Energy Proceedings
Vol 38, 2024
ISSN 2004-2965

Energy Scheduling Method for Wind-Solar-Storage Off-Grid Hydrogen Production System based on Adaptive Model Predictive Control

Yingzi Xian[1], Xuesong Chang[1], Bolong Mao[1], Lei Wang [1*]

1 College of Automation, Chongqing University, Chongqing, 400044, PR China
(*Corresponding Author: leiwang08@cqu.edu.cn)

ABSTRACT

The energy dispatch of wind-solar-hydrogen storage systems is an effective technique for mitigating the intermittency of renewable energy sources. Addressing issues such as power fluctuations in off-grid hydrogen production systems and substantial tracking errors, we present a two-stage optimization scheduling strategy based on Model Predictive Control (MPC). During the first stage, a day-ahead scheduling approach is developed by comprehensively considering the stochastic behavior of renewable energy and the operational lifespan of energy storage, with the objective of optimizing the economic performance of the system. In the second stage, a day-ahead rolling optimization and correction strategy based on MPC is proposed to handle power fluctuations stemming from forecast errors in renewable energy generation, while concurrently ensuring the stable operation of the system. To tackle the inadequacies of conventional MPC in dealing with sudden disturbances, we devise an adaptive temporal parameter controller capable of determining optimal predictive and control temporal parameters. This controller design enhances the control precision and stability of MPC when confronted with abrupt changes in renewable energy generation due to sudden increases or decreases. The effectiveness of the proposed model and algorithm is validated through a case study using a microgrid as an illustrative example.

Keywords: wind-solar coupling; hydrogen energy storage; model predictive control; energy management

1. INTRODUCTION

To combat resource depletion and environmental deterioration resulting from extensive fossil fuel usage, there's a substantial push for developing renewable energy sources like wind and solar power. Increasing the share of renewable energy generation is widely recognized. However, wind and solar power have inherent randomness and uncertainty, impacting grid stability and security when connected. In areas with abundant wind and solar resources but remote locations with costly grid infrastructure, standalone microgrids are established to meet local electricity needs. However, efficiently storing wind and solar-generated electricity is challenging. Insufficient microgrid capacity leads to the wastage of excess energy, known as "curtailment." Hydrogen, with its high energy density, efficiency, green attributes, and low carbon footprint, plays a vital role in mitigating curtailment. Using wind and solar power for on-site water electrolysis to produce hydrogen, coupled with hydrogen storage, is a key solution to address wind and solar curtailment.

Due to the random variability of renewable energy sources and loads, microgrid systems composed of renewable energy face complex operational challenges. Optimizing energy dispatch in microgrids is a vital means to ensure system reliability and enhance economic efficiency. For off-grid wind-solar-hydrogen integrated energy microgrids, rational energy dispatch strategies are crucial for coordinating the interactions between electricity and hydrogen sources, ensuring system stability. Traditional microgrid dispatch often employs multi-time-scale optimization methods. In a study [1], coordination optimization was carried out on independent microgrids at both daily and hourly time scales to ensure economically stable microgrid operation. While multi-level coordination and stepwise dispatch strategies can largely accommodate the intermittency of energy sources and load fluctuations, this open-loop optimization heavily relies on the predictive models of current wind and solar units, without considering real-time feedback corrections in the actual system [2]. This can lead to discrepancies with operational requirements when the prediction timescale is large. Model Predictive Control (MPC) as a closed-loop

This is a paper for 15th International Conference on Applied Energy (ICAE2023), Dec. 3-7, 2023, Doha, Qatar.

feedback strategy that considers system dynamics and employs rolling optimization can significantly improve dispatch accuracy in systems with large prediction timescales, effectively addressing operational errors.

In reference [3], to mitigate the impact of uncertainty on the economic dispatch of a combined cooling, heating, and power (CCHP) multi-energy microgrid system, a multi-step rolling optimization based on Model Predictive Control (MPC) is used within the day. This approach utilizes the real-time output values of combined devices in daily planning as reference values, enabling the smooth operation of each combined device for economic and safe operation. In reference [4], a three-time-scale optimization dispatch strategy, namely "day-ahead, intra-day, real-time," is proposed for regional integrated energy systems. In the real-time dispatch phase, Model Predictive Control theory is integrated, employing feedback correction and rolling optimization to adjust micro-source outputs. While these studies have improved the microgrid's capability to handle renewable energy uncertainty to a certain extent, they typically utilize conventional Model Predictive Control methods with fixed domain parameters, including prediction timescales, control timescales, and control intervals. Fixed domain parameters lack the flexibility to adapt to variations in renewable energy forecasting errors. In microgrid systems with wind-solar-hydrogen generation, which involve uncontrollable distributed energy sources like wind turbines, handling sudden disturbances caused by rapid increases or decreases in power production is challenging for traditional MPC controllers. Fixed prediction timescales and control timescales may lead to substantial errors in dispatch results and impact system stability.

In conclusion, this paper introduces a variable-step adaptive Model Predictive Control (MPC) controller, designed to dynamically adjust domain parameters based on renewable energy output forecasting errors and dispatch errors. In off-grid systems, where there is no interaction with the main grid, power imbalances and fluctuations between sources and loads can only be balanced by battery and hydrogen production systems. Given the differing characteristics of electrical and hydrogen energy storage, an adaptive MPC approach is proposed to optimize power allocation between electric and hydrogen storage and enhance the participation of hydrogen storage throughout the entire system, ultimately increasing hydrogen production.

2. SYSTEM DESCRIPTION

The architecture of the wind-solar-hydrogen energy system for off-grid hydrogen production is illustrated in Figure 1.

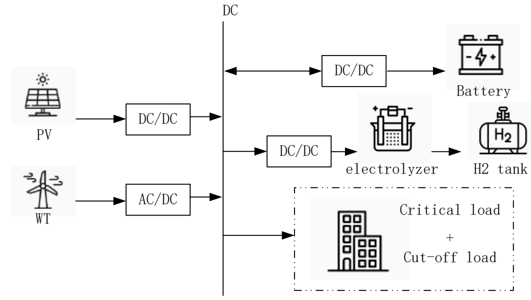

Fig.1. The architecture of the wind-solar-storage off-grid hydrogen production system

The architecture of the wind-solar-storage off-grid hydrogen production system consists of several key components: the power generation unit, the battery unit, the hydrogen storage unit, and the load unit. Each unit is interconnected to the DC bus through converters. The power generation unit includes both the wind power generation unit and the photovoltaic (PV) power generation unit. The hydrogen storage unit includes an electrolysis cell for hydrogen production and a hydrogen storage tank. The load unit comprises controllable loads and non-disconnectable critical loads. When the output of wind and solar power matches the power demand of the load, the renewable energy sources generate sufficient power to meet the load requirements without experiencing excess or shortfall. When the output of wind and solar power exceeds the load power demand, the surplus power is absorbed by the battery and stored in the form of electrical energy. If there is still excess power, it is absorbed by the electrolysis cell and stored in the form of hydrogen energy. When the output of wind and solar power falls below the load power demand, the battery compensates for the power shortfall in the system. To increase the storage density of hydrogen, pressure-based hydrogen storage techniques are used. The excess hydrogen stored in the hydrogen storage tank serves as a multi-purpose high-density clean energy carrier, which can be utilized in various industries such as automotive applications or be fed into industrial and commercial sectors through pipelines, such as introducing hydrogen into gas pipelines, metallurgy, chemical engineering, and other fields.

3. ENERGY DISPATCH STRATEGY FOR WIND-SOLAR-HYDROGEN OFF-GRID SYSTEMS BASED ON ADAPTIVE MODEL PREDICTIVE CONTROL

Given the characteristic of decreasing renewable energy power prediction errors as the prediction timescale shortens, microgrid optimization scheduling is typically divided into two stages: day-ahead scheduling and intraday rolling correction. During the day-ahead scheduling phase, based on the forecasted power values of renewable energy and loads for the day, while considering the remaining capacity of energy storage systems, the primary goal is to optimize the charging and discharging power of energy storage devices, the discharging power of controllable loads, and the output of the electrolyzer to achieve the most economically efficient operation of the system for the entire day. A basic power generation plan for each hour of the following day is formulated during this stage, and this plan is communicated in advance. During the intraday scheduling phase, the status of charging and discharging for the various units and energy storage devices within the microgrid is managed according to the day-ahead scheduling plan. Since this paper primarily discusses the optimization effects of adaptive Model Predictive Control (MPC) on intraday rolling scheduling, it does not provide a detailed description of the day-ahead scheduling model, with the net power of renewable energy serving as a reference trajectory.

3.1 Intra-Day Rolling Optimization Scheduling

3.1.1 MPC

MPC is a model-based closed-loop optimization control strategy that operates within a finite time horizon. It relies on building a model to predict the dynamic behavior of a system over a specified future time span. It continually performs rolling optimization, aiming to find the optimal control sequence while adhering to predefined objective functions and constraints. This approach allows for the implementation of current control actions. One of the key features of MPC is its ability to adapt to changing conditions and predict future system behavior in each step of the rolling optimization using real-time information. The control structure diagram for MPC is illustrated in Figure 2.

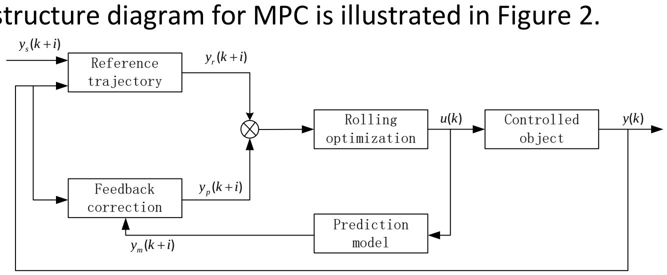

Fig.2. MPC Structure

3.1.2 MPC-Based Intra-Day Rolling Optimization Scheduling Model

In the context of intra-day optimization scheduling for the wind-solar-storage off-grid hydrogen production system, taking a microgrid consisting of wind turbines, photovoltaics (PV), electrolysis cells, energy storage devices, and loads as an example, the first step is to identify the state variables, control variables, disturbance variables, and output variables.

The power balance equation for the system.

$$P_{WT}+P_{PV}+P_{Bat}=+P_{EL}+P_{Load} \tag{1}$$

The equation for the net power of the system and the equation for the power generated by controllable energy sources are as follows.

$$\begin{cases} P_{Net}=P_{WT}+P_{PV} \\ P_{Con}=P_{EL}-P_{BAT}+P_{Load} \end{cases} \tag{2}$$

Where, P_{Net} is the net power and P_{Con} is the controllable power.

The state variables are represented by a vector $x(k)=\begin{bmatrix} P_{Net} & P_{Load} & P_{EL} & P_{Bat} & SOC \end{bmatrix}^T$, composed of the net power of the system, load power, electrolysis power, battery charging and discharging power, and the state of charge (SOC) of the battery. The control variables consist of a vector $u(k)=\begin{bmatrix} \Delta P_{Load} & \Delta P_{EL} & \Delta P_{Bat} \end{bmatrix}^T$,representing controllable load, electrolysis power, and the output increment of the battery. The output variables are a vector P_{Con},composed of load power, electrolysis power, battery power, and SOC. The disturbance variables consist of a vector $r(k)=\begin{bmatrix} \Delta P_{f\_Net} & \Delta P_{f\_Load} \end{bmatrix}^T$,representing the short-term forecast power increment of wind turbines, photovoltaic panels, and loads. The state-space model for the multi-input, multi-output wind-hydrogen coupled system is established as shown in equations (13) and (14).

$$x(k+i)=\begin{bmatrix} P_{Net}(k+i) \\ P_{Load}(k+i) \\ P_{EL}(k+i) \\ P_{Bat}(k+i) \\ SOC(k+i) \end{bmatrix}=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} P_{Net}(k) \\ P_{Load}(k) \\ P_{EL}(k) \\ P_{Bat}(k) \\ SOC(k) \end{bmatrix}+ \\ \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & \dfrac{-T_s}{3600E_{Bat}u_{Bat}} \end{bmatrix}\begin{bmatrix} \Delta P_{Load}(k) \\ \Delta P_{EL}(k) \\ \Delta P_{Bat}(k) \end{bmatrix}+\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} \Delta P_{f\_Net} \\ \Delta P_{f\_Load} \end{bmatrix} \tag{3}$$

$$y(k)=\begin{bmatrix} P_{Con}(k) \end{bmatrix}=\begin{bmatrix} 0 & 1 & 1 & -1 & 0 \end{bmatrix}\begin{bmatrix} P_{Net}(k) \\ P_{Load}(k) \\ P_{EL}(k) \\ P_{Bat}(k) \\ SOC(k) \end{bmatrix} \tag{4}$$

From equations (13) and (14), it is evident that based on the short-term power forecasting data of renewable energy sources and loads, by iteratively applying the state-space predictive model, forecasting ahead for p steps, it is possible to obtain a vector Y_c composed of the outputs of the electrolysis cell, battery, load, and the energy storage SOC, representing the estimated output values within the prediction time horizon. This is expressed as follows.

$$Y_c = [P_{Load}(k+1), P_{EL}(k+1), P_{Bat}(k+1), SOC(k+1), \cdots, P_{Load}(k+p), P_{EL}(k+p), P_{Bat}(k+p), SOC(k+p)]^T \quad (5)$$

The goal of the intra-day rolling optimization is to have the controlled outputs closely follow the day-ahead planned values while ensuring that the control adjustment increments for each unit are kept as small as possible. This objective is represented by the following equation (16).

$$\min J = \sum_{t=1}^{N_p} \left\| Y_c(k+t|t) - Y_{ref}(k+t) \right\|_Q^2 + \sum_{t=1}^{N_c} \left\| \Delta U(k+t|k) \right\|_R^2 \quad (6)$$

Where, $Y_{ref}(k+t)$ represents the reference trajectory obtained from the day-ahead optimization scheduling, variables N_p and N_c correspond to the prediction and control time domains respectively, and variables Q and R are weight matrices used for minimizing output discrepancies and encouraging smooth control adjustments.

The intra-day optimization scheduling must satisfy the following constraint conditions.

(1) Constraints on the controllable device output.

$$\Delta u_{\min} \le \Delta u(k+t|k) \le \Delta u_{\max} \quad (7)$$

$$P_{\min} \le P_0(k) + \sum_{t=1}^{i} \Delta u(k+t|k) \le P_{\max} \quad (8)$$

Where, $\Delta u_{\min}$ and $\Delta u_{\max}$ represent the upper and lower bounds on the control quantity of the controllable device, while $P_{\min}$ and $P_{\max}$ represent the maximum and minimum output power of the controllable device.

(2) Constraints on the State of Charge (SOC) of the battery.

$$SOC_{\min} \le SOC(k+t|k) \le SOC_{\max} \quad (9)$$

(3) Constraints on the hydrogen storage tank.

$$Pre_{\min} \le Pre(t) \le Pre_{\max} \quad (10)$$

The quadratic programming model described in equation (16) can be solved using the quadprog function provided by the MATLAB optimization toolbox. Upon solving, the optimized control sequence, consisting of the control input increments for the electrolysis cell, battery, and load within the control time domain, is obtained. Only the control sequence for the current time step and the first subsequent scheduling period are issued at the scheduling moment, and the process is repeated when the next scheduling period arrives, following the same rolling optimization process.

3.1.3 Improved MPC Based on Fuzzy Control Algorithm

The fuzzy control algorithm does not require the establishment of precise mathematical models for control systems. Instead, it uses fuzzy rules to describe the relationships between system variables. Fuzzy control offers rapid response, strong disturbance rejection capabilities, good fault tolerance, and robustness. In traditional MPC, the control horizon typically equals the prediction horizon or is slightly longer, with one or two additional steps. When there is a significant difference between the prediction and control horizons, it can lead to suboptimal control results. Therefore, by making full use of wind power, solar power, and load forecasting data, a fuzzy control algorithm is applied to select the optimal prediction horizon. Then, the control horizon is adjusted accordingly based on the selected prediction horizon. Finally, the optimized prediction and control horizons are updated in the intraday scheduling model.

This paper's time-domain adaptive step strategy involves taking the prediction error of uncontrollable input variables, denoted as e_p and the power tracking error, denoted as e_y and inputting them simultaneously into the prediction domain adaptive step module at each new sampling instance. The module calculates a new prediction domain based on the values of e_p and e_y, and subsequently adjusts the control domain according to this newly determined prediction domain. The optimized prediction and control domains are then integrated into the MPC (Model Predictive Control) controller, facilitating real-time updates to the intraday scheduling model. This approach allows for dynamic adaptation of prediction and control horizons based on real-time data, enhancing control effectiveness in response to evolving system dynamics.

The paper divides the prediction errors of uncontrollable input variables, the prediction errors of input variables, and the prediction horizon into seven fuzzy subsets: NB (very small), NM (small), NS (slightly small), ZO (moderate), PS (slightly large), PM (large), and PB (very large). Regarding the selection of membership functions, Gaussian-type membership functions are used at both ends of the domain to enhance control stability. In the middle region of the domain, triangular membership functions are employed to ensure a high level of accuracy and sensitivity.

3.2 Analysis of examples

3.2.1 Parameter setting

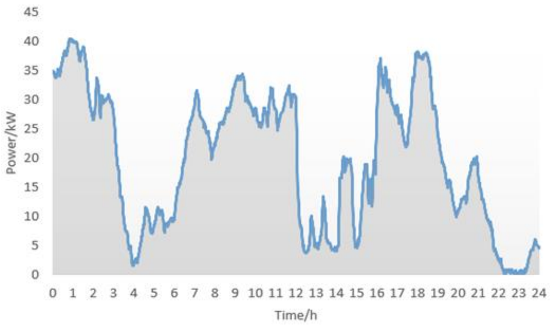

Fig.3. Wind power diagram

Table 1 System variables and parameter settings

variable	unit	value	variable	unit	value
T_s	min	5	$Pre_{\min}$	MPa	0.4
E_{Bat}	Ah	10000	$Pre_{\max}$	MPa	1.5
u_{Bat}	kV	0.012	$\Delta P_{EL,\min}$	kW	-20
$P_{EL,\min}$	kW	0	$\Delta P_{EL,\max}$	kW	20
$P_{EL,\max}$	kW	50	$\Delta P_{BAT,\min}$	kW	-40
$P_{BAT,\min}$	kW	-20	$\Delta P_{BAT,\max}$	kW	40
$P_{BAT,\max}$	kW	20	capacity of wt	kW	50
$SOC_{\min}$	%	20	capacity of pv	kW	40
$SOC_{\max}$	%	90	capacity of el	kW	50

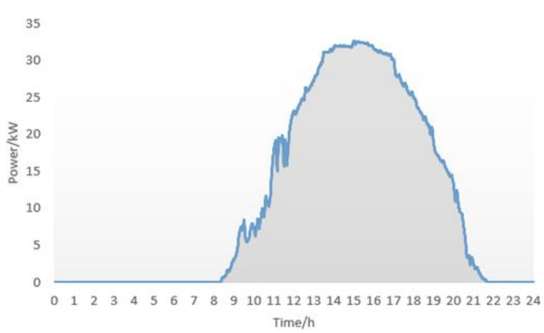

Fig.4. Photovoltaic power diagram

The variables and parameter Settings of the wind and off-grid hydrogen energy system are shown in Table 1. The data is sourced from reference [5].

3.2.2 Fixed control time domain and prediction time domain value analysis

The impact of fixed values for Np and Nc on power tracking performance is illustrated in the figure 6.

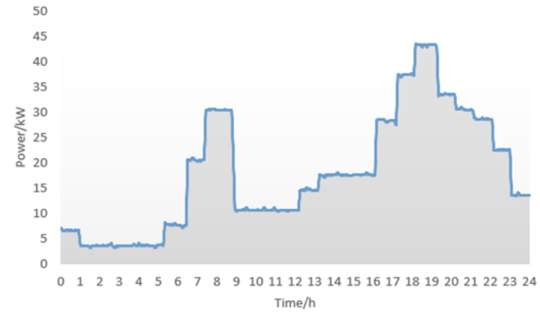

Fig.5. Electricity load power diagram

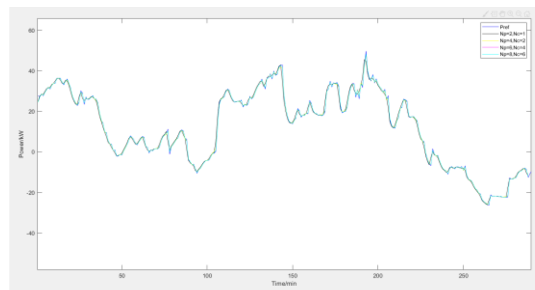

Fig.6. The impact of Np and Nc on power tracking performance

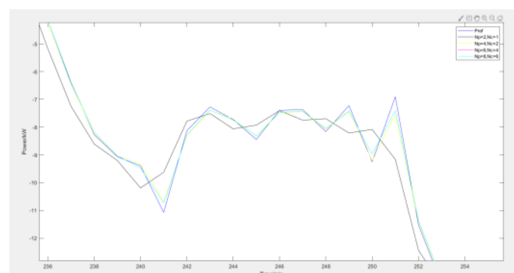

Fig.7. The tracking performance during the time interval from 235 -255 minutes

Table 2 The impact of different values of Np and Nc on the average error and runtime

Np	Nc	Average error/W	Running time/s
2	1	226.36	16.72
4	2	54.38	18.64
6	4	30.60	19.49
8	6	30.51	21.14

From Figure 6, it is evident that when Np and Nc have fixed values that are not equal, the power tracking performance varies. To analyze the impact of Np and Nc on power tracking within the time frame of 235 minutes to 255 minutes, as shown in Figure 7, it can be observed that with smaller Np and Nc values, power tracking is poorer. As Np and Nc increase, the power tracking performance gradually improves and gets closer to the given reference power. However, as shown in Figure 8 and Table 2, there is not much difference in power tracking performance between Np=6 and Nc=4 and Np=8 and Nc=6. The power tracking error between these two scenarios is nearly equal. Therefore, it cannot be assumed that larger Np leads to better control performance. In this particular case, Np=6 and Nc=4 already achieve a good tracking performance. Conversely, as indicated in Table 2, with the increase in Np and Nc, the time required for the controller to solve the optimization also increases. This, in turn, reduces the efficiency of energy scheduling.

3.2.3 *Analysis of the values for adaptive prediction and control domains*

Adaptive Np and Nc values, power tracking, and tracking error are illustrated in the following figure 7.

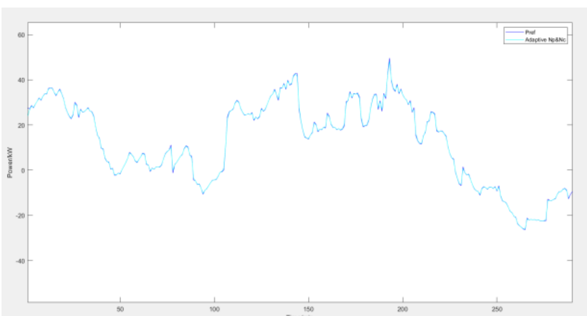

Fig.8. the power tracking

Table3 The impact of adaptive Np and Nc values on average error and runtime

Np	Nc	Average error/W	Running time/s
6	4	30.60	19.49
-	-	26.82	19.38

From Figure 8 and Table 3, it is evident that adaptive Np and Nc values lead to significantly improved tracking performance, with an average power tracking error of 26.82W. Compared to the scenario with Np=6 and Nc=4, the control performance is enhanced by 12.35%, and the computational time has also decreased. Considering both control precision and scheduling efficiency, the control effect of adaptive Np and Nc is superior.

4. CONCLUSIONS

This paper applies MPC theory to the energy scheduling of a wind-solar-hydrogen off-grid system. Addressing the issue in classical MPC, where a fixed prediction horizon length does not adapt well to the economic scheduling of microgrids, the paper introduces Adaptive Prediction Horizon Length MPC. It solves for an appropriate prediction horizon, resulting in lower computational times. Simulation experiments demonstrate that the proposed method effectively enhances the scheduling efficiency of the system.

ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (NO.51875058), Central University Frontier Discipline Special Project (NO. 2019CDQYZDH025), Chongqing Basic Science and Frontier Technology Research Special (NO. CSTC2018jcyjAX0 414) and Chongqing Municipal Education Commission Science and Technology Research Project (NO. KJQN20180118).

REFERENCE

[1] G.M. C,S.J. N,I.M. V, et al. Renewable medium-small projects in Spain: Past and present of microgrid development[J]. Renewable and Sustainable Energy Reviews,2022,165.

[2] Mostafa K, Peiyuan C, Lisa G, et al. A comprehensive optimal energy control in interconnected microgrids through multiport converter under N−1 criterion and demand response program[J]. Renewable Energy, 2022,199.

[3] XIAO Fei， AI Qian． Multiple time-scale optimal dispatch of demand response resource for microgrid based on model predictive control[J].Electric Power Automation Equipment，2018，38(5)：184-190．

[4] Shengwei Q,Ya-Xiong W,Xuelian X, et al. Disturbance prediction-based enhanced stochastic model predictive control for hydrogen supply and circulating of vehicular fuel cells[J]. Energy Conversion and Management, 2021,238.

[5] Yu, Jiamin. (2021). Research on Power Control Strategy of Wind-Solar-Hydrogen Coupling System Based on Model Predictive Control. [Dissertation]. Northeast Electric Power University. DOI: 10.27008/d.cnki.gdbdc. 2021.000198.