Optimization of microenergy grid including adiabatic compressed air energy storage by considering uncertainty of intermittent parameters

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Abstract
In recent years, zero-carbon energy resources such as adiabatic compressed air energy storage with thermal energy storage have been interested due to growing concerns over global warming. This study proposes a microenergy grid including heat and power networks connected through adiabatic compressed air energy storage with thermal energy storage, which can be considered hybrid energy storage supplying power for both networks. The power network is supplied with the main grid and wind turbine systems, and the heat network is provided with heat pumps. The objective function minimizes power purchased from the main grid and power demand of heat pumps in the heat network. Since uncertainty plays a key role in the operation of integrated energy systems, the uncertainty of intermittent parameters such as active and reactive load and wind speed data has been considered in this study. Therefore, predicted values are used in the optimization problem instead of using deterministic values for such uncertain parameters. To do this, an efficient 2-level corrective forecasting algorithm is proposed to have an accurate prediction for the day-ahead operation of the microenergy grid. Different scenarios are presented to show the importance of the forecasting method and the utilization of adiabatic compressed air energy storage with thermal energy storage in the system’s structure. The results indicate that corrective actions on the predicted load and wind speed data decrease the operation cost of the microenergy grid from 57.13% to 13.21%. Also, it is found that neglecting adiabatic compressed air energy storage with thermal energy storage in the structure of the microenergy grid increases operation cost to 3423 US$. Other obtained results also indicate the importance of coutilization of compressed air energy storage with thermal energy storage and 2-level corrective forecasting method leading to optimal operation of the microenergy grid.

Keywords
adiabatic compressed air energy storage, energy storage, integrated energy systems, uncertainty prediction, wind turbine
1 | INTRODUCTION

1.1 | Aim and scope

Greenhouse gas emissions and the global energy crisis have caused the transformation of conventional energy supplies such as fossil fuel–based power plants.1,4 Renewable energy sources (RESs) play a prominent role in addressing environmental issues.5–7 Solar photovoltaic (SPV) and wind turbine (WT) systems have attracted more attention than other RESs.8 Despite their fast developments in recent years, a considerable amount of power is curtailed annually. It has become an obstacle to the growth of these resources.9,10 As a practical solution for dealing with renewable power curtailment, utilization of multienergy carriers (MEC), including electricity, natural gas, heat, and cooling,11 is suggested. Integrated energy systems incorporate different MES by connecting gas/electricity networks to energy hubs (EHs).12,13 Through the utilization of EHs, they are able to transmit, convert, and store different energy carriers. Using various gas/electricity networks increases energy dispatch flexibility and improves the performance of renewable resources.14,15

CHP system is the primary source of EHs and provides electricity and heat simultaneously. This process is called cogeneration.12 The CHP system plays a crucial role in co-optimizing both electric and heat networks. The cogeneration capability of the CHP system results in the increased flexibility of the energy system and the reduction in curtailed renewable power. Since the CHP system consumes natural gas to produce energy, environmental issues such as greenhouse gas emissions are raised in recent years.16,17 Like the CHP system, compressed air energy storage (CAES) consumes natural gas to generate electricity. One of the concerns regarding the utilization of CHP and CAES systems is their contribution to global warming.18,19 To deal with this issue, thermal energy storage (TES) system can be added to CAES to construct a nonsupplementary fired compressed air storage (NFS) CAES. This technology is becoming popular due to its moderate costs, environmental benefits, and longer lifetime than batteries. Many pilot plants in MW scale have been built to explore the technology deployment potentials.20,21 Thermal energy generated by NFS CAES during the air compression process can be stored in air storage tanks and generate electricity in other processes.22,23 The heat generated in the compression process is stored in a separate thermal energy storage system. Then, the stored thermal energy is used to heat the air before expansion. Therefore, gas combustion is not required in NFS CAES.24,25 NFS CAESs are typically utilized in EHs to supply electricity and heat similar to the CHP systems. Since NFS CAES is a carbon-free system, it is possible to construct an emission-free integrated energy system.

Nevertheless, the uncertainties in operational parameters such as loads and RES output power are considerable challenges for the optimal operation and planning of integrated energy systems. Neglecting such uncertainties in integrated energy systems increases operation costs and deviates operational decisions from actual values.26–28 Therefore, it is essential to consider uncertainties in the proposed microenergy grid. Generally, there are two ways to consider intermittent parameters in the energy systems’ optimization modeling. One is predicting uncertain parameters, and the other is the uncertainty modeling technique.29–31 There are benefits and strengths in both of these strategies. The operation of the microenergy grid is accomplished at hourly intervals; hence, short-term prediction methods are suited for this task. It is possible to use classical and intelligent techniques for predicting uncertain parameters.32,33 Some of the popular classical methods are autoregressive integrated moving average (ARIMA),34 exponential smoothing,35 dynamic regression (DR),36 and generalized autoregressive conditional heteroskedasticity (GARCH).37 The most well-known intelligent methods in recent studies are artificial neural networks (ANNs),38 fuzzy systems,39 and support vector regression (SVR).40 In addition, some advanced techniques such as hybrid and multistage methods are also developed in recent works to boost the forecasting accuracy of uncertain parameters. On the other hand, it is possible to model stochastic behavior of operational parameters using mathematical-based methods, namely stochastic programming,41 robust optimization,42 and information gap decision theory (IGDT).43

1.2 | Literature review

The utilization of CAES and NFS CAES in heat and power networks has been interested in recent studies.44–51 Special attention has been dedicated to the optimal dispatch of heat and power networks using CAES and adiabatic CAES with TES. In Ref. 52, a comprehensive assessment of a hybrid hydrogen and CAES system is performed. The proposed model minimized the emissions of CAES technology. Additionally, uncertainties and electricity curtailment of the upstream grid with high penetration of RESs are also addressed. Another study investigated comprehensive economic, exergetic, and thermodynamic analyses of the hybrid system, including CAES, PV, and desalination units. In Ref. 53, a green CAES system integrated with two adjacent wind farms is proposed for peak shaving applications. Also, thermodynamic analysis of the CAES system in critical months and annually is conducted in this study. In a different study,44 a review on the development of CAES in China is conducted in which
technical and economic challenges to the commercialization of such systems are investigated. The integration and optimal scheduling of the WT systems and CAES are investigated in Refs. 44 and 45. In Ref. 46, a cost-effective two-stage optimization model is proposed for the microgrid (MG) planning and scheduling equipped with CAES and preventive maintenance. Uncertainty of wind speed is also modeled using stochastic programming in this study. In Ref. 47, day-ahead scheduling for the integrated heat and electrical system is proposed. Similar to Ref. 46, the wind speed uncertainty is also modeled using IGDT. In addition, CAES and DR programs are modeled to decrease system operation costs. However, both Refs. 46 and 47 neglected to consider load uncertainties. In Ref. 48, a tristate model of adiabatic CAES for optimal power system dispatch is modeled using mixed-integer linear programming (MILP). Nevertheless, uncertainties of operational parameters are not considered in this paper. In another study, the authors introduced an optimal planning framework for bulk-scale CAES combined with PV and WT systems to substitute fossil fuels in the power system. In addition, the feasibility of geological resources for bulk-scale CAES was assessed by taking the UK power system as a case study. The authors of Ref. 50 developed an optimization model to determine the performance of a hydro-thermal-WT-SPV hybrid power system with the possibility of integrating a CAES. Real-time operational constraints such as availability of RES outputs are included in the model, and two different metaheuristic algorithms such as differential evolution and modified bacteria foraging algorithm are used to solve the problem. Ref. 20 presented dynamic modeling and techno-economic analysis of NFS CAES in providing emergency backup power to supply MG operation. They found that the MW scale NFS CAES can naturally restore the power supply to critical loads within several minutes. In Ref. 51, an integrated energy system equipped with adiabatic CAES with TES is considered, which takes the thermal dynamic and pressure behavior into account in order to enhance dispatch flexibility. While the dispatch problem is formulated as a deterministic optimization problem, the authors emphasized the importance of uncertainty on the optimization results.

1.3 Contributions

Adopting the reviewed studies, this paper proposes a carbon-free integrated energy system equipped with adiabatic CAES with TES. The proposed integrated energy system is optimized to reduce operation costs and WT output power curtailment. Dispatch problem of power distribution network and district heating network and optimal operation of adiabatic CAES with TES is modeled as a mixed-integer nonlinear programming (MINLP). The nonlinear model is simplified to MILP. Also, on-load tap changers (OLTC) and reactive power compensators such as SVG are considered in the DistFlow model of the radial power distribution network. More importantly, predicting uncertain parameters such as active and reactive load and wind speed data is performed using an efficient two-level corrective forecasting method.

The most important novelties of this paper are listed as below:

1. An optimization problem considering a carbon-free microenergy grid equipped with adiabatic CAES is proposed to reduce the operation cost and WT power curtailment.
2. A two-level forecasting method based on feed-forward ANN is used for considering uncertainties of active and reactive loads and wind speed data.
3. Uncertainties of intermittent variables are considered in the optimization model according to the two-level corrective forecasting method.

2 METHODOLOGY

In this section, the system overview, including the integrated energy system structure and adiabatic CAES with TES, is discussed. The optimization model and linearization method are then presented comprehensively. Afterward, the forecasting method based on two-level corrective ANNs is implemented for the short-term prediction of active and reactive loads and wind speed data.

2.1 System architecture

Integrated energy systems usually consist of four different energy carriers, that is, electricity, natural gas, heat, and cooling. Figure 1 shows an overview of a typical integrated energy system in which energy carriers connect through storage and energy conversion devices. The focus of this paper is on the optimal scheduling of combined power and heat networks. The proposed system is composed of WT systems, electric and heat loads, adiabatic CAES with TES, and electric and heat networks. This system can be connected to public electricity/natural gas networks or operated independently. It is essential to mention that instead of utilizing CHP unit, adiabatic CAES with TES is used as the hub between power and heat networks.

The adiabatic CAES with TES is seen as an EH with the cogeneration of power and heat. The simplified structure of adiabatic CAES with TES is illustrated in Figure 2. The whole system consists of an air turbine unit, air
compressor unit, air storage unit, and heat regeneration unit. The air compressor uses curtailed and off-peak electricity to drive the compressor to produce high-pressure air and store it into the storage tank. Heat regeneration system improves operation efficiency of CAES by storing thermal energy along with air compressor. High-pressure air in the storage tank is released and preheated to drive the generator when there is a need for electricity. Therefore, the decoupling storage of molecular potential energy and thermal energy is realized. This process distinguishes adiabatic CAES with TES from conventional CAES. In this paper, an adiabatic CAES with TES composing of the two-stage turbine and two-stage compressor is considered. In order to save space, the complete formulation of adiabatic CAES with TES is not provided in this paper. However, a few of the most important formulas for CAES hub modeling, including compressor power consumption, turbine power generation, air storage tank, and regenerative system, are mentioned in this paper. Nevertheless, the complete formulation of the CAES hub can be found in the literature.51,55,56

In Ref. 1, the power consumption of the compressor during charging is denoted. The operation mechanism of the turbine can be regarded as an inverse process of the compressor. Thus, the formulation for the turbine can be easily inferred from that of the compressor. Equation (2) shows the power generated by the turbine. In (3), the pressure of high-pressure air in the storage tank at period $t-1$ is calculated. Equation (3) measures the state of charge (SOC) of adiabatic CAES with the TES hub. Thermal energy collected by the cooler equipped after compressor at period $t$ during charging can be depicted by (4). Similarly, thermal energy consumed by the heater equipped before the turbine during discharging can be computed by (5). The SOC of CAES's thermal energy storage system can be illustrated as (6) and (7). Equations (8) and (9) show the bounds of consumed and generated power of compressor and turbine, respectively. Equation (10) indicates the boundaries of air pressure in the air storage tank.

\[
p_c^t = \frac{\kappa_c}{\eta_c(\kappa_c - 1)} \frac{R_g T_t^{c,\text{in}}}{\frac{T_t^{c,\text{out}}}{\frac{T_t^{c,\text{in}}}} - 1}
\]

\[
p_{\text{tur}}^t = \frac{\kappa_c}{(\kappa_c - 1) \eta_{\text{tur}}} R_g T_t^{\text{tur,\text{in}}} qm_{\text{tur}}^t \left[ 1 - \left( \frac{p_{\text{tur}}^{\text{out}}}{p_{\text{tur}}^{\text{in}}} \right)^{\frac{T_t^{c,\text{out}}}{T_t^{c,\text{in}}}} \right]
\]

\[
p_{\text{st}}^t = p_{\text{st}}^{t+1} + \frac{1}{\nu} R_g T_t^{\text{st}} (qm_{\text{c}}^t - qm_{\text{tur}}^t)
\]

\[
h_{\text{tur}}^t = c_{\text{a}} qm_{\text{tur}}^t \left( T_t^{\text{tur,\text{out}}}/T_t^{\text{tur,\text{in}}} \right)
\]

\[
h_{\text{c}}^t = c_{\text{a}} qm_{\text{c}}^t \left( T_t^{\text{c,\text{out}}}/T_t^{\text{c,\text{in}}} \right)
\]

\[
H_{\text{st}}^t = H_{\text{st}}^{t-1} + u_{\text{c}} H_{\text{tur}}^t - u_{\text{tur}} H_{\text{c}}^t
\]

\[
H_{\text{st},l}^{t} \leq H_{\text{st},u}^{t} \leq H_{\text{st},u}^{t}
\]
2.2 Optimization model

In this subsection, the optimization model including objective function and technical constraints is presented. This paper considers the optimal operation of a typical microenergy grid combining power and heat networks with adiabatic CAES with TES. The CAES hub takes the thermal dynamic and pressure behavior into account to improve dispatch flexibility. A modified DistFlow model is then utilized to allow several discrete and continuous reactive power compensators to maintain the voltage quality of the power network. The optimal operation of the microenergy grid is initially modeled as MINLP. Several simplifications and transformations are performed to convert the problem as MILP. The flowchart representing the system modeling is shown in Figure 3. According to this flowchart, the adiabatic CAES with TES hub, including compressor, air storage tank, and regenerative system, is modeled. Then, the power network is formulated based on the radial network and DistFlow model. Similarly, heat network, heat pump (HP), and circulating water pump are formulated. The dispatch model is then linearized in the next step. By considering the uncertainties, the optimization model is solved using the CPLEX solver.

2.2.1 Objective function

In the proposed model, HP and adiabatic CAES are the primary sources of heat. In addition, HP purchases electricity directly from the main grid and not from the buses of the power network. Therefore, adiabatic CAES with TES is the only connection point of power and heat networks in the proposed integrated energy system. The objective function of the optimization problem is shown in (11). The objective is to reduce the operation cost of the integrated energy system during the optimization period. In (11), the electricity bought from the main grid for HP in the heat network is minimized in the first term, while heat power purchased for HP in the heat network is minimized in the second term. Since both terms are homogenous costs, the OF is a single-objective optimization problem.

\[
OF = \min \sum_{i=1}^{24} C_{t}^{\text{elec}} \left( P_{t}^{\text{hp}} + \sum_{j=t}^{n_{\text{hp}}} P_{t}^{\text{hp}} \right) \quad (11)
\]

### 2.2.2 Power network

The distribution power network usually has a radial topology that is different from the transmission power network. The radial topology of the power network is illustrated in Figure 4. In this paper, the DistFlow model is used for describing power flow. There are advantages to the DistFlow model. First of all, node voltage and reactive power are considered in the formulation. Second, the optimal solution is easily achieved by converting nonlinear equations to linear forms. The formulation of the DistFlow model is described as follows.\(^{57}\)

\[
P_{ij} + P_{ij} = r_{ij} P_{ij} = k \pi j \sum P_{jk} + P_{j}^{d} \quad (12)
\]

\[
Q_{ij} + Q_{ij}^{d} = k \pi j \sum Q_{jk} + Q_{j}^{d} \quad (13)
\]

\[
U_{j} = U_{1} - 2 ( r_{ij} P_{ij} + x_{ij} Q_{ij} ) + ( z_{ij} )^{2} \quad (14)
\]

\[
\begin{align*}
& \quad i_{ij} U_{i} = P_{ij}^{d} + Q_{ij}^{d} \\
& \quad i_{ij} \leq i_{ij}^{up} \\
& \quad U_{i} \leq U_{i} \leq U_{i}^{up} U_{0} = V_{a}^{2} \\
& \quad \begin{cases} 
P_{ij}^{\text{low}} \leq P_{ij}^{\text{up}} \\
Q_{ij}^{\text{low}} \leq Q_{ij}^{\text{up}}
\end{cases}
\end{align*} 
\quad (15)
\]

In (12) and (13), the active and reactive power balance of the power network is modeled. In (14), voltage drops in the distribution line \(l(i,j)\) are formulated. The relation between power, the square of current, and voltage is represented in (15). Other constraints regarding current, voltage, and active and reactive power are described in (16)-(18). The linearized form of the DistFlow is modeled as the following equation.\(^{58}\)

\[
P_{ij} + P_{ij} = k \pi j \sum P_{jk} + P_{j}^{d} \quad (19)
\]

\[
Q_{ij} + Q_{ij}^{d} = k \pi j \sum Q_{jk} + Q_{j}^{d} \quad (20)
\]

\[
U_{j} = U_{1} - \frac{( r_{ij} P_{ij} + x_{ij} Q_{ij} )}{U_{0}} \quad (21)
\]

\[
U_{i}^{\text{low}} \leq U_{i} \leq U_{i}^{up} \quad (22)
\]
The DistFlow model has been implemented to formulate the power network by assuming the power network has a radial network. To improve the DistFlow model’s performance, continued and discrete reactive power compensators and WT systems are incorporated in the model. Therefore, using the linearized form of the DistFlow model, the power network of the integrated energy system can be formulated as follows.

\[ P_{ij,t} + P_{WT,j,t} + P_{CAES,j,t} = k\pi j \sum Q_{jk,t} + Q_{j,t}^d \tag{24} \]

\[ Q_{ij,t} + Q_{j,t}^g + \frac{U_{j,t}}{K_{ij,t}^2} + Q_{j,t} = k\pi j \sum Q_{jk,t} + P_{j,t}^d \tag{25} \]

\[ \frac{U_{j,t}}{K_{ij,t}^2} = U_{i,t} - \frac{r_j P_{ij,t} + x_j Q_{ij,t}}{U_0} \tag{26} \]

\[ U_{j,t} = U_{i,t} - \frac{r_j P_{ij,t} + x_j Q_{ij,t}}{U_0} \tag{27} \]

\[ U_{i,t}^{low} \leq U_{i,t} \leq U_{i,t}^{up} \tag{28} \]

\[ P_{WT,j,t}^{low} \leq P_{WT,j,t} \leq P_{WT,j,t}^{up} \tag{29} \]

The active and reactive power distribution of the line \((i,j)\) is described in (24) and (25). Equation (26) indicates reactive power distribution with reactive power compensator utilized in bus \(j\). Equations (27) and (28) show the voltage of bus \(j\) with/without OLTS. Equation (29) is identical to (22) and (30) denotes available WT system output power.

2.2.3 | Heat network

In the proposed microenergy grid, the accurate formulation of the heat network is of great importance. Therefore,
Equations (31)–(40) are introduced to model the heat network. The flow continuity, as described in Refs. 60–62, should be satisfied for each node \(i \in h(N)\), according to (31) and (32).

\[
bf{i} \sum m_{b,t}^{i} + m_{l,t}^{d} = m_{b,t}^{d} + bki \sum m_{b,t}^{i} \quad \forall i, t \tag{31}
\]

\[
bf{i} \sum m_{b,t}^{i} + m_{l,t}^{d} = m_{b,t}^{d} + bki \sum m_{b,t}^{i} \quad \forall i, t \tag{32}
\]

Correlation between the temperature of pipe \(b \in h(P)\) and node \(i \in h(N)\) is formulated as (33) and (34).

\[
bk \sum \left( \theta_{b,t}^{i,\text{out}} \right) = \theta_{b,t}^{i,\text{in}}, bk \sum \left( \theta_{b,t}^{i} \right) \tag{33}
\]

\[
bk \sum \left( \theta_{b,t}^{i,\text{out}} \right) = \theta_{b,t}^{i,\text{in}}, bk \sum \left( \theta_{b,t}^{i} \right) \tag{34}
\]

Node and pipe temperatures are related, as indicated in (35). The mass flow limitations in (36) are implemented based on the physical characteristics of pipe \(b\) of supply and return networks.

\[
\begin{align*}
\theta_{b,t}^{s,\text{in}} &= \theta_{b,t}^{s} \\
\theta_{b,t}^{r,\text{in}} &= \theta_{b,t}^{r} \\
0 \leq m_{b,t}^{s} &\leq m_{b}^{s,\text{up}} \\
0 \leq m_{b,t}^{r} &\leq m_{b}^{r,\text{up}}
\end{align*} \tag{35}
\]

Also, the inlet/outlet pressure of pipe \(b\) is depicted in (37) and (38).\(^{62,63}\)

\[
p_{l,t}^{b} - p_{r,t}^{b} = \mu_{b}(m_{b,t}^{i})^{2} \tag{37}
\]

\[
p_{l,t}^{b} - p_{r,t}^{b} = \mu_{b}(m_{b,t}^{i})^{2} \tag{38}
\]

As can be seen, an exponential function is used to model temperature drops because it exponentially drops during recycle water flow in pipes.\(^{62}\)

\[
\theta_{b,t}^{s,\text{out}} = \left( \theta_{b,t}^{s,\text{in}} - \theta_{l,t}^{am} \right) e^{- \frac{\Delta t_{b,t}}{\omega_{l,s}}} + \theta_{l,t}^{am} \tag{39}
\]

\[
\theta_{b,t}^{r,\text{in}} = \left( \theta_{b,t}^{r,\text{in}} - \theta_{l,t}^{am} \right) e^{- \frac{\Delta t_{b,t}}{\omega_{l,s}}} + \theta_{l,t}^{am} \tag{40}
\]

Moreover, it is important to model heat load at node \(i\) of the heat network in the microenergy grid. The following equation is used for calculating heat load.

\[
P_{l,t}^{hd} = c_{w} m_{l,t}^{i} \left( \theta_{l,t}^{i} - \theta_{l,t}^{i} \right) \tag{41}
\]

The minimum return and supply pressure for the circulating water pump in each adiabatic CAES with TES connected to the microenergy grid is calculated.

\[
p_{l,t}^{i} - p_{r,t}^{i} \geq p_{l,t}^{i,\text{low}} \tag{42}
\]

The following constraint is used to limit the return water temperature at heat load \(i\).

\[
\theta_{l,t}^{i,\text{low}} \leq \theta_{l,t}^{i} \leq \theta_{l,t}^{i,\text{up}} \tag{43}
\]

### 2.2.4 | Circulating water pump and HP

Total thermal energy provided by the HP utilized at node \(i\) and adiabatic CAES with TES hub can be computed by the following Equation (44).

\[
P_{l,t}^{hp} + P_{l,t}^{CAES} = c_{w} m_{l,t}^{i} \left( \theta_{l,t}^{i} - \theta_{l,t}^{i} \right) \tag{44}
\]

The water temperature at each HP should be constrained to upper and lower limits.

\[
\theta_{l,t}^{i,\text{low}} \leq \theta_{l,t}^{i} \leq \theta_{l,t}^{i,\text{up}} \tag{45}
\]

Consumption power by circulating water pump utilized at node \(i\) is satisfied by Ref. 63.

\[
P_{l,t}^{cp} = m_{l,t}^{i} \frac{p_{l,t}^{i} - p_{r,t}^{i}}{\eta_{l,t}^{i} \rho} \tag{46}
\]

Similar to water temperature, the circulating water and HP power consumption can be constrained to upper and lower limits:

\[
P_{l,t}^{cp,\text{low}} \leq P_{l,t}^{cp} \leq P_{l,t}^{cp,\text{up}} \tag{47}
\]

\[
P_{l,t}^{hp,\text{low}} \leq P_{l,t}^{hp} \leq P_{l,t}^{hp,\text{up}} \tag{48}
\]

### 2.2.5 | Linearization of the MINLP problem

Aggregating the objective and constraints, the dispatch model of ZCE-MEI in terms of reducing system operation cost can be formulated as:
\[
\begin{align*}
\min \quad & (1) \\
\text{s.t.} \quad & (24) - (30), (31) - (48) 
\end{align*}
\] (49)

Dispatch model (49) is a large-scale MINLP problem, which is hard to be effectively solved. However, by linearizing the nonlinear equations, including power and heat networks, it is possible to convert the MINLP problem to an easily solved MILP problem by CPLEX.

In the proposed formulation of the power network, Equations (26) and (27) are nonlinear. Equation (26) could be linearized using the discrete formulation for nonlinear variables and the big \( M \) method.\(^{59,64} \)

\[
U_{j,t} = C^j_{\text{low}} U_{j,t} + s_j \left( 2^1 g_{j,0} U_{j,t} + \cdots + 2^n g_{j,n} U_{j,t} \right) \\
\forall j \in E (N) \cap E_D 
\] (50)

\[
\log_2 \left( \frac{C^\text{ap} - C^\text{low}}{s_j} + 1 \right) - 1 \leq v_j \leq \log_2 \left( \frac{C^\text{ap} - C^\text{low}}{s_j} + 1 \right) 
\] (51)

\[
U_{j,t} - M(1 - g_{j,k,t}) \leq g_{j,k,t} \leq U_{j,t} + M(1 - g_{j,k,t}) \\
- M g_{j,k,t} \leq g_{j,k,t} \leq M g_{j,k,t} 
\] (52) (53)

The left-side term of (27) as for the OLTC branch \( (i,j) \) could be expanded as (54).

\[
\frac{U_{j,t}}{K^2_{j,k,t}} = U_j \left( \frac{b_{j,1,t}}{K^2_{j,1}} + \frac{b_{j,2,t}}{K^2_{j,2}} + \cdots + \frac{b_{j,n_j,t}}{K^2_{j,n_j}} \right) 
\] (54)

Therefore, it is possible to linearize the term according to (55) as follows.

\[
\frac{U_{j,t}}{K^2_{j,k,t}} = \sum_{k=1}^{n_j} h_{j,k,t} \\
U_{j,t} - M(1 - b_{j,k,t}) \leq h_{j,k,t} \leq U_{j,t} + M(1 - b_{j,k,t}) \\
- M b_{j,k,t} \leq h_{j,k,t} \leq M b_{j,k,t} 
\] (56) (57)

Moreover, the widely used constant flow and constant supply temperature mode\(^{62,65} \) is implemented in this paper for simplicity. Therefore, Equations (41), (42), (47), and (48) are not necessary.

### 2.3 Uncertainty prediction method

This section describes the implemented two-level uncertainty prediction method applied to optimize the system’s operation cost. This method has been proposed by Faraji et al.,\(^{66} \) considering the fact that critical uncertain parameters such as wind speed and reactive power consumption have been neglected. The model was tested on the available active power consumption. However, in the same paper,\(^{66} \) it was suggested to validate the method by forecasting the output power of RESs. Therefore, this paper has been dedicated to predicting uncertain parameters of load demand and wind speed data. The proposed 2-level uncertainty prediction method consists of a time-series MLP-ANN algorithm in level 1, which is used for performing short-term uncertainty forecasting. The level 2 of the suggested approach is initialized whenever the accuracy of predicted data is lower than the threshold level. The accuracy of the uncertainty prediction is evaluated according to the comparison measured and the forecasted data. The main reason for utilizing MLP-ANN in the structure of the 2-level method is that it is more precise and beneficial than other ANNs, namely self-organizing map and radial basis function ANNs in short-term load prediction.\(^{57,68} \) In Figure 5, the initializing procedure of the 2-level uncertainty prediction and its structure has been illustrated. The proposed method is a 2-level prediction method, while the classical methods such as MLP-ANN are a single-level prediction method. In addition, no control or observation on forecasting results is anticipated in the classical MLP-ANN method. However, in the proposed method, a deviation criterion is defined to control the forecasting error, and corresponding corrections are applied when the accuracy criterion is violated.

In level 1, the day-ahead uncertainty prediction is implemented by the time-series MLP-ANN method. Time-series prediction is typically conducted by considering time delays in the input data. The time-series MLP-ANN structure is according to hierarchical processing units ordered in two or more distinct layers of neurons. The input layer is used for importing the historical data. Level 1 uncertainty prediction is of historical data with a matrix with dimensions \( 1 \times 8760 \) as (58):

\[
\psi^f_{\text{Level–1}} = \left[ \psi^f_1, \psi^f_2, \ldots, \psi^f_{8760} \right] 
\] (58)

The accuracy of the level 1 day-ahead forecasting is evaluated in (59) and (60). If the accuracy threshold is not fulfilled, corrective forecasting is performed using the feedforward (FF) ANN algorithm. More specifically, a set of patterns are given to the input of the FF MLP-ANN in level 2 uncertainty prediction. The input data are a matrix indicating hourly historical data for the previous thirty days. The number of columns is constant and considered to be thirty. The number of rows depends on the initialization time of level 2 uncertainty prediction. The input matrix of level 2 uncertainty forecasting can be introduced as (61).
\[ \Delta \psi_t = |\psi_t^{\text{Measured}} - \psi_t^{\text{Forecasted}}| \]  \hspace{1cm} (59)

\[ \Delta \psi_t \leq \varphi \]  \hspace{1cm} (60)

\[ \psi_{\text{Level-2}} = \begin{bmatrix} \psi_{1,1}^f, & \psi_{2,1}^f, & \cdots, & \psi_{30,1}^f \\ \psi_{1,2}^f, & \psi_{2,2}^f, & \cdots, & \psi_{30,2}^f \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{1,30}^f, & \psi_{2,30}^f, & \cdots, & \psi_{30,30}^f \end{bmatrix} \]  \hspace{1cm} (61)
If the modified values of the prediction are sufficiently accurate, they could be used for the re-optimization process. Otherwise, the suggested level 2 corrective prediction is performed again for the following hours using the last thirty days’ profiles. Figure 6 shows the flowchart of the implemented 2-level corrective forecasting method. After collecting the wind speed data, WT system output power is calculated using the following equation.26

\[ P_{WT}^t = \begin{cases} 0 & 0 \leq v_{st, t} < v_{c-in}, v_{c-out} > v_{st, t} \\ \frac{v_{st, t} - v_{c-in}}{v_{c-in} - v_{c-out}} & v_{c-in} < v_{st, t} < v_{c-in} \\ \frac{v_{st, t} - v_{c-out}}{v_{c-out} - v_{c-in}} & v_{c-out} < v_{st, t} < v_{c-out} \end{cases} \] (62)

3 RESULTS AND DISCUSSION

In this section, forecasting and optimization results are presented. In the first part, wind speed and active/reactive load prediction results are represented. In the second part of this section, optimization results are presented based on the introduced case studies.

3.1 Uncertainty prediction results

As mentioned previously, predicting wind speed and active/reactive load data is a considering challenge because of the intermittent nature of these parameters. Using the proposed 2-level forecasting method, uncertain parameters are predicted according to the available historical data. Therefore, in the first level, typical time-series forecasting is performed using historical values. Then, the predicted values for the optimization day are extracted and evaluated with the desirable threshold. If the results were satisfying, the first-level forecasting could be sufficient. However, suppose the forecasting error exceeds the threshold. In that case, the second-level forecasting should be used based on the previous thirty days’ historical data.

Figure 7 indicates historical active and reactive loads and wind speed data used for predicting time-series forecasting.69 As can be observed, variations are notable in all the datasets. However, variability is significant in wind speed data. Therefore, developing an efficient method to deal with such uncertainties is of great importance. Table 1 provides a summary of statistical values and desirable error thresholds for the uncertain parameters.

Using 24-h time delay \((t - 24)\), day-ahead forecasting is performed using time-series MLP-ANN.38 Level 1 forecasting results according to time-series MLP-ANNs are shown in Figures 8-10. It can be seen that level 1 prediction is along with some errors, especially in wind speed data. Nevertheless, the predicted wind speed patterns have more variations in comparison with reactive/active load data. Linear regression results for level 1 forecasting are achieved at 0.91616 and 0.91231, respectively. Wind speed data have not been adequately forecasted \((R = 0.41295)\). Therefore, there is a need for an accurate prediction approach to have a precise dispatch model.

To perform a day-ahead dispatch of the microenergy grid, it is required to collect forecasted data for the operation day. Figure 11 compares the forecasted values of active/reactive load and wind speed data with actual ones. Level 1 forecasted data are evaluated with the actual data. Where the accuracy is violated, the second-level corrective load forecasting is performed using previous thirty-day data patterns. According to Figure 11a,b, the desirable accuracy thresholds for the active and reactive load data are violated at the beginning of the day. Hence, a corrective prediction is performed using the previous thirty days’ data. However, for the wind speed data, the desirable accuracy threshold is violated at 7:00.

After implementing the corrective actions on the level 1 reactive/active load and wind speed data, the rest of the corrected data is used for the optimization. Again, the accuracy threshold is evaluated during the optimization process. If the newly corrected data violate the accuracy criteria, corrective actions would be necessary to enhance the accuracy. This process is repeated for each hour to the rest of the day. Figure 12 compares the corrective level 2 forecasting results with level 1 and actual load data. As illustrated, the active load data required three corrective actions at 1:00, 4:00, and 8:00. Furthermore, the reactive load data required two corrective actions at 1:00 and 15:00. Wind speed data required three corrective actions at 7:00, 10:00 and 15:00. After performing corrective actions, the prediction accuracy of the uncertain parameters is significantly improved. In the next section, the proposed 2-level corrective forecasting impacts on the optimization results are thoroughly analyzed.

3.2 Optimization results

In this subsection, optimization results of the dispatch problem are presented. The proposed system integrates heat and electrical networks through adiabatic CAES with TES. The system also is utilized with the WT system, which is an intermittent energy resource. As mentioned previously, the uncertainties of intermittent parameters have significant impacts on the operation of the microenergy grid. Three
scenarios are introduced based on the type of uncertain parameters and adiabatic CAES with TES, as follows.

- **Scenario 1**: Microenergy grid dispatch problem is solved using actual active/reactive load and wind speed data such as the optimization method of Ref. 51 (base case).

**FIGURE 7** Historical data for (A) active load; (B) reactive load; (C) wind speed

**TABLE 1** Statistical values and desirable error thresholds

| Type                | Maximum value | Minimum value | Average value | Error threshold |
|---------------------|---------------|---------------|---------------|----------------|
| Active load [MW]    | 8.4277        | 5.0799        | 6.1641        | 0.2            |
| Reactive load [MVar]| 4.2331        | 0.0040        | 0.9697        | 0.04           |
| Wind speed [m/s]    | 13.9000       | 0             | 4.2963        | 2 m/s          |
- **Scenario 2**: Microenergy grid dispatch problem is solved using level 1 forecasting active/reactive load and wind speed data such as the forecasting method of Ref. 38.

- **Scenario 3**: Microenergy grid dispatch problem is solved using the proposed 2-level corrective forecasting method.
Scenario 4: The impact of neglecting adiabatic CAES with TES on the operation cost of the microenergy grid is evaluated.

The configuration of the understudy microenergy grid is represented in Figure 13. The system is comprised of a 33-bus power network and an 8-node heat network, 8 WT units, an adiabatic CAES with TES, a HP, and reactive power compensators such as OLTC and SVG. A 1 MW WT is utilized in adiabatic CAES with TES in bus 2. Other WT units are equipped to the network in buses 7, 19, 26, all with a capacity of 0.6 MW. The HP is utilized in node 1 of the heat network. It has been assumed that HP purchases electricity from the upstream grid (not from the buses). As indicated in Figure 13, four OLTCs with maximum tap changer 1.05, minimum tap changer 0.95, and tap step 0.01 are utilized. The SVG is also equipped to provide continuous reactive power. Similarly, shunt capacitors/reactors with the minimum value of 0 and maximum value of 0.2 with 0.05 step are located in the specific lines. These components (OLTCs, SVG, and shunt capacitors/reactors) help maintain the power network’s voltage quality in the designed microenergy grid. Mass flow rate, heat load ratio of each node, and hourly electricity prices are illustrated in Figure 14. As early mentioned, the WT system’s output power is calculated based on wind speed data type. Figure 15 shows the output power of the WT system (for all scenarios), as well as heat load values. In addition, the power ratio of each bus in the microenergy grid is generated by each load divide system load of the standard data. The electricity efficiency and the round-trip energy efficiency are computed as follows: \[ \eta_e = \frac{1.46}{2.8} \times 100 = 52.14\% \] and \[ \eta_{CA-ES} = \frac{(1.46 + 0.4193)}{2.8} \times 100 = 67.12\% \]. The technical data for the parameters could also be found in Ref. 51.

3.2.1 | Scenario 1

In the first scenario, the microenergy grid optimization is performed using actual active/reactive load and wind speed data. In fact, this is a base scenario for evaluating the optimization results according to the level 1 and level 2 forecasted data. Optimization results regarding the base case are presented in Figure 16. In Figure 16a,b, SOC and charging/discharging power of TES and adiabatic CAES are illustrated. It can be observed that adiabatic CAES utilizes low-cost electricity at off-peak hours (23:00-06:00) and free WT power to charge the air into the air storage tank for storing the energy in two forms, that is, molecular potential energy in the air storage tank and thermal energy in TES. The molecular potential energy is then utilized to produce electricity in peak hours (9:00 and 20:00). Hence, the adiabatic CAES responds to the network’s price signals and optimally discharges at the network’s peak prices. Also, storing thermal energy in TES provides...
heat power for heat load to decrease the operation cost. Therefore, it can be concluded from Figure 16a,b that optimal operation of adiabatic CAES can significantly enhance the system’s performance in such a way that the operation cost of the system decreases due to lower purchase of electrical power. Although the HP provides most heat loads in the network, the thermal energy stored in TES during energy charging can be directly used to supply heat power for heat demand to save cost, such as at 07:00. Figure 16c indicates the HP and adiabatic CAES output power. The heat load pattern shows that the heat consumption is higher at night (01:00-07:00, 16:00-24:00) and decreases during day hours. As a result, heat pump generation increases during night hours in response to heat load consumption. Figure 16d shows the power purchased from the upstream grid and wind curtailment. It is clear that no wind curtailment has occurred. This could be due to the optimal operation of the microenergy grid and adiabatic CAES with TES. Moreover, it can be observed that grid-purchased power increases during the lower output of the WT systems and high load demand consumption. Therefore, WT generation has an important role in the system’s power provision.

The optimal temperature distribution of the district heat network of the designed microenergy grid at the peak heat load hour (6:00) and off-peak heat load hour (19:00) is indicated in Figure 16e. As it is evident, different heat loads at the off-peak period (6:00) and peak hour (19:00) are provided by adjusting the return water temperature. Under the same conditions for the supply water temperature, larger heat power can be met if the return water is smaller. In addition, the temperature of the outlet of supply and return water system is typically lower than that of the inlet of supply and return water system, which is similar to common sense. Figure 16f shows that the reactive power balance is maintained in the boundaries by adjusting the OLTCs and shunt reactors/capacitors at off-peak and peak periods. The operation cost of the microenergy grid is achieved at 13702 US$, including 9478.2 US$ for power network and 4223.6 US$ for heat district network.

### 3.2.2 Scenario 2

In this scenario, the optimization of the microenergy grid is performed using level 1 predicted data. Day-ahead operation results are indicated in Figure 17. It can be seen from Figure 17a that inaccuracies in prediction violate adiabatic CAES operation from its real operation. We can see that adiabatic CAES is charged in off-peak hours. This is mainly due to the abundant generation of WT units, which results from deviation in wind speed prediction (Figure 15).
More specifically, the adiabatic CAES stores the surplus generation of WT unit discharges at specific hours of the day. According to Figure 17a,b, major power discharges occurred primarily during peak hours (19:00 and 21:00). Storing surplus generation of WT system in the adiabatic CAES with TES prevents wastage of produced electricity, which can be used for supplying electrical and heat power demand. In a different result from Scenario 1, Figure 17c shows that purchasing power from the upstream grid is significantly decreased during the operation day. One of the reasons could be inaccuracies in predicting WT output power showing higher power generation from the actual values. In addition, deviations in the predicted load demand also affected the results because consumption values are forecasted to be lower than the actual data. Since similar head demand is considered for both scenarios, the performance of HP has not significantly changed. However, thermal energy stored in TES is used to supply heat power for heat load in three hours, as depicted in Figure 17d. In addition, almost similar results are achieved for temperature
according to Figure 17e because the focus of this study was mainly on RES output power and electric load data than heat load. Figure 17f also shows that the reactive power is maintained in peak periods.

The total operation cost of the microenergy grid is achieved 5119.1 US$. In addition, operation costs of the power network and heat district network are obtained as 849.143 US$ and 4269.9 US$, respectively. The reason for such a reduction in the total operation cost of the microenergy grid is the deviation in the forecasting of load and WT output data. In fact, the main difference is in the power network operation cost. It is significantly lower than the operation cost of the first scenario. In the second scenario, the WT units had abundant power generation. This led to a reduction in purchasing power from the upstream grid and decreased total operation cost. Therefore, the accuracy of operation cost is highly dependent on the prediction results of uncertain parameters.

3.2.3 | Scenario 3

In previous Scenario 2, it was observed that operational decisions of the microenergy grid components and operation cost are highly related to the prediction accuracy of
uncertain parameters. In this scenario, the level 2 corrective actions are applied to the level 1 prediction results. Level 1 forecasting is a conventional time-series prediction using the MLP-ANN algorithm.

The optimization results of the understudy system are depicted in Figure 18. According to Figure 18a,b, a more accurate charging and discharging strategy can be seen in this scenario. The TES and molecular tanks are mostly charged during off-peak hours while they are discharged in peak hours. Power purchasing from the upstream grid is also increased in this scenario due to the deficiency of WT power generation. This is in line with the charging/discharging results obtained using the actual data in Scenario 1. It is imperative to note that the desired prediction accuracy (error threshold) plays a crucial role in final results. It can be seen that no correction is performed on wind speed data between 1:00 and 6:00 because the accuracy threshold has not been violated (2 m/s) in that period. This is the main reason for observing similar operational behaviors for the adiabatic CAES and power purchased from the upstream grid.

All in all, the values of uncertain parameters had a considerable impact on the system’s operation, including adiabatic CAES with TES. The HP output power, as well as heat power output of adiabatic CAES, is shown in Figure 18c. As previously mentioned, heat consumption is greater in night hours, and it decreases during day hours. As a result, HP generation is raised during night hours in response to the heat load consumptions. Figure 18d illustrates the power purchased from the upstream grid and wind curtailment. Similar to the scenarios with actual data, no wind curtailment has occurred in this scenario. The optimal operation of the microenergy grid and adiabatic CAES with TES are two main reasons for such performance.

The HP and the temperature had similar results to the first scenario, the study’s base case. According to Figure 18f, the reactive power is maintained balance in peak hours. The operation cost of the whole system is obtained at 11891 US$. The power network operation cost is achieved at 7671.7 US$, and the heat district network is obtained at 4219.7 US$. It could be seen that more realistic results of power network operation cost are achieved by using level 2 forecasting data. As a result, it can be concluded that the overall results of Scenario 3 are more like the base case; hence, the suggested method for predicting uncertain parameters was effective.

### 3.2.4 | Scenario 4

In this scenario, the impacts of the adiabatic CAES with TES on the operation cost of the system have been studied. To do this, previous scenarios are conducted under the assumption that the adiabatic CAES with TES is unavailable. It could be inferred that there is no energy storage in the structure of the system. To save the space, only the operation costs of the previous scenarios are analyzed here. Table 2 shows the detailed operation costs of the microenergy grid, including power network cost and heat district cost. It can be seen that the operating costs are increased by neglecting the utilization of adiabatic CAES with TES in the system’s structure. The actual operation cost of the power network is increased by 3340.8 US$. As a result, the total operation cost of the microenergy grid is faced with a growth of 3423 US$. Another significant result is the impact of adiabatic CAES with TES on the heat district network’s operation cost. As it is evident, the optimal operation of the TES led to saving costs. However, when the adiabatic CAES with TES is neglected, the operation cost increases and does not change under different uncertainties. In addition, more accurate results are achieved.
using the 2-level corrective forecasting method even if adiabatic CAES with TES is neglected in the microenergy grid structure. However, the impacts of uncertainties are decreased by ignoring the storage unit in the system structure. For instance, the operation cost of the power network is significantly reduced by using adiabatic CAES with TES. It can be conceived that forecasting accuracy would be more important by using hybrid
storage units such as adiabatic CAES with TES because inaccuracies in prediction can deviate charging/discharging strategies and, finally, the operation costs of the system.

4 | CONCLUSIONS

In this paper, a dispatch problem of microenergy grid including integrated energy systems is proposed...
considering the uncertainties of variable parameters. Special attention has been paid to the adiabatic CAES with TES, which could be regarded as hybrid energy storage (heat and power) with no emission production. The purpose of using adiabatic CAES with TES was to reduce power purchasing from the...
grid and WT power curtailments. Since uncertain parameters such as active-reactive load and renewable output have a significant impact on operational behaviors of the power grids, this paper applied an efficient 2-level corrective forecasting method to deal with the uncertainties of load and wind speed data. The following results have been achieved in this paper.

Time-series prediction using the MLP-ANN algorithm could be beneficial for datasets with particular daily patterns such as active and reactive load data with RMSE values of 0.2503 and 0.2668, respectively. The RMSE values for such parameters indicate an adequate level of prediction accuracy. However, for high intermittence parameters such as wind speed, time-series prediction data would not lead to desirable results. As indicated in the paper, performing corrective actions on uncertain parameters can significantly improve the forecasting accuracy of the varying parameters.

Optimization results showed that inaccuracies in prediction significantly affect operational behaviors of the microenergy grid, including charging and discharging power of adiabatic CAES with TES, hourly purchased power from the grid, and WT curtailed power. Operation cost is achieved 5119.1 US$. However, more realistic results are achieved when the proposed corrective level 2 forecasting method is employed, such as optimal charging and discharging of adiabatic CAES with TES and power purchased from the upstream grid. In this condition, the operation cost is achieved 11891 US$, which is much closer to its actual value $13702 US$. Comparing the optimization results for cases with and without adiabatic CAES with TES shows the impact of such hybrid energy storage in the operation of the microenergy grid. It was shown that neglecting adiabatic CAES can increase the operation cost of the system by more than 3400 US$. Furthermore, the effects of uncertainties are more significant when using adiabatic CAES because any inaccuracies in the prediction of such parameters lead to violation of operational behaviors of adiabatic CAES with TES.

### Table 2 Summary of the operation costs of the understudy system

| Scenario | $\mathcal{C}_{\text{power}}$ | Err. $\mathcal{C}_{\text{power}}$ | $\mathcal{C}_{\text{heat}}$ | Err. $\mathcal{C}_{\text{heat}}$ | $\mathcal{C}_{\text{total}}$ | Error |
|----------|------------------|-----------------|-----------------|-----------------|------------------|-------|
| Scenario 1 | 9478.2 | Base | 4223.6 | Base | 13702 | Base |
| Scenario 2 | 849.143 | 88.88% | 4269.9 | 4.54% | 5119.1 | 57.13% |
| Scenario 3 | 7671.7 | 19.05% | 4219.7 | 2.94% | 11891 | 13.21% |
| Scenario 4 | 12819 | Base | 4305.7 | Base | 17125 | Base |
| Scenario 5 | 11747 | 8.36% | 4305.7 | 0% | 16053 | 6.25% |
| Scenario 6 | 12583 | 1.84% | 4305.7 | 0% | 16889 | 1.37% |

### Nomenclature

- $b_{ij,t}$, $b_{ij,n_t}$: Binary variable where $\sum_{k=1}^{n_t} b_{ij,k,t} = 1$
- $C_{\text{elec}}$: Electricity price
- $C_{j,t}$: Value of shunt capacitors/reactors
- $C_a$: Constant pressure-specific heat of air
- $c_w$: Recycle water constant pressure-specific heat
- $C_{j,\text{up}}, C_{j,\text{low}}$: Upper and lower bound of shunt capacitors/reactors
- $f(i), k(i)$: Set of pipes with node $i$ as from/to node
- $E_D$: Set of buses for shunt reactors/capacitors
- $g_{i,j}$: Binary variables
- $H_{\text{st}}$: The heat of heat regeneration system
- $H_{\text{st},\text{up}}, H_{\text{st},\text{up}}$: Lower and upper limits of heat can be stored in the heat regeneration system
- $h_{i,j,k,t}$: Dummy variable
- $h_{c,i}$: Collected heat by the cooler
- $h_{c,i}$: Consumed heat by the heater
- $i_{\text{up}}$: Upper bound of current through line $l(i,j)$
- $i_{l,j}$: Square of current through line $l(i,j)$
- $K_{i,j,t}$: Tap ratio of OLTC on line $l(i,j)$
- $L_b$: Length of pipe $b$
- $m_{\text{up}}^{\text{water}}$: Upper limit of recycle water mass flow rate through pipe $b$
- $m_{\text{up}}^{\text{water}}, m_{\text{up}}^{\text{water}}$: Recycle water mass flow rate of heat load unit and heat generation at node $i$
- $m_{\text{up}}^{\text{water}}, m_{\text{up}}^{\text{water}}$: Recycle water mass flow rate of return and supply water system of pipe $b$
- $M$: A big number
- $n_{\text{hp}}$: Number of equipped heat pumps (HP)
- $P_s$: Power bought from grid
- $P_{l,j}^{\text{Q}}, P_{l,j}^{\text{Q}}$: Active and reactive power flow of line $l(i,j)$
- $P_{l,j}^{\text{Q}}, P_{l,j}^{\text{Q}}$: Active and reactive power production of generation unit at bus $j$
- $P_{l,j}^{\text{Q}}, P_{l,j}^{\text{Q}}$: Active power and reactive power demand at bus $j$
- $P_{l,j}^{\text{Q}}, P_{l,j}^{\text{Q}}$: Lower and upper limits of active power output of generation unit
- $P_{\text{WT}, \text{up}}, P_{\text{WT}, \text{up}}$: Power output of wind turbine (WT) system and adiabatic CAES hub equipped at bus $j$
Nominal WT system output power $P_{WT,\text{rated}}$

Power output of adiabatic CAES hub at bus $j$ $P_{\text{CAES}}^{j,t}$

Power demand of adiabatic CAES hub $P_{\text{demand}}^{j,t}$

Heat load demand $P_{\text{hd}}^{j,t}$

Power demand of HP in district power network $P_{\text{HP}}^{j,t}$

Pressure of return and supply water at node $i$ $P_{\text{p}}^{i,t}$

Power demand of circulating water pump at node $i$ $P_{\text{p}}^{i,t}$

Lower and upper limits of power used for circulating water pump utilized at node $i$ $P_{\text{p},\text{low}}^{i,t}, P_{\text{p},\text{up}}^{i,t}$

Power demand of compressor and turbine $P_{\text{c}}^{\text{tur},i}, P_{\text{t}}^{\text{tur},i}$

Lower and upper limits of power demand of compressor $P_{\text{c},\text{low}}^{\text{tur},i}, P_{\text{c},\text{up}}^{\text{tur},i}$

Lower and upper limits of power consumption of HP equipped at node $i$ $P_{\text{p},\text{low}}^{\text{tur},i}, P_{\text{p},\text{up}}^{\text{tur},i}$

Outlet and inlet air pressure of the compressor $P_{\text{tur},\text{out}}^{i,t}, P_{\text{tur},\text{in}}^{i,t}$

Outlet and inlet air pressure of the turbine $P_{\text{t},\text{out}}^{i,t}, P_{\text{t},\text{in}}^{i,t}$

Pressure of air storage tank $P_{\text{st}}^{i,t}$

Lower and upper limits of the pressure of air storage tank $Q_{\text{st},\text{low}}^{i,t}, Q_{\text{st},\text{up}}^{i,t}$

Supplemented reactive power of continuous compensator $q_{\text{m}}^{\text{c}}, q_{\text{m}}^{\text{tur}}$

Mass flow rate of air of compressor and turbine $\dot{m}_{\text{t}}^{\text{c}}, \dot{m}_{\text{t}}^{\text{tur}}$

Gas constant $R_{\text{g}}$

Resistance, reactance, and impedance of line $l(i,j)$ $r_{ij}, x_{ij}, z_{ij}$

Step size of shunt reactors/capacitors $s_{j}$

Voltage amplitude of bus $i$ $U_{i}$

Binary variable that is equal to 1 if compressor and turbine are working $u_{i}^{\text{c}}, u_{i}^{\text{t}}$

Volume of air storage tank $V_{\text{st}}$

Voltage of slack bus $V_{\text{f}}$

Integer variable $v_{i}$

Wind speed at time $t$ $v_{t}$

Cut-in and cut-out wind speed $v_{c,\text{in}}, v_{c,\text{out}}$

Rated wind speed $v_{r}$

Outlet temperature of pipe $b$ of return and supply system $\theta_{b,\text{out}}^{\text{p},i,t}$

Outlet temperature of pipe $b$ of return and supply system $\theta_{b,\text{in}}^{\text{p},i,t}$

Inlet temperature of pipe $b$ of return and supply system $\theta_{b,\text{in}}^{\text{r},i,t}$

Ambient temperature $\theta_{b}$

Pressure loss coefficient of pipe $b$ $\mu_{b}$

Temperature loss coefficient of pipe $b$ $\lambda_{b}$

Accuracy threshold $\varphi$

Forecasted data $\psi_{\text{f}}$

Measured data $\psi_{\text{m}}$

The difference between the measured and forecasted load data $\Delta \psi_{\text{f}}$

Adiabatic efficiency of compressor and turbine $\eta_{\text{c}}, \eta_{\text{t}}$

Inlet temperature of compressor and turbine $T_{\text{tur},\text{in}}^{i,t}, T_{\text{tur},\text{in}}^{i,t}$

Outlet temperature of compressor and turbine $T_{\text{tur},\text{out}}^{i,t}, T_{\text{tur},\text{out}}^{i,t}$

Temperature of air storage tank $T_{\text{st}}^{i,t}$

Adiabatic exponent of air $k_{c}$

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