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Economic model predictive control for multi-energy system considering hydrogen-thermal-electric dynamics and waste heat recovery of MW-level alkaline electrolyzer

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ABSTRACT

A large-scale alkaline electrolyzer (AE), can convert renewable electricity into green hydrogen and recoverable heat, and consequently unlock great flexibility to accommodate renewable power variability. This paper proposes an economic model predictive control (EMPC) based daily optimal operation strategy for a multi-energy system (MES) which unleashes the cross-sectoral operational flexibility of AE. A dynamic power-to-hydrogen&heat (P2H\textsuperscript{2}) model for AE is presented, considering heat recovery and efficiency variation under different loading conditions. Instead of incorporating the nonlinear P2H\textsuperscript{2} model into the operating optimization model of MES, this paper has developed a more computationally efficient algorithm that uses the P2H\textsuperscript{2} model for post-evaluation of optimal scheduling derived from a mixed-integer linear programming (MILP)-based EMPC. Comparative cases based on real data of a Danish energy island Bornholm, demonstrate the effectiveness, robustness of the proposed method and the potential value of AE's operational flexibility in the MESs. The results reveal that the proposed method contributes to additional operation cost savings of 59% and 38% compared to a traditional rule-based strategy and an economic strategy without P2H\textsuperscript{2} model.

1. Introduction

Energy sustainability and carbon emission reduction have received increasing attention worldwide due to the rapid depletion of fossil fuels and related environmental pollution problems. Some relevant works have recently focused on natural resources optimization [1,2], CO\textsubscript{2} emission of industrial processes [3], providing feasible solutions for energy-saving and carbon reduction. Another alternative solution is to exploit clean fuels for end-consumers such as chemical industries and transportation. In particular, green hydrogen from water-electrolysis technologies consuming renewable electricity is highly considered as a promising solution, due to its significant contributions to energy decarbonization, emission reduction and sustainability. The techno-economic feasibility of hydrogen energy via renewable power has been explored globally [4-6]. The renewable-based green hydrogen has been proved to be already cost-competitive in niche applications like wind parks integrated with power-to-gas facilities in Germany and Texas for small and medium-scale supply, and will have a continuous cost reduction within a decade [7].

Moreover, the water-electrolysis system (i.e. electrolyzer) converting power to hydrogen (P2H) also offers flexibility via load regulation and energy storage to a multi-energy system (MES) [8], which supports optimal operations of distributed energy resources (DERs) [9]. Several rule-based strategies (RBSs) have been presented to manage the energy flow between electrolyzers and other DERs in order to achieve an optimal sizing in various MES setups, such as standalone hybrid energy system with storage [10-12], an off-grid wind-hydrogen production system [13], a grid-connected wind-hydrogen system [14,15]. In the RBSs, the operation of DERs follow pre-set rules. For instance, a simple power balancing rule under excess renewable power in an off-grid system is to first allocate the excess power to charge battery-ESS (BESS), then hydrogen-ESS (HESS) [10,12]. The main drawback of the RBSs is their inefficiency of operating systems incorporated with numerous DERs due to the increased level of rule complexity. Meanwhile no economic criteria in the RBS possibly causes a relatively higher operation cost. To overcome these barriers, the authors use a unit commitment framework to formulate a mixed-integer linear programming (MILP) based operation strategy [16,17], which is integrated into the sizing algorithm for a standalone microgrid with BESS and HESS. Besides, the daily optimal operation on electrolyzer installed in an active distribution network [18], electricity-hydrogen integrated energy system [19] and a

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E-mail address: yizo@elektro.dtu.dk (Y. Zong).
A summary of the aforementioned studies is given in Table 1, which also indicates some existing limitations. Firstly, most studies utilize a hierarchical MPC for optimally managing a hybrid ESS-based building microgrid [27], a data-driven algorithm and MPC are integrated into a two-level operation management into investment planning, which also demonstrates the effectiveness of using EMPC to achieve operation cost reduction. In electricity markets. In [25], the authors utilize a particle swarm optimization (PSO) algorithm to solve an EMPC controller to achieve the optimal economic dispatch of a hydrogen-based microgrid. A bi-level decision framework proposed in [26] incorporates EMPC-based operation management into investment planning, which also demonstrates the effectiveness of using EMPC to achieve operation cost reduction. In [27], a data-driven algorithm and MPC are integrated into a two-level hierarchical MPC for optimally managing a hybrid ESS-based building microgrid. The data-driven algorithm can improve the MPC model accuracy, and in real-time adjust the cost function to satisfy the annual self-consumption rate at the minimum cost.

Abbreviation

AE  Alkaline electrolyzer
BESS  Battery energy storage system
CHP  Combined heat and power
DER  Distributed energy resources
DHS  District heating system
EMPC  Economic model predictive control
EPS  Electrical power system
Ely  Electrolyzer
HE  Heat exchanger
HESS  Hydrogen energy storage system
HHV  Higher heat value
MES  Multi-energy system
MILP  Mixed-integer linear programming
MINLP  Mixed-integer nonlinear programming
MPC  Model predictive control
PEM  Proton exchange membrane electrolyzer
PSO  Particle swarm optimization
P2H  Power-to-hydrogen
P2H2  Power-to-hydrogen & heat
RBS  Rule-based strategy
SOC  State of charge
VLH  Volume level of hydrogen

Subscript

| t/k  | Predicated value at time t based on time k |

Parameters

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{ele}}^{\text{fuel}}$</td>
<td>Electricity price (€/MWh), heat price(€/MWh), hydrogen price (€/kg), penalty cost for wind curtailment (€/MWh)</td>
</tr>
<tr>
<td>$C_{\text{capex}}$, $C_{\text{opex}}$, $C_{\text{fuel}}$</td>
<td>Capital cost of BESS, AE plant, fuel cell plant (€/kWh)</td>
</tr>
<tr>
<td>$C_{\text{om}}^{\text{AE}}$, $C_{\text{om}}^{\text{fuel}}$, $C_{\text{om}}^{\text{cap}}$</td>
<td>Operation and maintenance cost of AE and fuel cell plant (€/h)</td>
</tr>
<tr>
<td>$C_{\text{hump}}$</td>
<td>Lump heat capacitance of AE stack (MWh/°C)</td>
</tr>
<tr>
<td>$N_{\text{cycles}}$, $N_{p}$</td>
<td>Lifetime of AE plant and fuel cell plant (h), $N_{p}$</td>
</tr>
<tr>
<td>$N_{\text{cycles}}$, $N_{p}$</td>
<td>Number of life cycles for BESS</td>
</tr>
<tr>
<td>$T_{h}$</td>
<td>Prediction horizon (h), total operating horizon (h)</td>
</tr>
<tr>
<td>$P_{\text{min}}^{\text{fc}}$, $P_{\text{max}}^{\text{fc}}$</td>
<td>Minimum and maximum produced power of fuel cell plant (MW)</td>
</tr>
<tr>
<td>$P_{\text{min}}^{\text{fc}}$, $P_{\text{max}}^{\text{fc}}$</td>
<td>Minimum and maximum consumed power of AE plant (MW)</td>
</tr>
<tr>
<td>$P_{\text{min}}^{\text{batt}}$, $P_{\text{max}}^{\text{batt}}$</td>
<td>Minimum and maximum discharging power of BESS (MW)</td>
</tr>
<tr>
<td>$P_{\text{min}}^{\text{grid}}$, $P_{\text{max}}^{\text{grid}}$</td>
<td>Minimum and maximum power purchased from grids (MW)</td>
</tr>
</tbody>
</table>

Electricity markets. In [25], the authors utilize a particle swarm optimization (PSO) algorithm to solve an EMPC controller to achieve the optimal economic dispatch of a hydrogen-based microgrid. A bi-level decision framework proposed in [26] incorporates EMPC-based operation management into investment planning, which also demonstrates the effectiveness of using EMPC to achieve operation cost reduction. In [27], a data-driven algorithm and MPC are integrated into a two-level hierarchical MPC for optimally managing a hybrid ESS-based building microgrid. The data-driven algorithm can improve the MPC model accuracy, and in real-time adjust the cost function to satisfy the annual self-consumption rate at the minimum cost.

A summary of the aforementioned studies is given in Table 1, which also indicates some existing limitations. Firstly, most studies utilize a linear electrolyzer model to characterize the relation of electricity...
Table 1  
Current studies regarding optimal energy transaction of hydrogen-based energy system.

<table>
<thead>
<tr>
<th>Research</th>
<th>System Configuration</th>
<th>Operating Strategy</th>
<th>Electrolyzer</th>
<th>Electrolyzer model between consumed power and H₂ production</th>
<th>Heat recovered of electrolyzer</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10–13]</td>
<td>PV/BEss/HESS or</td>
<td>RBS</td>
<td>PEM (kW-level)</td>
<td>Linear (constant efficiency) or Linear (empirical function)</td>
<td>None</td>
</tr>
<tr>
<td>[14]</td>
<td>WT/Eely + Grid</td>
<td>RBS</td>
<td>PEM (MW level)</td>
<td>Linear (constant efficiency) or Linear (empirical function)</td>
<td>None</td>
</tr>
<tr>
<td>[15]</td>
<td>WT farm/HESS + Grid</td>
<td>Power allocating</td>
<td>PEM (MW level)</td>
<td>Linear (constant efficiency) or Linear (empirical function)</td>
<td>None</td>
</tr>
<tr>
<td>[16,17]</td>
<td>PV/BEss/HESS (DC-bus)</td>
<td>MILP based cost</td>
<td>AE (kW level)</td>
<td>Linear (empirical linear function from regression)</td>
<td>None</td>
</tr>
<tr>
<td>[18]</td>
<td>PV/WT/CHP/Ely/ADN/DHS</td>
<td>Robust cost optimization</td>
<td>AE (kW level)</td>
<td>Linear (piecewise linearization)</td>
<td>Yes</td>
</tr>
<tr>
<td>[19]</td>
<td>PV/WT/Eley/Bolier/ADN/NGN/heat storage</td>
<td>Stochastic and robust cost optimization</td>
<td>AE (kW level)</td>
<td>Linear (piecewise linearization)</td>
<td>Yes</td>
</tr>
<tr>
<td>[20]</td>
<td>PV/Ely/Bolier</td>
<td>MPC-based running state</td>
<td>AE (kW level)</td>
<td>Linear (piecewise linearization)</td>
<td>Yes</td>
</tr>
<tr>
<td>[21]</td>
<td>WT/CHP/BEss/Ely/Bolier</td>
<td>MILP based cost</td>
<td>AE (MW level)</td>
<td>Linear (piecewise linearization)</td>
<td>Yes</td>
</tr>
<tr>
<td>[22]</td>
<td>WT farm/HESS + Grid</td>
<td>EMPC-based optimization</td>
<td>PEM (kW level)</td>
<td>Linear (constant efficiency)</td>
<td>None</td>
</tr>
<tr>
<td>[23]</td>
<td>PV/WT/BEss/SC + Grid</td>
<td>EMPC-based optimization</td>
<td>PEM (kW level)</td>
<td>Linear (constant efficiency)</td>
<td>None</td>
</tr>
<tr>
<td>[24]</td>
<td>PV/WT/biomass/BEss/HESS</td>
<td>EMPC-based optimization</td>
<td>kW level</td>
<td>Nonlinear (smoothing spline)</td>
<td>None</td>
</tr>
<tr>
<td>[25]</td>
<td>PV/WT/biomass/BEss/HESS</td>
<td>Hierarchical EMPC based cost optimization</td>
<td>PEM (kW level)</td>
<td>Linear (Piecewise linearization)</td>
<td>None</td>
</tr>
<tr>
<td>[26]</td>
<td>PV/WT/BEss/HESS(DC-bus)</td>
<td>EMPC-based optimization</td>
<td>PEM (kW level)</td>
<td>Linear (Piecewise linearization)</td>
<td>None</td>
</tr>
<tr>
<td>[27]</td>
<td>PV/BEss/HESS(DC-bus in building) + Grid</td>
<td>EMPC-based optimization</td>
<td>PEM (kW level)</td>
<td>Linear (Piecewise linearization)</td>
<td>None</td>
</tr>
<tr>
<td>[28]</td>
<td>PV/BEss/HESS (DC-bus)</td>
<td>RBS</td>
<td>AE + PEM (kW level)</td>
<td>Nonlinear (polynomial fitting efficiency curve)</td>
<td>None</td>
</tr>
</tbody>
</table>

Fig. 1. System configuration of an equivalent MES for Bornholm island.

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consumed vs hydrogen production (E-H relation) in an AE, via assuming a constant electrolysis efficiency for AE in its operation range, or utilizing a piece-wise linearization method to assume a constant efficiency for each piece of the operation range. Besides, an empirical linear function is also directly utilized to formulate the E-H relation. Therefore, further research is needed regarding how to integrate nonlinear dynamic behaviors of MW-level AE due to heat recovery and varying electrolysis efficiency into a techno-economic optimal operation problem that can be solved within a timeframe for real-time operation. In this respect, this paper develops an EMPC oriented operation strategy for an MES integrated with a power-to-hydrogen & heat (P2H²) model for AE. The main contributions of this paper include:

1. Clarifying an integrated P2H² model to characterize the nonlinear interaction of electricity-heat-hydrogen energy flow in an AE system, considering its dynamic heat recovery and varying electrolysis efficiency. This model distinguishes itself by exploiting the enhanced operational flexibility of AE due to enabling waste heat recovery.
3. Modelling of AE plant

3.1. Electrochemical model

AE system is a kind of commercial water-based electrolyzer with MW-level application currently. It mainly consists of an electrolyzer stack combined with many cells and ancillary devices [18,32]. Fig. 2 shows the topology and internal power flow of an AE system consuming DC electricity to produce hydrogen while releasing waste heat during the electrolysis process. Regarding the electrical part, a temperature-based U-I model is utilized to characterize the relation between stack voltage and current while considering the stack temperature effect [32], which can be expressed by:

$$U_{t, stack}^m = N_{cell}(U_{t}^{pre} + U_{t}^{loss} + U_{t}^{f, stack}) = f_{1}(T_{t}^{elem}, I_{t}^{pre})$$ (1)

Besides, the electrolysis efficiency could be approximately characterized by the ratio of the cell voltage and thermoneutral voltage [33], which can be expressed by:

$$\eta_{elem}^{f, stack} = N_{cell}U_{t}^{pre} \frac{U_{t}^{f, stack}}{f_{1}(T_{t}^{elem}, I_{t}^{pre})} = f_{2}(T_{t}^{elem}, I_{t}^{pre})$$ (2)

The detailed formulations of (1) and thermoneutral voltage in (2) are presented in Appendix B according to [34–36], which are indicated that the f(·) in (1)–(3) are nonlinear functions. Based on (1) and (2), the stack-level power flow relation in an AE system is derived as:

$$\begin{align*}
    P_{t}^{elem} &= \eta_{elem}^{f, stack}P_{t}^{stack} = f_{2}(T_{t}^{elem}, I_{t}^{pre}) \\
    P_{t}^{heat} &= (1 - \eta_{elem}^{f, stack})U_{t}^{f, stack}P_{t}^{stack} = f_{2}(T_{t}^{elem}, I_{t}^{pre})
\end{align*}$$ (3)

Equation (3) implies that f(·) with respect to the stack temperature and consumed power captures the nonlinear power flow relation in AE system due to the nonlinear relation between time-variant temperature and electrolysis efficiency. Many researchers try to simplify the power flow relation into a linear model by assuming a constant efficiency meanwhile ignoring the impact of time-variant stack temperature. However, this assumption will naturally reduce the model accuracy on the dynamic behaviors of AE.

3.2. Dynamic temperature model

In terms of heat-transfer process, as shown in Fig. 2, a water cycling subsystem is setup to provide an allowable operating temperature for the AE system. Considering the AE stack as an equivalent thermal tank with a lumped capacitance, the discrete dynamic temperature response can be modelled by [32]:

$$T_{t+1}^{elem} = T_{t}^{elem} + \frac{P_{t}^{elem} - (T_{t}^{elem} - T_{a})/R_{t}^{elem} - H_{t}^{rec}}{C_{t}^{elem}}$$ (4)

Equation (4) indicates the stack temperature could be manipulated by controlling the released waste heat ($P_{t}^{heat}$) during electrolysis and the recovered heat ($H_{t}^{rec}$) via heat exchanging with DHS. Due to $P_{t}^{heat}$ non-linearly varying with the consumed power as indicated by (3), the
temperature evolution appears in a nonlinear process under the variable consumed power.

3.3. Hydrogen production model

Regarding the hydrogen production of the AE system, the higher heat value (HHV) of hydrogen \( Q_{\text{HHV}} \) is introduced to evaluate the total hydrogen production rate, due to the relatively low operating temperature of AE [37]. Hence, the mass rate of hydrogen produced over a time horizon can be expressed by:

\[
\dot{m}_{\text{H}_2} = \frac{\eta_{\text{HHV}} P_{\text{HHV}, t}}{Q_{\text{HHV}}} \Rightarrow \dot{m}_{\text{H}_2} = \frac{\eta_{\text{HHV}}}{Q_{\text{HHV}}} T_{\text{s}}
\]

(5)

Assuming a constant \( Q_{\text{HHV}} \), the mass rate of hydrogen produced will be proportional to the consumed power to produce hydrogen (\( P_{\text{HHV}, t} \)). Thus, it will nonlinearly vary with the consumed power, because of the nonlinear relation between and consumed power according to (3).

3.4. Integrated P2H\textsuperscript{2} model

Combining the three sub-models formulated by (1)–(5), an integrated P2H\textsuperscript{2} model with high nonlinearity is obtained, as visualized in Fig. 3(a). It characterizes the interaction of the AE stack from a cross-sectoral perspective including electricity, thermal and hydrogen, by capturing the dynamic behavior of stack temperature and electrolysis efficiency. Compared to the traditional P2H role, more operational flexibility could be unlocked by introducing the additional flexibility characterizing the dynamic evolution of electrolysis efficiency during the operation process. However, if assuming a constant operating temperature like 70 °C, thereby lowering the operational flexibility. In addition, it also indicates the electrolysis efficiency is varying (the black dotted line) instead, thereby lowering the operational flexibility from a cross-sectoral perspective, meaning the operation range of AE which represents the cross-sectoral power interaction in terms of characterizes the operation range of AE which represents the cross-sectoral power interaction in terms of.

4. EMPC-MILP based operating strategy

In order to achieve an economic operation of MES, an economic operation model is firstly developed, where the objective of minimizing the operation cost is conducted while constrained by physical limits of MES. Furthermore, in order to handle the computation complexity due to the nonlinearity of the P2H\textsuperscript{2} model, an EMPC-MILP solution is proposed to implement the economic operation model meanwhile keeping the model accuracy of AE system. The economic operation model in the EMPC framework can be formulated as MILP model considering a determined electrolysis efficiency, which is easy and fast to solve. Also, the EMPC framework will update the determined electrolysis efficiency based on the P2H\textsuperscript{2} model and solutions of the MILP optimizer in each prediction horizon, thereby retaining the model accuracy of the P2H\textsuperscript{2} model for AE system.

4.1. Economic operation model

4.1.1. Objective function

The optimization objective in the economic operation model is aiming to achieve the minimization of total operation cost consisting of the variable operation cost, and the utilization costs for BESS and HESS [16]. The variable operation cost over a given prediction horizon \( N_p \) at time \( k \) can be formulated by:

\[
J_{\text{op}} = \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c-1} \left( c_{\text{ele}}^{i,k} P_{\text{grid},t}^{i,k} \right) + \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c-1} \left( c_{\text{rec}}^{i,k} P_{\text{rec},t}^{i,k} \right)
\]

\[
- \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c-1} \left( c_{\text{ele}}^{i,k} H_{\text{ele},t}^{i,k} \right) - \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c-1} \left( c_{\text{heat}}^{i,k} P_{\text{heat},t}^{i,k} \right)
\]

\[
\forall t, k
\]

(6)

where the first term describes the cost of electricity purchased from external EPS, and the second term shows the penalty cost for wind curtailment. Besides, the revenues from selling heat recovered of AE and selling hydrogen are considered as well, as denoted by the third and fourth terms respectively.

Regarding the utilization costs for BESS and HESS, a major concern of battery is its aging and degradation, which determines the allowable lifetime of BES. Thus the utilization cost of BESS during charging and discharging mainly considers its capital cost and degradation as given by (7). HESS utilization costs is composed of the capital cost, and the operation and maintenance cost as expressed by (8). A binary variable \( \delta_k^i \) is introduced for the fuel cell to determine on/off states, but the electrolyzer is assumed to always be operating to prevent the repeated startup, thereby avoiding an additional startup cost.

\[
J_{\text{bat}} = \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c} \left( \frac{C_{\text{bat}}}{N_b} P_{\text{bat},t}^{i,k} \right) + \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c} \left( \frac{C_{\text{bat}}}{N_b} P_{\text{bat},t}^{i,k} \right) \delta_k^i \forall t, k
\]

(7)

\[
J_{\text{HESS}} = \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c} \left( \frac{C_{\text{HESS}}}{N_h} \right) T_{\text{bat}} + \sum_{t=0}^{N_p-1} \sum_{i=0}^{N_c} \left( \frac{C_{\text{he}}}{N_h} + C_{\text{OM}} \right) T_{\text{he}}\delta_k^i \forall t, k
\]

(8)
4.1.2. Constraints

The constraints for characterizing the physical limits of MES in the economic operation model are subsumed under the following categories:

(a) **Power balance**: the power production must be equal to the electricity demands for each hour, as indicated by (9).

(b) **Boundary of power purchased and wind curtailment**: the electricity purchased from EPS and the wind power curtailment should be within the allowable range, which is formulated by (10)~(11).

(c) **Operation limits of BESS model**: the temporal SOC model regarding the charging/discharging power, and their boundaries need to follow (12)~(15).

(d) **Operation limits of HESS model**: the temporal volume level of hydrogen (VLH) of hydrogen tank and related boundaries are constrained by (16)~(17). The power production of fuel cell plant is limited by (18). Besides, the operation of AE system should follow the developed P2H model as indicated by (1)~(5). Moreover, due to the AE stack always being operating, the consumed power of AE is constrained by (19), meanwhile following an operating temperature limit by (20) for the safe operation of AE stack.

\[
P_{ch}^t + P_{el}^t + P_{fcl}^t + P_{el}^{dis} + P_{ch}^{max} + P_{dis}^{max} 
\forall t, k
\]  
\[
\delta t_{ch}^k \leq P_{ch}^{max} \leq \delta t_{dis}^k \leq P_{dis}^{max} 
\forall t, k
\]  
\[
\left(1 - \delta t_{ch}^k\right)P_{grid}^t \leq P_{ch}^t \leq \left(1 - \delta t_{dis}^k\right)P_{grid}^t 
\forall t, k
\]  
\[
SOC_{ch+1} = SOC_{ch} + P_{ch}^t T_{ch}^t + P_{ch}^t T_{ch}, 
\forall t, k
\]  
\[
SOC_{ch}, SOC_{dis} \leq SOC_{max} 
\forall t, k
\]  
\[
\delta t_{ch}^k P_{ch}^t \leq \theta t_{ch}^k P_{ch}^t \leq \delta t_{dis}^k P_{dis}^{max} 
\forall t, k
\]  
\[
\left(1 - \delta t_{ch}^k\right)P_{ch}^t \leq \left(1 - \delta t_{dis}^k\right)P_{grid}^t 
\forall t, k
\]  
\[
VLH_{ch} = VLH_{ch} + \frac{\left(\theta t_{ch}^k P_{ch}^t - P_{ch}^t\right)T_{ch}}{\eta t_{ch}^k} - \delta t_{ch}^k 
\forall t, k
\]  
\[
VLH_{min} \leq VLH_{ch} \leq VLH_{max} 
\forall t, k
\]  
\[
\delta t_{ch}^k P_{ch}^t \leq \eta t_{ch}^k P_{ch}^t \leq \delta t_{dis}^k P_{dis}^{max} 
\forall t, k
\]  
\[
P_{ch}^t \leq \left(1 - \delta t_{ch}^k\right)P_{grid}^t \leq \left(1 - \delta t_{dis}^k\right)P_{grid}^t 
\forall t, k
\]  
\[
T_{ch}^t \leq T_{ch}^{max} 
\forall t, k
\]  

\[
\min_{\Delta} \left(J_{op} + \alpha J_{cur} + \beta J_{cur} \right) = \min_{\Delta} \sum_{t=0}^{N_p-1} f(x_{rk}, u_{rk}, \delta_{rk})
\]  
\[
\begin{align*}
\forall t, k & : g(x_{rk}, u_{rk}, \delta_{rk}) = 0 \\
\forall t, k & : h(x_{rk}, u_{rk}, \delta_{rk}) = 0 \\
\forall t, k & : x_{rk+1} = f(x_{rk}, u_{rk}, \delta_{rk}) \\
\end{align*}
\]  
\[
U = \left\{ u_{rk}, \ldots, u_{rk-1} \right\}
\]  
\[
\delta_{rk} = \left\{ \delta t_{ch}^k, \ldots, \delta t_{dis}^k \right\}, \\
\Delta = \left\{ \delta t_{ch}^k, \ldots, \delta t_{dis}^k \right\}, \\
x_{rk} = \left\{ SOC_{ch}, VLH_{ch}, T_{ch}^{opt}, \eta t_{ch}^k \right\}, \\
t \in \{0, [N_p - 1]\}, \quad k \in \{1, [N]\}
\]  

where two weight factors ($\alpha$ and $\beta$ equal 0.1) are used to scale the utilization costs of BESS and HESS, in order to highlight the significance of the first variable operation cost, thereby exploiting the operational flexibility of DERs as possible on contributing to an economic operation. 

In (21), the constraints related to the function $f(.)$ are nonlinear due to the strong nonlinearity of the P2H model, and several binary variables are introduced. Therefore, the economic operation model is formulated as a typical mixed-integer nonlinear programming (MINLP) which is not easily fast to find the global optimal solutions when directly solving it. However, (21) indicates the nonlinearity of P2H model is essentially due to the nonlinear relation between electrolysis efficiency and power consumed. When utilizing a constant efficiency, the dynamic temperature model and hydrogen production model will be thus linearized.
Consequently, in the presented EMPC-MILP solution, the state variables in (21) are replaced with the new forms by (22), and considering a constant electrolysis efficiency given by (23). The original MINLP will be accordingly converted to be a MILP which is easy to solve based on existing commercial solvers (e.g. Gurobi [38]). Meanwhile, the utilized constant efficiency will be continuously updated in the plant modular of the EMPC framework before receding the prediction horizon.

\[
\tilde{x}_t|_k = \{\text{SOC}_t|_k, \text{VLH}_t|_k, T_{\text{ely}}^t|_k\} \tag{22}
\]

\[
\eta_{\text{ely}}^t|_k = \eta_{\text{ely}}^{\text{opt}}|_k \tag{23}
\]

Fig. 4 shows the control diagram of the proposed EMPC-MILP based algorithm for implementing an economic operation of MES. The detailed implementing procedure is as follows:

**Step 1:** To sample the historical data of Bornholm island in terms of the electricity profiles and energy prices over a prediction horizon \(N_p\) at time \(k\). The initial values of state variables and electrolysis efficiency are given as input profiles.

**Step 2:** According to (22) and (23), the optimizer could be modelled as a MILP optimization under a given \(\eta_{\text{ely}}^{\text{opt}}|_k\). Solving the MILP optimization, the optimal control sequence \(u_{\text{opt}}(0|k)\) is obtained. But only the first element \(u_{\text{opt}}(0|k)\) is chosen as the final optimal control demands while the remaining solutions are discarded. Hence, the control horizon equals one hour.

**Step 3:** To predict the states variables at time \(k + 1\) in the nonlinear plant model, using a series of linear temporal functions indicated by (4), (12) and (16) based on the obtained \(u_{\text{opt}}(0|k)\) and state variables at time \(k\). Besides, the electrolysis efficiency at time \(k + 1\) is also predicted according to the developed nonlinear P2H\(^2\) model by inputting \(P_{\text{ely}}^{\text{opt}}\) in \(u_{\text{opt}}(0|k)\) and \(T_{\text{ely}}^{\text{opt}}\) at time \(k\), and hence obtaining the updated \(\eta_{\text{ely}}^{\text{opt}}\).

**Step 4:** To recede the prediction horizon by increasing \(k\) to \(k + 1\), and returning to step 1 and repeating step (1) ~ step (4) until finishing the whole simulation (\(N = 24\) h).

5. Case studies

5.1. Case description

In order to validate the proposed EMPC-MILP based operating algorithm for MES, the real data of Bornholm island in 2018 are used as input datasets for the proposed algorithm to evaluate its performance and relevant robustness, and the whole algorithm is run on the Julia 1.5.3 with JuMPv0.21.6.

Firstly, as shown in Fig. 5, the energy portfolio of wind power, CHP power, demands and energy prices in Bornholm island on June 21, 2018

Fig. 5. Input power profiles and energy prices on June 21, 2018.
are utilized, where energy prices include the day-ahead electricity price for DK2 from Nordpool \cite{38} and the heat price offered by a DHS operator in Denmark. Besides, a constant low price of about 0.9 € is adopted to sell hydrogen considering the deployment of the hydrogen energy towards a decreasing price in the future. In order to evaluate the economic benefits and superiority of the proposed algorithm, three cases under different operating strategies are conducted for comparisons, based on the given energy portfolio:

- Case 1: Rule-based strategy \cite{39}
- Case 2: MILP based strategy with constant electrolysis efficiency
- Case 3: The proposed EMPC-MILP based strategy with the P2H\(^2\) model

Case 1 is set as a baseline related to a non-economical operating strategy, where an improved RBS is carried out for the MES of Bornholm island. The detailed principle is presented in our previous work \cite{39}. The deployment of network power \((P_{\text{net}})\) between the two ESSs groups follows the rules: 1) BESS has a higher priority than HESS; 2) after meeting the BESS and HESS, the rest power will be exchanged with the external power grid. Thus, the cost-effectiveness of the proposed strategy (Case 3) can be directly proved by their comparisons between Case 1 and Case 3. Case 2 executes an economic optimization-based operation strategy with the assumption of constant electrolysis efficiency of AE, just like what a few studies have done \cite{23,24}. Such a case will facilitate the economic operation for an MES compared with RBS. However, the assumption of constant electrolysis efficiency might lead to an inaccurate estimation of the gross operation cost, and even some physical states break operation limitations. Consequently, the impact and importance of varying electrolysis efficiency in the proposed strategy can be revealed from the comparisons between Case 2 and Case 3.

In addition, to evaluate the robustness of the proposed algorithm and clarify the impact of input parameters, the sensitivity analysis of this algorithm is conducted. The performance comparison of the aforementioned three cases is implemented by choosing different initial states of ESSs, and different energy portfolios on other days in 2018 particularly including a wind-rich day with negative electricity price (January 1, 2018) and a wind-deficit (December 9, 2018) day.

5.2. Comparative analysis of operation results

5.2.1. Benefits on wind curtailment reduction

Fig. 6 shows the power scheduling results of different DERs in the MES under the three cases. During the wind-deficit period (at 6:00–14:00), Fig. 6(a) and (b) show the BESS and fuel cell are forced to generate electricity as much as possible to compensate for the local production shortage from WT and CHP. Due to their capacity limits, the MES needs to purchase electricity from the grid. Fig. 6(c) shows the amounts of electricity purchased from the grid are almost the same in Table 2

<table>
<thead>
<tr>
<th>Case</th>
<th>Total Wind Curtailment (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>77.53</td>
</tr>
<tr>
<td>Case 2</td>
<td>40.61</td>
</tr>
<tr>
<td>Case 3</td>
<td>31.38</td>
</tr>
</tbody>
</table>

Table 3

Comparison of variable operation cost under three cases (€).

<table>
<thead>
<tr>
<th>Case</th>
<th>Cost(_{\text{pur}}) (^1)</th>
<th>Cost(_{\text{cur}}) (^2)</th>
<th>Cost(_{\text{H}}) (^3)</th>
<th>Cost(_{\text{heat}}) (^4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>2514.43</td>
<td>10078.69</td>
<td>-746.52</td>
<td>83.32</td>
</tr>
<tr>
<td>Case 2</td>
<td>2490.37</td>
<td>5279.32</td>
<td>-1091.64</td>
<td>-98.92</td>
</tr>
<tr>
<td>Case 3</td>
<td>2687.79</td>
<td>2039.71</td>
<td>-1820.58</td>
<td>-28.27</td>
</tr>
</tbody>
</table>

\(^1\) Cost\(_{\text{pur}}\): electricity cost purchased from grid.
\(^2\) Cost\(_{\text{cur}}\): wind curtailment cost.
\(^3\) Cost\(_{\text{H}}\): Cost of selling hydrogen (negative value means revenue).
\(^4\) Cost\(_{\text{heat}}\): Cost of selling heat to DHS (negative value means profits).

Table 4

Comparison of various cost terms under three cases (€).

<table>
<thead>
<tr>
<th>Case</th>
<th>Cost(_{\text{op}}) (^1)</th>
<th>Cost(_{\text{bess}}) (^2)</th>
<th>Cost(_{\text{hess}}) (^3)</th>
<th>Cost(_{\text{sum}}) (^4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>11929.92</td>
<td>408.98</td>
<td>2438.66</td>
<td>14777.56</td>
</tr>
<tr>
<td>Case 2</td>
<td>6579.13</td>
<td>355.03</td>
<td>2438.66</td>
<td>9372.82</td>
</tr>
<tr>
<td>Case 3</td>
<td>2877.64</td>
<td>282.88</td>
<td>2399.97</td>
<td>5560.49</td>
</tr>
</tbody>
</table>

\(^1\) Cost\(_{\text{op}}\): total variable operation cost.
\(^2\) Cost\(_{\text{bess}}\): utilization cost of BESS.
\(^3\) Cost\(_{\text{hess}}\): utilization cost of HESS.
\(^4\) Cost\(_{\text{sum}}\): Total operation cost.

are utilized, where energy prices include the day-ahead electricity price for DK2 from Nordpool \cite{38} and the heat price offered by a DHS operator in Denmark. Besides, a constant low price of about 0.9 € is adopted to sell hydrogen considering the deployment of the hydrogen energy towards a decreasing price in the future. In order to evaluate the economic benefits and superiority of the proposed algorithm, three cases under different operating strategies are conducted for comparisons, based on the given energy portfolio:

\[\text{Heat recovered (MW)}\]

\[\text{Selling hydrogen (m³)}\]

\[\text{Temperature (°C)}\]

\[\text{SOC (State of Charge)}\]

\[\text{VLH (Volume Loss of Hydrogen)}\]

Fig. 7. Heat and hydrogen production performance of AE system under the three cases: (a) Recovered heat; (b) Selling hydrogen.

Fig. 8. Operating state performance in terms of stack temperature, SOC and VLH under the three cases.
the three cases. However, their patterns of wind curtailment are quite different during the wind-rich period particularly at 15:00–24:00 according to Fig. 6(f). It indicates the proposed algorithm in Case 3 always contributes to sharply reducing the wind curtailment, because the surplus electricity is vastly consumed by electrolyzer to produce hydrogen during this period compared to Case 1 with the RBS algorithm, as shown in Fig. 6(e). Also, Fig. 6(d) shows the BESS assists in consuming the surplus electricity via charging. Although the wind curtailment of Case 2 is overall mitigated compared to Case 1, it still leads to a higher curtailment at 16:00–17:00 than Case 3. Table 2 compares the total wind curtailment under three cases, which shows that Case 3 has the lowest wind curtailment of about 31.38 MW, even less than half of that in Case 1. Therefore, the proposed algorithm can effectively enhance wind integration.

### Table 5
Detailed comparison of operation cost under three cases at the two typical dates (€).

<table>
<thead>
<tr>
<th>Case</th>
<th>Cost_pur</th>
<th>Cost_cur</th>
<th>Cost_H2</th>
<th>Cost_heat</th>
<th>Cost_op</th>
<th>Cost_bess</th>
<th>Cost_hess</th>
<th>Cost_sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>20.41</td>
<td>18062.56</td>
<td>-1137.57</td>
<td>204.69</td>
<td>1719.27</td>
<td>197.85</td>
<td>2129.11</td>
<td>19436.23</td>
</tr>
<tr>
<td>January 1, 2018 (wind-rich)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 2</td>
<td>5873.67</td>
<td>0</td>
<td>177.27</td>
<td>159.98</td>
<td>5856.37</td>
<td>454.43</td>
<td>2864.29</td>
<td>9175.09</td>
</tr>
<tr>
<td>Case 3</td>
<td>5522.22</td>
<td>0</td>
<td>1243.78</td>
<td>11.31</td>
<td>4266.13</td>
<td>272.66</td>
<td>2516.05</td>
<td>7054.83</td>
</tr>
<tr>
<td>December 9, 2018 (wind-deficit)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Fig. 9.** Daily operation costs for the whole year.

**Fig. 10.** Operating temperature of AE and VLH of hydrogen tank during the whole year: (a) Case 1; (b) Case 2; (c) Case 3.

**Fig. 11.** Operational costs with different initial SOC, VLH and stack temperature under the three cases.
Table A1
Parameters of various HESS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Alkaline Electrolyzer</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rated power of one stack</td>
<td>26.6</td>
<td>kW</td>
</tr>
<tr>
<td>Number of stacks</td>
<td>323</td>
<td></td>
</tr>
<tr>
<td>Maximum power ($P_{max}^{ely}$)</td>
<td>8.6</td>
<td>MW</td>
</tr>
<tr>
<td>Minimum power ($P_{min}^{ely}$)</td>
<td>1.73</td>
<td>MW</td>
</tr>
<tr>
<td>Lifetime ($N_L^{ely}$)</td>
<td>30,000</td>
<td>h</td>
</tr>
<tr>
<td>Capital cost ($C_{cap}^{ely}$)</td>
<td>3200</td>
<td>€/KWh</td>
</tr>
<tr>
<td>Operation and maintenance cost ($C_{OM}^{ely}$)</td>
<td>0.2</td>
<td>€/h</td>
</tr>
<tr>
<td>Higher heat value of hydrogen ($Q_{hly}^{ely}$)</td>
<td>0.0394</td>
<td>MWh/kg</td>
</tr>
<tr>
<td>Lump heat capacitance of stack ($C_{cap}^{ely}$)</td>
<td>300,000</td>
<td>J/K</td>
</tr>
<tr>
<td>Heat resistance of stack ($R_{hly}^{ely}$)</td>
<td>0.018</td>
<td>K/W</td>
</tr>
<tr>
<td>Maximum stack temperature ($T_{hly}^{max}$)</td>
<td>80</td>
<td>°C</td>
</tr>
<tr>
<td>Maximum stack temperature ($T_{hly}^{min}$)</td>
<td>60</td>
<td>°C</td>
</tr>
<tr>
<td>Ambient temperature ($T_{hly}$)</td>
<td>20</td>
<td>°C</td>
</tr>
<tr>
<td>Hydrogen Tank</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rated capacity</td>
<td>128.205</td>
<td>Nm3</td>
</tr>
<tr>
<td>Maximum capacity (VLH$_{max}$)</td>
<td>102.564</td>
<td>Nm3</td>
</tr>
<tr>
<td>Maximum capacity (VLH$_{min}$)</td>
<td>25.641</td>
<td>Nm3</td>
</tr>
<tr>
<td>Hydrogen density ($ρ_{hly}$)</td>
<td>7.8</td>
<td>kg/Nm3</td>
</tr>
</tbody>
</table>

**Fuel cell**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum power ($P_{max}^{ch}$)</td>
<td>3</td>
<td>MW</td>
</tr>
<tr>
<td>Minimum power ($P_{min}^{ch}$)</td>
<td>0</td>
<td>MW</td>
</tr>
<tr>
<td>Lifetime ($N_L^{ch}$)</td>
<td>30,000</td>
<td>h</td>
</tr>
<tr>
<td>Capital cost ($C_{cap}^{ch}$)</td>
<td>4000</td>
<td>€/KWh</td>
</tr>
</tbody>
</table>

**Operation and maintenance cost ($C_{OM}^{ch}$)**

Table A2
Parameters of various BESS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated capacity</td>
<td>20</td>
<td>MWh</td>
</tr>
<tr>
<td>Maximum capacity (SOC$_{max}$)</td>
<td>16</td>
<td>MWh</td>
</tr>
<tr>
<td>Minimum capacity (SOC$_{min}$)</td>
<td>4</td>
<td>MWh</td>
</tr>
<tr>
<td>Maximum charging power ($P_{ch}^{max}$)</td>
<td>4</td>
<td>MW</td>
</tr>
<tr>
<td>Minimum charging power ($P_{ch}^{min}$)</td>
<td>0</td>
<td>MW</td>
</tr>
<tr>
<td>Maximum discharging power ($P_{ch}^{max}$)</td>
<td>4</td>
<td>MW</td>
</tr>
<tr>
<td>Minimum discharging power ($P_{ch}^{min}$)</td>
<td>0</td>
<td>MW</td>
</tr>
<tr>
<td>Number of life cycles ($N_{cycle}$)</td>
<td>2000</td>
<td></td>
</tr>
<tr>
<td>Capital cost ($C_{cap}^{ch}$)</td>
<td>470</td>
<td>€/KWh</td>
</tr>
</tbody>
</table>

Table A3
Boundaries of exchanged power with grid and wind curtailment.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum power from grid ($P_{max}^{grid}$)</td>
<td>200</td>
<td>MW</td>
</tr>
<tr>
<td>Minimum power from grid ($P_{min}^{grid}$)</td>
<td>0</td>
<td>MW</td>
</tr>
<tr>
<td>Maximum wind curtailment ($P_{max}^{cur}$)</td>
<td>200</td>
<td>MWh</td>
</tr>
<tr>
<td>Minimum power from grid ($P_{min}^{grid}$)</td>
<td>0</td>
<td>MW</td>
</tr>
</tbody>
</table>

Table A4
Unit cost of various energy sectors.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity cost ($C_{ele}^{k}$)</td>
<td>Nordpool$^1$</td>
<td>€/MWh</td>
</tr>
<tr>
<td>Heat cost ($C_{heat}^{k}$)</td>
<td>DHS$^2$</td>
<td>€/MWh</td>
</tr>
<tr>
<td>Penalty cost for wind curtailment ($C_{pen}^{cur}$)</td>
<td>67</td>
<td>€/MWh</td>
</tr>
<tr>
<td>Hydrogen cost ($C_{h}^{k}$)</td>
<td>1</td>
<td>€/kg</td>
</tr>
</tbody>
</table>

$^1$ Electricity cost ($C_{ele}^{k}$) is the day-ahead hourly price in Nordpool.

$^2$ Heat cost is equal to the price provided by DHS operator in Denmark.

5.2.2. Benefits on operation cost reduction

Table 3 summarizes the detailed comparisons of the variable operation costs under the three cases. It shows Case 3 prompts the lowest curtailment cost of 2039.71€ due to effectively avoiding enormous wind curtailment. It also contributes to the highest profits from selling hydrogen compared to the other two cases, and higher profits of heat recovery than Case 1. Accordingly, the sharp reduction of wind curtailment cost and higher profits from selling hydrogen in Case 3 overall arise to the lowest variable operation cost (Cost$_{op}$) of 2877.64€ than Case 1 and Case 2, as shown in Table 4. It also indicates that the proposed algorithm is able to achieve an economic operation of BESS and HESS by optimizing their charging/discharging power of BESS and power produced by fuel cell, decreasing utilization costs to a lower level than Case 1 and Case 2. Therefore, the proposed algorithm ensures the lowest total operation cost (Cost$_{sum}$) of 5560.49€, which implies additional cost savings of 59% (9217.07€) and 38% (5404.74€) compared to Case 1 and Case 2, respectively.

5.2.3. Benefits on operation flexibility of ESSs

Fig. 7 illustrates the proposed P2H model can enable the AE system to produce hydrogen and simultaneously recover waste heat, which unleashes cross-sectoral flexibility of the AE system. Fig. 7(a) shows the amount of heat recovered in Case 1 is quite rare during the electrolysis process even absorbing heat from DHS to maintain the required temperature of electrolyzer most of time. In contrast, both Case 2 and Case 3 during 15:00-24:00, recycle much waste heat due to the economic incentive to earn profits from heat recovery. It should be noted that the electrolyzer in the two cases needs the heat supplying from DHS to maintain the lowest temperature during 6:00-14:00, which is because the low consumed power causes the low heat production by itself. Besides, Fig. 7(b) indicates Case 3 brings a higher benefits than Case 2 via hydrogen selling, thereby exploiting more profits from hydrogen.

Due to the time-variant heat recovered, the stack temperature is also varying, as shown in Fig. 8. It illustrates Case 3 brings a more stable operating temperature response with slightly varying around the initial set-point of 60 °C, which implies the proposed algorithm is expected to maintain the ideal operating temperature by pre-setting a desired operating point. Besides, the SOCs in Case 2 and Case 3 do not reach their maximum (80% rated capacity), which indicates the high charging power of battery is not be restricted by its capacity limitation, thus the cost-optimization algorithm enhances the operational flexibility of BESS to some extent compared to RBS. Similarly, the hydrogen tank has more flexibility in Case 2 and Case 3, because their VLH is adjusted to a lower level instead of being limited by its maximum capacity.

It is thus concluded that the proposed strategy is able to unleash more operational flexibility of ESSs via optimal operation, performing more reserved capacity in operations. Moreover, it enables the cross-sectoral flexibility of the AE system from recovering heat and producing hydrogen meanwhile avoiding large deviation of operating temperature.

5.3. Sensitivity analysis

5.3.1. Impact of input energy portfolios

Firstly, considering two energy portfolios under two typical days representing a wind-rich and wind deficit period in 2018, at which negative electricity prices occurred, the results of operation cost are summarized in Table 5. During the wind-rich day, the proposed algorithm is expected to earn a profit of 720.14€ for MES, instead of paying for its operations like what is required with the other two algorithms (430.01€ and 19436.23€). This is mainly due to the sharp drop of Cost$_{op}$ of ~ 3209.66€ in Case 3, by utilizing the free wind-based electricity to produce the green hydrogen, achieving a considerable reduction of Cost$_{cur}$ and more profits of selling hydrogen. Moreover, the high negative electricity price will bring additional profits owing to purchasing power from grid, and lead to a negative Cost$_{pur}$ in the three
cases. Therefore, the proposed algorithm will force electrolyzer to continuously consume power for a high hydrogen production rate for a longer time, thereby earning much profit Cost$_{H_2}$ of 3849.93€. Besides, the three cases have almost same utilization costs of BESS and HESS, especially the same Cost$_{bess}$ of 2129.11€.

During the wind-deficit day, wind curtailment will not happen and the curtailment cost equals zero in the three cases. Overall, the EMPC-based algorithm still contributes to a preferable operation cost with the lowest value of 7054.83€ especially turning out a visible operation cost reduction compared with Case 1. This mainly benefits from the high profits of selling hydrogen of about 1243.78€ which is several times than that in the other two cases. It should be noted that the cost optimization mechanism in Case 2 also facilitates a lower cost of purchasing electricity and more heat recovered, thereby bringing a relatively low total operation cost of 7169.04€.

Therefore, the proposed EMPC-based algorithm is expected to a dramatic reduction in operation cost even additional profits can be obtained under the wind-rich scenario with negative electricity price, meanwhile maximize the profits of selling hydrogen on the wind-deficit day thereby effectively reducing the total operation cost.

Furthermore, the daily operation costs of the whole year are calculated based on daily energy portfolios, as shown in Fig. 9. In terms of the Cost$_{op}$ and Cost$_{bess}$, both Case 2 and Case 3 have a visible lower level than Case 1 overall during the whole year, due to the economic optimization incentive in their operating strategies. Also, Cost$_{bess}$ is quite close among the three cases. Consequently, the proposed algorithm in Case 3 can bring a preferable Cost$_{sum}$ over the whole year, which is always much lower than RBS in Case 1 and as low as the traditional economic strategy in Case 2. Hence, it has good robustness to variations of input energy portfolios at different operating periods.

Nevertheless, the economic optimization in case 2 is based on the assumption of constant electrolysis efficiency, which inevitably causes a deviation of the real operating states of AE and ESSs. Fig. 10 compares the operating temperature of AE and the VLH of hydrogen tank during the whole year when implementing the three operating strategies. It indicates that Case 2 will frequently cause AE to operate at an abnormal temperature point which even reaches to be less than 10°C on some operating days and strongly exceeds the preset boundary. This will be not practically feasible for a safe operation on AE, and fail to implement the operating strategy for MES. Besides, the VLH in Case 2 is also over the maximum capacity of hydrogen tank for some days. However, the proposed EMPC-MILP based algorithm fully considers the dynamic behavior of electrolysis efficiency by continuously updating it before each optimization calculation, hence the number of abnormal temperature points is dramatically reduced, moreover completely ensuring a normal VLH within the required range over the whole year. It should be noted that the RBS is improved by updating the electrolysis efficiency between two regulating events as well. Case 3 can therefore ensure more feasible scheduling for the electrolyzer in the MES meanwhile creating a preferable lower operation cost over the whole year, compared to the other two cases (which only satisfy either physical limitations or economic operations instead).

5.3.2. Impact of initial states of ESSs
Considering June 21, 2018 as an operating day, the operation costs under different initial states of ESSs in terms of the SOC, VLH and operating temperature (T$_{op}$) of AE stack are evaluated for the three operating strategies. Fig. 11 indicates that Case 3 always has a lower variable operation cost (Cost$_{op}$) and approximate the same utilization cost of ESSs (Cost$_{bess}$, Cost$_{hess}$) regardless of initial SOC, compared to the other two cases. Accordingly, the lowest total operation cost Cost$_{sum}$ always occurs in Case 3 whatever the initial SOC value is, due to the dominance of Cost$_{op}$ in the total operation cost. Similarly, when changing either the initial VLH or operating temperature of the AE system, Case 3 always has much lower in Cost$_{op}$ meanwhile little difference in Cost$_{bess}$ and Cost$_{hess}$, compared to the other two cases, accordingly always achieving the lowest Cost$_{sum}$. Therefore, the proposed EMPC-MILP based algorithm can also have good robustness to variations of input initial states of ESSs.

6. Conclusion
This paper presents an EMPC-MILP based optimal operating strategy for an MES integrated with a P2H model of AE to unleash its operational flexibility cross the energy sectors of electricity-heat-hydrogen. The internal nonlinear interaction of the electricity-heat-hydrogen energy flow of AE is characterized by the presented P2H model. Moreover, the EMPC-MILP framework is used to integrate the P2H model into a MILP-based economic operating model which is computationally effective and ensures the AE model accuracy by continuously updating the P2H model before each receding horizon. The real data of Bornholm in 2018 are used to test the proposed method, and results have revealed that:

1) The proposed EMPC-based operating strategy can achieve an economic operation for MES via optimally scheduling various DERs. It contributes to additional operation cost savings of 59% (9217.07€) and 38% (5404.74€) compared to RBS and the economic strategy without P2H model respectively. Especially in the cases of a wind-rich day with negative electricity prices, the MES can even earn profits of about 720.14€ from its operation.

2) Compared to the RBS, the proposed algorithm unleashes more operational flexibility of MES performing in effectively reducing the operation costs meanwhile enhancing the wind integration by wind curtailment reduction.

3) Compared to the traditional economic operating strategy, the proposed algorithm reduces the deviation of operating states regarding stack temperature and hydrogen level from their allowable operating ranges due to the real-time evolution of AE model, thus contributing to feasible scheduling for electrolyzers meanwhile ensuring more economic benefits.

Regarding future work, the proposed operating optimization model still needs to be extended under a stochastic scenario by considering the uncertainty of wind power, and also introducing an electricity market mechanism to explore more flexibility services for grid stability and reliability.

CRediT authorship contribution statement

Chunjun Huang: Conceptualization, Methodology, Software, Validation, Writing – original draft. Yi Zong: Methodology, Resources, Supervision, Funding acquisition, Writing – review & editing. Shi You: Investigation, Supervision, Funding acquisition, Writing – review & editing. Chresten Træholt: Resources, Writing – review & editing.}

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.

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Appendix A

Appendix A provides information on the parameters of MES. These relevant parameters of the MES and for EMPC controller are listed in Table A1–A4.

Appendix B

Appendix B provides detailed formulation of the electro-chemical model of AE. The three voltage terms of the nonlinear \( U-I \) model by (1) are formulated by (B.1)–(B.3) respectively [32,34]. Due to the quadratic and logarithmic relationship in these voltage terms, the function \( f_I \) in (1) is nonlinear.

\[
U_{\text{act}}(T_4, f_4) = n_1 + n_2 
\]

\[
U_{\text{ele}}(T_4, f_4, I_4) = \frac{I_4/n}{A} = \frac{V_{\text{cell}}}{A}
\]

\[
U_{\text{nonlinear}}(T_4, f_4, I_4) = s \log \left( \left( \frac{n_1}{n_2 I_4} + \frac{n_2}{T_4} \right) \times \frac{V_{\text{cell}}}{A} + 1 \right)
\]

Besides, the thermoneutral voltage in (1) is described as (B.4)–(B.10) [35]. It can be seen the \( U^{\text{th}} \) is a highly nonlinear function regarding the stack temperature.

\[
U^{\text{th}} = U^{\text{th}, \infty} + \frac{\varphi}{n_F} Y + f_{\text{th}, \text{inf}}(T_4, I_4, P_4) \approx U^{\text{th}, \infty} + \frac{\varphi}{n_F} Y
\]

\[
U^{\text{th}, \infty} = 1.4756 + 2.252 \times 10^{-5} (T_4 - 273.15) + 1.52 \times 10^{-8} (T_4 - 273.15)^2
\]

\[
\varphi = 1.5 \times \frac{P_\text{th}}{P_\text{el}}
\]

\[
\ln P_\text{th} = 0.01621 - 0.138 n_0 + 0.1933 \sqrt{m} + 1.024 \ln P_\text{el}
\]

\[
\ln P_\text{el} = 37.04 - 6276 \times 10^{-5} \times 3.416 \ln T_4
\]

\[
m(T_4, P_4) = \frac{W_{1} \times (183.1221 - 0.568457 T_4 + 984.5679 e^{-252 T_4})}{100 \times 56.105}
\]

\[
Y = 42.96 + 40.762 (T_4 - 273.15) - 0.06682 (T_4 - 273.15)^2
\]

References


