

State Estimation Approach for Combined Heat and Electric Networks

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Abstract—State estimation (SE) is essential for combined heat and electric networks (CHENs) to provide a global and self-consistent solution for multi-energy flow analysis. This paper proposes an SE approach for CHEN based on steady models of electric networks (ENs) and district heating networks (DHNs). A range of coupling components are considered. The performance of the proposed estimator is evaluated using Monte Carlo simulations and case studies. Results show that a relationship between the measurements from ENs and DHNs can improve the estimation accuracy for the entire network by using the combined SE model, especially when ENs and DHNs are strongly coupled. The coupling constraints could also provide extra redundancy to detect bad data in the boundary injection measurements of both networks. An analysis of computation time shows that the proposed method is suitable for online applications

Index Terms—Bad data identification, combined heat and electric networks, coupling component, state estimation, steady model.

NOMENCLATURE

A. Indices and Parameters

A	Node-branch incidence matrix.
B	Loop-branch incidence matrix.
Υ	Latent heat of vaporisation of water (kJ/kg).
η	Efficiency of a circulation pump.
K	Resistance coefficient of each pipe.
g	Acceleration due to gravity (kg m/s ²).
λ	Overall heat transfer coefficient per unit length (W/(m K)).
C_p	Specific heat of water (J/(kg K)).
L	Pipe length (m).
T_a	Ambient temperature (°C).
k	Heat to power ratio.
Z	Z ratio that describes the trade-off between heat supplied to site and electrical power.
P^{Con}	Electrical power generation of the extraction unit in full condensing mode (MW).

COP	Coefficient of performance of heat pump.
z	Measurement vector.
x	State variable vector.
r	Residual vector.
ε	Gaussian noise vector.
$\hat{x}$	Estimated value of state variable.
ω	Lagrange multiplier.
σ	Standard deviation of measurement noise.
r_N	Normalized residual.
F/C	Jacobian matrix of measurement function /constraints.
W	Weight matrix.
R	Sensitivity matrix of residual.

B. Variables

$m^{\text{PI}}/m^{\text{CP}}$	Mass flow rate within a pipe/circulation pump (kg/s).
m^{q}	Mass flow rate injected to the node (kg/s).
$m_{\text{in}}/m_{\text{out}}$	Mass flow rate coming into/leaving the node (kg/s).
h	Head pressure loss (m).
$H_{\text{start}}^{\text{PI}}/H_{\text{end}}^{\text{PI}}$	Head pressure at the start/end of the pipe (m).
$H_{\text{in}}^{\text{CP}}/H_{\text{out}}^{\text{CP}}$	Head pressure of water flowing into/out of a circulation pump (m).
$H^{\text{s}}/H^{\text{r}}$	Head pressure at each node of supply/return network (m).
$T_{\text{start}}/T_{\text{end}}$	Temperature at the start/end of the pipe (°C).
$T_{\text{in}}/T_{\text{out}}$	Temperature before/after mixture at the node (°C).
$T^{\text{s}}/T^{\text{r}}$	Mixture temperature at each node of supply/return network (°C).
$\Phi^{\text{S}}/\Phi^{\text{L}}$	Heat power generated by heat source/consumed by heat load (MW).
$\Phi^{\text{CHP}}/\Phi^{\text{HP}}$	Heat power generated by a CHP unit/heat pump (MW).
V^{bus}	Bus voltage magnitude (V).
θ^{bus}	Bus voltage angle (rad).
$P^{\text{bf}}/P^{\text{bt}}$	Active power at the start/end of a line (MW).
$Q^{\text{bf}}/Q^{\text{bt}}$	Reactive power at the start/end of a line (MVar).
P^{inj}	Active power injected to a bus (MW).
Q^{inj}	Reactive power injected to a bus (MVar).
P^{CHP}	Active power generated by a CHP unit (MW).
$P^{\text{HP}}/P^{\text{CP}}$	Active power consumed by a heat pump /circulation pump (MW).

Manuscript received December 26, 2019; revised March 29, 2020; accepted May 20, 2020. Date of online publication April 6, 2020; date of current version September 2, 2020. This work was supported in part by the National Natural Science Foundation of China (61733010), and the China Postdoctoral Science Foundation (2019M650675).

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DOI: 10.17775/CSEEJPES.2019.03440

I. INTRODUCTION

RAPID development of integrated energy systems (IESs) has been seen in recent years as a response to the challenges of renewable energy integration and energy efficiency improvement [1]–[7]. One of the characteristics of IES is the integration of isolated systems, such as electricity, district heating, cooling, or natural gas systems. Among these systems, the district heating network (DHN) has proven to be very promising for energy-saving and carbon emission reduction.

DHN was pioneered in many European countries [8], [9] and has been rapidly developed worldwide for heat energy supply. In a DHN, heat power is delivered from the heat source and transferred by hot water or steam through pipelines to the consumers. Various energy sources could be utilized to generate heat power for a DHN, such as fossil fuel, complementary energy, renewable energy, and combined heat and power (CHP) units. The modeling and optimization of DHNs have been studied [10]–[13]. With additional coupling components, such as CHP, circulation pumps, and heat pumps (HPs), integrated into the combined heat and electric networks (CHENs), the electric network (EN) and DHN can interact with each other. Pan *et al.* studied the interaction mechanism of CHENs based on quasi-steady energy flow, in which the time-scale characteristics of different networks were considered [14]. Li *et al.* modeled the thermal inertia of district heating pipelines as storage for day ahead economic dispatch [15] and unit commitment [16]. The flexibility of a CHEN means that it can help to provide capacity alongside wind power consumption. Additionally, a DHN could also provide an extra security margin for the electric power system as an equivalent power source [17]. As the coupling between an EN and DHN becomes tighter, conventional analytical methods, namely, isolated methods, are no longer suitable for CHENs. Many studies have focused on planning, optimising and assessing CHENs. For example, Liu *et al.* studied the model and power flow analysis for a CHEN [17]. In addition, Pan *et al.* considered the building thermal inertia in a DHN when participating in combined economic dispatches [18], [19]. Deng *et al.* also proposed a new multiple-energy-coupling pricing mechanism for a CHEN [20].

In a CHEN, real-time operating data of the combined network are gathered via a supervisory control and data acquisition (SCADA) system, which provides the possibility for online assessment, dispatch, and control. However, any form of the advanced application for a CHEN necessitates reliable information about the present state of the system. In reality, the measurements available are limited, especially in a DHN [21]. Only a few telemetered values of pressures, temperatures and mass flow at the supply or consumer nodes are available, which hardly provide a complete picture of the system state. Moreover, the sensor network occasionally generates bad data in the monitoring process for several reasons, such as failure of a meter, time skew or communication noise. This bad data, if not eliminated, will cause a gross error in real-time assessment and control [22]–[24].

State estimation (SE) is widely utilized in electric networks when estimating and forecasting system operating conditions

with real-time redundant measurements. In the energy management system (EMS), SE serves as the basic function of other applications for providing a global and self-consistent solution for power flow. In [22], methods of SE for an isolated EN are summarized. Present SE methods for ENs perform well enough in computation speed and identification of bad data [22]–[27]. Regarding SE methods for a DHN, some researchers have studied estimation regimes for water distribution systems, such as the nodal pressure method proposed by Bargiela [28], Sterling *et al.* [29] and Preis *et al.* [30], or the loop flow method proposed by Arsene *et al.* [31]. In these methods, only the hydraulic model was considered. However, unlike water supply networks, heat transfer in a DHN is a combined hydraulic and thermal process; thus, the thermal flow in the pipeline and distribution of nodal temperature must be taken into account. Fang *et al.* proposed an estimation approach for a DHN based on customer data [21]; however, the pressure loss along the pipeline was not considered in the model.

The estimation methods for a EN and DHN use limited measurements from single energy systems and could not be used to obtain a globally consistent power flow solution for a CHEN as the coupling components are not considered. The large mismatch at the boundary states of related systems may cause convergence problems during real-time optimization, or wrong decisions could be made by the online control module. Dong *et al.* first studied the issue of estimating the states of a CHEN, and proposed a combined steady SE method for a CHEN [32], which utilized the measurements from both a EN and DHN. Their results showed that the combined SE method, when compared with isolated methods, had the advantages of improving estimation accuracy and reducing the quantity of boundary mismatches. In [33] and [34], two novel SE approaches are proposed respectively with the dynamics in pipelines also being considered. In [35], a framework is proposed to solve the state estimation model in a decentralized approach.

Though dynamics in pipelines are considered in some studies, in real applications, the DHN is only adjusted in some periods but stays in steady state for most of the time. Thus, it is still important to propose a practical steady-state SE approach. The foundation of the previously reported method involved utilizing a simplified thermal model that ignored the relationship of different nodal temperatures. In this paper, we expand the SE method for a CHEN on the basis of [32]. The major contributions include:

- 1) A generalized node-branch model of the DHN is proposed, based on which the steady-state hydraulic model and thermal model of the DHN are established.
- 2) Key techniques of the SE approach for a CHEN are developed, in which multiple coupling components were taken into account including CHP units, heat pumps and circulation pumps.

The remainder of this paper is organized as follows: Section II introduces the steady-state model of the DHN. Section III describes key techniques of modeling and solving the combined SE problem. Section IV presents the results of a numerical simulation and case study. Section V presents the

conclusions and directions for future study.

II. MODEL OF DISTRICT HEATING NETWORKS

The district heating network (DHN) consists of a number of components, such as pipes, heat sources and heat consumers. The heat source can be a heating station that delivers heat in the form of hot water or steam. The heat consumer can be a heat exchange station that connected the primary network and secondary network, or a radiator to deliver heat at the terminal of a DHN. When analyzing a DHN, the entire network is usually separated into a hydraulic model, and a thermal model. The following assumptions are made when establishing the model of a DHN:

- 1) The fluid flow is one-dimensional, incompressible and fully developed. The flow is represented with the lumped mass model, which means the network hydraulic is in a static condition at each observation.
- 2) The variation of the supply temperature at each heat source is negligible during the entire heating season. The heat storage of the fluid and pipe is not considered, which means the heat power supply is nearly equal to the summation of heat power consumption and heat loss from all parts of the DHN.
- 3) The material properties of the fluid and fittings in the DHN are constant in time and uniform in space and temperature independent.

A. Generalized Node-branch Model of a DHN

A diagram of a typical DHN is shown in Fig. 1. A real DHN is a dual pipe system, containing the supply network and return network. Each network consists of pipelines and their junctions, expressed as lines and dots with different color in Fig. 1. Heat sources and consumers are boundary areas of the DHN which link the supply and return networks. In this paper, a generalized node-branch model of a DHN is established. In this model, a pipeline located in the supply or return network is modeled as a “common branch”; a heat source (together with the circulation pump) or a heat consumer at the boundary is modeled as a “special branch”. Each branch is a dual port component connecting two different nodes of the network. The

rated positive direction of the heat source is from the return network to the supply network, whereas the heat consumer is the opposite.

In the generalized node-branch model, the entire DHN becomes a closed loop network, which is represented with a set of nodes and branches. As illustrated in Fig. 2, the nodes in the supply network (red dots) are numbered first and then those in the return network (blue dots). Similarly, the common branches in the supply network are first numbered (red lines), then those in the return network (blue lines), and finally the special branches (black dash lines). Obviously, this model is applicative for a DHN with either symmetrical or dissymmetrical topology.

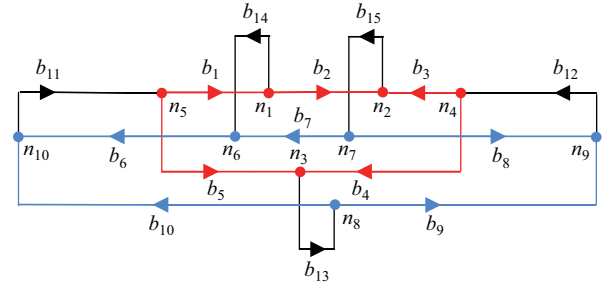


Fig. 2. The generalized node-branch model of the DHN illustrated in Fig. 1 containing special branches (black dash lines).

To describe the topology of the DHN, the following matrices are introduced:

- 1) The node-branch incidence matrix $\mathbf{A}$, which describes the relationships between nodes and branches in the generalized node-branch model of a DHN.
- 2) The positive node-branch incidence matrix $\mathbf{A}_f$, defined as $\mathbf{A}_f := \{\mathbf{A}|A_{ij} > 0\}$, which describes the relationships between nodes and the branches leaving the nodes.
- 3) The negative node-branch incidence matrix $\mathbf{A}_t$, defined as $\mathbf{A}_t := \{-\mathbf{A}|A_{ij} < 0\}$, which describes the relationships between nodes and the branches coming to the nodes.

The incidence matrices of the DHN illustrated in Fig. 2 is given in Appendix A. In the following 2 sections, the hydraulic model (Sec. 2.2) and thermal model (Sec. 2.3) of a DHN are introduced using the generalized node-branch model.

B. Hydraulic Model

The hydraulic model describes the relationship between the mass flow rate in each branch and head pressure at each node, which is represented by the flow continuity equation and head loss equation (1) is the matrix form of the flow continuity equation, which states the conservation of mass at each node of the network.

$$\mathbf{A}\mathbf{m}_b = 0 \quad (1)$$

where $\mathbf{A}$ is the node-branch incidence matrix; $\mathbf{m}_b$ is the vector of mass flow rate in each branch (kg/s). Considering common branches and special branches, $\mathbf{m}_b$ can be expressed as:

$$\mathbf{m}_b = \begin{bmatrix} \mathbf{m}_b^p \\ \mathbf{m}_b^{sp} \end{bmatrix} \quad (2)$$

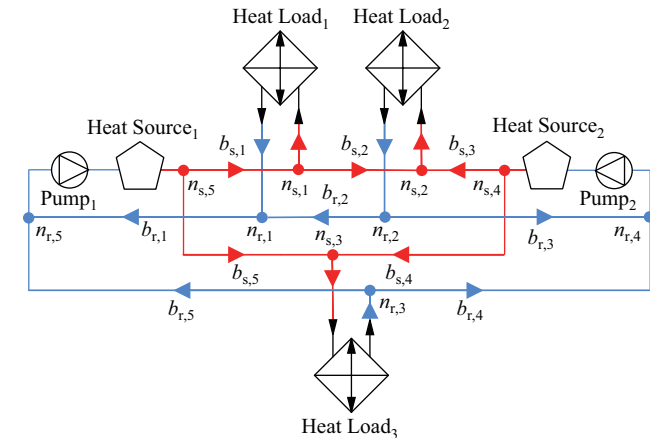


Fig. 1. The simple symmetrical DHN containing supply network (red dots and lines), return network (blue dots and lines) and boundary areas (heat sources and consumers).

where $\mathbf{m}_b^p$ is the vector of mass flow rate in each common branch (kg/s), and $\mathbf{m}_b^{sp}$ is the vector of mass flow rate in each special branch (kg/s).

The head loss equation is represented as the difference of the nodal head pressure of each branch, which is expressed in (3) with the matrix form.

$$\mathbf{A}^T \mathbf{H}_n = \Delta \mathbf{H}_b - \mathbf{H}_p \quad (3)$$

where $\mathbf{H}_n$ is the vector of nodal head pressure (m); $\mathbf{A}^T$ is the transpose of matrix $\mathbf{A}$; $\Delta \mathbf{H}_b$ is the vector of head loss of each branch (m); $\mathbf{H}_p$ is the vector of head supply of each branch (m).

The head loss of each branch in $\Delta \mathbf{H}_b$ is caused by the friction of the pipe when fluid is flowing through it. The relationship between the head loss and the mass flow is described with the well-known Darcy-Weisbach formula [36]. In this paper, a deformation of the formula is used, which is introduced in [16] and expressed as:

$$\Delta \mathbf{H}_b = K_b \cdot \mathbf{m}_b \cdot |\mathbf{m}_b| \quad (4)$$

where K_b is the resistance coefficient of the branch. The method of calculating K_b is introduced in [16].

The head supply of each branch in $\mathbf{H}_p$ is provided by circulation pumps. A circulation pump is usually adjacent to a heat source, and modeled as the special branch jointly with the relative heat source. As for a common branch without a circulation pump, $H_p = 0$.

C. Thermal Model

The thermal model is used to describe the temperature distribution at each node. To clearly introduce the thermal model, the following notations are made first.

1) The temperature at each node is denoted as T_n , which is defined as the temperature of water after full mixing at each node.

2) According to the flow direction of a branch, the temperature at the start of a branch is denoted as T_{bf} , and the temperature at the end is denoted as T_{bt} .

The temperature at the start of each branch leaving the node is equal to the nodal temperature after mixture. By using the positive node-branch incidence matrix, the relationship between nodal temperature and start temperature of each branch could be expressed as follows:

$$\mathbf{T}_{bf} = \mathbf{A}_f^T \mathbf{T}_n \quad (5)$$

where $\mathbf{T}_n$, $\mathbf{T}_{bf}$ are the vector form of T_n and T_{bf} ($^{\circ}\text{C}$).

Equation (6) shows the nodal temperature mixture equation, which presents the ideal water mixture process and reflects the conservation of heat energy.

$$\left(\sum m_{out} \right) T_n = \sum (m_{in} T_{in}) \quad (6)$$

where m_{out} represents the mass flow rate of the pipe that leaves the node (kg/s); m_{in} represents the mass flow rate of the pipe that comes to the node (kg/s); T_{in} is the temperature of mass flow before mixture ($^{\circ}\text{C}$).

By replacing T_{in} with T_{bt} , the matrix form of (6) is expressed as:

$$\text{diag}(\mathbf{A}_f \mathbf{m}_b) \mathbf{T}_n = \mathbf{A}_t \text{diag}(\mathbf{m}_b) \mathbf{T}_{bt} \quad (7)$$

where $\mathbf{T}_{bt}$ is the vector form of T_{bt} ($^{\circ}\text{C}$); $\mathbf{A}_f$ and $\mathbf{A}_t$ are the positive and negative node-branch incidence matrices defined in Sec. 2.1; $\text{diag}(\cdot)$ means the diagonal matrix of a vector.

Equation (8) is the matrix form of temperature drop equation of the pipeline, representing the heat loss along the pipe caused by heat transfer to the ambient surroundings.

$$\mathbf{T}_{bt}^p - T_a = (\mathbf{T}_{bf}^p - T_a) e^{-\lambda L / C_p \mathbf{m}_b^p} \quad (8)$$

where $\mathbf{T}_{bf}^p$, $\mathbf{T}_{bt}^p$ are the vector of temperature at the start/end of the pipeline ($^{\circ}\text{C}$); $\mathbf{m}_b^p$ is the vector of mass flow rate of each common branch (kg/s); T_a is the ambient temperature ($^{\circ}\text{C}$); λ is the overall heat transfer coefficient of the pipe per unit length (W/(m·K)); L is the length of the pipe; C_p is the specific heat of water (J/(kg·K)).

The heat power generated by a heat source or consumed by a heat load is calculated as:

$$\Phi = C_p \mathbf{m}_b^{sp} (\mathbf{T}_{bf}^{sp} - \mathbf{T}_{bt}^{sp}) \quad (9)$$

where Φ is the heat power (W); $\mathbf{m}_b^{sp}$ is the mass flow rate in the relative special branch (kg/s); $\mathbf{T}_{bf}^{sp}$, $\mathbf{T}_{bt}^{sp}$ is the vector of temperature at the inlet/outlet of the heat source of consumer ($^{\circ}\text{C}$). According to the rated positive direction of special branches defined in Sec. 2.1, the heat power of the heat consumer is positive, whereas it is negative for the heat source.

III. STATE ESTIMATION PROBLEM FORMULATION AND SOLUTION

Figure 3 shows the structure of a CHEN consisting of a 4-bus EN and a 10-node DHN. The EN includes 4 bus bars (denoted with bs). The DHN is a symmetrical network presented in Fig. 1, including 5 nodes in the supply network (represented in color red and denoted with n_1 – n_5) and 5 nodes

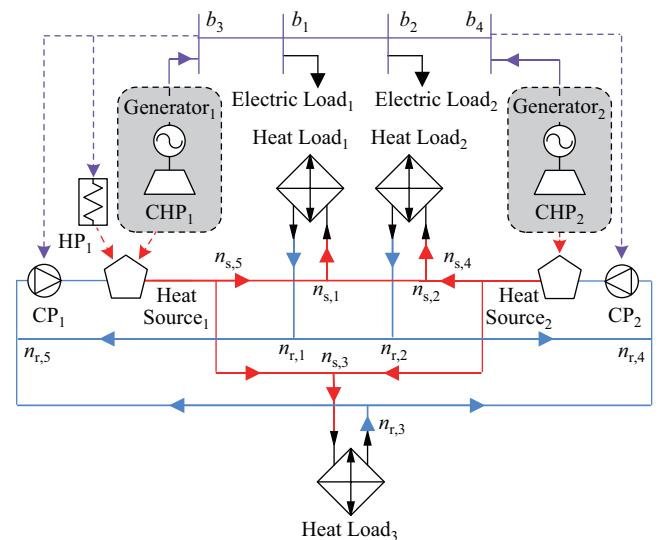


Fig. 3. The structure of a CHEN consisting of a 4-bus EN (purple lines), a 5-node DHN (red and blue lines), and coupling components.

in the return network (represented in color blue and denoted with n_6-n_{10}).

State estimation of the combined heating and electricity networks utilizes measurements from both the EN and DHN. The boundary states of the networks are coupled with the constraints of the coupling components.

A. Measurement Input and State Variables

The electricity network model, composed of buses and lines, is used for the electricity network in this paper. The most commonly used measurements in the electricity network include the magnitude of the voltage at each bus, namely, V_{bus} ; active power and reactive power at both ends of the line, specifically, $P_b = [P_{\text{bf}}, P_{\text{bt}}]^T$ and $Q_b = [Q_{\text{bf}}, Q_{\text{bt}}]^T$; and the electrical power injection at each bus, specifically, P_{inj} and Q_{inj} . The state variables are the magnitude and phase angle of the bus voltage, specifically, V_{bus} and θ_{bus} . Note that one of the voltage phases in θ_{bus} should be chosen as a reference phase angle. The measurement vector of the electricity network is represented in (10) and the state vector in (11):

$$z^e = [V_{\text{bus}}, P_{\text{bf}}, P_{\text{bt}}, P_{\text{inj}}, Q_{\text{bf}}, Q_{\text{bt}}, Q_{\text{inj}}]^T \quad (10)$$

$$x^e = [V_{\text{bus}}, \theta_{\text{bus}}]^T \quad (11)$$

As for a DHN, the measurements are usually located at the heat source or consumer nodes, as well as some important pipelines [21]. In this paper, the measurement allocation problem of a DHN is not discussed, thus we assume that the following four types of real-time measurements are available:

- 1) Head pressure at each node of the networks, including supply network and return network, denoted as H_n .
- 2) Temperature at each node of the networks, including supply network and return network, denoted as T_n .
- 3) Mass flow rate of each branch of the networks, including common branch and special branch, denoted as m_b .
- 4) Heat power generated by each heat source or consumed by each heat load, denoted as Φ .

In [29], the nodal head pressure and injected flow are selected as the state variables in the water distribution system. However, they are not sufficient for thermal calculations in the DHN as heat power transferred by mass cannot be determined by the nodal head pressure and the mass flow rate in the pipelines. In this paper, the head pressure of each node, and the temperature at the start and end of each branch are selected as state variables of the DHN, denoted as H_n , T_{bf} , and T_{bt} . The measurement vector and state vector of the DHN are represented in (12) and (13):

$$z^h = [H_n, T_n, m_b, \Phi]^T \quad (12)$$

$$x^h = [H_n, T_{\text{bf}}, T_{\text{bt}}]^T \quad (13)$$

B. Constraints of Coupling Components

The EN and DHN are combined with coupling components. In this paper, three types of coupling components are considered: the CHP unit, the heat pump (HP) and the circulation pump (CP), and are shown in Fig. 4.

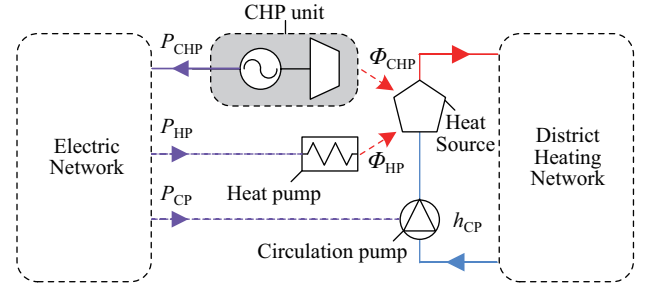


Fig. 4. Coupling components of the EN and DHN.

1) CHP Units

CHP units generate heat power and electrical power at the same time. Different types of CHP units are generalized as an electricity and heat interface with adjustable heat-to-power ratio [16]. Gas turbines and internal combustion reciprocating engines are modeled with (14), and extraction steam turbines are modeled in (15):

$$k = \Phi^{\text{CHP}} / P^{\text{CHP}} \quad (14)$$

$$Z = \frac{\Phi^{\text{CHP}} - 0}{P^{\text{Con}} - P^{\text{CHP}}} \quad (15)$$

where P^{CHP} , Φ^{CHP} are the electrical/heat power generation of the CHP unit; k is the heat to power ratio of the gas turbine or the internal combustion reciprocating engine; Z is the ratio that describes the trade-off between heat supplied to site and electrical power of the extraction steam turbine; P^{Con} is the electrical power generation of the extraction unit in full condensing mode (MW).

2) Heat Pumps

Heat pumps leverage heat from the surrounding ground or air and use electricity to provide heat power. Heat pumps are more energy-efficient than gas boilers, and can typically produce three units of heat for every unit of electricity [16]. The efficiency of a heat pump is described with the coefficient of performance (COP):

$$COP = - \frac{\Phi^{\text{HP}}}{P^{\text{HP}}} \quad (16)$$

where Φ^{HP} is the heat power generation of the heat pump (MW), and P^{HP} is the relative electrical power consumption (MW).

3) Circulation Pumps

A circulation pump consumes electrical power to supply the pressure difference for the DHN. The relationship between its pressure supply and electrical power consumption is shown as:

$$P^{\text{CP}} = \frac{m^{\text{CP}} g H^{\text{CP}}}{\eta} \quad (17)$$

where H^{CP} is the head pressure supplied by the circulation pump (m); m^{CP} is the mass flow rate within the pump (m); P^{CP} is the relative electrical power consumption of the pump (MW); η is the efficiency of the pump; $g = 9.8 \text{ (kg} \cdot \text{m/s}^2)$ is the acceleration of gravity.

C. Pseudo-Measurements

Pseudo-measurements are commonly used in state estima-

tion when it is difficult to get real measurements [37], [38]. This has two advantages: First, it enhances the observability of the system, as the pseudo-measurements take areas that are ignored in the real measurements into consideration. Second, it increases the measurement redundancy, which helps improve the accuracy in the state estimation, especially when the state estimation is under low or no redundancy. In this paper, two types of pseudo-measurements are introduced:

1) The heat power Φ^L consumed by a heat load, represented in (8) and (9), is obtained from a load prediction process using a historical load profile [39].

2) The total amount of electric power injected into one bus, including power generation and consumption, represented in (10) as P^{inj} , is formed as a pseudo-measurement and calculated as:

$$P_n^{\text{inj}} = \sum P_i, \quad P_i \in \text{bus } n \quad (18)$$

Similarly, the total amount of heat power, generated by different sources and injected into one node, represented in (12) as Φ^S , is also formed as a pseudo-measurement and calculated as:

$$\Phi_1^S = \sum \Phi_j, \quad \Phi_j \in \text{node} \quad (19)$$

For example, in Fig. 2, the coupling components CHP 1, heat pump 1 and circulation pump 1 are connected to bus 3 in the power network; and CHP 2 and circulation pump 2 are connected to bus 4. Therefore, the total amount of electric power injected to bus 3 or bus 4 is formed as a pseudo-measurement and represented as the sum of power generation from a CHP unit and the consumption from a heat pump and/or circulation pump, that is,

$$\begin{aligned} P_3^{\text{inj}} &= P_1^{\text{CHP}} + P_1^{\text{HP}} + P_1^{\text{CP}} \\ P_4^{\text{inj}} &= P_2^{\text{CHP}} + P_2^{\text{CP}} \end{aligned} \quad (20)$$

Similarly, the heat power injection of heat source 1 is expressed as the sum of heat power generated by CHP 1 and heat pump 1, that is,

$$\begin{aligned} \Phi_1^S &= \Phi_1^{\text{CHP}} + \Phi_1^{\text{HP}} \\ \Phi_2^S &= \Phi_2^{\text{CHP}} \end{aligned} \quad (21)$$

D. Per-unit Normalization

The per-unit normalization technique is applied in the combined estimation approach to avoid ill-conditioning of the gain matrix caused by discrepant orders of measurement weights [22]. In the electrical network calculation, the reference values have the following relationship:

$$V_B = Z_B I_B \quad (22)$$

$$S_B = V_B I_B \quad (23)$$

According to (4), (8) and (9), the reference values of the district heating network should have the following relationships:

$$H_B = K_B m_B^2 \quad (24)$$

$$\lambda_B L_B = C_{pB} m_B \quad (25)$$

$$\Phi_B = C_{pB} m_B T_B \quad (26)$$

The electricity network and district heating network are coupled with power. When analyzing the combined network, the reference values of electrical power and heat power should satisfy the following relationships:

$$S_B = \Phi_B \quad (27)$$

where V_B is the reference value of voltage; I_B is the reference value of current; Z_B is the reference value of impedance; S_B is the reference value of electrical power; H_B is the reference value of head pressure; m_B is the reference value of mass flow rate; K_B is the reference value of resistance coefficient of the pipe; T_B is the reference value of temperature; Φ_B is the reference value of heat power; λ_B is the reference value of heat transfer coefficient of the pipe; L_B is the reference value of the length of the pipe; and C_{pB} is the reference value of the specific heat of water.

E. Model and Solution of the Combined Estimation Approach

The measurements and state variables are related to the measurement function in (28). Usually, the error $\varepsilon \sim \mathcal{N}(0, \sigma)$ is assumed to be a Gaussian random vector.

$$z = f(x) + \varepsilon \quad (28)$$

In the combined estimation approach, the most probable state of the system is determined based on the quantities that are measured, together with the constraints of the coupling components. The combined state estimator is modeled with a constrained weighted-least-square (CWLS) method, and represented as the following optimization problem:

$$\begin{aligned} \min J(x) &= [z - f(x)]^T W [z - f(x)] \\ \text{s.t. } c(x) &= 0 \end{aligned} \quad (29)$$

where $z = [z^e, z^h]^T$ is the entire measurement vector; $x = [x^e, x^h]^T$ is the entire state vector; $f(\cdot)$ is the measurement function for the entire network; W is the weight matrix, which is a diagonal matrix formed with the weight of each measurement; $c(x) = 0$ represents the equality constraints in this model, including the three parts in (30).

$$c(x) = [c^e(x) \quad c^h(x) \quad c^c(x)] \quad (30)$$

where $c^e(x)$ represents the constraints of the electricity network; $c^h(x)$ represents the constraints of the district heating network; and $c^c(x)$ represents the coupling constraints of the combined network.

The Lagrange multipliers are employed to solve the optimization problem in (29) by forming the equivalent problem of minimizing

$$L(x, \omega) = J(x) + \omega^T c(x) \quad (31)$$

The minimizer $\hat{x}$ for the CWLS objective is obtained as the limit of a sequence of states $\{\hat{x}_i\}$ by means of a recursive scheme. The step is calculated with (32), and the detail of this method is introduced in [40].

$$\begin{bmatrix} F^T W F & C^T \\ C & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \omega \end{bmatrix} = \begin{bmatrix} F^T W \Delta z \\ -\Delta c \end{bmatrix} \quad (32)$$

F. Bad Data Detection and Identification

Bad data occasionally appears in the metering process. The combined estimator should be able to detect and eliminate bad data in the measurement vector to provide a dependable database for the operation and control of the integrated system. Conventional bad data identification methods include chi-square detection, weighted residual detection, normalized residual detection and other methods such as intelligent algorithms. In this paper, bad data is detected by the normalized residual detection method.

After the combined estimation, the absolute residuals of measurements are calculated as:

$$\mathbf{r} = \mathbf{z} - \mathbf{f}(\hat{\mathbf{x}}) \quad (33)$$

According to properties of measurement residuals [22], the absolute residuals are the linear combination of the error in different measurements, which is represented with (34) and (35) gives the function to calculate the sensitivity matrix, i.e. $\mathbf{R}$, between the absolute residual and the gross error. Then, the normalized residual of measurement is obtained with (36) and (37).

$$\mathbf{r} = \mathbf{R}\boldsymbol{\varepsilon} \quad (34)$$

$$\mathbf{R} = \mathbf{I} - \mathbf{F}(\mathbf{F}^T \mathbf{W} \mathbf{F})^{-1} \mathbf{F}^T \mathbf{W} \quad (35)$$

$$\mathbf{D} = \text{diag}[\mathbf{R}\mathbf{W}^{-1}] \quad (36)$$

$$\mathbf{r}_N = \sqrt{\mathbf{D}^{-1}} \mathbf{r} \quad (37)$$

In normalized residual detection, $r_{Ni} \sim \mathcal{N}(0, 1)$ is assumed to be normally distributed with a zero mean and variance 1. The measurement that gives the maximum absolute value of the normalized residual is compared with a given threshold γ

in (34).

$$\mathcal{I} = \arg \max_i \{r_{Ni} : \text{s.t. } r_{Ni} > \gamma\} \quad (38)$$

If the i th r_N is larger than γ , the relative measurement is determined as bad data, and eliminated from the measurement vector. After that, the combined estimation is re-conducted until there is no r_N larger than γ . γ is chosen as 2.81 or 3 depending on the confidence interval [22].

G. Framework of the Combined Estimation Approach

The framework of the proposed combined estimation approach is presented in Fig. 5. Main steps of the approach are introduced as follows:

Step 1: Input topology and parameters of the networks. The following parameters are needed:

- EN: impedance of each branch.
- DHN: K_b , T_a , λ , L , and C_p .
- Coupling components: k , Z , COP , and η .

Step 2: Input the real-time measurement data and the relative measurement weight.

Step 3: Conduct the per-unit normalization with already selected base values.

Step 4: Initialize all the state variables, and set the iteration index $i = 1$.

Step 5: Form the generalized node-branch model of DHN and the relative node-branch matrices $\mathbf{A}$, $\mathbf{A}_f$ and $\mathbf{A}_t$.

Step 6: Form the measurement function and constraints with the known parameters and matrices.

Step 7–8: Calculate the Jacobian matrices, then calculate the correction of state variables with (32).

Step 9: If the solution is convergence, i.e. $\max |\Delta x_i| < \delta$, where δ is the given convergence criterion, go to step 13 and

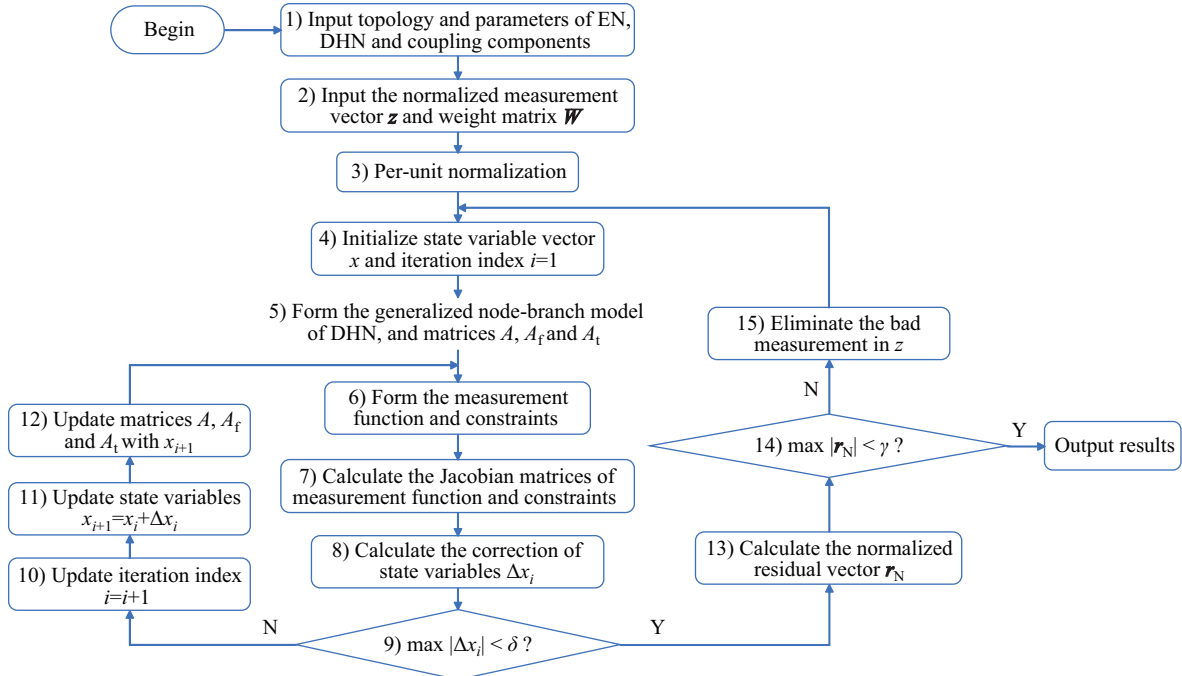


Fig. 5. The proposed combined estimation approach.

start the bad data identification process; otherwise, go to Step 10 and continue the iteration until convergence.

Step 10–12: Update state variables and update the node-branch matrices with newly estimated state variables in the DHN, then start a new iteration.

Step 13–15: Detect bad measurement data using the normalized residual detection method introduced in Sec. 3.5. If all the normalized residuals are within the given threshold, i.e. $\max |r_N| < \gamma$, output the results of the estimator; otherwise, eliminate the measurement with the largest normalized residual, and restart the estimation process from Step 4.

Note that the node-branch matrices of DHN, i.e. $\mathbf{A}$, $\mathbf{A}_f$ and $\mathbf{A}_t$, are updated in each iteration. Therefore, the proposed approach can handle the arbitrary flow direction of each branch in the DHN.

IV. NUMERICAL SIMULATION AND CASE STUDY

A. Test Set-up

The numerical simulation was carried out on a ThinkPad laptop with Intel Core i5-6200U CPU @2.40 GHz to demonstrate the advantages of the proposed CHENSE method. Two self-sufficient test systems, which means that they were isolated from external systems, were explored.

The first system is 4-bus and 5-node CHEN shown in Fig. 2, denoted as the 4B-5N system. In this system, two CHP units and a heat pump are considered as heat sources to connect to the electric and district heating networks, where: CHP 1 is a gas turbine unit, with $k_1 = 1.3$; and CHP 2 is a steam

extraction turbine unit, with $Z_2 = 10$ and $P^{\text{Con}} = 1.5$. The COP of the heat pump is 2.7.

The second system is the Barry Island system with 9 electric bus bars and 32 heating nodes shown in Fig. 6. Three CHP units interconnect the electric and district heating networks: CHP 1 is a gas turbine unit with $k_1 = 1.3$; CHP 2 is an extraction steam turbine unit with $Z_2 = 8.1$ and $P^{\text{Con}} = 0.6$; and CHP 3 is a reciprocating engine unit with $k_3 = 1/0.79$.

Both of the systems were introduced in detail elsewhere [17]. Brief information is provided in Table I.

TABLE I
BRIEF INFORMATION OF THE TEST SYSTEMS

System information	4B-5N System	Barry Island System
Bus No.	4	9
Line No.	3	8
Node No.	10	64
Pipe No.	10	64
CHP No.	2	3
HP No.	1	0
CP No.	2	3
State No. of EN	7	17
State No. of DHN	20	128
Meas. No. of EN	26	59
Meas. No. of DHN	42	240
Cons. No. of $c^e(\mathbf{x})$	0	0
Cons. No. of $c^h(\mathbf{x})$	0	16
Cons. No. of $c^B(\mathbf{x})$	5	6

Three methods were compared in the following analysis: 1) isolated SE for the EN and DHN without considering the constraints in (6) and (7), denoted as ISE; 2) the combined SE method proposed in [32], which did not consider the con-

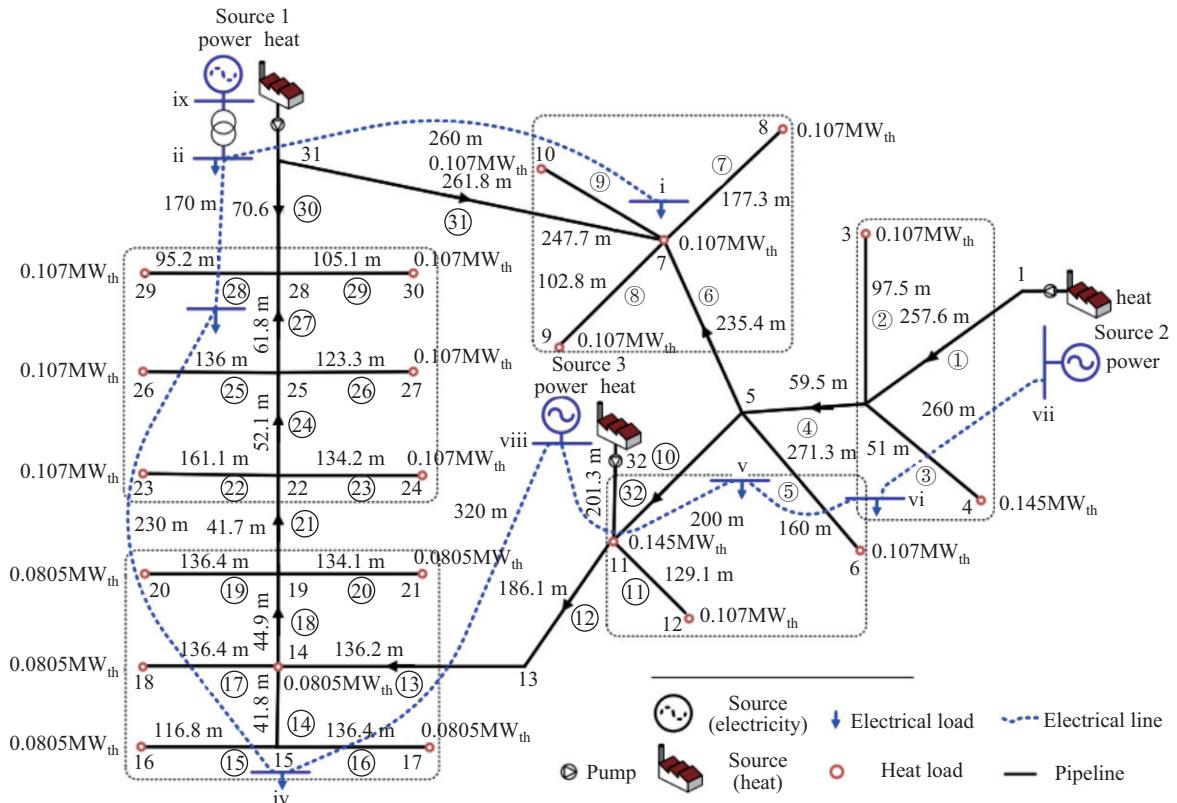


Fig. 6. The schematic diagram for the EN and DHN on the Barry Island system.

straints in (6) and (7), denoted as CSE; and 3) the combined SE method newly proposed in this paper, denoted as NCSE. Practical programs of the three methods were developed in MATLAB, and the bad data identification code was used in each program.

The results of the power flow calculated in [17] were assumed to be true values of the measurements and states. Full measurement sets of the EN and DHN were installed, and the deviations were σ^e and σ^h , respectively. The convergence criterion was set as $\max_i |\Delta x_i| \leq 0.0001$.

B. Monte Carlo Simulation

A Monte Carlo simulation was used to test the performance of the different state estimators for accuracy and computational time. The accuracy of the different estimators is evaluated with the following indexes:

$$S_M = \frac{1}{N} \sum_{n=1}^N \left[\frac{1}{M} \sum_{i=1}^M \left(\frac{z_{i,n} - h_i(x_{\text{true}})}{\sigma_i} \right)^2 \right]^{\frac{1}{2}} \quad (39)$$

$$S_H = \frac{1}{N} \sum_{n=1}^N \left[\frac{1}{M} \sum_{i=1}^M \left(\frac{h_{i,n}(x) - h_i(x_{\text{true}})}{\sigma_i} \right)^2 \right]^{\frac{1}{2}} \quad (40)$$

where M is the number of measurement points; N is the total time of the Monte Carlo experiments; σ_i is the standard deviation of the measurements; S_M describes the accuracy of the measurements; and S_H describes the accuracy of the estimated results. The ratio $\kappa = S_H/S_M$ is usually used as an index to evaluate the filtering effects of different state estimators [22]. A smaller value of κ indicates better performance of an estimator. When σ_i took a value, 5000 sets of raw measurement data were generated by adding the randomly generated error $\varepsilon_i \sim \mathcal{N}(0, \sigma_i)$ to each of the true values.

Estimation accuracy of a single network is represented in Tables II–V, in which different estimators were tested on three measurement sets with $\sigma = 0.01$ p.u., 0.05 p.u. and 0.1 p.u. Tables II and IV show that, upon comparing NCSE with CSE, the estimation accuracy for the EN was improved by 13.3% using the combined model; however, little improvement was observed in the complete thermal model (4.4%). With regard to the DHN results shown in Tables III and V, the advantage of using the combined model is clear. Comparing NCSE with ISE and CSE, the estimation accuracy of the DHN was improved by 50.7% and 33.9% for the 4B-5N system, and 51.7% and 34.1% for the Barry Island system, respectively. The

TABLE II
ESTIMATION ACCURACY OF THE EN IN THE 4B-5N SYSTEM

σ	S_M	S_H		
		ISE	CSE	NCSE
0.01	0.9897	0.5185	0.4537	0.4313
0.05	0.9919	0.5183	0.4478	0.4374
0.1	0.9863	0.5111	0.4531	0.4295

TABLE III
ESTIMATION ACCURACY OF THE DHN IN THE 4B-5N SYSTEM

σ	S_M	S_H		
		ISE	CSE	NCSE
0.01	0.9971	0.7106	0.5348	0.3517
0.05	0.9929	0.7131	0.5243	0.3546
0.1	0.9965	0.7122	0.5299	0.3509

TABLE IV
ESTIMATION ACCURACY OF THE EN IN THE BARRY ISLAND SYSTEM

σ	S_M	S_H		
		ISE	CSE	NCSE
0.01	0.9969	0.5310	0.5061	0.4978
0.05	0.9967	0.5329	0.5004	0.4901
0.1	0.9929	0.5288	0.4979	0.4917

TABLE V
ESTIMATION ACCURACY OF THE DHN IN THE BARRY ISLAND SYSTEM

σ	S_M	S_H		
		ISE	CSE	NCSE
0.01	0.9999	0.7309	0.5349	0.3561
0.05	0.9992	0.7255	0.5214	0.3418
0.1	0.9981	0.7216	0.5224	0.3429

improvement is primarily caused by increasing redundancy of the thermal part in the DHN.

The filtering effects of the entire network are shown in Figs. 7 and 8. In these simulations, the measurement deviations of the EN and DHN (i.e. σ^e and σ^h) varied from 0.01 to 0.1. Results show that the index κ is at about 0.633, 0.501 and 0.408 for the 4B-5N system, and 0.637, 0.515 and 0.427 for the Barry Island system when utilizing ISE, CSE and NCSE, respectively. The change of κ with the variation of σ^e and σ^h is trivial in each figure. According to the Monte Carlo simulation results, the combined estimator could obtain a more accurate global solution for the entire network.

Generally, the deviations of measurement from the electric network (such as voltage and current) and those from the DHN (such as temperature, pressure and mass flow) are different, due to the different measuring principles and communication modes (wired/wireless). Figs. 9 and 10 show the influences

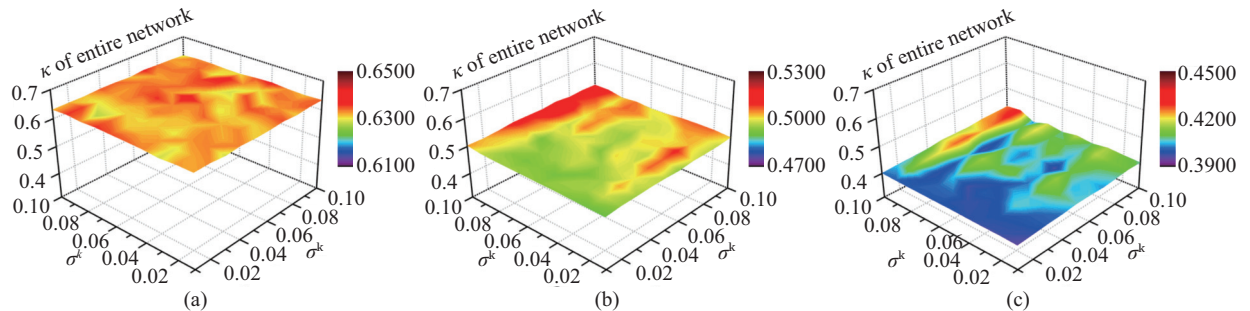


Fig. 7. Filtering effects of the entire network for the 4B-5N system. (a) ISE. (b) CSE. (c) NCSE.

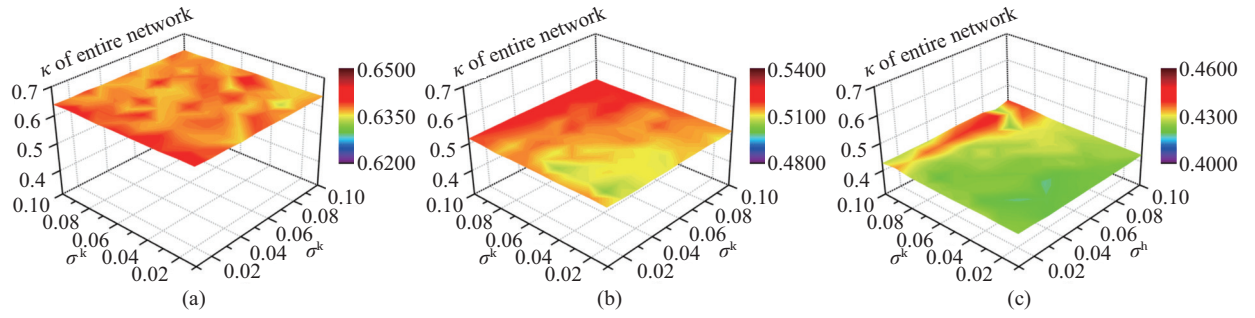


Fig. 8. Filtering effects of the entire network for the Barry Island system. (a) ISE. (b) CSE. (c) NCSE.

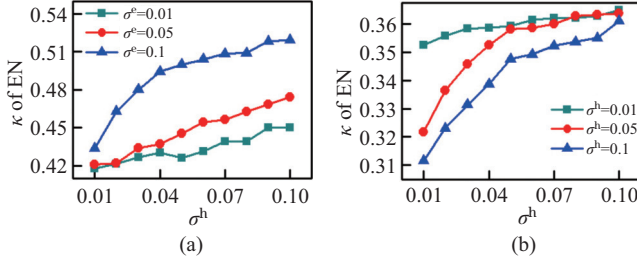


Fig. 9. Influences of measurements with different standard deviation. (a) EN. (b) DHN in the 4B-5N system.

between measurements from different networks in NCSE. The estimation accuracy of a single network (EN/DHN) was evaluated with the deviations of its measurements (σ^e/σ^h) fixed at 0.01 p.u., 0.05 p.u. or 0.1 p.u., while the deviations of the measurements from the other network (σ^h/σ^e) varied from 0.01 p.u. to 0.1 p.u. at steps of 0.01 p.u.

For the 4B-5N system, in Fig. 9(a), the blue and red curves show that the estimation accuracy of the EN is improved as σ^h decreases, especially when σ^e has a large value; however, when σ^e is small, the improvement is not as significant, as shown by the dark cyan curve. A similar trend is observed for the accuracy of the DHN when σ^e decreases, as shown in Fig. 9(b). This result means that, in NCSE, when the measurement from network A (EN or DHN) is less accurate, a more accurate measurement from network B (DHN or EN) can improve the estimation in network A; however, when a measurement from network A is accurate enough, the improvement brought in by the measurement from network B is limited.

For the Barry Island system, in Fig. 10, the estimation effect of a single network (EN or DHN) is also improved with increasingly accurate measurements from the other network. Compared with Fig. 9 however, the improvement is not that obvious. That is because measurements from the EN and DHN interact via coupling constraints, which relate to the two networks. According to the measurement allocation of test systems in Table 1, the ratio of the coupling constraint number to the total measurement number (including other constraints) is 6/315 for the Barry Island system, much smaller than 5/68 for the 4B-5N system. This means that, in the 4B-5N system, the influence of the measurements from the EN and DHN is much stronger than that of the Barry Island system.

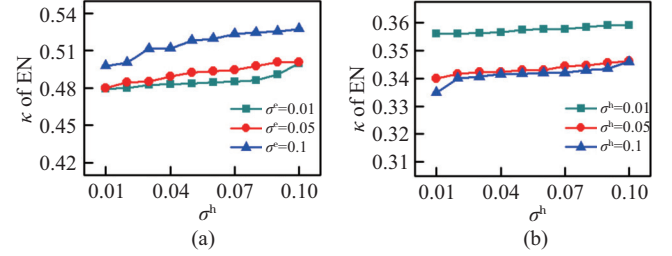


Fig. 10. Influences of measurements with different standard deviation. (a) EN. (b) DHN in the Barry Island system.

C. Bad Data Identification

The bad data identification ability of the three estimators was tested on the 4B-5N system with two cases. In case a), the measurement data of the electric power output from CHP 2 to bus bar 4 fell to 0 due to a communication failure (true value 0.2308 MW). In case b), the return temperature measurement data at node 3 was incorrectly metered as 80 °C (true value 50 °C).

The result of case a) is shown in Table VI. Bad data at P_2^{CHP} resulted in poor quality of the sum of the electric power injection to bus 4 (i.e. P_4^{inj}). The isolated SE for the EN could detect P_4^{inj} as bad data; however, it failed to identify the specific location of this bad data (i.e. P_2^{CHP} or P_2^{CP}) due to a lack of redundancy. When utilizing the combined SE model, P_2^{CHP} and P_2^{CP} could be identified with measurements from the DHN, and the correct estimated value is obtained by CSE and NCSE.

TABLE VI
BAD DATA IDENTIFICATION RESULT FOR CASE A

Measurement	True value	Measured value	Estimated value		
			ISE	CSE	NCSE
P_4^{inj} (MW)	0.2245	-0.0069(BD)	0.2262	0.2213	0.2251
P_2^{CHP} (MW)	0.2308	0(BD)	*(BD)	0.2297	0.2299
P_2^{CP} (MW)	0.0063	0.0069	*(BD)	0.0084	0.0048

In case b), when using ISE and CSE, bad data at T_3^{r} contaminated T_3^{s} and Φ_3^{load} and caused a gross error in the estimated values of these normal measurements, as shown in Table III. This is because, in ISE and CSE, the constraints between nodal temperatures were not considered, which means T_3^{r} was only coupled with T_3^{s} via heating load Φ_3^{load} . Besides T_3^{r} , in NCSE, T_3^{r} was coupled with T_4^{r} and T_5^{r} via the thermal constraints of the nodal temperature in (6) and (7). These

constraints provided extra redundancy to identify bad data at T_3^r , as shown in the last column in Table VII.

TABLE VII
BAD DATA IDENTIFICATION RESULT FOR CASE B

Measurement	True value	Measured value	Estimated value		
			ISE	CSE	NCSE
T_3^r (°C)	50	80(BD)	74.35(BD)	73.85(BD)	49.88
T_3^s (°C)	97.57	97.26	108.87(BD)	106.04(BD)	97.10
ϕ_3^{load} (MW)	0.3	0.3025	0.2004(BD)	0.2215(BD)	0.2931

D. Computational Efficiency

The average iteration and computation time for different estimators are listed in Tables VIII and IX.

TABLE VIII
COMPUTATION TIME AND ITERATIONS OF THE 4B-5N SYSTEM

Methods	Computation time (s)		Iterations	
	EN	DHN	EN	DHN
ISE	0.0028	0.0031	3.0000	3.0376
CSE		0.0155		3.0648
NCSE		0.0228		3.1078

TABLE IX
COMPUTATION TIME AND ITERATIONS OF THE BARRY ISLAND SYSTEM

Methods	Computation time (s)		Iterations	
	EN	DHN	EN	DHN
ISE	0.0054	0.0128	3.0006	2.7736
CSE		0.0279		3.0008
NCSE		0.1022		3.8806

Results show that the combined estimators require more computation time than the sum of the isolated SE for EN and DHN cases; however, the difference is not large. When considering the accurate thermal model, the estimator will spend more time calculating the Jacobian matrix, and the time cost increases with the complexity of the combined network, comparing Table VIII with Table IX. For all that, the computation time is still short enough for real-time dispatching. The comparisons of iteration time show that the convergence of the estimation approach does not change much when the combined SE model is applied.

V. CONCLUSION

This paper proposes a CHENSE method, which is based on the steady models of the EN, DHN and coupling components. Compared to former methods, the proposed method utilizes an accurate thermal model. Various coupling components are considered, including CHP units, heat pumps and circulation pumps. Simulation results using the combined SE model show that the influence of measurements from one network can improve the estimation accuracy for the other and, hence, the entire network, especially when the networks are strongly coupled. The coupling constraints could also provide extra redundancy in detecting bad data from boundary injection measurements in both networks. The computational time shows that the proposed method is suitable for online applications.

This research is an elementary step in exploring the SE problems of a CHEN. In reality, the operational model of a

CHEN is far more complicated than the steady model because the time inertias of an EN and DHN are different. In a DHN, the heat power is transferred via mass flow and the time inertia could be minutes to hours. Under these circumstances, the dynamic characteristics of a DHN could not be ignored when compared with an EN. Moreover, the accuracy of parameters in the SE model should be considered, and the historical data may be used to improve the performance of the combined state estimator.

APPENDIX A

Network parameters of the 4B-10 N system illustrated in Fig. 3 are supplied in the following tables.

TABLE AI
PARAMETERS OF THE 4-BUS ELECTRICITY NETWORK

Line No.	From bus	To bus	r (p.u.)	x (p.u.)	b (p.u.)
1	1	2	0.09	0.1577	0
2	1	3	0.09	0.1577	0
3	2	4	0.09	0.1577	0

TABLE AII
PARAMETERS OF THE 10-NODE DISTRICT HEATING NETWORK

Pipe No.	From node	To node	L (m)	K	λ (W/(m·K))
1	5	1	400	0.0175	0.2
2	1	2	400	0.0198	0.2
3	4	2	400	0.0178	0.2
4	4	3	400	0.0218	0.2
5	5	3	400	0.0177	0.2
6	6	10	400	0.0175	0.2
7	7	6	400	0.0198	0.2
8	7	9	400	0.0178	0.2
9	8	9	400	0.0218	0.2
10	8	10	400	0.0177	0.2

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