Hierarchical online energy management for residential microgrids with Hybrid hydrogen–electricity Storage System

Wu, Jingxuan; Li, Shuting; Fu, Aihui; Cvetković, Miloš; Palensky, Peter; Vasquez, Juan C.; Guerrero, Josep M.

DOI
10.1016/j.apenergy.2024.123020

Publication date
2024

Document Version
Final published version

Published in
Applied Energy

Applied Energy 363 (2024) 123020

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Hierarchical online energy management for residential microgrids with Hybrid hydrogen–electricity Storage System☆

Jingxuan Wu [a,*], Shuting Li [a], Aihui Fu [b], Miloš Cvetković [b], Peter Palensky [b], Juan C. Vasquez [a], Josep M. Guerrero [a,c,d]

[a] Aalborg University, Pontoppidanstraede 111, Aalborg, 9220, Denmark
[b] Delft University of Technology, Delft, 2600 AA, The Netherlands
[c] BarcelonaTech (UPC), Barcelona East School of Engineering (EEBE), Barcelona, 08019, Spain
[d] Catalan Institution for Research and Advanced Studies (ICREA), Pg. Lluís Companys 23, Barcelona, 08010, Spain

ARTICLE INFO

Keywords:
Energy management
Fuzzy logic
Hybrid storage system
Microgrid

ABSTRACT

The increasing proportion of renewable energy introduces both long-term and short-term uncertainty to power systems, which restricts the implementation of energy management systems (EMSs) with high dependency on accurate prediction techniques. A hierarchical online EMS (HEMS) is proposed in this paper to economically operate the Hybrid hydrogen–electricity Storage System (HSS) in a residential microgrid (RMG). The HEMS dispatches an electrolyzer-fuel cell-based hydrogen energy storage (ES) unit for seasonal energy shifting and an on-site battery stack for daily energy allocation against the uncertainty from the renewable energy source (RES) and demand side. The online decision-making of the proposed HEMS is realized through two parallel fuzzy logic (FL)-based controllers which are decoupled by different operating frequencies. An original local energy estimation model (LEEM) is specifically designed for the decision process of FL controllers to comprehensively evaluate the system status and quantify the electricity price expectation for the HEMS. The proposed HEMS is independent of RES prediction or load forecasting, and gives the optimal operation for HSS in separated resolutions: the hydrogen ES unit is dispatched hourly and the battery is operated every minute. The performance of the proposed method is verified by numerical experiments fed by real-world datasets. The superiority of the HEMS in expense-saving manner is validated through comparison with PSO-based day-ahead optimization methods, fuzzy logic EMS, and rule-based online EMS.

1. Introduction

Renewable energy has been promoted all over the world during the past two decades due to the public awareness of environment-friendly power systems and the technical challenges of energy supply in remote areas. In residential Microgrids (RMGs), renewable energy sources (RESs) bring considerable profits as well as uncertainty and instability, leading to the comprehensive implementation of energy storage (ES) systems and energy management systems (EMSs) [1]. Besides, the randomness of the demand side and the flexible electricity price further exacerbate the unpredictability of the system status, and bring challenges to the EMSs [2].

On-site battery banks are essential objectives to directly address the uncertainty and intermittence introduced by RESs and the demand side in most RMGs [3]. Many studies focus on the schedule of the batteries to allocate the energy supply and load within a designated time frame [4,5]. The utilization of mixed-integer programming (MIP) for day-ahead optimization is a well-recognized approach [6]. For systems with a higher proportion of RESs, heuristic algorithms like particle swarm optimization (PSO) [7], and genetic algorithms [8] are deployed to solve complex mathematical problems. Nevertheless, a critical drawback of these optimization techniques lies in their reliance on predictive models or forecasting methods [9] for future RES power generation and load, which experience a significant decline in accuracy as the forecasting horizon increases.

Based on the hierarchical control of Microgrids, modern control theories are introduced to the EMS [10]. Model predictive control (MPC) is an efficient solution to operate the batteries in real-time [11] and address the influence of uncertainty [12]. Some studies regard the EMS as an online decision-making problem and integrate data-driven techniques for iterative operation of the ES system [13]. To obtain

☆ This work was supported in part by the China Scholarship Council (CSC).
* Corresponding author.
E-mail addresses: jinwu@energy.aau.dk (J. Wu), shuli@energy.aau.dk (S. Li).

https://doi.org/10.1016/j.apenergy.2024.123020
Received 12 October 2023; Received in revised form 19 February 2024; Accepted 9 March 2024
Available online 26 March 2024

valid operation rules, decision methods such as fuzzy logic (FL) [14,15], game theory [16] and Bayesian optimal algorithm [17] are implemented. However, the energy density of battery stacks limits their application in long-term energy-shifting to handle issues caused by climate change or seasonal uncertainty, leading to the implementation of hybrid ES systems.

A hybrid ES system is composed of two or more ES units with different dynamic characteristics. In RMG systems, on-site batteries can shift the load and RES power during the day and Ultra-capacitors are essential solutions to high-frequency oscillation within seconds [18]. For long-term EMS, fuel cell (FC)-based backup energy supply [19] and electrolyzer-FC system [20] provide economical and efficient solutions to seasonal energy shifting due to their high energy density and easy implementation [21]. To schedule the hybrid hydrogen–electricity storage system (HSS), multi-objective optimization methods are deployed. In [22], the gravitational search algorithm (GSA) is utilized to optimize the operation of HSS. In [23], an economic EMS based on marine predator algorithm (MPA) is designed to control the FC for operation cost reduction. Online decision methods can also be implemented for HSSs. With MPC-based primary controllers, rule-based EMS is designed for several scenarios in [24,25]. In [26], the forgetting factor recursive least square (FFRLS) algorithm is used as the decision rule with the consideration of FC degradation, hydrogen (H2) consumption, and operating efficiency. To take the system status into account, FL-based supervisory controls [27,28] and MPC-based EMS [29] are designed. In HSS, efficiency is an essential factor for ES unit operation, which directly defines the specific functions of ES units. In most literature, efficiency is used to decide the priority of the ES units in the ruled-based EMS, however, the seasonal energy oscillation caused by climate change is not considered or solved. The uncertainty from the energy market is also hard to analyze due to the complexity of the system.

The research scopes of the existing literature are summarized in Table 1. Although the current EMS for HSSs achieves good results in economic and system stability manner, there are still some research gaps that have not been well addressed.

1. The optimal economical operations of HSSs in most studies require accurate prediction of system states. However, in RMG with a high proportion of solar or wind energy, accurate multi-step forecasting is hard to achieve due to the uncertainty from weather and consumers. Consequently, conventional EMS based on the prediction will encounter unexpected accidents in implementation.
2. ES units always have distinct functions according to their dynamic characteristics and energy efficiency. Given the minimal storage loss, lower energy conversion efficiency, and constraints on mode switching, the H2 ES unit should adapt its long-term load-shifting and energy strategies. Batteries should allocate the energy in the short term due to the limited energy density. Therefore, EMS design without considering the horizon-based optimization target of storage units is not applicable in most cases [30].
3. The power consumption of the compressor and the dynamic response of FC, which contributes to a reduction in energy conversion efficiency, has been relatively overlooked in recent research. However, the H2 pressurization and warm-up procedure of FC consumes extra energy from the RMG system [31]. In this sense, ignoring the dynamics of H2 units in EMS design may not be held in most cases.

To solve the technical gaps above, a hierarchical EMS (HEMS) is presented in this paper to control an HSS, including a battery and an H2 ES unit, in a grid-connected RMG with integrated RES and household loads. The research achievement couple be extended to other Microgrids suffering from a high proportion of uncertainty from renewable energy, demand side, and energy market. In the proposed HEMS, two parallel frequency-decoupled FL controllers are proposed to realize the economical and stable operation of the HSS. To guide the decision process of the FL controllers, a local energy estimation model (LEEM) is designed to generate the electricity price expectation. The proposed HEMS is verified through numerical experiments with realistic data and statistical models from a real-world Internet of Things (IoT) laboratory. The main contributions of the paper can be summarized as follows.

1. An LEEM is proposed in the HEMS to grant the HEMS sufficient intelligence for cost-effective energy resource dispatch without dependency on forecasting of RES and load power. The LEEM quantifies the electricity price expectation in the seasonal horizon for the H2 ES unit and the daily horizon for the battery, respectively. The proposed LEEM incorporates historical data and constructs a cumulative evaluation for the HSS operation, taking the energy price and internal supply–demand balance into consideration.
2. A hierarchical EMS structure which is composed of two decoupled FL controllers is proposed to facilitate collaborative energy balance among ES units. The FL controllers operate the ES units towards distinct target objectives according to their dynamics, and the decoupling of the controllers avoids system oscillation caused by conflicts in decision-making. The HEMS structure further exhibits excellent scalability and adaptability when dealing with various types of ES systems.
3. The dynamic characteristics of the electrolyzer and FC are considered in the FL controllers. To mitigate the frequent transitions of the H2 ES unit between charging and discharging, a purpose-built operating logic is implemented. Additionally, the system formulation and controller design incorporates the energy consumption of the compressor.

The rest of the paper is organized as below. The architecture of the objective RMG is presented in Section 2 as the scenario of the paper. In Section 3, the design of LEEM is studied. The parallel FL Controllers are presented, and the coordination between the two layers is analyzed in Section 4. The numerical experiment is implemented for the proposed HEMS and the result is shown and analyzed in Section 5. At last, a conclusion is drawn in Section 6.

2. Architecture of the residential microgrid system

Renewable energy has been promoted rapidly in RMGs during the last decades. The flexible electricity price is also a consequence of the increasing proportion of wind and solar generation in energy markets. To shave the load peak and shift the renewable energy, ES systems are deployed to operate the RMG system under the guidance of EMSs. This paper studies a typical RES-supplied RMG with a HSS as presented in Fig. 1. Considering the noise of wind turbines, a PV system is employed here as the green energy generator. The HSS is composed of a Lithium-ion battery for inter-day operation and an H2 ES unit for seasonal energy shifting. The H2 ES unit contains an electrolyzer, a compressor, a high-pressure H2 tank, and a proton exchange membrane (PEM) FC system. Discharging of the H2 ES unit is realized by the FC which consumes the liquid H2 in the tank to generate power for the RMG; Charging of the H2 ES unit involves an electrolyzer and compressor. The energy consumption of the compressor will be measured and considered in the HEMS. The system's topology and sizing are based on the IoT laboratory of Aalborg University and the Green Village of Delft University of Technology. The data acquisition system is realized through the local IoT server which connects the smart meters and sensors. The HEMS accesses the IoT cloud to grasp beneficial data for the decision process and outputs the reference power of the H2 ES unit and battery through RESTful API service.

The utility grid is connected to the AC bus directly to ensure the power supply of the RMG. The PV system consistently operates at

Table 1
Research scope of existing literature and the proposed approach.

Approaches	ES type		Constraints		Uncertainty source				EMS type	
	Electricity	H2	Capacity	Efficiency	Weather	Climate	User	Market	Online	Offline
[4,5,7,11,13]	Y		Y		Y		Y			Y
[6,17]	Y		Y		Y		Y	Y		Y
[12,14,18]	Y		Y		Y		Y		Y	
[10,15]	Y		Y		Y		Y	Y	Y	
[23]	Y	Y	Y		Y		Y			Y
[22]	Y	Y	Y		Y		Y	Y		Y
[30]		Y	Y	Y	Y		Y		Y	
[27,32]	Y	Y	Y						Y	
[24,25]	Y	Y	Y	Y					Y	
[28,29]	Y	Y	Y		Y		Y		Y	
Proposed	Y	Y	Y	Y	Y	Y	Y	Y	Y	

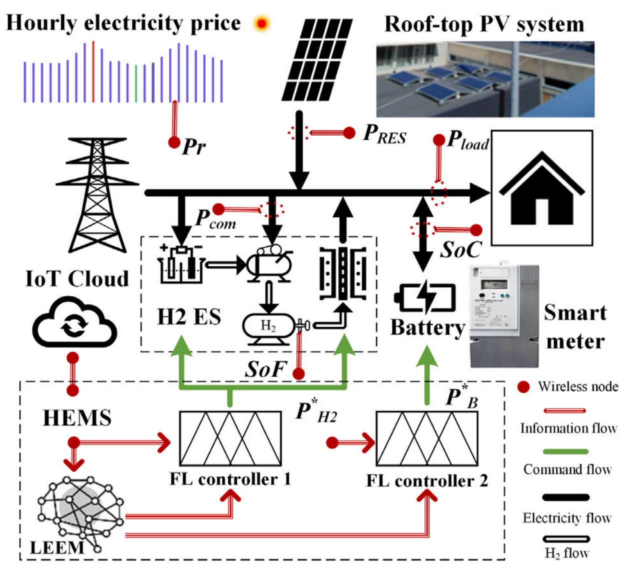

Fig. 1. Architecture of the proposed RMG and HEMS.

its maximum power point. To prioritize consumer comfort, various appliances such as refrigerators, ovens, televisions, laptops, microwave ovens, coffee machines, and cooking equipment are left unregulated. Surplus power is redirected back to the grid and energy purchasing happens when the local energy supply is lower than demand. The electricity contract indicates a flexible price that is updated hourly by the energy supplier.

The HEMS for this RMG is integrated with two distinct FL controllers: FL controller1 manages the H2 ES unit, while FL controller2 oversees the battery. A LEEM is designed to generate the electricity price expectation for the FL controllers. The HEMS is connected to the IoT cloud through a wireless node, enabling real-time communication with the devices within the RMG, including sampling data and sending commands.

3. Proposed local energy estimation model in HEMS

The high proportion of RESs, especially solar and wind energy, brings uncertainty and intermittence to the RMGs, presenting challenges to EMSs. In addition to the daily power fluctuations caused by both loads and RESs, RMG EMSs must consider long-term changes in renewable energy availability and fluctuations in electricity prices. However, balancing a global perspective with sensitivity to short-term dynamics can lead to conflicts in EMS design. To address this issue, the LEEM is designed in this paper to establish the accumulated electricity price expectation in separated sampling rates, providing distinct horizons to ES units. The LEEM includes an external and an internal energy estimation algorithm.

3.1. External energy estimation

The external energy estimation algorithm assesses the incoming energy value of the ES units based on the real-time electricity price. For the H2 ES unit, the energy trading between the RMG and utility grid is considered since it works in a global view to detect excessive renewable energy and cheap electricity, while on the battery view, the internal trading among devices is the primary factor and the estimated price is defined by the market. Hence, the estimation is formulated as (1) shows.

$$\begin{cases} \bar{Pr}^{H2} = \frac{\kappa_D \kappa_S}{\eta} Pr, \\ \bar{Pr}^{B} = Pr. \end{cases} \tag{1}$$

in which, $\bar{Pr}$ donated the energy value estimation; Pr is the real-time electricity price; κ_D and κ_S are the factors of power demand and state of backup energy supply; η represents the overall efficiency of energy conversion. The superscript H2 means parameters for the H2 layer and B represents the battery layer. For the H2 ES unit, the estimated price is affected by not only the electricity price in the market but also the supply–demand balance and electricity storage in the local system. The over-supply and sufficient storage will lead to the drop of $\bar{Pr}$, and vice versa.

In the H2 layer, the LEEP updates the estimation with sampling time τ_1; In the battery layer, the sampling time of LEEP is τ_2. Hence, the power demand for the two layers is calculated by,

$$\begin{cases} P_d^{H2}(t) = \frac{1}{n}\sum_{i=0}^{n-1}(P_{load}(t-i\tau_2) - P_{RES}(t-i\tau_2)), \\ P_d^{B}(t) = P_{load}(t) - P_{RES}(t) - P_{H2}(t) + P_{com}, \\ n = \tau_1/\tau_2. \end{cases} \tag{2}$$

the $P_d^{H2}(t)$ represents the power demand for τ_1 layer while $P_d^B(t)$ for τ_2 layer; the $P_{load}(t)$ is the real-time load power sampled by smart meter; $P_{RES}(t)$ donates the PV power; P_{com} is the power consumption of the compressor which works together with the electrolyzer; P_{H2} is the output power of the H2 ES unit. The κ_D function for the H2 ES unit is designed based on the P_d.

$$\kappa_D(t) = 1 + tanh(P_d^{H2}(t)), \tag{3}$$

The κ_S involves the backup energy supply in the estimation, while the battery is regarded as the backup storage of the H2 layer and the battery operates without backups. The κ_S function is designed as,

$$\kappa_S(t) = 2(1 - SoC), \tag{4}$$

in which, SoC represents the battery state of charge (SoC).

The η in (1) indicates the energy conversion efficiency of the H2 ES unit. The energy loss of the electrolyzer, compressor, and FC is huge compared with the battery. Hence, the energy loss of the battery is neglected while the efficiency of the H2 layer is considered as,

$$\eta = \eta_e \eta_c \eta_f, \tag{5}$$

the η_e, η_c, η_f represents the efficiency of the electrolyzer, compressor, and FC which is defined by the specific devices. In most cases, the η_e

is around 75%; If the H2 storage pressure is 30 MPa, η_c will be around 70%; The PEM FC usually has a 50% efficiency on rated working condition. The total η will be around 25%.

3.2. Internal energy estimation

The internal energy estimation establishes the operating experience of ES units according to the historical electricity trading information. It is represented by a local energy worth function ξ which records the total value of the local energy. The energy value is defined by the external energy estimation in the meantime.

During the charging process, the ξ will track the $\bar{Pr}$ and the ξ component of the LEEM could be calculated by

$$\begin{cases} \xi^{H2}(t+1) = \frac{SoF(t)\xi^{H2}(t)+\Delta SoF\cdot\bar{Pr}^{H2}}{SoF(t+1)}, \\ \xi^{B}(t+1) = \frac{SoC(t)\xi^{B}(t)+\Delta SoC\cdot\bar{Pr}^{B}}{SoC(t+1)}. \end{cases} \tag{6}$$

where the ΔSoF and ΔSoC represent the state change of the ES unit during the time interval. The Eq. (6) could be simplified as

$$\Delta\xi = \frac{\Delta S(\bar{Pr}-\xi(t))}{S(t+1)}, \tag{7}$$

the S means the state of ES units, SoC for the battery, and state of fuel (SoF) for the H2 ES unit.

If the ES unit was discharging, the ξ should remain constant and the combined equation is formulated as

$$\xi(t+1) = \frac{(S(t)+\Delta S)\cdot\xi(t)}{S(t+1)}, \tag{8}$$

and

$$\Delta\xi = 0, \tag{9}$$

In summary the ξ could be described by the combination of Eqs. (7) and (9), as

$$\xi(t+1) = \xi(t) + \Delta\xi, \tag{10}$$

$$\Delta\xi(t) = \begin{cases} \frac{\Delta S(\bar{Pr}-\xi(t))}{S(t+1)}, & 0 < \Delta S, \\ 0, & \Delta S \le 0. \end{cases} \tag{11}$$

ξ is the primary component of the internal energy estimation, it introduces the historical experience into the decision process. However, to guide the operation of HSS, the RMG system status and the current state of ES units should also be considered.

Supply–demand balance is an essential factor of the system estimation. According to the fundamental market rules, oversupply leads to a decrease in price while supply shortage results in a price rise. A supply–demand balance evaluation marked as K_D is introduced to describe the status of the RMG system. K_D works as a coefficient of ξ.

$$K_D(t) = 1 + \left(\frac{P_d(t)}{MAX(|P_{load}-P_{RES}|)}\right)^{2\sigma+1}, \tag{12}$$

in which, $MAX(|P_{load}-P_{RES}|)$ represents the theoretical maximum absolute value of supply–demand difference. σ, which is an integer over zero, adjusts the sensitivity of the function.

K_D is sensitive when the supply–demand difference is huge. The LEEM output would be suppressed if the power supply is much higher than the demand, and vice versa.

The state of ES units is an essential factor for future operation margin. Since the proposed HEMS does not rely on forecasting, the possibility for future operation must be reserved, which means the state of ES units has to be maintained among an acceptable region, an extreme state will limit the operation of the next step. Hence, the ES state evaluation K_S is introduced into the internal energy estimation.

$$K_S(t) = 1 - \left(\frac{(S(t)-0.5)}{MAX(|S-0.5|)}\right)^{2\upsilon+1}, \tag{13}$$

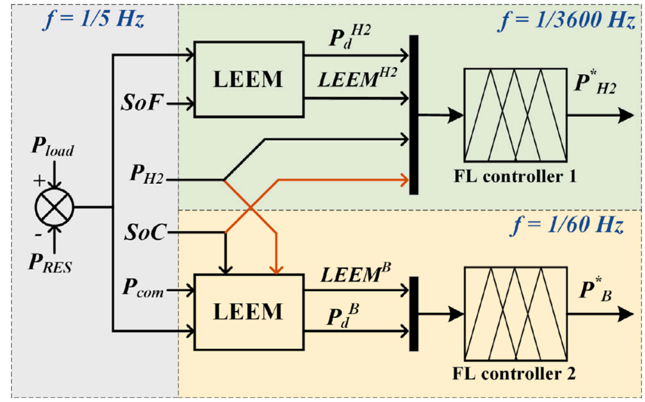

Fig. 2. Internal connection of LEEM and FL controller with different operating frequency.

where $MAX(|S-0.5|)$ means the maximum range of state oscillation with a center at 0.5. υ is a integer over zero and defines the sensitivity of K_S.

K_S has little effect on the LEEM when the SoC or SoF is around 50%, but in an extreme state, the LEEM will be modified accordingly to maintain the future operation margin.

In summary, the internal energy estimation is constructed with the basic local energy worth function and two coefficients, K_D for supply–demand evaluation and K_S for state evaluation, using optimal stopping theory, as presented in (14).

$$LEEM(t) = \frac{1}{\mu}\sum_{i=0}^{\mu-1}(K_S(t-i\tau_2)\cdot K_D(t-i\tau_2)\cdot\xi(t-i\tau_2)), \tag{14}$$

the sample size μ is defined by the energy dispatching period T, as

$$\mu = \frac{T}{\tau_2}, \tag{15}$$

The T here defines the horizons of the estimation model, for the battery, it will be the length of a day while for the H2 ES unit, it should be set to the length of a season.

Based on the LEEM, the overall architecture of the LEEM and FL controllers is presented in Fig. 2. The FL controllers operate the target devices in different frequency domains, The sampling system updates the data every 5 s to ensure the accuracy of the controllers. FL controller 1 operates the H2 ES every hour and FL controller 2 operates the battery every minute, which means that FL controller 2 has 60 cycles to react according to the decision of FL controller 1. In this way, the decoupling of decision-making is achieved. The cooperation of the two FL controllers is realized in the design of FL. The data exchange of the H2 ES and battery is marked red in the figure. In the decision-making of each ES unit, the status of the other unit is considered. In FL 1, the SoC of the battery is considered to allocate the energy globally, and in FL 2, the power of H2 ES, including the electrolyzer, fuel cell, and compressor, is considered to achieve the local power balance.

4. Proposed frequency-decoupled FL controllers in HEMS

Online EMSs have developed fast in the past decades, including FL-based EMS [15]. FL is one of the artificial intelligence control methods to realize the nonlinear control logic of a multi-input multi-output system through 3 steps: fuzzification, decision, and defuzzification. The computation process is presented in Fig. 3, The input MFs transfer the input signals into the membership degrees and logic. The degrees are handled by the aggregation algorithm and the logic is judged in the decision rules. The output of the controller is figured based on the output degree function and degree using a specific defuzzification algorithm [33]. In the proposed HEMS, the decision rules are formulated

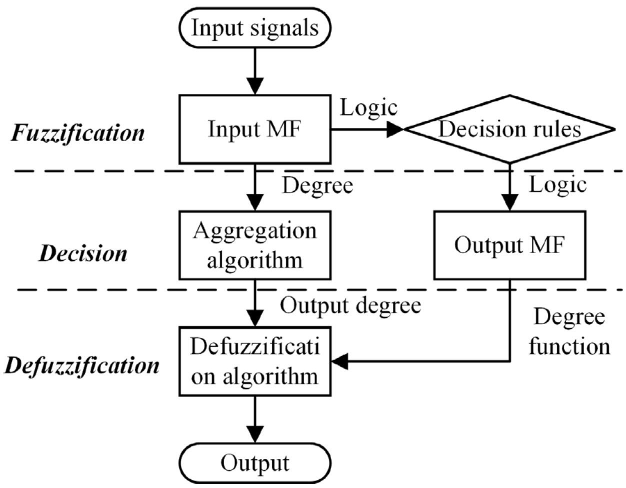

Fig. 3. Flow chart of the FL controllers.

Table 2
Working modes of the HSS.

H2 storage	Battery Charging	Holding	Discharging
charging	M1	M1	M4
holding	M1	M2	M3
discharging	M4	M3	M3

into fuzzy logic. For each ES unit, three working statuses are provided including charging, discharging, and holding. The detailed modes of the HSS are listed in Table 2. When one of the ES units is charging while the other is not discharging, the HSS is charging, marked as M1; If both ES units hold, the HSS holds, marked as M2; When one of the ES units is discharging while the other is not charging, the HSS is discharging, marked as M3; M4 happens if the ES units are exchanging energy to adjust their states. The decision process of the EMS is realized by two parallel FL Controllers. FL Controller1, which operates the H2 ES unit, decides in a global view to adjust the working mode of HSS according to the system status and LEEM. FL Controller2, concentrating on the detailed power balance in RMG, regulates the output power of the battery to maximize profits.

4.1. Fuzzy logic-based controller1 for H2 ES unit

The H2 ES unit operation considers not only the seasonal renewable energy and electricity price distribution but also the dynamic feature of the electrolyzer and FC. For most PEM FC, if the system works on a low electric power holding status, the efficiency will be low, and if it is completely shut down, the restart requires a warm-up which takes around thirty minutes. Hence, the operation of the H2 ES unit should restrain the switching between charging, discharging, and holding. In FL Controller1, the initial status of the H2 ES unit is introduced as membership function (MFs) shown in Fig. 4(a) to prevent the status changes from transient oscillation. MFs in Fig. 4(b) indicates the power demand P_d^{H2} in the RMG system. In Fig. 4(c), the SoC of the battery is introduced as a factor to decide whether it is urgent to switch the H2 ES unit. To involve the energy market and operation experience, LEEM output and electricity are compared in another MF group shown in Fig. 4(d). In FL controller 1, the output power of H2 ES unit will track the power demand and be suppressed by the initial state and battery SoC. The price input only affects the charging state. Hence, the MFs for power demand, initial power, and battery SoC are designed as linear functions, and the MFs for LEEM are designed to modify the logic judgment. The output MFs generate the reference power of the H2

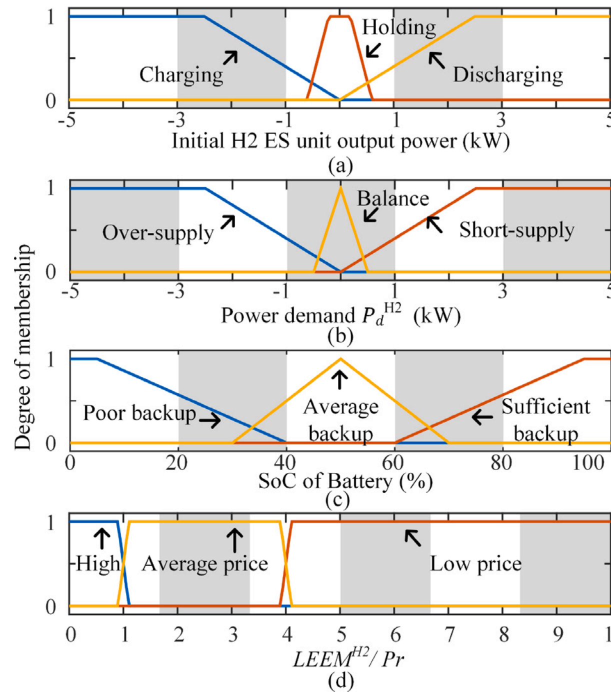

Fig. 4. Input MFs of the FL Controller1.

Table 3
Decision rules of FL Controller1, the expression is simplified as over-supply (OS), short-supply (SS), Balance (B), poor backup (PB), average backup (AB), sufficient backup (SB), high price (HP), average price (AP), low price (LP).

Initial state	Power demand	battery SoC	Market price	Expected modes	H2 storage
Charging	OS	/	HP|AP	M1	Charge
Charging	SS	SB	HP|AP	M1|M4	Charge
Charging	SS	AB	HP|AP	M2|M3	Hold
Charging	SS	PB	HP|AP	M3	Discharge
Discharging	OS	PB|AB	HP|AP	M1	Hold
Discharging	OS	SB	HP|AP	M1	Charge
Discharging	SS	PB|AB	HP|AP	M3|M4	Discharge
Discharging	SS	SB	HP|AP	M2|M3	Hold
Holding	OS	SB	HP|AP	M1	Charge
Holding	OS	PB|AB	HP|AP	M1	Hold
Holding	B	/	HP|AP	M2	Hold
Holding	SS	AB|SB	HP|AP	M3	Hold
Holding	SS	PB	HP|AP	M3|M4	Discharge
/	/	/	LP	M1	Charge

ES unit, so a linear function is utilized here to ensure output accuracy. The range of the input function which must cover all the system state is defined by the size of the MG. The turning point of initial power MFs and power demand MFs is defined by the operating range of the ES units. In the HEMS, the range of the battery is (−2.5 kW, 2.5 kW), the same as the H2 ES unit, and the total range of the ES system is (−5 kW, 5 kW), which is enough for the size of the MG. The turning point of SoC MFs affects the sensitivity of the H2 ES in the cooperation with battery which is defined empirically. However, the performance in the economic aspect is not influenced by the factor. The range of output MFs is defined by the operating range of the ES unit, and the range of "Hold" is reserved for the holding state of the fuel cell or electrolyzer, which is defined by the minimum work power of the devices.

The decision rules based on the MFs and operation modes are presented in Table 3.

The decision process always encourages the H2 ES unit to keep its original state. Based on the initial state, the decision rules identify if it is urgent and worth switching the H2 storage regarding the power demand. If the state of the H2 storage matches the power demand

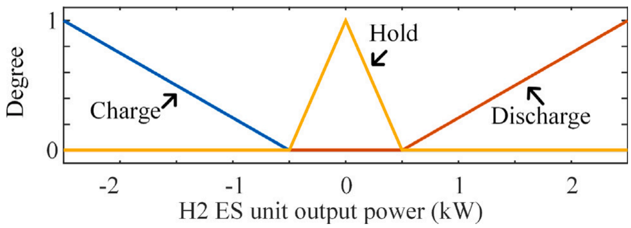

Fig. 5. Output MFs of the FL Controller1.

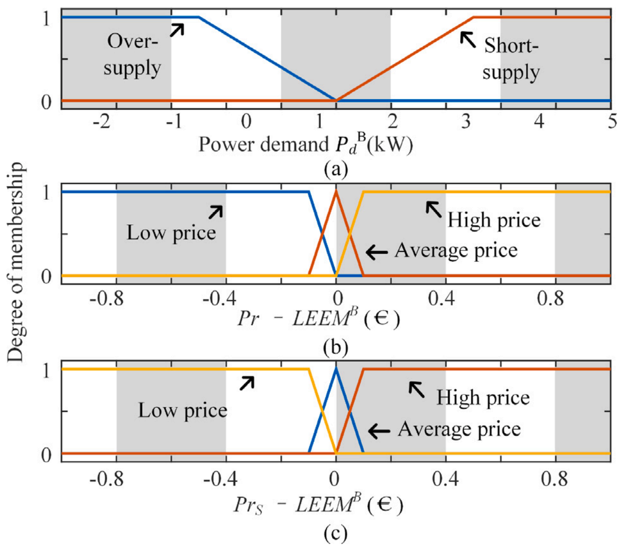

Fig. 6. Input MFs of the FL Controller2.

well, the state will be kept, else the decision rules could judge if it is urgent according to battery SoC and if it is worth regarding the electricity price. Only when it is critical and worthwhile, the state will be switched.

To ensure that the H2 ES unit power tracks the power demand well, the results of input MFs are multiplied, and the algebraic sum is chosen as the aggregation method. The output power is calculated through the defuzzification method using the smallest of maximum (SOM), which selects the smallest value for which the output fuzzy set is the maximum, based on the output MFs as shown in Fig. 5.

4.2. Fuzzy logic-based controller2 for battery

The battery is decoupled from the H2 ES unit by operating frequency, working in a minute resolution. The FL Controller2 for battery concentrates on tracking the energy demand in its time scale. The power demand after the compensation by the H2 ES unit has to be flattened by the battery, so the P_d^B is introduced as MFs as shown in Fig. 6(a). Meanwhile, considering the energy efficiency of the battery, energy trading is feasible, so the electricity selling price Pr_S is introduced. The MFs for energy purchasing and selling are shown in Figs. 6(b) and 6(c). In FL controller 2, the definition of the MFs is similar to that for FL controller 1. The power demand MFs are designed as a linear function, and the range and turning point are defined according to system parameters and battery configuration. The price MFs are designed like logic signals. The design of output MFs follows the same rules as FL controller 1. The charging and discharging curve turns flat at maximum charging and discharging power.

The decision rules of FL Controller2 are presented in Table 4. The energy trading will be activated when the purchasing and the selling price could make profits. If the output of $LEEM^B$ stays between the

Table 4
Decision rules of FL Controller2, the expression is simplified as over-supply (OS), short-supply (SS), high price (HP), average price (AP), low price (LP).

Power demand	Purchasing	Selling	Battery
/	LP	/	Charge
/	/	HP	Discharge
OS	HP|AP	AP|LP	Charge
SS	HP|AP	AP|LP	Discharge

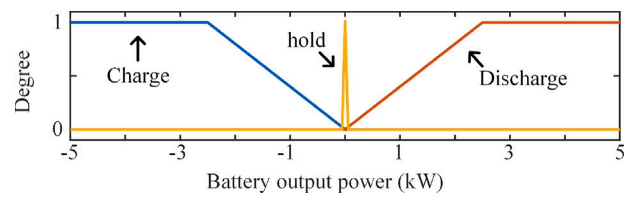

Fig. 7. Output MFs of the FL Controller2.

Table 5
Configuration of main devices in the RMG system.

Power configuration	PV rated power (1000 W/m^2, 25 °C)	4 kW
	battery maximum charging power	2.5 kW
	battery maximum discharging power	2.5 kW
	maximum electrolyzer input power	2.5 kW
	maximum FC output power	5 kW
Storage configuration	battery capacity	5 kWh
	battery maximum SoC	95%
	battery minimum SoC	10%
	H2 tank capacity (30 MPa)	5 kg

selling price and purchasing price, the FL Controller2 will operate the battery according to power demand P_d^B, which considers not only the power of FC and the electrolyzer but also the compressor. The battery power is generated with output MFs presented in Fig. 7. To achieve a good tracking performance to P_d^B, the minimum degree of input MFs is selected, and the maximum algorithm is chosen as the aggregation method. The defuzzification method is SOM.

The framework of the HEMS is constructed by the FL controllers which are decoupled with each other. The HEMS operates the HSS according to the decision made by the FL controllers with separated horizons provided by the proposed LEEM. Not only the internal supply–demand balance of the RMG but also the oscillation of the flexible energy market is considered in the proposed HEMS to achieve the economical and stable dispatch of ES units.

5. Numerical experiments

The performance of the proposed HEMS is verified in the RMG platform mentioned in Section 2. The system configuration is listed in Table 5. The characteristic of the H2 ES unit is shown in Fig. 8. The energy conversion efficiency of the H2 ES unit system is around 45%, which is marked as $\eta_e\eta_f$. The compressor pressurizes the H2 to 30 MPa, which leads to η_c reaching 70%.

To take the seasonal difference and computation efficiency into a joint account, a 50-day time sequence data set including information from 5 months is fed to the RMG system. The data set is combined by five 10-day time series sampled in the IoT laboratory at Aalborg University in May 2022, Aug 2022, Nov 2022, Feb 2023, and May 2023. The P_{load}, P_{RES}, and Pr time sequence are presented in Fig. 9, together with the daily statistical information. According to the energy contract, Pr_S is 0, which means there will not be any refund if the RMG feeds electricity back to the utility grid. The electricity price is updated hourly while the power data is sampled every minute. The detailed time sequence data is marked as the dark area in Fig. 9. The box plot is deployed for the statistical analysis of the data. On each

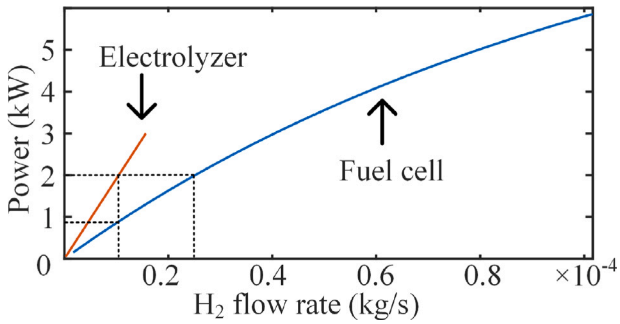

Fig. 8. Steady state characteristics of the electrolyzer and fuel cell.

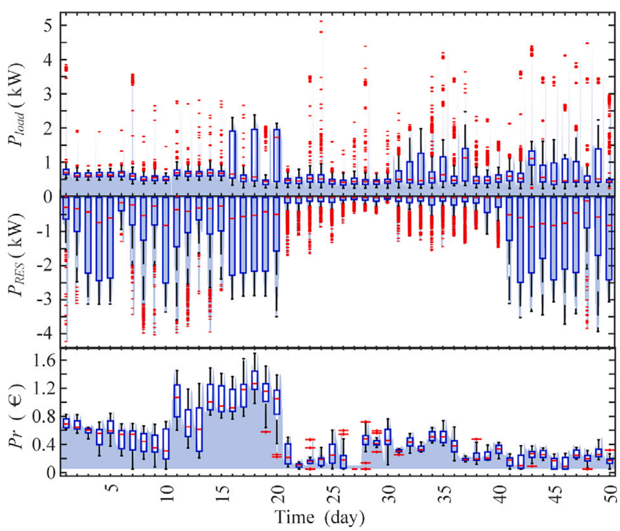

Fig. 9. PV power, load power, and electricity price of the experiment scenario.

box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25_{th} and 75_{th} percentiles, respectively. The whiskers extend to the most extreme data points, and the outliers are plotted individually.

To verify the superiority of the proposed HEMS, comparison results with the state-of-arts are implemented.

5.1. Performance analysis of the proposed HEMS

The HEMS operates the battery in minute resolution and the H2 ES unit hourly. The main functions of the HEMS include 3 aspects: (1) Store the exceeding renewable energy in the battery first and convert the rest electricity to H2 and store it in the tank; (2) Detect the low energy price region and purchase cheap electricity to charge the HSS; (3) Support the loads when the renewable energy is insufficient and the electricity price is not low enough.

The performance of HEMS on the first aspect is shown in Fig. 10. The green zone donates P_{H2}, the orange zone represents battery power, marked as P_B, they are stacked in the figure, and the dotted line shows the power demand which is calculated by $P_{load} - P_{RES}$. The grid power is marked as the black curve, and the electricity price is marked as the purple line. The figure below shows the SoC and SoF change during the period. In each case, 3-day results are studied, and the days are distinguished by the background color. The priority of the ES units during the charging process is clear in Fig. 10. When the renewable exceeds the loads, the battery will be charged first and the Electrolyzer will be activated after the SoC reaches a high level. In this case, according to the grid power curve, the energy purchasing from the utility grid is suppressed, and the system mainly works in a self-sufficient mode. During the charging of the H2 ES unit, the battery absorbs the oscillation caused by RES and load power to prevent energy purchasing from the utility grid. At night, when the RES power is less than the loads, the energy in the battery will be consumed first due to its high conversion efficiency, after the SoC decreases to a low level, the FC works to support the primary loads and the battery takes charge of dynamic power balance. Besides, the battery allocates the energy not only according to the RES power supply but also the electricity price. When the electricity price comes to a local minimum value, the battery will charge and shift the cheap energy to the high price duration. The H2 ES unit only switches one time per day according to the P_{H2} curve and from the SoC curve, it is easy to find that the battery also works smoothly.

The performance of the proposed HEMS on the second aspect is shown in Fig. 11. When the time came to November 2022, the electricity price dropped rapidly compared with that in August. The power purchasing from the utility grid is significantly encouraged when the electricity price drops. In low-price regions, the state of ES units will affect power purchasing. The slightly low price is first detected by the FL controller2, and when the price drops to a very low level, the electrolyzer is activated with maximum power to charge the H2 ES unit, when the price goes up again, the charging power decreases accordingly. Until the electricity price drops again, the H2 ES unit charges with maximum power. During the low-price region, the loads will be supported by the utility grid if renewable energy is scant.

The roof-top PV system cannot generate much power during winter due to the limited solar irradiation and daytime, making the function of HEMS on the third aspect necessary. Hence the HEMS will dispatch the energy in HSS to support the loads as shown in Fig. 12. When the electricity price is partially low, the battery will be used to shift the cheap energy to the high-price duration. The FC will be activated when the SoC is too low to support the loads and the electricity price is not beneficial. The energy purchasing in this case is intelligently defined by the HEMS. From the grid power and electricity price, it can be found that the power purchasing happened after the peak price or in the valley due to the intelligent decision-making of the proposed HEMS.

The energy shifting among seasons depends on not only the production of renewable energy but also the overall trend of the electricity market. The distribution of daily power purchasing is presented as box charts in Fig. 13. The dark area represents the daily average electricity price; The red curve below indicates the SoF trend. It is easy to find that the maximum energy purchasing event and the charge of the H2 ES unit happen during the global minimum price period. When the electricity price is high, the RMG system works in a self-sufficient mode, the energy exchanged with the utility grid is greatly restrained. The exceeding renewable energy is stored in the HSS and shifted to the low RES power period. The proposed HEMS quantifies the concept of whether the current electricity is cheap or expensive for battery charging and H2 ES unit charging, respectively, making the decision process more intelligent.

5.2. Comparison with state-of-art methods on energy expense

To validate the superiority of the proposed HEMS, some baselines are implemented in the RMG platform. the energy cost is calculated by,

$$Cost = \int P_{Grid} \cdot Prdt \tag{16}$$

The seasonal cost intercepts the expenses of the durations. Considering the feasibility of different methods, the ES system structures are modified accordingly. For single battery, an FL-based EMS, and a PSO-based day-ahead schedule method are implemented. A rule-based EMS is designed for the HSS same as the proposed HEMS.

The FL-based EMS operates the battery every minute with a decision process that considers the electricity price, SoC, and power demand.

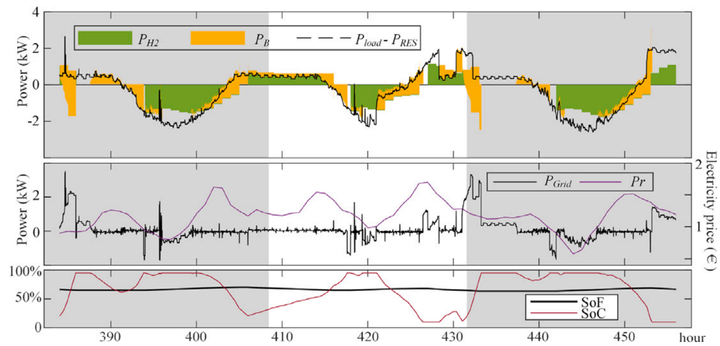

Fig. 10. Performance of HEMS when the renewable is sufficient but the electricity price is high.

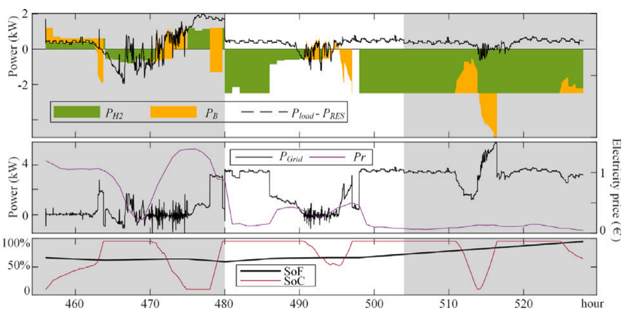

Fig. 11. Performance of HEMS when the low electricity price detected.

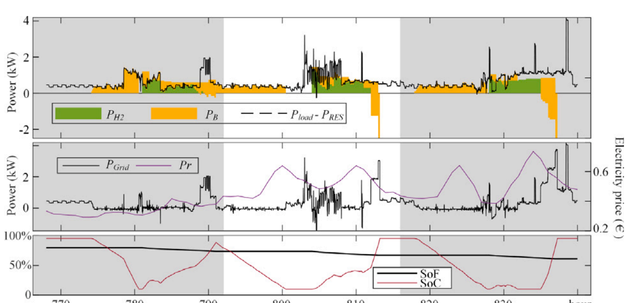

Fig. 12. Performance of HEMS on energy shortage condition.

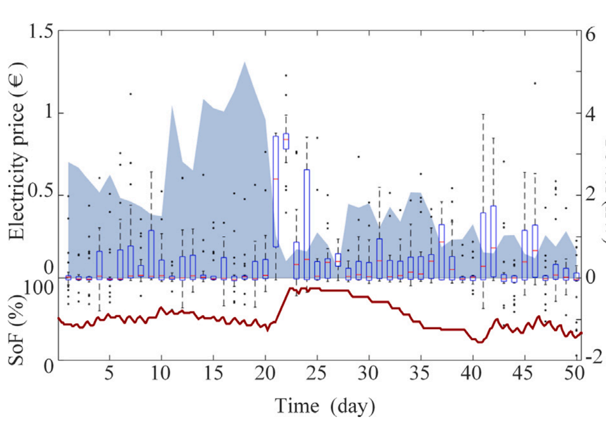

Fig. 13. Daily power purchasing on a global view.

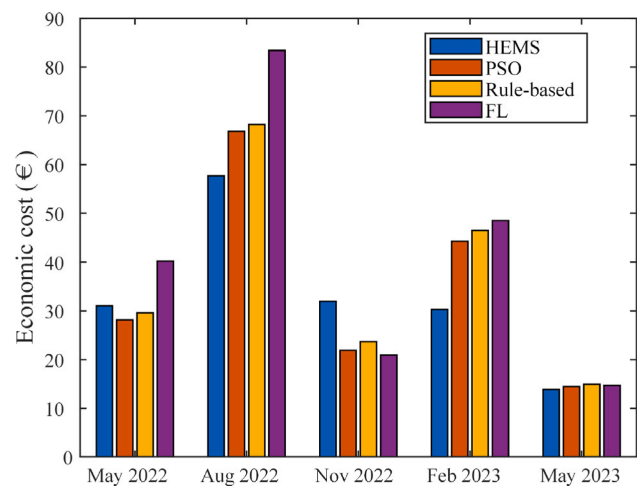

Fig. 14. Comparison between the proposed HEMS and existing methods in an economic manner.

When the SoC is not low, the EMS will operate the battery to track the power demand; If the electricity decreases or the SoC drops to a low level, the battery will be charged.

The PSO-based EMS schedules the hourly operation of the battery for the coming day. At the end of each day, the PSO algorithm will be activated to generate 24 operation points for the next day based on the 24-step-ahead prediction of RES power, load, and electricity price. In the baseline, the accurate data is fed to the algorithm to achieve the theoretical optimal results. However, the result is nonexistent in the real world since even if the price data could be provided by the energy supplier, the 24-step-ahead forecasting with 100% accuracy of RES and load power is still unavailable.

The rule-based EMS operates the HSS according to a preset priority. The capacity of the battery will be dispatched first to store excessive energy from RES and support the loads. The H2 ES unit is excited when the battery is fully charged or discharged. Considering the restart process, the operation of the H2 ES unit is on hour resolution while the battery can be operated every minute.

The energy cost for each season is presented in Fig. 14, and the consumption data is listed in Table 6.

The electricity price is presented in Fig. 9, indicating that the highest price among the 5 seasons happens in Aug 2022 while the lowest happens in Nov 2022. Fig. 14 shows that the proposed HEMS significantly decreases the economic cost during high energy price periods compared with other methods, besides, when the price is low, the electricity purchasing from the utility grid will be encouraged by

Table 6
Seasonal energy cost (€) comparison between the proposed HEMS and existing methods.

Season	Battery		HSS	
	FL	PSO	Rule-based	HEMS
May 2022	40.21	**28.18**	29.60	31.02
Aug 2022	83.40	66.83	68.23	**57.86**
Nov 2022	**20.93**	21.90	23.68	31.96
Feb 2023	48.53	44.29	46.52	**30.31**
May 2023	14.76	14.47	14.96	**13.90**
Total	207.87	175.68	183.03	**164.89**

the HEMS. Benefiting from the encouraged charging event in Nov 2022, the electricity cost of the next season when the price rises again is reduced.

In summary, the proposed HEMS outperforms the existing methods from a global view. The total economic cost of the RMG is decreased by the online control of HEMS. Compared with rule-based EMS, which is always implemented as the basic control method for ES systems, a 9% improvement is achieved. The decision process of the HEMS also overcomes the side effect of low energy conversion efficiency of the H2 ES unit, obtaining a 21% cost saving compared with the common single battery-based RMG, and even better than the theoretical optimal result in this case.

6. Conclusion

This paper proposed an HEMS for HSS, including a battery and an H2 ES unit, in a RES-integrated RMG to decrease the economic cost. The advantages of H2 storage, high energy density, and low storage loss, are utilized to realize the long-term energy-shifting while the economic loss caused by its shortcoming of low energy conversion efficiency is addressed by the proposed HEMS. The main works are summarized in three aspects.

1. The electricity price expectation is quantified through the proposed LEEM, enabling intelligent decision-making for HSS operation. The LEEM performs an accumulated evaluation for the HSS and establishes distinct horizons for the H2 ES unit and battery. It combines historical charge and discharge events, electricity prices, and supply–demand balance for real-time evaluation. The LEEM is underpinned by robust mathematical principles and operates independently of empirical parameters.
2. A hierarchical EMS structure is proposed in which decoupled FL controllers are designed for the battery and H2 ES unit separately to avoid the system oscillation caused by decision-making conflicts. The ES units cooperate to maintain the internal energy balance in the RMG, each with its own distinct objectives and time horizons. The H2 ES unit is responsible for long-term energy shifting, while the battery manages short-term power balance. Additionally, the energy conversion efficiency is considered for the H2 ES unit in the FL Controller design, addressing the unexpected loss from the H2 ES unit operation.
3. The intact validation is conducted with high-resolution real-world data. The proposed HEMS overcomes the influence of uncertainty from the RES and demand side without using prediction methods. The results indicate that the HEMS is intelligent enough to detect renewable energy and assess the electricity price for charging event decisions of the battery and the H2 ES unit with different standards. Compared to existing rule-based EMS and single battery-based EMS, the proposed HEMS reduces the overall energy cost by 9% and 21%, respectively.

However, potential limitations of the proposed approach, identified based on both theoretical foundations and practical implementation, will be addressed in future research endeavors.

1. The proposed EMS approach works as a central controller, requiring real-time data from the devices in the Microgrid system. Considering the distribution and size of the Microgrid system, stable wireless communication is necessary to implement the approach in real-world applications.
2. The design of the HEMS highly relies on the artificial experience, and the difficulty increases if more ES units are involved. Hence, deeper AI approaches are expected to be introduced to address to problem.
3. The proposed HEMS is an experience-based approach, independent from the forecasting methods, avoiding the influence of inaccurate prediction results. However, the lack of foresight leads to the HEMS missing optimal operations in some specific situations. For example, the HEMS may not consistently guarantee power purchases happen in the valley of electricity prices.

CRediT authorship contribution statement

Jingxuan Wu: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Shuting Li:** Writing – review & editing, Visualization, Validation, Formal analysis. **Aihui Fu:** Writing – review & editing, Resources, Formal analysis. **Miloš Cvetković:** Writing – review & editing, Supervision, Formal analysis. **Peter Palensky:** Writing – review & editing, Supervision, Resources, Investigation. **Juan C. Vasquez:** Writing – review & editing, Supervision, Investigation, Funding acquisition. **Josep M. Guerrero:** Writing – review & editing, Supervision, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] Raya-Armenta Jose Maurilio, Bazmohammadi Najmeh, Avina-Cervantes Juan Gabriel, Sáez Doris, Vasquez Juan C, et al. Energy management system optimization in islanded microgrids: An overview and future trends. Renew Sustain Energy Rev 2021;149.

[2] Alizadeh Ali, Kamwa Innocent, Moeini Ali, Mohseni-Bonab Seyed Masoud. Energy management in microgrids using transactive energy control concept under high penetration of Renewables; A survey and case study. Renew Sustain Energy Rev 2023;176.

[3] Yang Yuqing, Bremner Stephen, Menictas Chris, Kay Merlinde. Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review. Renew Sustain Energy Rev 2022;167.

[4] Thirugnanam Kannan, Moursi Mohamed Shawky El, Khadkikar Vinod, Zeineldin Hatem H, Hosani Mohamed Al. Energy management strategy of a reconfigurable grid-tied hybrid AC/DC microgrid for commercial building applications. IEEE Trans Smart Grid 2022;13:1720–38.

[5] Deng Youjun, Luo Fengji, Zhang Yongxi, Mu Yunfei. An efficient energy management framework for residential communities based on demand pattern clustering. Appl Energy 2023;347.

[6] Arkhangelski Jura, Abdou-Tankari Mahamadou, Lefebvre Gilles. Day-ahead optimal power flow for efficient energy management of urban microgrid. IEEE Trans Ind Appl 2021;57.

[7] Aguila-Leon Jesus, Vargas-Salgado Carlos, Chiñas-Palacios Cristian, Díaz-Bello Dácil. Energy management model for a standalone hybrid microgrid through a particle Swarm optimization and artificial neural networks approach. Energy Convers Manage 2022;267.

[8] Chen Shuang, Hu Minghui, Lei Yanlei, Kong Linghao. Novel hybrid power system and energy management strategy for locomotives. Appl Energy 2023;348.

[9] Zhao Dafang, Watari Daichi, Ozawa Yuki, Taniguchi Ittetsu, Suzuki Toshihiro, Shimoda Yoshiyuki, et al. Data-driven online energy management framework for HVAC systems: An experimental study. Appl Energy 2023;352:121921.
[10] Vasak Mario, Banjac Anita, Hure Nikola, Novak Hrvoje, Marusic Danko, Lesic Vinko. Modular hierarchical model predictive control for coordinated and holistic energy management of buildings. IEEE Trans Energy Convers 2021;36:2670–82.
[11] Chen Huan, Xiong Rui, Lin Cheng, Shen Weixiang. Model predictive control based real-time energy management for hybrid energy storage system. CSEE J Power Energy Syst 2021;7:862–74.
[12] Zhao Zhuoli, Guo Juntao, Luo Xi, Lai Chun Sing, Yang Ping, Lai Loi Lei, et al. Distributed robust model predictive control-based energy management strategy for islanded multi-microgrids considering uncertainty. IEEE Trans Smart Grid 2022;13:2107–20.
[13] Chen Tengpeng, Cao Yuhao, Qing Xinlin, Zhang Jingrui, Sun Yuhao, Amaratunga Gehan AJ. Multi-energy microgrid robust energy management with a novel decision-making strategy. Energy 2022;239.
[14] Jafari Mohammad, Malekjamshidi Zahra, Zhu Jianguo, Khooban Mohammad Hassan. A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids. IEEE J Emerg Sel Top Power Electron 2020;8:1391–404.
[15] Teo Tiong Teck, Logenthiran Thillainathan, Woo Wai Lok, Abidi Khalid, John Thomas, Wade Neal S, et al. Optimization of fuzzy energy-management system for grid-connected microgrid using NSGA-II. IEEE Trans Cybern 2021;51:5375–86.
[16] Mondal Ayan, Misra Sudip, Obaidat Mohammad S. Distributed home energy management system with storage in smart grid using game theory. IEEE Syst J 2017;11:1857–66.
[17] Dong Guangzhong, Chen Zonghai. Data-driven energy management in a home microgrid based on Bayesian optimal algorithm. IEEE Trans Ind Inf 2019;15:869–77.
[18] Hartani Mohamed Amine, Rezk Hegazy, Benhammou Aissa, Hamouda Messaoud, Abdelkhalek Othmane, Mekhilef Saad, et al. Proposed frequency decoupling-based fuzzy logic control for power allocation and state-of-charge recovery of hybrid energy storage systems adopting multi-level energy management for multi-DC-microgrids. Energy 2023;278.
[19] Shah MAK Yousaf, Lu Yuzheng, Mushtaq Naveed, Yousaf Muhammad, Akbar Nabeela, Xia Chen, et al. Semiconductor-membrane fuel cell (SMFC) for renewable energy technology. Renew Sustain Energy Rev 2023;185.
[20] Sorrenti Ilaria, Rasmussen Theis Bo Harild, You Shi, Wu Qiuwei. The role of power-to-X in hybrid renewable energy systems: A comprehensive review. Renew Sustain Energy Rev 2022;165.
[21] Li Na, Cui Xiaoti, Zhu Jimin, Zhou Mengfan, Liso Vincenzo, Cinti Giovanni, et al. A review of reformed methanol-high temperature proton exchange membrane fuel cell systems. Renew Sustain Energy Rev 2023;182.
[22] Niknam Taher, Golestaneh Faranak, Malekpour Ahmadreza. Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm. Energy 2012;43:427–37.
[23] Ferahtia Seydali, Rezk Hegazy, Djeroui Ali, Houari Azeddine, Fathy Ahmed, Abdelkareem Mohammad Ali, et al. Optimal heuristic economic management strategy for microgrids based PEM fuel cells. Int J Hydrogen Energy 2022.
[24] Arjanaki Ali Abdollahi, Kolagar Arash Dehestani, Pahlavani Mohammad Reza Alizadeh. A two-level power management strategy in a DC-coupled hybrid microgrid powered by fuel cell and energy storage systems with model predictive controlled interface converter. J Energy Storage 2022;52.
[25] Gugulothu Ramesh, Nagu Bhookya, Pullaguram Deepak. Energy management strategy for standalone DC microgrid system with photovoltaic/fuel cell/battery storage. J Energy Storage 2023;57.
[26] Wang Tianhong, Li Qi, Qiu Yibin, Chen Weirong, Breaz Elena, Ravey Alexandre, et al. Power optimization distribution method for fuel cell system cluster comprehensively considering system economy. IEEE Trans Ind Electron 2022;69:12898–911.
[27] Kumar Kuldeep, Bae Sungwoo. Two-layer energy management strategy for renewable power-to-gas system-based microgrids. J Energy Storage 2023;61.
[28] Fathy Ahmed, Ferahtia Seydali, Rezk Hegazy, Yousri Dalia, Abdelkareem Mohammad Ali, Olabi AG. Optimal adaptive fuzzy management strategy for fuel cell-based dc microgrid. Energy 2022;247.
[29] Pajares A, Vivas FJ, Blasco X, Herrero JM, Segura F, Andújar JM. Methodology for energy management strategies design based on predictive control techniques for smart grids. Appl Energy 2023;351.
[30] Ding Xiaoyi, Sun Wei, Harrison Gareth P, Lv Xiaojing, Weng Yiwu. Multi-objective optimization for an integrated renewable, power-to-gas and solid oxide fuel cell/gas turbine hybrid system in microgrid. Energy 2020;213.
[31] Kumar Kuldeep, Alam Mohd, Dutta Viresh. Energy management strategy for integration of fuel cell-electrolyzer technologies in microgrid. Int J Hydrogen Energy 2021;46:33738–55.
[32] Zhang Yong, Wei Wei. Model construction and energy management system of lithium battery, PV generator, hydrogen production unit and fuel cell in islanded AC microgrid. Int J Hydrogen Energy 2020;45:16381–97.
[33] Zadeh LA. Fuzzy sets *. Infor Atio Control 1965;8:338–53.

Jingxuan Wu received the B.S. degree in electrical engineering and automation in 2017 from Dalian Maritime University, Dalian, P.R. CHINA and the M.S degree in electrical engineering in 2020 from Fuzhou University, Fuzhou, P.R. CHINA. He worked as an R&D engineer for sensors technology in Nari Technology CO., LTD from 2020 to 2021. He is working towards a Ph.D. degree in Microgrids with the Center for Research on Micrograms (CROM), Aalborg University, Aalborg, Denmark. His main research interests include energy management systems (EMS) and machine learning.

Shuting Li received the B.S. degree in electronic information engineering in 2016 from Southwest Jiaotong University, Chengdu, P.R. CHINA and the M.S degree in electrical engineering in 2019 from Southwest Jiaotong University, Chengdu, P.R. CHINA She is working towards the Ph.D. degree in Microgrids with Center for research on Microgrids (CROM), Aalborg University, Aalborg, Denmark. Her main research interests include distributed generation and power quality enhancement.

Aihui Fu received the B.S. degree in electric engineering from China Agricultural University and the M.S. degree in electrical engineering from Shandong University. She is currently pursuing the Ph.D. degree with the Delft University of Technology. Her research interests include distributed optimization control, power system stability analysis, renewable energy resources, and battery ES.

Miloš Cvetković received the B.Sc. degree in electrical engineering from the University of Belgrade, Belgrade, Serbia, in 2008, and the M.Sc. and Ph.D. degrees in electrical and computer engineering from Carnegie Mellon University, Pittsburgh, PA, USA, in 2011 and 2013, respectively. He is an Assistant Professor with the Electrical Sustainable Energy Department, at Delft University of Technology, Delft, The Netherlands. He worked as a Postdoctoral Researcher with the Active-Adaptive Control Laboratory at, the Massachusetts Institute of Technology. His research interests include the development of co-simulations for energy grids and modeling for the control and optimization of electricity grids.

Peter Palensky received the Ph.D. and Habilitation degrees from the Vienna University of Technology, Austria in 2015. He co-founded a Envidatec and joined the Lawrence Berkeley National Laboratory, Berkeley, CA, USA, as a Researcher and the University of Pretoria, South Africa, in 2008. In 2009 he became an Appointed Head of Business Unit on Sustainable Building Technologies with the Austrian Institute of Technology (AIT) and later the First Principle Scientist for Complex Energy Systems with AIT. In 2014, he was appointed as a Full Professor of Intelligent Electric Power Grids, TU Delft. His main research fields are energy automation networks, smart grids, and modeling intelligent energy systems. He is active in international committees like ISO or CEN and serves as IEEE IES AdCom member-at-large in various functions for the IEEE. He is the Editor in Chief of the IEEE Industrial Electronics Magazine and an Associate Editor for several other IEEE publications, and regularly organizes IEEE conferences.

Juan C. Vasquez received the Ph.D. degree in automatic control, robotics, and computer vision from BarcelonaTech-UPC, Spain in 2009. In 2019, He became a full professor and currently he is the codirector of CROM. His current research interests include operation, advanced hierarchical and cooperative control applied to distributed generation in AC/DC Microgrids, maritime microgrids. Prof. Vasquez is an Associate Editor of IET POWER ELECTRONICS and IEEE Systems Journal, and a guest editor of IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS. He is currently a member of the IEC System Evaluation Group SEG4 on LVDC Distribution and Safety for use in Developed and Developing Economies, the Renewable Energy Systems Technical Committee TCRES in IEEE Industrial Electronics, PELS, IAS, and PES Societies.

Josep M. Guerrero received the Ph.D. degree in power electronics from the Technical University of Catalonia, Barcelona, in 2003. Since 2011, he has been a Full Professor at AAU Energy, Aalborg University, Denmark, where he is responsible for the research of Microgrids (crom.et.aau.dk). In 2023 he joined the Technical University of Catalonia as an ICREA Research Professor. His research interests are oriented to different microgrid aspects, including power electronics, distributed energy-storage systems, and hierarchical and cooperative control. Prof. Guerrero is an Associate Editor for several IEEE TRANSACTIONS. He received the best paper award of the IEEE Transactions on Energy Conversion for the period 2014–2015, and the best paper prize of IEEE-PES in 2015. As well, he received the best paper award from the Journal of Power Electronics in 2016. In 2014, 2015, 2016, and 2017 he was awarded by Thomson Reuters as Highly Cited Researcher. In 2015 he was elevated as IEEE Fellow for his contributions on “distributed power systems and microgrids”.