s = 1, \ldots, S \]  

III. MPC

For each time step \( t \), the MPC based microgrid energy management solves the two-stage SP problem as illustrated in section II, on the basis of updated system state (such as the SoC of battery), yet only the control actions for the first time step is implemented. Then, the second stage correction actions were implemented according to the particular realization of real scenario. Based on the first-stage control actions and the second-stage correction actions, the system responses to those control actions will be measured as the updated information for solving the two-stage SP problem in the next period. By implementing these steps with a MPC strategy, a feedback mechanism is involved that can further compensate the uncertainty in MG. The detail process of two-stage SP based MPC is shown in Fig. 2.

IV. NUMERICAL EXPERIMENTS

In this paper, a MG with two controllable distributed generators (DGs), a battery storage system, PV generators and wind turbines is considered for case study. The forecast and re-
al aggregated power production of PV and Wind as well as the load demand are collected and modified from ELIA [16], as shown in Fig. 3 and Fig. 4. The price of imported power from the utility (i.e. \( \text{Price}_{\text{import}} \)) and the degradation cost of battery (i.e. \( \text{Price}_{\text{bat}} \)) is collected from [2], as shown in Fig. 4. In order to incite locally use of PV and wind power to reduce the negative impacts to external grid, the selling price (i.e. \( \text{Price}_{\text{export}} \)) is always set lower than purchasing price [17] and the price for power recourse in the second-stage (\( \text{Price}_{\text{recourse}} \)) is higher than purchasing price [2]. We assume the price of exported power to the utility (i.e. \( \text{export}_{\text{tPrice}} \)) is 0.2 multiplying the purchasing price while the price for power recourse in the second-stage (i.e. \( \text{recourse}_{\text{tPrice}} \)) is 5 multiplying the purchasing price. The normalized standard deviations (i.e. \( \delta_{PV}, \delta_{Wind}, \delta_{Load} \)) of forecast error for PV, wind and load is collected from [18]. All the data used for simulation is shown in Table I.

The simulations were run on a PC with Intel(R) Core(TM) i7-2600 CPU @3.40GHz and 4.00 GB memory. The IBM ILOG CPLEX v12.60 optimization solver is utilized for solving the MICQP model, MATLAB 2015b and YALMIP toolbox [19] are used for linking the CPLEX solver and computing the model.

In order to analyze the superiority of the proposed two-stage SP based MPC, the following strategies are implemented for comparison: 1) Benchmark with perfect forecast, it assumes that the operator knows all the future realizations of the uncertainties in PV, wind and Load demand; 2) only the two-stage SP is used; 3) only the MPC is used; 4) the proposed two-stage SP based MPC is used. The comparison results are shown in Table II. As shown in Table II, the proposed two-stage SP based MPC is much closer to the benchmark. That is because the two-stage SP can provide a robust scheduling plans which minimize the risk from the impact of uncertainties, the MPC can effectively avoid short sighting and further compensate the uncertainty within the MG through a feedback mechanism, while the two-stage SP based MPC combines the advantages of both two-stage SP and MPC.

Fig. 5 shows the optimal power schedule of benchmark based on perfect forecast. As shown in this figure, during 3:00-5:00, the price of imported power is lower, so the battery is charging until the SoC is limited by its capacity. During 10:00-12:00 the price is higher, so the MG exports power to the utility. At 13:00, the price is lower, DG1 is shut-down and stop exporting power to the utility. At 14:00, the price is higher again, the DG1 is start-up, the battery is discharging, and the MG exports power to the utility.

### Table I: Data Used for Simulation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta_{PP} ), ( \delta_{Wind} ), ( \delta_{Load} )</td>
<td>5.1%, 11.9%, 2.6%</td>
</tr>
<tr>
<td>( \text{Price}_{\text{bat}} )</td>
<td>0.0135 ($/kWh)</td>
</tr>
<tr>
<td>( p_{DG_{1}}^{\text{min}} ), ( p_{DG_{1}}^{\text{max}} )</td>
<td>3 (kW), 30 (kW)</td>
</tr>
<tr>
<td>( p_{DG_{2}}^{\text{min}} ), ( p_{DG_{2}}^{\text{max}} )</td>
<td>6 (kW), 60 (kW)</td>
</tr>
<tr>
<td>( \text{SoC}<em>{\text{min}}, \text{SoC}</em>{\text{max}} )</td>
<td>0(kWh), 15 (kWh)</td>
</tr>
<tr>
<td>( p_{\text{bat}}^{\text{max}} )</td>
<td>5 (kW)</td>
</tr>
<tr>
<td>( S_{DG_{1}}^{\text{DG}} ), ( S_{DG_{2}}^{\text{DG}} )</td>
<td>0.11 ($), 0.11 ($)</td>
</tr>
<tr>
<td>( S_{DG_{1}}^{\text{DG}} ), ( S_{DG_{2}}^{\text{DG}} )</td>
<td>0.2 ($), 0.2 ($)</td>
</tr>
<tr>
<td>( a_{1}, b_{1}, c_{1} )</td>
<td>0.000111($/kW\cdot h$), 0.0583($/kWh$), 0.52($/h$)</td>
</tr>
<tr>
<td>( a_{2}, b_{2}, c_{2} )</td>
<td>0.000111($/kW\cdot h$), 0.034($/kWh$), 1.47($/h$)</td>
</tr>
<tr>
<td>( \eta^{\text{f}}, \eta^{\text{d}} )</td>
<td>0.95, 0.95</td>
</tr>
</tbody>
</table>

### Table II: MG Operation Cost Based on Different Operation Strategies.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Total cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark with perfect forecast</td>
<td>82.30</td>
</tr>
<tr>
<td>Two-stage SP</td>
<td>96.75</td>
</tr>
<tr>
<td>MPC</td>
<td>92.59</td>
</tr>
<tr>
<td>Proposed two-stage SP based MPC</td>
<td>91.25</td>
</tr>
</tbody>
</table>

![Fig. 5 Optimal power schedule of benchmark based on perfect forecast.](image1)

![Fig. 6 Optimal power schedule based on two-stage SP based MPC.](image2)
Fig. 6 shows the optimal power schedule based on two-stage SP based MPC. As it does not know the perfect future realizations, the schedule is not optimal, but it can reduce the risk of uncertainty. The battery system can help to reduce the operating cost by reducing the higher cost power recourse of the utility in the second-stage.

V. CONCLUSION

In this paper, we propose a two-stage stochastic programming based MPC strategy for microgrid energy management under uncertainties. Two-stage SP can provide a more robust scheduling plan which minimizes the risk from the impact of uncertainties, the MPC can effectively avoid short sighting and further compensate the uncertainty within the MG through a feedback mechanism, while the two-stage SP based MPC combines the advantages of both two-stage SP and MPC. The main contributions of this paper are: (1) the formulation of a combined control strategy based on two-stage SP and MPC. (2) In order to avoid the simultaneous charging and discharging of battery system, a proper strategy is proposed to guarantee a correct behavior while keeping the model as a MICQP model, which is solvable without resorting to any heuristic algorithms.

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