

ADMM-based Distributed State Estimation for Integrated Energy System

Yaxin Du, Wen Zhang, *Member, IEEE*, and Tingting Zhang, *Student Member, IEEE*

Abstract—In order to have an accurate knowledge of system-wide operation states, it is necessary to perform state estimation for the integrated energy system (IES) as the basis of energy management and control. Centralized state estimation is practically infeasible for IES due to the unreliability of communication, the barrier on privacy, and the large scale of integrated systems. This paper proposes a distributed state estimation algorithm based on the alternating direction method of multipliers (ADMM) for IES containing electricity, heat, and natural gas. Various coupling units are taken into full consideration in modeling of IES state estimation to reflect the harmonization of multi energy. On the basis of bilinear measurement model, the state estimation considering nonlinear measurements can be replaced by an equivalent three-stage problem containing two linear state estimations and an intermediate transformation to avoid non-convex optimization. The three-stage procedure for IES state estimation can be further decoupled over three sub-systems with coordination on coupling units, yielding a fully distributed scheme based on ADMM. A modified ADMM with the self-adjusting penalty parameter is also adopted to enhance the convergence. Simulation results demonstrate the validity and superiority of the proposed algorithm.

Index Terms—Alternating direction method of multipliers, coupling units, distributed state estimation, integrated energy system.

I. INTRODUCTION

THE energy system worldwide is undergoing deep restructuring, traditional single energy system is gradually transforming to integrated energy system (IES) with harmonization of multi energy [1]. There are some advantages of various energy carriers integrated in a whole system. On the one hand, comprehensive planning and operation of multi energy forms can further optimize the allocation of resources and improve energy efficiency by exploiting their complementation and synergies. On the other hand, taking advantage of the potential energy storage capacity of heat and natural gas systems, IES can make up for the intermittence and unpredictability of renewable energy through energy conversion, thus promoting its consumption. It is predicted that in 30 to 50 years, IES will become the primary energy carrier in the whole world [2].

This paper focuses on the harmonization of electricity, heat and natural gas these three energy systems. The extensive utilization of a variety of coupling units makes an increasingly tight coupling among these systems. Natural gas-based combined heat and power units (CHP), one of the most important coupling units in IES, are efficient and environmentally friendly energy supplies with an energy utilization rate of over 80% [3]. Motor compressors consume electricity to maintain the required pressure level of natural gas systems. The combination of power to gas equipment (P2G) and gas-powered generators enable the bi-directional energy conversion between electricity and gas, significantly enhancing the interaction between electricity and natural gas systems [4]. Hence, modeling of these coupling units is considered necessary when studying the coordination among various energy systems.

The full and accurate awareness of the system operating status is the basis of energy management and control. As with electricity systems, there are large numbers of measurement meters in heat and natural gas systems configured for security monitoring and billing requirements. However, the redundant measurements are generally incomplete and accompanied with varying degrees of noises. Therefore, it is necessary and feasible to perform state estimation for IES to filter out measurement noises and accurately estimate global states.

State estimation researches on electricity systems are relatively mature, while few on heat and natural gas systems [5]–[7]. A model is established in [5] to compute the optimal least squares estimates for the states of district heating systems based on hourly customer measurements. In [6], dynamic state estimation of natural gas systems is proposed based on Kalman filter, through which real-time estimation can be obtained under transient flow condition. As for IES, state estimation for combined heat and electricity systems is firstly presented in [8] where the combined measurement model is exploited to get a global solution. On this basis, a two-stage state estimation approach for combined heat and electricity systems is proposed in [9] considering the dynamic peculiarity of heat power transmission. In [10], the joint state estimation of combined heat and electricity systems is proposed and an iterative method is adopted to cope with the temperature quasi-dynamics. In [11], a steady state estimation model for coupling electric-gas systems is established to obtain combined states, taking the characteristic of compressors and the bad data identification into account. Considering the delay of gas transmission, state estimation of regional interconnected electricity and gas systems with bi-directional energy conversion is presented in [12]. However, studies on state estimation for

Manuscript received February 12, 2019; revised April 12, 2019; accepted May 10, 2019. Date of publication June 30, 2019; date of current version May 25, 2019.

Y. X. Du, W. Zhang (corresponding author, e-mail: zhangwen@sdu.edu.cn), and T. T. Zhang are with the Key Laboratory of Power System Intelligent Dispatch and Control of Ministry of Education, Shandong University, Jinan 250061, China.

DOI: 10.17775/CSEEJPES.2019.00400

IES combining electricity, heat, and gas systems are almost blank, calling for more complete state estimation algorithms.

Furthermore, it is worth noting that different sub-systems that compose IES are operated by different energy system operators, leading to communication inconvenience and privacy protection among sub-systems. In addition, there is a heavy computational burden when performing a centralized state estimation for large-scale regional or cross-regional IES. Therefore, distributed scheme is needed for IES state estimation to obtain global state estimates with high efficiency and minimal communication.

Many distributed state estimation algorithms have been proposed in electricity systems, based on different criteria for the computing and coordination scheme. In [13], a two-step distributed state estimation algorithm is developed where the system-wide voltage profile is acquired through the central coordinator from local estimates of each sub-region. A distributed solution methodology based on the coupling constraints optimization technique is derived in [14] without strict guaranteed convergence. The auxiliary problem principle is applied in [15], but some parameters have to be readjusted. In [16], on the basis of the alternating direction method of multipliers (ADMM), a novel algorithm is proposed to perform distributed state estimation for electricity systems with linear measurement of PMUs, exhibiting low communication load and good convergence performance. Convexity is the precondition for reliable convergence of most distributed optimization algorithms based on dual decomposition, while most of early studies do not handle the non-convex issue of nonlinear state estimation. In [17], bilinear theory is introduced to state estimation for electricity systems with nonlinear measurements to avoid non-convex optimization and then ADMM is utilized for distributed solution. These distributed algorithms can be applied to state estimation for IES by analogy.

This paper proposes an ADMM-based distributed state estimation algorithm for IES. Main contributions are:

(1) State estimation model for IES containing electricity, heat and natural gas is established, taking various coupling units into full consideration to reflect the harmonization of multi energy.

(2) A bilinear measurement model for IES is proposed to avoid non-convex optimization. The exact linearization forms of nonlinear measurement equations of heat and natural gas systems are derived for the first time, considering different physical rules of their respective systems.

(3) A fully distributed scheme of state estimation for IES is proposed based on ADMM, yielding the global estimation results satisfying coupling constraints with high efficiency and little communication.

(4) A modified ADMM with the self-adjusting penalty parameter is adopted to enhance the convergence performance, thus further improving the computational efficiency.

The paper is organized as follows. The state estimation model for IES considering various coupling units is established in Section II. The bilinear measurement models of three sub-systems are derived in Section III. Then, Section IV introduces the ADMM-based distributed state estimation for IES. Validity and superiority of the proposed algorithm are verified in

Section V. Final conclusion is drawn in Section VI.

II. STATE ESTIMATION FOR IES CONSIDERING VARIOUS COUPLING UNITS

IES considered in this paper is composed of the electricity sub-system, the heat sub-system, the natural gas sub-system, and various coupling units such as CHPs, gas-powered boilers, gas-powered generators, P2G, and motor compressors. The electricity sub-system mainly includes generators, loads and transmission lines; the heat sub-system consists of heat sources, heat loads, supply and return water pipelines; the natural gas sub-system contains gas sources, gas loads, gas pipelines and compressors.

A. State Estimation Model for IES

Weighted least squares (WLS), the most commonly used method in state estimation, can be applied to the state estimation for IES. The objective of the WLS criterion is to minimize the weighted sum of squares of the differences between the actual measurements and the estimated ones [18]. Thus, the state estimation model for IES can be expressed as follows

$$\begin{cases} \min J(\mathbf{x}) = J_e(\mathbf{x}_e) + J_h(\mathbf{x}_h) + J_g(\mathbf{x}_g) \\ \quad = [\mathbf{z}_e - \mathbf{h}_e(\mathbf{x}_e)]^T \mathbf{R}_e^{-1} [\mathbf{z}_e - \mathbf{h}_e(\mathbf{x}_e)] \\ \quad \quad + [\mathbf{z}_h - \mathbf{h}_h(\mathbf{x}_h)]^T \mathbf{R}_h^{-1} [\mathbf{z}_h - \mathbf{h}_h(\mathbf{x}_h)] \\ \quad \quad + [\mathbf{z}_g - \mathbf{h}_g(\mathbf{x}_g)]^T \mathbf{R}_g^{-1} [\mathbf{z}_g - \mathbf{h}_g(\mathbf{x}_g)] \\ \text{s.t. } \mathbf{S}(\mathbf{x}) = \mathbf{0} \end{cases} \quad (1)$$

where $\mathbf{x}_e$, $\mathbf{x}_h$, and $\mathbf{x}_g$ are vectors of state variables of the electricity sub-system, the heat sub-system, and the gas sub-system, respectively; $\mathbf{z}_e$, $\mathbf{z}_h$, and $\mathbf{z}_g$ are vectors of measurements gathered from three sub-systems and the chosen pseudo-measurements; $\mathbf{h}_e(\mathbf{x}_e)$, $\mathbf{h}_h(\mathbf{x}_h)$, and $\mathbf{h}_g(\mathbf{x}_g)$ are vectors of measurement functions; $\mathbf{R}_e$, $\mathbf{R}_h$, and $\mathbf{R}_g$ are called the covariance matrices of measurement errors; $\mathbf{x} = [\mathbf{x}_e, \mathbf{x}_h, \mathbf{x}_g]^T$ is the state vector of the entire system.

For the electricity sub-system, nodal voltage magnitudes and voltage phase angles (except the reference node) are taken as state variables, denoted by $\mathbf{x}_e = [\mathbf{V}, \boldsymbol{\theta}]^T$. The measurements include nodal voltage magnitudes, active and reactive power flows on the branches, and nodal power injections as pseudo-measurements, which can be summarized in a vector as $\mathbf{z}_e = [\mathbf{V}^{\text{meas}}, \mathbf{P}_b^{\text{meas}}, \mathbf{Q}_b^{\text{meas}}, \mathbf{P}^{\text{meas}}, \mathbf{Q}^{\text{meas}}]^T$. The superscript “meas” indicates that the variables are measurements.

State variables of the heat sub-system include the mass flow rate in each pipeline, supply and return temperature at each node, denoted by $\mathbf{x}_h = [\mathbf{m}, \mathbf{T}_s, \mathbf{T}_r]^T$. The nodal water demands, mass flow rates of pipelines, the heat powers generated by heat sources or consumed by heat loads, and nodal supply and return temperatures are adopted in the measurement vector $\mathbf{z}_h = [\mathbf{l}^{\text{meas}}, \mathbf{m}^{\text{meas}}, \boldsymbol{\Phi}^{\text{meas}}, \mathbf{T}_s^{\text{meas}}, \mathbf{T}_r^{\text{meas}}]^T$, in which heat powers are pseudo-measurements gotten by prediction.

As for the gas sub-system, let $\pi_i = p_i^2$ be the square of gas pressure at node i and combine them into the state vector $\mathbf{x}_g = [\boldsymbol{\pi}]^T$. Measurements include the squares of each nodal gas pressure, gas flows in the pipelines, and nodal gas demands, summarized by the vector $\mathbf{z}_g = [\boldsymbol{\pi}^{\text{meas}}, \mathbf{f}^{\text{meas}}, \mathbf{F}^{\text{meas}}]^T$.

$S(x) = \mathbf{0}$ is the vector of equality constraints satisfied by IES, reflecting energy conversion relationships on various coupling units.

B. Coupling Unit Constraints

1) CHP

CHP, the most common coupling unit in IES, generates high-quality electricity by consuming natural gas and uses waste heat to provide heat energy, linking the electricity, heat and natural gas sub-systems simultaneously. The energy conversion relationship of CHP [19] can be simply described as

$$\begin{cases} c^{\text{CHP}} = \frac{\phi^{\text{CHP}}}{P^{\text{CHP}}} \\ F^{\text{CHP}} = \frac{P^{\text{CHP}} + \phi^{\text{CHP}}}{c_{\text{gas}} \eta^{\text{CHP}}} \end{cases} \quad (2)$$

where P^{CHP} , ϕ^{CHP} and F^{CHP} respectively represent the electricity power output, heat power output and natural gas consumption of the CHP; c^{CHP} represents the heat-to-power ratio; c_{gas} is the heating value of gas and η^{CHP} is the total efficiency of CHP.

2) Gas-powered Generator and Gas-Powered Boiler

The gas-powered generator and the gas-powered boiler consume natural gas to generate electricity and heat, respectively, as partial coupling units within IES. The relationship between the natural gas consumption and the generated power can be formulated as the following conversion efficiency model

$$\begin{cases} P^{\text{GG}} = c_{\text{gas}} \eta^{\text{GG}} F^{\text{GG}} \\ \phi^{\text{GB}} = c_{\text{gas}} \eta^{\text{GB}} F^{\text{GB}} \end{cases} \quad (3)$$

where F^{GG} and F^{GB} denote the natural gas consumption of the gas-powered generator and the gas-powered boiler; P^{GG} and ϕ^{GB} are the electric and heat power output, respectively.

3) P2G

P2G, enabling bi-directional energy conversion between electricity and natural gas sub-systems, has recently appeared in the investigation of IES. The production chain of P2G is a two-step process [4]: First, electrolyze water to produce hydrogen and oxygen; then, synthesize methane with hydrogen and carbon dioxide. The relationship between the amount of consumed electricity power P^{P2G} and produced gas F^{P2G} in P2G is simply given by

$$\begin{cases} E^{\text{P2G}} = c^{\text{P2G}} \eta^{\text{P2G}} P^{\text{P2G}} \\ F^{\text{P2G}} = \frac{E^{\text{P2G}}}{c_{\text{gas}}} \end{cases} \quad (4)$$

4) Motor Compressor

Compressors in natural gas systems are used to maintain the system-wide gas pressure at desired levels [20], divided into motor compressors and gas compressors according to the power source. Motor compressors connected to the electricity sub-system as active loads can be considered as coupling units [21], whose energy conversion relationship is calculated by

$$P^{\text{MC}} = \frac{f^{\text{in}} \tau}{\eta^{\text{MC}} (\tau - 1)} ((k^{\text{MC}})^{\frac{\tau-1}{\tau}} - 1) \quad (5)$$

where P^{MC} is the electricity power consumption of the motor compressor; f^{in} denotes the natural gas flow rate through the compressor; k^{MC} denotes the compression ratio, which is the ratio between the outlet pressure and the inlet pressure of the compressor.

To sum up, energy conversion relationships on these coupling units can be expressed as equality constraints and introduced into the state estimation model for IES to reflect the coordination and interaction among three energy sub-systems. Vectors of coupling unit constraints can be simplified given by (6), in which A, B, D, E, G , and I are all constant coefficient matrices. It is worth to noting that all coupling units mentioned above are considered in (6). If there are only a few coupling units, only the corresponding constraints will be selected, which is equivalent to the simplified form of the constraint model proposed in this paper.

$$\begin{cases} P^{\text{CHP}} = A \Phi^{\text{CHP}} = B F^{\text{CHP}} \\ P^{\text{GG}} = D F^{\text{GG}} \\ \Phi^{\text{GB}} = E F^{\text{GB}} \\ P^{\text{P2G}} = G F^{\text{P2G}} \\ P^{\text{MC}} = I f^{\text{MC}} \end{cases} \quad (6)$$

III. BILINEAR MEASUREMENT MODEL

Measurement equations, as shown in (7), are nonlinear when considering nonlinear measurements, which makes the conventional state estimation based on WLS criterion a typical non-convex issue.

$$z = h(x) + e \quad (7)$$

However, convexity is the precondition for guaranteed convergence of many distributed optimization algorithms based on dual decomposition. In order to cope with this non-convexity of nonlinear state estimation problems, a bilinear measurement model is adopted as a valuable alternative to the original one [22]. According to the bilinear theory, the original state estimation can be converted to an equivalent three-stage problem by introducing auxiliary variables and the intermediate transformation. The bilinear measurement model is given in terms of (8)–(10). Among them, the intermediate transformation is adopted to transform auxiliary variables and thus connects the two linear measurement equations, with the help of which the accurate linearization expansion of the original nonlinear measurement equations is realized.

$$z = H y + e_z \quad (8)$$

$$u = f(y) \quad (9)$$

$$u = C x + e_u \quad (10)$$

First, an appropriate set of intermediate state variables y is introduced to linearly express the original measurements. Based on linear measurement equations (8) where H is a constant Jacobian matrix for the linear relationships and e_z is the vector of original measurement errors, it is clear that the first stage of the bilinear state estimation is a linear estimation problem which is a convex optimization under WLS structure. Then, in the second stage, the nonlinear transformation $f(\cdot)$

is applied to intermediate state variables $\mathbf{y}$ estimated before to derive the set of auxiliary measurements $\mathbf{u}$ linearly related to the original states. In the third stage, the linear measurement equations relating auxiliary measurements with the original state variables $\mathbf{x}$ are formulated as (10) in which $\mathbf{C}$ is the constant Jacobian matrix and $\mathbf{e}_u$ is the vector of auxiliary measurement errors. Then, the original state variables $\mathbf{x}$ can be obtained from the second linear estimation without iteration.

Thus, based on the bilinear measurement model, the original state estimation problem can be replaced by a three-stage procedure containing two linear WLS estimation problems avoiding non-convex optimization and a transformation stage for connection.

The bilinear measurement models of electricity, heat, and natural gas sub-systems will be derived below, respectively.

A. Electricity Sub-system

The bilinear measurement model of electricity sub-system is exactly the same as that proposed in [22], which will be summarized in the following.

1) First Linear Stage

For the branch joining buses i and j , the following two intermediate variables are defined.

$$K_{ij} = V_i V_j \cos(\theta_i - \theta_j) \quad (11)$$

$$L_{ij} = V_i V_j \sin(\theta_i - \theta_j) \quad (12)$$

In addition, squared voltage magnitudes

$$U_i = V_i^2 \quad (13)$$

are also included in the intermediate state vector $\mathbf{y}_e = [\mathbf{U}, \mathbf{K}, \mathbf{L}]^T$.

Then, measurement equations in the first linear stage can be formulated in terms of variables defined above, as (14).

$$\begin{cases} (V_i^{\text{meas}})^2 = U_i + e_{Vi} \\ P_{bij}^{\text{meas}} = g_{ij}U_i - g_{ij}K_{ij} - b_{ij}L_{ij} + e_{Pbij} \\ Q_{bij}^{\text{meas}} = -b_{ij}U_i + b_{ij}K_{ij} - g_{ij}L_{ij} + e_{Qbij} \\ P_i^{\text{meas}} = \sum_{\langle i,j \in \Theta_{ei} \rangle} (g_{ij}U_i - g_{ij}K_{ij} - b_{ij}L_{ij}) + e_{Pi} \\ Q_i^{\text{meas}} = \sum_{\langle i,j \in \Theta_{ei} \rangle} (-b_{ij}U_i + b_{ij}K_{ij} - g_{ij}L_{ij}) + e_{Qi} \end{cases} \quad (14)$$

2) Intermediate Nonlinear Transformation

The auxiliary measurement vector is defined by $\mathbf{u}_e = [\alpha^{\text{meas}}, \varsigma^{\text{meas}}, \sigma^{\text{meas}}]^T$, which can be acquired through nonlinear transformations shown as follows

$$\begin{cases} \alpha_i^{\text{meas}} = \ln U_i \\ \varsigma_{ij}^{\text{meas}} = \ln(K_{ij}^2 + L_{ij}^2) \\ \sigma_{ij}^{\text{meas}} = \arctan(L_{ij}/K_{ij}) \end{cases} \quad (15)$$

3) Second Linear Stage

A slightly modified state vector $\mathbf{x}'_e = [\alpha, \theta]^T$, where the logarithmic version α replaces the original voltage magnitude V in $\mathbf{x}_e$, is utilized in this stage. Once α is obtained, V can

be directly computed. The linear measurement equations are given by

$$\begin{cases} \alpha_i^{\text{meas}} = \alpha_i + e_{\alpha i} \\ \varsigma_{ij}^{\text{meas}} = \alpha_i + \alpha_j + e_{\varsigma ij} \\ \sigma_{ij}^{\text{meas}} = \theta_i - \theta_j + e_{\sigma ij} \end{cases} \quad (16)$$

B. Heat Sub-system

1) First Linear Stage

For the pipeline from bus i to bus j , the following pair of intermediate variables is defined

$$M_{ij} = m_{ij} T_{si} \quad (17)$$

$$N_{ij} = m_{ij} T_{ri} \quad (18)$$

The intermediate state vector is denoted by $\mathbf{y}_h = [\mathbf{m}, \mathbf{M}, \mathbf{N}, \mathbf{T}_s, \mathbf{T}_r]^T$ and linear measurement equations in the first stage is given by means of

$$\begin{cases} l_i^{\text{meas}} = \sum_{\langle i,j \in \Theta_{hi} \rangle} m_{ij} + e_{li} \\ m_{ij}^{\text{meas}} = m_{ij} + e_{mij} \\ \phi_i^{\text{meas}} = C_p \left(\sum_{\langle i,j \in \Theta_{hi} \rangle} M_{ij} - \sum_{\langle i,j \in \Theta_{hi} \rangle} N_{ij} \right) + e_{\phi i} \\ T_{si}^{\text{meas}} = T_{si} + e_{Tsi} \\ T_{ri}^{\text{meas}} = T_{ri} + e_{Tri} \end{cases} \quad (19)$$

2) Intermediate Nonlinear Transformation

The auxiliary measurement vector $\mathbf{u}_h = [\beta^{\text{meas}}, \chi^{\text{meas}}, \nu^{\text{meas}}, \gamma_s^{\text{meas}}, \gamma_r^{\text{meas}}]^T$ can be derived from the following nonlinear logarithmic transformation

$$\begin{cases} \beta_{ij}^{\text{meas}} = \ln m_{ij}^2 \\ \chi_{ij}^{\text{meas}} = \ln M_{ij}^2 \\ \nu_{ij}^{\text{meas}} = \ln N_{ij}^2 \\ \gamma_{si}^{\text{meas}} = \ln T_{si}^2 \\ \gamma_{ri}^{\text{meas}} = \ln T_{ri}^2 \end{cases} \quad (20)$$

3) Second Linear Stage

To retain linear measurement equations, state vector $\mathbf{x}'_h = [\mathbf{m}', \mathbf{T}'_s, \mathbf{T}'_r]^T$ composed of the logarithm of squares of original state variables is exploited in this stage, yielding the measurement equations (21). The original state vector $\mathbf{x}_h$ can be acquired by taking the logarithm and then taking the square root of the results.

$$\begin{cases} \beta_{ij}^{\text{meas}} = m'_{ij} + e_{\beta ij} \\ \chi_{ij}^{\text{meas}} = m'_{ij} + T'_{si} + e_{\chi ij} \\ \nu_{ij}^{\text{meas}} = m'_{ij} + T'_{ri} + e_{\nu ij} \\ \gamma_{si}^{\text{meas}} = T'_{si} + e_{\gamma si} \\ \gamma_{ri}^{\text{meas}} = T'_{ri} + e_{\gamma ri} \end{cases} \quad (21)$$

C. Natural Gas Sub-system

1) First Linear Stage

$\mathbf{y}_g = [\kappa, \Pi]^T$ is defined as the intermediate state vector of natural gas sub-systems, in which

$$\kappa_i = \pi_i \quad (22)$$

$$\Pi_{ij} = (\pi_i - \pi_j)^{1/k} \quad (23)$$

Thus, measurement equations of the first stage can be linearly expressed by

$$\begin{cases} \pi_i^{\text{meas}} = \kappa_i + e_{\pi i} \\ f_{ij}^{\text{meas}} = s_{ij}(s_{ij}/KK_{ij})^{1/k}\Pi_{ij} + e_{fij} \\ F_i^{\text{meas}} = \sum_{\langle i,j \rangle \in \Theta_{gi}} s_{ij}(s_{ij}/KK_{ij})^{1/k}\Pi_{ij} + e_{Fi} \end{cases} \quad (24)$$

where k , s_{ij} , and KK_{ij} are constant coefficients.

2) Intermediate Nonlinear Transformation

The auxiliary measurement vector here is denoted by $\mathbf{u}_g = [\delta^{\text{meas}}, \omega^{\text{meas}}]^T$, which can be obtained through the following nonlinear transformation

$$\begin{cases} \delta_i^{\text{meas}} = \kappa_i \\ \omega_{ij}^{\text{meas}} = (\Pi_{ij})^k \end{cases} \quad (25)$$

3) Second Linear Stage

In this linear stage, measurement equations relating the auxiliary measurements with the original states are given by

$$\begin{cases} \delta_i^{\text{meas}} = \pi_i + e_{\delta i} \\ \omega_{ij}^{\text{meas}} = \pi_i - \pi_j + e_{\omega ij} \end{cases} \quad (26)$$

IV. DISTRIBUTED STATE ESTIMATION FOR IES

A. Distributed State Estimation Algorithm Based on ADMM

The state estimation for IES based on WLS criterion is essentially a minimization optimization problem with coupling constraints. ADMM, an algorithm that has been exploited to solve many distributed optimization problems [23], is adopted to derive the distributed scheme for IES state estimation.

It is worth to highlight that, there is no strict mathematical proof for the convergence of ADMM for the non-convex state estimation problem. However, based on the bilinear measurement model established above, the original state estimation problem has been replaced by the intermediate transformation without participation in the optimization and two linear estimation problems satisfying the convergence premise of ADMM.

The entire state estimation for IES containing electricity, heat, and natural gas can be decomposed into three sub-systems state estimation with coordination on nodes where coupling units placed, yielding the distributed state estimation scheme. The distributed state estimation algorithm based on ADMM, employed in the first linear stage, will be described below.

The objective function of state estimation for IES can be transformed equivalently into form (27) in terms of intermediate state variables, subjected to the constraints in (6).

$$\begin{aligned} \min \mathbf{J}(\mathbf{y}) &= \mathbf{J}_e(\mathbf{y}_e) + \mathbf{J}_h(\mathbf{y}_h) + \mathbf{J}_g(\mathbf{y}_g) \\ &= [\mathbf{z}_e - \mathbf{H}_e \mathbf{y}_e]^T \mathbf{R}_e^{-1} [\mathbf{z}_e - \mathbf{H}_e \mathbf{y}_e] \\ &\quad + [\mathbf{z}_h - \mathbf{H}_h \mathbf{y}_h]^T \mathbf{R}_h^{-1} [\mathbf{z}_h - \mathbf{H}_h \mathbf{y}_h] \\ &\quad + [\mathbf{z}_g - \mathbf{H}_g \mathbf{y}_g]^T \mathbf{R}_g^{-1} [\mathbf{z}_g - \mathbf{H}_g \mathbf{y}_g] \end{aligned} \quad (27)$$

The augmented Lagrange function is defined as

$$\begin{aligned} L_\rho(\mathbf{y}_e, \mathbf{y}_h, \mathbf{y}_g, \boldsymbol{\lambda}) &= \mathbf{J}_e(\mathbf{y}_e) + \mathbf{J}_h(\mathbf{y}_h) + \mathbf{J}_g(\mathbf{y}_g) \\ &\quad + \boldsymbol{\lambda}_1^T (\mathbf{P}^{\text{CHP}} - \mathbf{A}\boldsymbol{\Phi}^{\text{CHP}}) + \boldsymbol{\lambda}_2^T (\mathbf{P}^{\text{CHP}} - \mathbf{B}\mathbf{F}^{\text{CHP}}) \\ &\quad + \boldsymbol{\lambda}_3^T (\mathbf{A}\boldsymbol{\Phi}^{\text{CHP}} - \mathbf{B}\mathbf{F}^{\text{CHP}}) + \boldsymbol{\lambda}_4^T (\mathbf{P}^{\text{GG}} - \mathbf{D}\mathbf{F}^{\text{GG}}) \end{aligned}$$

$$\begin{aligned} &+ \boldsymbol{\lambda}_5^T (\boldsymbol{\Phi}^{\text{GB}} - \mathbf{E}\mathbf{F}^{\text{GB}}) + \boldsymbol{\lambda}_6^T (\mathbf{P}^{\text{P2G}} - \mathbf{G}\mathbf{F}^{\text{P2G}}) \\ &+ \boldsymbol{\lambda}_7^T (\mathbf{P}^{\text{MC}} - \mathbf{I}\mathbf{f}^{\text{MC}}) + \frac{\rho}{2} (\|\mathbf{P}^{\text{CHP}} - \mathbf{A}\boldsymbol{\Phi}^{\text{CHP}}\|_2^2 \\ &+ \|\mathbf{P}^{\text{CHP}} - \mathbf{B}\mathbf{F}^{\text{CHP}}\|_2^2 + \|\mathbf{A}\boldsymbol{\Phi}^{\text{CHP}} - \mathbf{B}\mathbf{F}^{\text{CHP}}\|_2^2 \\ &+ \|\mathbf{P}^{\text{GG}} - \mathbf{D}\mathbf{F}^{\text{GG}}\|_2^2 + \|\boldsymbol{\Phi}^{\text{GB}} - \mathbf{E}\mathbf{F}^{\text{GB}}\|_2^2 \\ &+ \|\mathbf{P}^{\text{P2G}} - \mathbf{G}\mathbf{F}^{\text{P2G}}\|_2^2 + \|\mathbf{P}^{\text{MC}} - \mathbf{I}\mathbf{f}^{\text{MC}}\|_2^2) \end{aligned} \quad (28)$$

where $\boldsymbol{\lambda}_i$ is the vector of Lagrange multipliers corresponding to the i -th constraints; $\rho > 0$ is the constant penalty parameter.

According to the scheme of ADMM [20], intermediate state variables of three sub-systems and Lagrange multipliers are updated alternately. The $(k+1)$ -th iteration can be written as follows

$$\begin{cases} \mathbf{y}_e^{k+1} := \arg \min L_\rho(\mathbf{y}_e, \mathbf{y}_h^k, \mathbf{y}_g^k, \boldsymbol{\lambda}_i^k) \\ \mathbf{y}_h^{k+1} := \arg \min L_\rho(\mathbf{y}_e^{k+1}, \mathbf{y}_h, \mathbf{y}_g^k, \boldsymbol{\lambda}_i^k) \\ \mathbf{y}_g^{k+1} := \arg \min L_\rho(\mathbf{y}_e^{k+1}, \mathbf{y}_h^{k+1}, \mathbf{y}_g, \boldsymbol{\lambda}_i^k) \\ \boldsymbol{\lambda}_1^{k+1} := \boldsymbol{\lambda}_1^k + \rho(\mathbf{P}^{\text{CHP},k+1} - \mathbf{A}\boldsymbol{\Phi}^{\text{CHP},k+1}) \\ \boldsymbol{\lambda}_2^{k+1} := \boldsymbol{\lambda}_2^k + \rho(\mathbf{P}^{\text{CHP},k+1} - \mathbf{B}\mathbf{F}^{\text{CHP},k+1}) \\ \boldsymbol{\lambda}_3^{k+1} := \boldsymbol{\lambda}_3^k + \rho(\mathbf{A}\boldsymbol{\Phi}^{\text{CHP},k+1} - \mathbf{B}\mathbf{F}^{\text{CHP},k+1}) \\ \boldsymbol{\lambda}_4^{k+1} := \boldsymbol{\lambda}_4^k + \rho(\mathbf{P}^{\text{GG},k+1} - \mathbf{D}\mathbf{F}^{\text{GG},k+1}) \\ \boldsymbol{\lambda}_5^{k+1} := \boldsymbol{\lambda}_5^k + \rho(\boldsymbol{\Phi}^{\text{GB},k+1} - \mathbf{E}\mathbf{F}^{\text{GB},k+1}) \\ \boldsymbol{\lambda}_6^{k+1} := \boldsymbol{\lambda}_6^k + \rho(\mathbf{P}^{\text{P2G},k+1} - \mathbf{G}\mathbf{F}^{\text{P2G},k+1}) \\ \boldsymbol{\lambda}_7^{k+1} := \boldsymbol{\lambda}_7^k + \rho(\mathbf{P}^{\text{MC},k+1} - \mathbf{I}\mathbf{f}^{\text{MC},k+1}) \end{cases} \quad (29)$$

In (29), the intermediate state vector $\mathbf{y}_e^{k+1}$ of the electricity sub-system is firstly updated by minimizing the augmented Lagrange function L_ρ while keeping the other two state vectors $\mathbf{y}_h^k$ and $\mathbf{y}_g^k$ and all Lagrange multipliers $\boldsymbol{\lambda}_i^k$ fixed to their previous iteration values. Likewise, the intermediate state vector $\mathbf{y}_h^{k+1}$ and $\mathbf{y}_g^{k+1}$ of the heat and the natural gas sub-system are then updated successively according to the second and third formulas in (29). Finally, the Lagrange multipliers $\boldsymbol{\lambda}_i^{k+1}$ corresponding to the coupling constraints are updated with the step size ρ using the latest updated coupling variables. The sequential update procedure is iterated until the convergence criterion (30) is satisfied.

$$\|\mathbf{r}^k\|_\infty \leq \varepsilon^{\text{pri}} \quad \text{and} \quad \|\mathbf{s}^k\|_\infty \leq \varepsilon^{\text{dual}} \quad (30)$$

where $\mathbf{r}^k$ denotes the primal residual at iteration k reflecting mismatches of coupling variables among sub-systems and $\mathbf{s}^k$ denotes the dual residual describing the stability of iterations.

B. ADMM with the Self-Adjusting Penalty Parameter

ADMM is often criticized for its relatively slow convergence rate which is significantly affected by the penalty parameter corresponding to constraint equations [23]. In the original ADMM with the fixed penalty parameter, the convergence rate drops obviously in the late iteration and is greatly dependent on the initial value of the penalty parameter. To cope with these problems, a modified ADMM is employed in this paper, of which the penalty parameter self-adjusts per iteration as the convergence information updated.

The adjusting rule for the penalty parameter is given by

$$\rho^{k+1} = \begin{cases} \rho^k \left[1 + \lg \left(\frac{\|r^k\|_\infty}{\|s^k\|_\infty} \right) \right] & \text{if } \|r^k\|_\infty > \mu \|s^k\|_\infty \\ \rho^k / \left[1 + \lg \left(\frac{\|s^k\|_\infty}{\|r^k\|_\infty} \right) \right] & \text{if } \|s^k\|_\infty > \mu \|r^k\|_\infty \\ \rho^k & \text{otherwise} \end{cases} \quad (31)$$

where $\mu = 10$ is the typical choice [24].

The motivation behind this adjusting rule is: when the primal residual r^k appears much larger than the dual residual s^k , increase ρ^k to accelerate the convergence of the primal residual; conversely, when the dual residual s^k seems relatively larger, reduce ρ^k to speed up the convergence of the dual residual. Moreover, the logarithm of the ratio of primal residual norms to dual residual norms is taken as the self-adjusting reference to avoid the oscillation caused by over-adjustment in the iterative process by utilizing the saturation of the logarithm function.

C. Fully Distributed Scheme for IES State Estimation

On the basis of the bilinear measurement model, the state estimation for IES is decomposed into three stages. Each of the three stages is further decoupled over three sub-systems, yielding a fully distributed scheme for IES state estimation.

1) Distributed Scheme in the First Linear Estimation Stage

The distributed state estimation algorithm based on ADMM, which has been described above, is employed for the first linear estimation stage. In the alternate update procedure of ADMM, each sub-system sequentially performs local linear state estimation and sends the latest coupling variables on coupling units calculated through local intermediate state variables to the other sub-systems for coordination. The sequential procedure is iterated until the convergence criterion of ADMM is satisfied. Harmonization among electricity, heat, and natural gas sub-systems is reflected by the satisfaction of coupling constraints, providing the global estimated results of intermediate state variables of three sub-systems in IES.

2) Local Transformation Stage

Nonlinear transformations are implemented to the electricity, heat, and gas sub-systems respectively to derive auxiliary measurements from the intermediate estimates obtained in the first stage. The local transformations in this stage can be performed in a parallel way among three sub-systems without any communication on coupling nodes, further reducing the computation time.

3) Distributed Scheme in the Second Linear Estimation Stage

The auxiliary measurements arising after nonlinear transformations are collected as the input of the second linear estimation stage which is based on the linear measurement equations (10) in the bilinear measurement model.

For a sub-system i , where $i = e, h, g$ respectively represents the electricity, heat, and natural gas sub-system, the estimated intermediate state $\tilde{y}_i$, covariance $\text{cov}(\tilde{y}_i)$ and corresponding measurements $\tilde{u}_i$ have been obtained before. Then, the covariance matrix of measurement errors in the second estimation

stage can be derived as follows

$$R_{ui} = JF_{ui} \text{cov}(\tilde{y}_i) JF_{ui}^T \quad (32)$$

where JF_{ui} is the Jacobian matrix of $f_i(\cdot)$ computed at $\tilde{u}_i$.

The linear WLS state estimations for three sub-systems are performed individually in this stage, which can be directly solved by computing (33) without iteration.

$$\tilde{x}_i = [C_i^T R_{ui}^{-1} C_i]^{-1} C_i^T R_{ui}^{-1} \tilde{u}_i \quad (33)$$

Finally, the global solution of original state variables satisfying coupling constraints is obtained through the three-stage distributed scheme.

V. CASE STUDY

The proposed distributed state estimation algorithm for IES is applied to a case study to verify its validity and superiority. Electricity, heat and natural gas sub-systems constitute the 91-bus IES in this case through the connection of coupling units. For the electricity sub-system, the standard IEEE 57-bus system is exploited, as shown in Fig. 1. The utilized 14-bus heat sub-system is shown in Fig. 2. The 20-bus Belgian natural gas system shown in Fig. 3 is also included. Data about the sub-systems are available in [20].

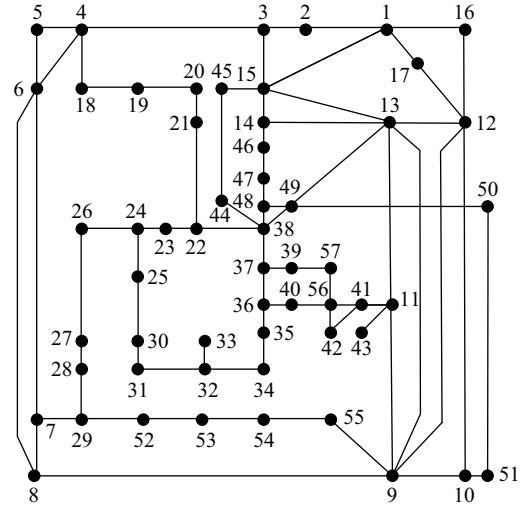


Fig. 1. Schematic diagram of the IEEE 57-bus electricity sub-system.

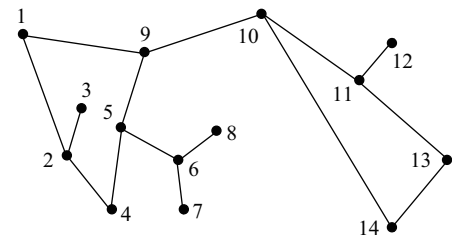


Fig. 2. Schematic diagram of the 14-bus heat sub-system.

All the quantities acquired from the multi energy flow calculation are taken as true values, to which random Gaussian noises are added for measurement simulation. Measurement

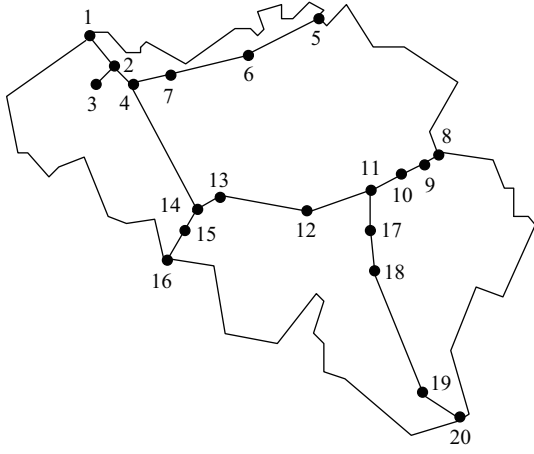


Fig. 3. Schematic diagram of the 20-bus Belgian natural gas sub-system.

noises are simulated as independent zero-mean Gaussians with triple standard deviation equaling to 1% and 20% of true values for actual and pseudo measurements, respectively. Monte Carlo simulations are adopted to deal with the uncertainty of measurement errors to test the effects of the proposed algorithm. The number of Monte Carlo trials is set to 500. The proposed algorithm was developed in MATLAB R2014a and solved by GUROBI.

The relative root mean square errors (RMSEs) of estimated state variables are adopted here to assess the estimation precision, calculated by

$$RMSE_{x_i} = \frac{1}{mc} \sum_{j=1}^{mc} \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{\hat{x}_i - x_{i,true}}{x_{i,true}} \right)^2 \right]^{\frac{1}{2}} \quad (34)$$

where mc is the times of Monte Carlo trials; n is the number of state variables in state vector x_i ; $\hat{x}_i$ is the set of estimated values; $x_{i,true}$ is the true value vector.

In the following, the performance of the proposed distributed state estimation (DSE) algorithm is compared to that of the individual state estimation (ISE) for each sub-system without coordination and to that of the centralized state estimation (CSE) carried out on the whole IES without decomposition to verify its validity and superiority. Then, different conditions of network coupling and measurement observability are set to prove the applicability of the proposed algorithm and analyze the advantage of the distributed scheme over the centralized counterpart under different conditions.

A. Compared with Individual State Estimation

The type and location of coupling units are shown in Table I. For the measurement configuration, full measurement set is available. Errors of the proposed distributed state estimation algorithm are shown in Table II, compared with those of the individual state estimation.

As shown from the table, the proposed distributed algorithm for IES has higher precision on state estimation of sub-systems than the individual one, mainly due to the increase in measurement redundancy by considering constraints on coupling units. When the distributed scheme converges globally, the maximum residual of coupling variables is 7.29×10^{-4} , demonstrating

TABLE I
THE TYPE AND LOCATION OF COUPLING UNITS

Coupling Unit	Electricity Bus	Heat Bus	Natural Gas Bus
CHP	1	13	6
CHP	8	14	3

TABLE II
COMPARISON OF THE ESTIMATED ERRORS ($\times 10^{-3}$)

	$RMSE_V$	$RMSE_\theta$	$RMSE_m$	$RMSE_{T_s}$	$RMSE_{T_r}$	$RMSE_\pi$
ISE	3.10	3.90	3.20	3.90	3.20	6.10
DSE	1.10	2.20	2.50	3.10	3.00	1.50

that the estimated results acquired by the proposed algorithm are the global states for IES with good consistency on coupling nodes. Thus, measurement mismatches among sub-systems on coupling units can be well eliminated, which is significant when measurement noises of coupling variables are large.

B. Compared with Centralized State Estimation

The coupling condition and measurement configuration are the same as given previously. Errors of the proposed distributed state estimation algorithm are shown in Table III, compared with those of the centralized state estimation.

TABLE III
COMPARISON OF THE ESTIMATED ERRORS ($\times 10^{-3}$)

	$RMSE_V$	$RMSE_\theta$	$RMSE_m$	$RMSE_{T_s}$	$RMSE_{T_r}$	$RMSE_\pi$
CSE	0.98	1.80	2.20	3.50	2.30	0.52
DSE	1.10	2.20	2.50	3.10	3.00	1.50

Estimated errors of the distributed scheme are generally close to those of the centralized one, which proves that the accuracy of the proposed algorithm is sufficient. The state estimation time is 0.63 sec for the proposed distributed algorithm versus 10.87 sec for the centralized one, yielding a 94.20% time saving in this 91-bus IES. The significant improvement in efficiency of the proposed algorithm comes from the bilinear transformation to the original WLS estimation problem avoiding iterations and the ADMM-based distributed solution. Moreover, the modified ADMM with the self-adjusting penalty parameter accelerates the convergence and thus further improves the computational efficiency, whose validity can be clearly verified by comparing the convergence process of ADMM with and without the self-adjusting penalty parameter, as shown in Fig. 4. It is also worth to highlight that the proposed algorithm has a good scalability that growth on state estimation time with the expansion of system scales is very small.

C. Comparison Under Different Conditions of Network Coupling

According to the type and location of coupling units shown in Table IV, we increase the number of coupling units one by one on the basis of the coupling scenario described above. State estimations are applied to scenarios where the number of coupling units increases from 2 to 8, which means the coupling in IES is getting tighter and tighter. In each scenario, the measurement configuration is the same as given previously.

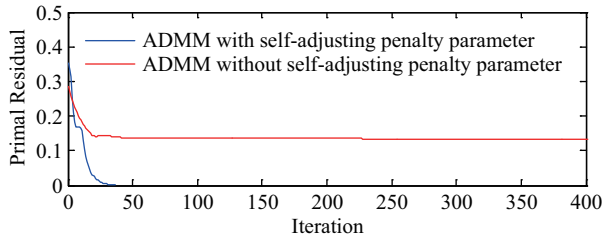


Fig. 4. Comparison of the convergence process of ADMM with and without self-adjusting penalty parameter.

TABLE IV
THE TYPE AND LOCATION OF COUPLING UNITS

Coupling Unit	Electricity Bus	Heat Bus	Natural Gas Bus
CHP	1	13	6
CHP	8	14	3
P2G	5	—	2
P2G	43	—	18
Gas-powered Generator	21	—	7
Gas-powered Generator	34	—	16
Gas-powered Boiler	—	4	15
Gas-powered Boiler	—	8	10

The performances of the proposed distributed algorithm in estimated errors and time are respectively shown in Fig. 5 and Fig. 6, compared with those of the centralized algorithm. The mean of RMSEs of all state variables in IES is used to reflect the estimated accuracy.

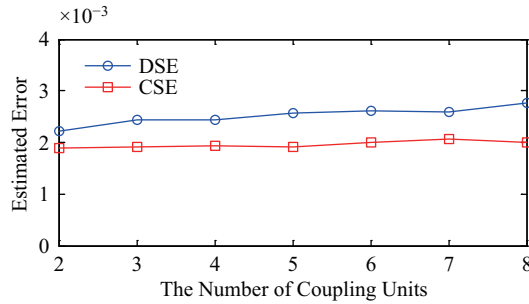


Fig. 5. Comparison of the estimated errors.

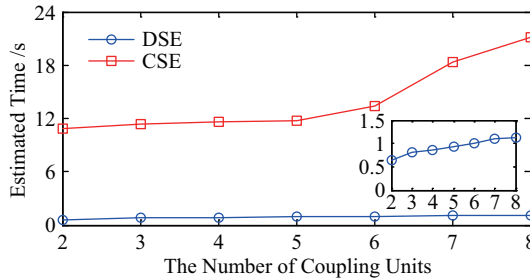


Fig. 6. Comparison of the estimated time.

As the coupling among sub-systems gets tighter, estimated errors of the distributed algorithm increase slightly, while the estimated accuracy still meets the requirements of applications and is close to that of the centralized algorithm within the range of permitted errors. The increase in coupling units leads to more data interaction among sub-systems. In addition, in

order to achieve the global convergence satisfying all coupling constraints, more iterations are needed for coordination. As a result, the estimated time of the distributed state estimation algorithm increases with the increase in coupling units, yielding the 80.18% growth of time under the tightest coupling condition compared to the initial coupling condition. Similarly, for the centralized scheme, the increase in coupling units causes the expansion of the dimension of the Jacobian matrix and even numerical problems, leading to the increase in the estimated time by a maximum of 94.04%. However, it is obvious that under every coupling condition, the distributed state estimation algorithm all shortens the estimated time by more than 92.04% compared with the centralized algorithm, showing significant advantages in computational efficiency.

Therefore, the proposed distributed algorithm has the good applicability to the state estimation for IES under different conditions of network coupling, yielding the estimated results with sufficient accuracy and significantly improved efficiency compared with the centralized counterpart.

D. Comparison Under Different Conditions of Measurement Observability

In general, observability is the premise of state estimation, which is reflected by the full rank of the Jacobian matrix in the conventional WLS state estimation. In the above cases, the full measurement set is available, ensuring that the IES is fully observable. Under such measurement observability condition, it has been demonstrated that the distributed state estimation algorithm has the acceptable accuracy and the significant advantage in efficiency over the centralized counterpart.

To compare the performance of these two algorithms under measurement condition that the local observability is not available, all related measurements of the node 11 in the natural gas sub-system of IES are removed from the measurement set. And no coupling units are placed on this node, thus the natural gas sub-system of IES is locally unobservable. The estimated errors of two algorithms are compared in Table V.

TABLE V
COMPARISON OF THE ESTIMATED ERRORS ($\times 10^{-3}$)

	$RMSE_V$	$RMSE_\theta$	$RMSE_m$	$RMSE_{T_s}$	$RMSE_{T_r}$	$RMSE_\pi$
CSE	—	—	—	—	—	—
DSE	1.20	2.40	2.00	2.80	3.80	—

It can be seen that when the local observability is absent in a sub-system, the centralized state estimation algorithm is infeasible because the Jacobian matrix with zero columns is singular which makes it impossible to carry out matrix inversion in the iteration. However, correct estimated results of all sub-systems except the one which is locally unobservable can be still obtained by the proposed distributed algorithm. The reasons can be considered from the following two aspects: on the one hand, observability is not necessary for the convergence of ADMM in the first linear estimation stage of the distributed scheme; on the other hand, the second linear state estimations are performed independently in sub-systems without affecting each other. Thus, even under the measurement condition where local unobservability occurs,

state estimations based on the proposed distributed scheme can be applied as usual to the observable sub-systems, which weakens the adverse effect on state estimation for IES.

In a word, the proposed distributed state estimation algorithm has the relatively better applicability than the centralized counterpart to different conditions of measurement observability.

VI. CONCLUSION

This paper proposes an ADMM-based distributed state estimation algorithm for IES, yielding the global state estimation results with sufficient accuracy and reliable convergence. Based on bilinear theory and the modified ADMM technique, the state estimation for IES is performed in a fully distributed way significantly enhancing the computational efficiency. Besides, only some coupling variables on coupling units will be interacted among sub-systems for coordination, exhibiting low demands on communication and superiority on privacy protection. In future works, the state estimation for IES will take the placement of measurements into account.

REFERENCES

- [1] D. Wang, L. Liu, H. J. Jia, W. L. Wang, Y. Q. Zhi, Z. J. Meng, and B. Y. Zhou, "Review of key problems related to integrated energy distribution systems," *CSEE Journal of Power and Energy Systems*, vol. 4, no. 2, pp. 130–145, Jun. 2018.
- [2] M. Geidl and G. Andersson, "Optimal power flow of multiple energy carriers," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 145–155, Feb. 2007.
- [3] Y. P. Yang, Z. X. Lin, and J. R. He, "Chosen method of optimum cold source thermal-system heater in heat and power cogeneration system," *Proceeding of the CSEE*, vol. 30, no. 26, pp. 1–6, Sep. 2010.
- [4] Q. Zeng, J. K. Fang, J. H. Li, and Z. Chen, "Steady-state analysis of the integrated natural gas and electric power system with bi-directional energy conversion," *Applied Energy*, vol. 184, pp. 1483–1492, Dec. 2016.
- [5] T. T. Fang and R. Lahdelma, "State estimation of district heating network based on customer measurements," *Applied Thermal Engineering*, vol. 73, no. 1, pp. 1211–1221, Dec. 2014.
- [6] H. A. Behrooz and R. B. Boozarjomehry, "Modeling and state estimation for gas transmission networks," *Journal of Natural Gas Science and Engineering*, vol. 22, pp. 551–570, Jan. 2015.
- [7] İ. Durgut and M. K. Leblebicioğlu, "State estimation of transient flow in gas pipelines by a Kalman filter-based estimator," *Journal of Natural Gas Science and Engineering*, vol. 35, pp. 189–196, Sep. 2016.
- [8] J. N. Dong, H. B. Sun, Q. L. Guo, and Z. G. Pan, "State estimation for combined electricity and heat networks," *Power System Technology*, vol. 40, no. 6, pp. 1635–1641, Jun. 2016.
- [9] T. T. Sheng, Q. L. Guo, H. B. Sun, Z. G. Pan, and J. Y. Zhang, "Two-stage state estimation approach for combined heat and electric networks considering the dynamic property of pipelines," *Energy Procedia*, vol. 142, pp. 3014–3019, Dec. 2017.
- [10] T. Zhang, Z. Li, Q. H. Wu, and X. Zhou, "Dynamic state estimation of combined heat and power system considering quasi-dynamics of temperature in pipelines," in *Proceedings 2018 International Conference on Power System Technology*, Guangzhou, China, 2018, pp. 232–237.
- [11] J. N. Dong, H. B. Sun, Q. L. Guo, T. T. Sheng, and Z. Qiao, "State estimation of combined electric-gas networks for energy internet," *Power System Technology*, vol. 42, no. 2, pp. 400–408, Feb. 2018.
- [12] S. Y. Ge, X. O. Liu, L. K. Ge, H. Liu, and J. F. Li, "State estimation of regional interconnected electricity and gas networks," *Energy Procedia*, vol. 142, pp. 1920–1932, Dec. 2017.
- [13] T. Van Cutsem, J. L. Howard, and M. Ribbens-Pavella, "A two-level static state estimator for electric power systems," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-100, no. 8, pp. 3722–3732, Aug. 1981.
- [14] D. M. Falcão, F. F. Wu, and L. Murphy, "Parallel and distributed state estimation," *IEEE Transactions on Power Systems*, vol. 10, no. 2, pp. 724–730, May 1995.
- [15] R. Ebrahimian and R. Baldick, "State estimation distributed processing [for power systems]," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1240–1246, Nov. 2000.
- [16] V. Kekatos and G. B. Giannakis, "Distributed robust power system state estimation," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1617–1626, May 2013.
- [17] W. Y. Zheng, W. C. Wu, A. Gomez-Exposito, B. M. Zhang, and Y. Guo, "Distributed robust bilinear state estimation for power systems with nonlinear measurements," *IEEE Transactions on Power Systems*, vol. 32, no. 1, pp. 499–509, Jan. 2017.
- [18] F. C. Schwepe, "Power system static-state estimation, Part III: implementation," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-89, no. 1, pp. 130–135, Jan. 1970.
- [19] Y. R. Wang, B. Zeng, J. Guo, J. Q. Shi, and J. H. Zhang, "Multi-energy flow calculation method for integrated energy system containing electricity, heat and gas," *Power System Technology*, vol. 40, no. 10, pp. 2942–2950, Oct. 2016.
- [20] A. Shabanpour-Haghighi and A. R. Seifi, "An integrated steady-state operation assessment of electrical, natural gas, and district heating networks," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3636–3647, Sept. 2016.
- [21] G. Zhang, F. Zhang, L. Zhang, J. Liang, and X. S. Han, "Distributed algorithm for the power flow calculation of integrated electrical, gas, and heating network considering various coupling units," *Proceeding of the CSEE*, vol. 38, no. 22, pp. 6594–6604, Nov. 2018.
- [22] A. Gomez-Exposito, C. Gomez-Quiles, and A. de la Villa Jaen, "Bilinear power system state estimation," *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 493–501, Feb. 2012.
- [23] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends in Machine Learning*, vol. 3, no. 1, pp. 1–122, Jan. 2011.
- [24] Y. X. Han, L. J. Chen, Z. J. Wang, W. Liu, and S. W. Mei, "Distributed optimal power flow in direct current distribution network based on alternative direction method of multipliers with dynamic step size," *Transactions of China Electrotechnical Society*, vol. 32, no. 11, pp. 26–37, Jan. 2017.



Yaxin Du received the B.S. degree in Electrical Engineering from Shandong University, Jinan, China, in 2018, where she is currently pursuing the M.S. degree with the School of Electrical Engineering.

She is currently with the Key Laboratory of Power System Intelligent Dispatch and Control of Ministry of Education, Shandong University. Her current research interests include power system state estimation and integrated energy system.



Wen Zhang (M'14) received the B.S., M.S., and Ph.D. degrees from Shandong University, Jinan, China, in 1989, 1992, and 2006, respectively, all in Electrical Engineering.

She is currently a Professor with the Key Laboratory of Power System Intelligent Dispatch and Control of Ministry of Education, Shandong University. Her current research interests include power system analysis and control, demand-side response, and application of artificial intelligence to power systems.



Tingting Zhang (S'18) received the B.S. degree in Electrical Engineering from Shandong University, Jinan, China, in 2017. She is currently pursuing the Ph.D. degree with the School of Electrical Engineering.

She is currently with the Key Laboratory of Power System Intelligent Dispatch and Control of Ministry of Education, Shandong University. Her current research interests include distribution system state estimation and dynamic state estimation.