A Comprehensive MPC based Energy Management Framework for Isolated Microgrids

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***Abstract*—Isolated regions and remote islands are facing problems such as imported fossil-fuel dependency, increasing electricity prices, and low electricity quality. Isolated microgrids technologies which integrate large scale of renewable energy resources, energy storages, flexible loads, traditional fossil-fuel generators and advanced electric electrical devices have been seen as the answer the above problems. In addition, a closed-loop based energy management operation framework is needed to accommodate the fluctuated renewable energy generation with a comprehensive energy management optimization strategy considering integer variables/discrete constraints and complex operation constraints in generators and energy storage models. To this end, this paper proposed a model predictive control (MPC) based energy management and operation framework for isolated microgrids where the optimal energy management for the microgrid is formulated as a mixed integer quadratic programming problem (MIQP). Numerical results demonstrate the effectiveness of our approach.**

***Index Terms*—Isolated microgrids, renewable energy, model predictive control.**

I. Introduction

The concept of microgrid has drawn great attention from the research and industrial community over the last decade, due to its great potential to reliably and efficiently integrate large scale renewable energy resources (RESs) into today's power system and future smart grid in a distributed way [1]. The microgrid can be coordinated and perceived as a single unit by the external grid, and it can be operated in grid-connected mode and isolated mode.

Isolated microgrids for remote communities are turning to renewable energy resources and energy storages in order to reduce the dependency on fossil fuels [2], which can help improve the power quality, provide spinning reserve, and reduce the transmission and distribution costs [3]. The energy storage system and traditional fossil generators are regarded as two key components to guarantee a stable and reliable isolated microgrids. However, it is well recognized that the energy management models for energy storage and fossil generator are very challenging due to inherent integer variables and corresponding discrete constraints.

The research on tackling challenges on energy management system (EMS) for isolated microgrids can be approximately categorized into two groups: open loop based and closed loop based strategies. For open loop based strategies, [4] proposed a mixed-integer linear programming and a virtual power producer to manage the operation generation and their load control of isolated microgrids. [4] investigated the impacts of uncertainty and risk aversion on unit commitment decisions in isolated power systems with high renewable energy penetration. [5] proposed an energy management strategy of battery storage in isolated microgrid where the simulation results show that the security and reliability of the microgrid can be improved significantly. Although the above literatures present valuable insights on isolated microgrids energy management, they are all open-loop based energy management strategies and their control performances will degrade sharply when the renewable energy penetration level increases.

For closed loop based strategy, [6] proposed a mathematical formulation of a centralized energy management system for island microgrids, and model predictive control (MPC) technique is implemented to reduce the negative impacts introduced by uncertainties of renewable energy generations. Later, the same author also proposed a stochastic-predictive energy management system for the isolated microgrids [7]. A combined unit commitment and optimal power flow model based on MPC implementation is proposed in [8] for integrated energy management in isolated microgrids whereas a sustainable energy management system considering generation carbon emission and demand response is proposed in [9] for isolated microgrids. Note that the above literatures only consider automatic generation control (AGC) based generators in their models whereas traditional generators [10] which do not have automatic generation control (AGC) functions and usually have discrete model constraints are not considered.

Motivated by the above analysis, in this paper we propose a comprehensive MPC based energy management framework for isolated microgrids where all important microgrids components (including various types of generators) and their corresponding key features are modelled. Compared to the above recent works of isolated microgrids energy management, the main contributions of our study are summarized as follow:

- We model traditional generators with minimum up/down times and discrete generation constraints explicitly in our microgrid energy management framework, which is currently missing in the existing literatures.
- A comprehensive energy management framework based on model predictive control is proposed, which simultaneously considers generation-side (unit commitment for all types of generators) and demand-side (smart loads) energy management problems, as well as charge/discharge

dynamics of energy storage systems under the penetration of renewable energy resources.
- A comparison study is conducted in this paper to elaborate the effectiveness of our proposed approach by comparing with other state-of-the-art approach.

The remainder of this paper are organized as follows: Section II provides the detailed problem formulation for microgrid energy management model; Section III presents the MPC based microgrid operation framework; Simulation results are given in Section IV and this paper is concluded in Section V.

II. Problem Formulation

The basic structure of an isolated microgrid discussed in present paper is illustrated as Fig. 1. This microgrid comprises RESs such as wind and PV, controllable fossil generators (CFG)such as diesel and micro-turbines, energy storage systems (ESSs) such as battery, and smart loads such as critical, power flexible loads. The high power quality, stable voltage and frequency, and energy management of the microgrid is support by EMS through coordinating operation schedules of traditional fossil generators, charging/discharging actions of ESSs and the power adjustment of flexible loads. The optimization and control sequence is calculated according to power outputs of RESs and load demand. We should note that, some fossil generators known as traditional discrete output generators (TDOG), are deployed decades ago, and they do not have AGC function. Therefore, the power generation schedules should be operated by corresponding operators. To reduce the operation burden of such operators, the operation plan of these generators sent from the EMS is in staircase and discrete form, and the operation status of the TDOGs will be kept the same over certain periods.

A. Objective Function

The mathematical formulations of the energy management problem for isolated microgrid are shown as follows. It aims to minimize the expected microgrid operation cost C_{MG}.

$$\begin{aligned}
&\min \textstyle\sum_{t=1}^{T} \big\{ \sum_{i=1}^{N} \big[C\big(P_{i,DG}(t)\big) + \\
&C_{i,DG}^{up} \times \max\{\delta_{i,DG}(t) - \delta_{i,DG}(t-1), 0\} + \\
&C_{i,DG}^{down} \times \max\{\delta_{i,DG}(t-1) - \delta_{i,DG}(t), 0\}\big] + \\
&\textstyle\sum_{i=1}^{M} \big[C\big(P_{i,AGC}(t)\big) + \\
&C_{i,AGC}^{up} \times \max\{\delta_{i,AGC}(t) - \delta_{i,AGC}(t-1), 0\} + \\
&C_{i,AGC}^{down} \times \max(\delta_{i,AGC}(t-1) - \delta_{i,AGC}(t), 0)\big] + \\
&c_{ESS}^{O\&M}\big(P_{ESSc}(t) + P_{ESSd}(t)\big)\triangle t + \\
&c_{F}^{curt}\theta_F(t) l_F(t)\triangle t\big\}
\end{aligned} \tag{1}$$

where T is the control and prediction horizon of the optimization problem; N and M are the number of TDOGs and AGC based generators respectively. $P_{i,DG}(t)$ and $\delta_{i,DG}(t)$ are power production and running state of the i^{th} TDOG in period t where $P_{i,DG}(t)$ is a discrete integer variable and $\delta_{i,DG}(t)$ is a binary variable. $C_{i,DG}^{\text{up}}$ and $C_{i,DG}^{\text{down}}$ are the start-up and shut-down cost coefficients for the i^{th} TDOG. $C\left(P_{i,\mathrm{DG}}(t)\right)$ is the fuel cost for the i^{th} TDOG. $P_{i,AGC}(t)$ and $\delta_{i,AGC}(t)$ are the power production and running state of the i^{th} AGC based generators in period t where $P_{i,AGC}(t)$ is a continuous

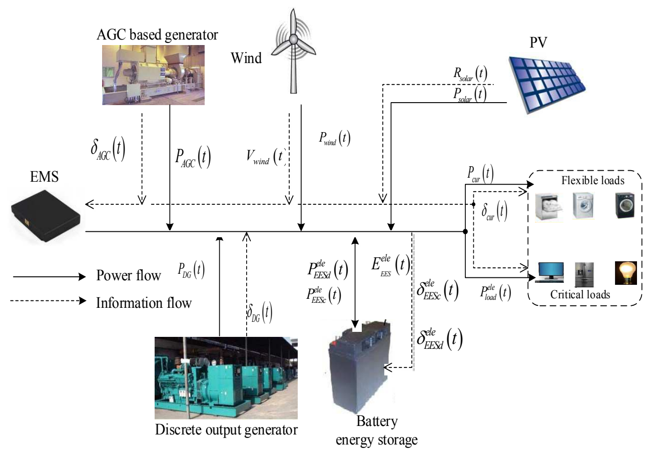

Fig. 1: Schematic diagram of an isolated microgrid.

variable and $\delta_{i,AGC}(t)$ is a binary variable. $C_{i,AGC}^{\text{up}}$ and $C_{i,AGC}^{\text{down}}$ are the start-up and shut-down cost coefficients for the i^{th} AGC based generators. $C\left(P_{i,\mathrm{AGC}}(t)\right)$ is the fuel cost for the i^{th} AGC based generator. $c_{\mathrm{ESS}}^{O\&M}$is the maintenance and degradation cost coefficient for ESS unit. $P_{\mathrm{ESSc}}(t)$ and $P_{\mathrm{ESSd}}(t)$ are charging and discharging power at period t respectively. c_F^{curt} is the penalty cost coefficient for flexible loads. $\theta_F(t)$ and $l_F(t)$ are the power curtailment ratio and the forecast flexible load demand in period t respectively. $\triangle t$ is the duration of each optimization period.

When the optimization scheme is applied, the total operation cost over the control horizon is calculated according to Eq. (1) where relevant constraints are to be shown in the following subsection. It is a mixed integer quadratic programming (MIQP) problem. The first term of Eq.(1) denotes the operation cost of the TDOG units which includes the fuel consuming cost, start-up action cost, and shut down action cost; the second term denotes the operation cost of the AGC based generators which also includes the fuel consuming cost, start-up action cost, and shut down action cost; the third term is the operation and maintenance cost of the ESS units; and the last term is the flexible power curtailment penalty cost.

B. Constraints

1) Power balance constraint: The essential work of the isolated microgrid is to guarantee the supply-demand balance in each period, which is shown as Eq. (2).

$$\begin{aligned}
&\sum_{i=1}^{N} P_{i,\mathrm{DG}}(t) + \sum_{i=1}^{M} P_{i,\mathrm{AGC}}(t) + P_{\text{wind}}(t) + \\
&P_{\mathrm{PV}}(t) + P_{\mathrm{ESSd}}(t) = P_{\mathrm{ESSc}}(t) + l_{\text{load}}(t)
\end{aligned} \tag{2}$$

where $P_{\text{wind}}(t)$, $P_{\mathrm{PV}}(t)$ are the power output of wind generation and PV generation in period t respectively. $l_{\text{load}}(t)$ is the total load demand in period t. The loads in this microgrid include critical loads and flexible loads as shown in Eq. (3).

$$l_{load}(t) = l_{\text{cri}}(t) + l_F(t)\left(1 - \theta_F(t)\right) \tag{3}$$

where $l_{\text{cri}}(t)$ is the power of critical loads in period t.

2) Load constraints: The operation constraints for different kinds of loads are shown as follows:

$$0 \le \theta_F(t) \le \theta_F^{\max} \tag{4}$$
$$0 \le l_F(t) \le l_F^{\max} \tag{5}$$
$$0 \le l_{\text{cri}}(t) \le l_{\text{cri}}^{\max} \tag{6}$$

where $\theta_F^{\max}$, $l_F^{\max}$ are the maximum curtailment ratio and the maximum power demand of the flexible loads respectively. $l_{\text{cri}}^{\max}$ is the maximum power demand of the critical loads.

For power flexible loads, the adjustment ratio and power consumption must be bounded in certain ranges to keep users' comfort, as shown in Eqs. (4)-(5). We should note that, the power curtailment for the flexible loads should be punished with high penalty cost; therefore, the curtailment action will only be implemented in emergency conditions. For critical loads, although their demands cannot be adjusted, the forecast power must be within a certain range to keep the system run reliably, which is reflected as Eq. (6).

3) ESS operation constraints: ESS units need to satisfy energy level, charging/ discharging power, operation status, and energy dynamic varying constraints as Eqs. (7) -(11).

$$E_{ESS}^{\min} \le E_{ESS}(t) \le E_{ESS}^{\max} \tag{7}$$
$$\delta_{ESSc}(t)P_{ESSc}^{min} \le P_{ESSc}(t) \le \delta_{ESSc}(t)P_{ESSc}^{max} \tag{8}$$
$$\delta_{ESSd}(t)P_{ESSd}^{min} \le P_{ESSd}(t) \le \delta_{ESSd}(t)P_{ESSd}^{max} \tag{9}$$
$$\delta_{ESSc}(t) + \delta_{ESSd}(t) \le 1 \tag{10}$$
$$\begin{aligned} E_{ESS}(t+1) = E_{ESS}(t) + \big(&\eta_{ESSc}P_{ESSc}(t) - \\ &1/\eta_{ESSd}P_{ESSd}(t)\big)\triangle t - \varepsilon_{ESS} \end{aligned} \tag{11}$$

where $E_{\text{ESS}}(t)$ is the ESS energy level in period t. η_{ESSc} and η_{ESSd} are the charge and discharge efficiencies of ESS respectively. ε_{ESS} is the self-discharge loss of ESS unit. $P_{\text{ESSc}}^{\min}$ and $P_{\text{ESSc}}^{\max}$ are the minimum and maximum charging power respectively whereas $P_{\text{ESSd}}^{\min}$and $P_{\text{ESSd}}^{\max}$ are the minimum and maximum discharging power respectively.

In the above, Eq. (11) indicates that the energy level of energy storage system at time $t+1$ is equal to that at t plus the electricity charged minus the electricity discharged and the electricity loss due to self-discharge. The ESS dynamics model Eq. (11) can effectively express the mixed logic dynamic feature of ESS without introducing extra auxiliary variables.

4) Fossil generators: The fossil generators used in this isolated microgrid have two types: TDOG and AGC based generators [10]. The first type generators (TDOG) are traditional generators deployed decades ago, and they must be operated manually. The power outputs of such generators are discrete. The second type generators (AGC) are modern generators, which can be automatic controlled by embedded digital system. Note that the TDOG units usually have larger output power than AGC based generators. Therefore, it should include the minimum up and down time constraints in the model of TDOG whereas AGC based generators can be frequently start up and shut down and do not need such constraints.

As a result, for TDOG, it needs to satisfy the power output, minimum up time, minimum down time, and ramp up/down power constraints, which are as shown in Eqs. (12)-(15) respectively.

$$P_{i,DG}^{\min}\delta_{i,DG}(t) \le P_{i,DG}(t) \le \delta_{i,DG}(t)P_{i,DG}^{\max} \tag{12}$$
$$\delta_{i,DG}(t) - \delta_{i,DG}(t-1) \le \delta_{i,DG}(\tau_1) \tag{13}$$
$$\delta_{i,DG}(t-1) - \delta_{i,DG}(t) \le \delta_{i,DG}(\tau_2) \tag{14}$$
$$-R_{i,DG} \le P_{i,DG}(t) - P_{i,DG}(t-1) \le R_{i,DG} \tag{15}$$

where $\tau_1 = t, \cdots, min\{t + T_{i,DG}^{\text{up}} - 1, T\}$, and $\tau_2 = t, \cdots, min\{t + T_{i,DG}^{\text{down}} - 1, T\}$ are auxiliary variables and used for expressing the minimum up and down time constraints respectively. $T_{i,DG}^{\text{up}}$ and $T_{i,DG}^{\text{down}}$ are the minimum up and down times of the i^{th} TDOG. $R_{i,DG}$ is the maximum ramp power; $P_{i,DG}^{\max}$ and $P_{i,DG}^{\min}$ are the maximum and minimum power outputs of the i^{th} TDOG unit respectively.

The AGC based generators needs to satisfy the power output, and ramp up/down power constraints, as shown in Eqs. (16)-(17) respectively.

$$P_{i,AGC}^{\min}\delta_{i,\text{AGC}}(t) \le P_{i,AGC}(t) \le \delta_{i,AGC}(t)P_{i,AGC}^{\max} \tag{16}$$
$$-R_{i,AGC} \le P_{i,AGC}(t) - P_{i,AGC}(t-1) \le R_{i,AGC} \tag{17}$$

where $R_{i,AGC}$ is the maximum ramp power of i^{th} AGC based generator. $P_{i,AGC}^{\max}$ and $P_{i,AGC}^{\min}$ are maximum and minimum power outputs of i^{th} AGC based generator respectively.

The fuel cost functions of the TDOGs and the AGC based generators both can be expressed by quadratic function [11].

$$\begin{aligned} C(P_{i,DG}(t)) = a_{i,DG}(P_{i,DG}(t))^2 + \\ b_{i,DG}P_{i,DG}(t) + c_{i,DG} \end{aligned} \tag{18}$$
$$\begin{aligned} C(P_{i,AGC}(t)) = a_{i,AGC}(P_{i,AGC}(t))^2 + \\ b_{i,AGC}P_{i,AGC}(t) + c_{i,AGC} \end{aligned} \tag{19}$$

where $a_{i,\text{DG}}$, $b_{i,\text{DG}}$, $c_{i,\text{DG}}$ are the cost coefficients for the i^{th} TDOG unit respectively, and $a_{i,\text{AGC}}$, $b_{i,\text{AGC}}$, $c_{i,\text{AGC}}$ are the cost coefficients for the i^{th} AGC based generators respectively.

We should note that the power output $P_{i,DG}(t)$ of the i^{th} TDOG is a discrete and integer viable. However, the power output $P_{i,AGC}(t)$ of the i^{th} AGC based generator is a continuous variable. Therefore, the optimization model integrates TDOG unit is more complex than the case with only AGC based generators.

5) Renewable generations: Due to the forecast uncertainties of RESs generation, to reduce negative impacts introduced by forecast uncertainties, the forecasts of PV and wind in each period must be bounded in their rated capacities.

$$0 \le P_{\text{PV}}(t) \le P_{\text{PV}}^{\max} \tag{20}$$
$$0 \le P_{\text{wind}}(t) \le P_{\text{wind}}^{\max} \tag{21}$$

where $P_{\text{PV}}^{\max}$and $P_{\text{wind}}^{\max}$ are the rated capacities of the PV plant and wind farm respectively.

In order to promote the power supply capability and reduce negative impacts introduced by high penetration level of RESs, additional spinning reserve constraints should be implemented.

$$\sum_{i=1}^{N}\delta_{i,DG}(t)P_{i,DG}^{\max}+\sum_{i=1}^{N}\delta_{i,AGC}(t)P_{i,AGC}^{\max}+P_{\text{PV}}(t) \\ +P_{\text{wind}}(t)+P_{\text{ESSd}}(t)-P_{\text{ESSc}}(t)\geq(1+Res)\,l_{\text{load}}(t) \tag{22}$$

where *Res* is the spinning reserve coefficient. Eq. (22) indicates that the maximum power supply ability of isolated microgrid must be greater than the forecast load demand.

III. MPC based Energy Management Framework

The performance of the traditional open-loop based day-ahead programming energy management strategy deteriorates rapidly when the penetration level of the RESs becomes high due to their intermittent and random nature. The MPC technique has been widely used in a variety of complex dynamic system. Recently, MPC also has drawn much attention of the power system community due to it can incorporate both forecasts and newly updated information to decide the future behaviors of system and handle different kinds of system constraints efficiently. The proposed MPC based energy management strategy is illustrated in Figure 2, which consists of two stages: the pre-scheduling stage, and the real-time power compensation stage. The operation of the pre-scheduling stage is to determine the microgrid schedule for time periods from $t+1$ to $t+T$ by solving Eq. (1) according to the generation and load forecasts at time t; the operation of real-time power compensation stage is implemented for time period $t+1$ by adjusting operations of flexible units (i.e. AGC based generators and curtailable loads in this study) to compensate the power imbalances incurred by the renewable generation/load forecast error at time period t.

Finally, the detailed MPC based energy management procedure is given in Algorithm 1.

IV. Simulation and Results

A. Test description

In order to verify the proposed MPC based energy management strategy, we consider an isolated microgrid system as shown in Fig. 1. There are two TDOG units, two AGC based generators, one battery energy storage system, a wind farm, a PV plant, several power flexible loads and critical loads.

The simulations are carried out with history data of renewable generation/load given as in Fig. 3. The wind, PV and load data is collected and modified form ELIA, the Belgium's electricity transmission system operator [12]. The capacity of the PV plant is 1.5 MW, the capacity of the wind farm is 1.2 MW, and the maximum load demand is 4 MW. Due to there is not enough history data of flexible load, we assume the ratio of power demand of flexible loads in each period to that of critical loads is 0.4. Further, we assume the maximum curtailment ratio $\theta_F^{\max}$ of flexible loads is 0.5.

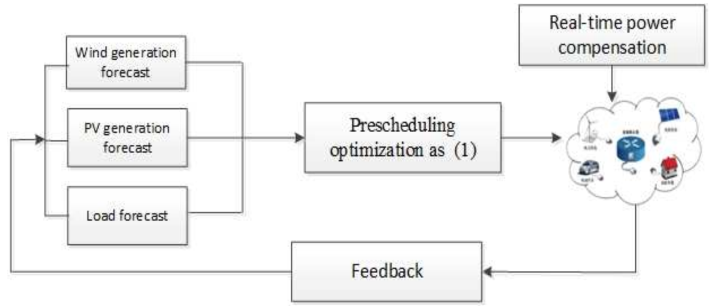

Fig. 2: Schematic MPC based energy management framework.

Algorithm 1 MPC based energy management procedure

1: Step 1: At the end of time interval t, obtain the forecasts of RESs generation and load demand for time periods between $t+1$ and $t+T$ according their forecasting models.
2: Step 2: Obtain the microgrid control sequence over the control horizon by solving Eq. (1) based on renewable energy/demand forecasts and system operation constraints.
3: Step 3: Implement only the first control action of the control sequence obtained in Step 2 for time period $t+1$.
4: Step 4: When obtaining the actual RESs generation/load status at time $t+1$, adjust the real-time power output of AGC based generators and flexible loads if necessary to meet the power balance constraint.
5: Step 5: $t=t+1$, go to Step 1 till the end of simulation time horizon.

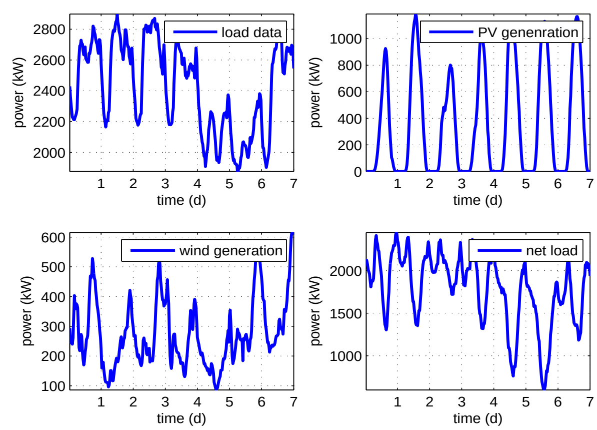

Fig. 3: History data of the microgrid.

The parameters for fossil generators are shown in Table I. The power varying intervals for both TDOG units are 20 kW. The spinning reserve ratio for the isolated microgrid is 0.05.

For ESS, the maximum charging/discharging power for is 300 kW, and the minimum charging/discharging power is 1 kW. The energy capacity is 800 kWh, and the depth of discharge (DoD) is 75%. The charging and discharging efficiencies are both set to 0.95 in this study. The self-discharge rate is 0.01 kW. We treat each 30 minutes as one time period. We set the prediction and control horizon to 24 hours respectively, that is T=48.

TABLE I: Parameters of the fossil generators

Device type	Max/Min power	Min up/down time	Ramp rate	Start-up/ shut-down cost	Fuel coefficients
TDOG 1	2000/40	4/4	1500	15/6	$(10, 0.28, 7 \times 10^{-4})$
TDOG 2	3000/60	4/4	2000	21/8	$(20, 0.36, 8.2 \times 10^{-4})$
AGC 1	400/5	–	300	6/5	$(5, 0.86, 4 \times 10^{-3})$
AGC 2	100/1	–	100	5/4	$(4, 0.74, 1.2 \times 10^{-2})$

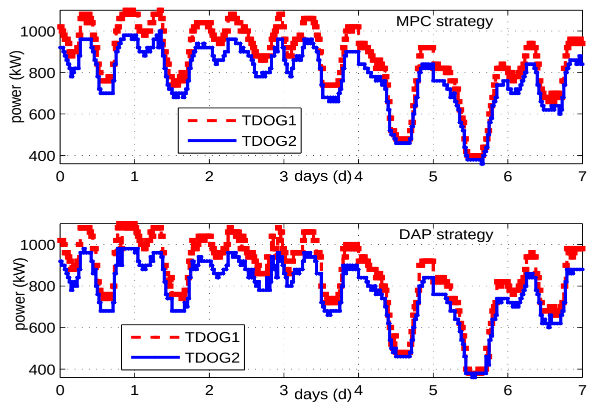

Fig. 4: Operation schedules of TDOG units under the MPC strategy and the DAP strategy.

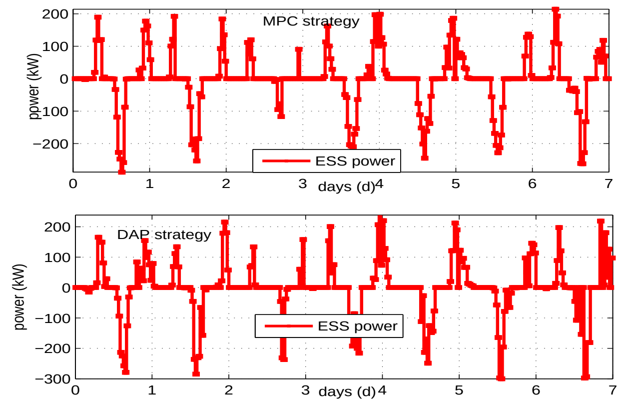

Fig. 5: Operation schedules of ESS unit under the MPC strategy and the DAP strategy.

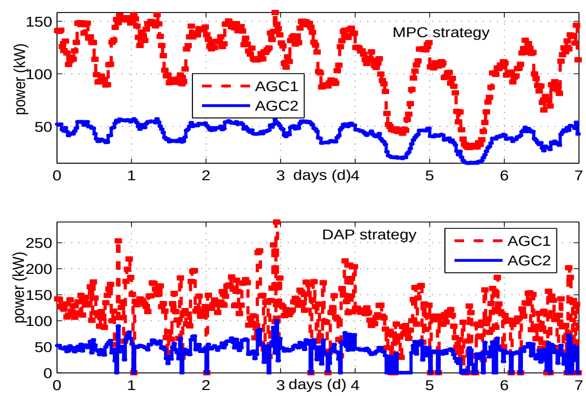

Fig. 6: Operation schedules of AGC based generators under the MPC strategy and the DAP strategy.

B. Simulation Results

All simulations were run on a PC with Intel(R) Core(TM) i5-3470 CPU @3.2GHz and 8.00GB memory. The ILOG's CPLEX v.12 optimization solver is utilized for solving the MIQP model.

In order to evaluate the performance of our proposed method, we will implement the traditional day-ahead programming (DAP) strategy [13] as a benchmark, which also has two stages: the pre-scheduling stage and the real-time power compensation stage. Different from MPC based strategy, in the pre-scheduling stage of DAP, Eq. (1) is only solved once to obtain the control sequence of microgrid at the beginning of each day. The real-time compensation stage of DAP is similar to that of MPC and is omitted here.

The detailed operation schedules for dispatchable units in the isolated microgrid under MPC strategy and DAP strategy are shown in Figs. 4 - 6 whereas the corresponding total energy outputs or charge/discharge are summarized in Table II. Note that the '*Difference*' in Table II is calculated using DAP as the reference.

As illustrated in Figs. 4 and 5, the operation schedules of TDOG units and ESS unit under MPC strategy are less fluctuated than those under DAP. In addition, from Table II, we could see that the total energy generations of TDOG units and the ESS unit under MPC strategy over the simulation horizon are more than those under DAP strategy with an absolute percentage difference of 0.22%, 0.15%, and 2.95%/ 3.53% respectively. For ESS unit, due to the energy loss during charging or discharging action and the self-discharge over the simulation horizon, the total discharged energy is less than total charged energy.

Although there exist differences in operation schedules for MPC strategy and DAP strategy that can be seen from the above results of TDOG units and ESS unit, such differences are not significant. The reason lies in that these units do not participate in real-time power compensation adjustments. Further, the superiority of the MPC strategy can be more clearly shown by comparing the operation schedules of AGC based generators (which take part in the real time compensation) under MPC and DAP, which is shown as Fig. 6.

From Fig. 6, we can find out that operation schedules of AGC based generators under DAP are far more fluctuated than those under MPC. For instance, for more than half of the total simulation horizon (51.8%, i.e. 174 out of 336 total time periods), power outputs of AGC 1 under DAP are larger than those under MPC. Furthermore, there are 63 time periods (almost 19% of total simulation periods) where the power outputs of AGC 1 under DAP are greater than 150 kW whereas only 15 time periods (less than 4.5%) happened for AGC 1 under the MPC strategy. In addition, when look at Table II, we could find out that total energy generations of AGC1 and

TABLE II: Operation details of Dispatchable Units

Device	Total Energy Generation or Charge/Discharge Under MPC	Total Energy Generation or Charge/Discharge Under DAP	Difference (%)
TDOG 1	144370 kWh	144050 kWh	0.22%
TDOG 2	130650 kWh	130450 kWh	0.15%
AGC 1	18640 kWh	19520 kWh	–4.51%
AGC 2	6881 kWh	6981 kWh	–1.43%
ESS	3942 /3510 kWh	3829/3390 kWh	2.95% / 3.53%

TABLE III: Microrgid operation costs

Strategies	Prescheduling costs ($)	Total costs ($)
MPC strategy	4.3254×10^5	4.3266×10^5
DAP strategy	4.2686×10^5	4.6118×10^5

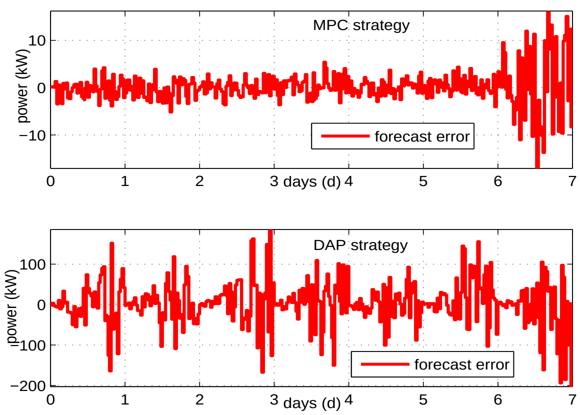

Fig. 7: Power mismatch in the isolated microgrid under MPC strategy and DAP strategy.

AGC2 under MPC over the simulation horizon are less than than those under DAP with an absolute percentage difference of 4.51% and 1.43% respectively.

Due to high penalty cost, there are no flexible loads being curtailed under both strategies. Further, the power mismatch of the isolated microgrid under MPC and DAP are shown in Fig. 7. Due to the close-loop nature of MPC strategy, the power mismatch under MCP is much less than DAP. The largest power mismatch under MPC is less than 20 kW whereas the largest power mismatch under DAP is greater than 100 kW.

Finally, the operation costs for the isolated microgrid under MPC strategy and DAP strategy are shown in Table. III. Table. III indicates that the operation costs of microgrid in the pre-scheduling stage under DAP strategy and MPC strategy are almost the same. Actually, the cost in pre-scheduling stage under DAP (e.g., due to lower energy generations of TDOG units and charge/discharge energy outputs of ESS unit under DAP) is even a little lower than that under MPC. However, due to the open-loop nature, the negative impacts introduced by forecast errors under DAP are more significant than those under MPC, which results in a higher adjustment operation cost in real-time power compensation stage (e.g., due to a much higher energy outputs of real time compensation adjustment units (AGC)) and therefore a higher total cost under DAP than that under MPC.

V. Conclusions

This paper proposes a model predictive control based energy optimization and scheduling strategy for an isolated microgrid which has wind and PV based renewable energy resource, discrete power output and continuous output fossil generators, energy storage system, and smart loads. The energy management model for the isolated microgrid at each time interval can be denoted as a mixed integer quadratic programming model. By comparing with the traditional day-ahead programming based open-loop strategy, simulation results confirm the superiority of the proposed strategy. Future work will be focused on cooperative operations of multiple isolated microgrids for maximum utilization of renewable energy resources.

Acknowledgment

This research was financially supported by the National Natural Science Foundation of China (61403404) and the Outstanding Natural Science Foundation of Hunan Province (2017JJ1001). The second author would like to thank Durham Energy Institute for the DEI Small Grant funding.

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