IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 9, 2019, accepted September 22, 2019, date of current version December 19, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2943998

Hybrid Possibilistic-Probabilistic Energy Flow Assessment for Multi-Energy Carrier Systems

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This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 61433004, Grant 61573094, and Grant 61773109, and in part by the National Key Research and Development Project under Grant 2018YFA0702200.

ABSTRACT The uncertainty is a pivotal problem in Multi-Energy Carrier (MEC) systems, which leads to the strong demand of reasonable tools to evaluate uncertainties. When both possibilistic and probabilistic uncertainties exist in the real MEC systems, traditional possibilistic or probabilistic methods are no more suitable to be applied. Therefore, this paper proposes a hybrid possibilistic-probabilistic energy flow assessment method to evaluate these uncertainties. Firstly, to build a more precise uncertain model, the probabilistic and possibilistic uncertainties are respectively modeled by considering different uncertainties of sources, networks and loads of MEC systems, and the correlations among wind generation and energy loads. Then, the product t-norms of the extension principle plus α-cut method is firstly implemented in processing fuzzy energy flow, which can reduce overestimation compared with the sole α-cut method. Next, on the basis of Dempster-Shafer evidence theory, the hybrid possibilistic-probabilistic energy flow assessment approach is presented. Finally, two cases are carried out to verify the effectiveness and practicability of the proposed method.

INDEX TERMS Multi-energy carrier, possibilistic uncertainty, probabilistic uncertainty, uncertain energy flow.

I. INTRODUCTION

Currently, with increasingly global energy crisis and intricate interactions among electricity, gas and heat networks, the development of Multi-Energy Carrier (MEC) systems draws extensive attention worldwide. Meanwhile, Renewable Energy Resources (RESs), such as wind power and photovoltaics, predominate in the sustainable transformation of energy systems, which also devotes to establishing complementary utilization of multiple energy carriers [1], [2]. In the numerous investigation about MEC systems, the uncertainty assessment is a critical issue. As there are various uncertainties (e,g., the variability and intermittency of the RESs [3], [4], stochastic fluctuations in energy loads [5]) in MEC systems, a reasonable tool to evaluate the uncertainties is indispensable to quantify and control the operational and planning risks of MEC systems.

Deterministic energy flow calculation provides available measures for uncertain energy flow calculation, and it lays the foundation for planning analysis and optimal operation of MEC systems. The steady-state energy flow of electrical, gas and heat network is firstly investigated on the basis of Newton-Raphson technique considering interactions among different networks [6]. Due to the sensitivity of Newton method to initial guesses, a fast decomposing strategy is proposed to solve energy flow in large scale MEC systems [7]. However, the results of deterministic energy flow cannot be fully used as a basis for MEC systems' planning designers to make a decision under the uncertainties of data. The uncertain energy flow calculation, which is based on steady-state energy flow, is regarded as an efficient tool to deal with uncertainties in MEC systems by offering more useful information for decision-making and planning as well.

Probabilistic methods are the main approaches being dealt with such uncertainties when sufficient historical data with respect to uncertain variables is available. To simulate such probabilistic problems, several techniques such as Monte Carlo Simulation (MCS) method, analytical methods, and approximate methods have been adopted to handle uncertainties. Ref. [8] combined MCS and multi-linear method to solve probabilistic energy flow for integrated electricity-gas systems. As one of the analytical methods, cumulant method

The associate editor coordinating the review of this manuscript and approving it for publication was Bin Zhou.

and Gram-Charlier expansion are utilized to build the model of probabilistic energy flow for MEC systems [9]. Due to the computational burden of MCS method, and simplification of problem by mathematical assumption of analytical methods, the Point Estimate Method (PEM) in approximate methods is applied to investigate probabilistic energy flow to overcame uncertainties regarding the operation of MEC systems [10], [11]. However, both uncertainties of RESs and loads correlation are left out of consideration in the corresponding researches of probabilistic energy flow calculation.

Another approach to analyze uncertainties is based on the fuzzy set and possibility theory when there is insufficient data or the nature of numerical changes for uncertain variables does not obey a particular probability distribution. Although there is no investigation on fuzzy energy flow calculation so far, a lot of fuzzy power flow studies have been done. Most of them employ α-cut method to implement fuzzy arithmetic due to its simplicity [12], [13]. However, α-cut method reduces the interpretability of the fuzzy results because of its overestimation of uncertainties [14].

In reality, some uncertain variables in MEC systems are probabilistic and some are possibilistic, neither the conventional only probabilistic nor only possibilistic methods can be performed. Ref. [15] proposed a hybrid possibilistic-probabilistic approach to evaluate the impact of DGs on the performance of distribution systems, taking into account the uncertainties of loads, RESs generation, operating, and investment decisions of distribution generation operators. Ref. [16] adopted a hybrid approach [17] to jointly propagates probabilistic and possibilistic uncertainty considering the uncertainties of RESs output, the decision of the distributed generation owners, and the power profiles of electric vehicles. Nevertheless, there is a severe lack of the investigation associated with possibilistic-probabilistic energy flow in MEC systems. Additionally, more uncertainties in MEC systems should be involved to establish a more accurate model, and a more precise tool should be implemented when evaluating operational safety. To solve the above problems, the main contribution of this paper can be summarized:

1) A hybrid possibilistic-probabilistic multi-energy flow (HPPMEF) assessment approach is presented to evaluate uncertainty for analyzing security and assessing risk of MEC systems, which comprises of electricity, natural gas and heating sub-network.

2) A more accurate uncertain model is established for the MEC systems by considering the uncertainties of RESs generation, various energy loads, parameters of pipelines in gas and heating network, and related parameters of interdependencies from the perspective of the structure "source-network-load". The correlations among RESs generation and energy loads are taken into account as well.

3) The product t-norms of extension principle approach plus α-cut method is firstly applied in the fuzzy energy flow calculation to reduce overestimation compared with sole α-cut method, which make the proposed method more precise.

II. SYSTEM MODELING

A. NATURAL GAS NETWORK

Natural gas resources are transported from gas producers to customers through natural gas transmission network. The steady-state model for natural gas network mainly focuses on pipelines, compressor stations and nodal gas flow balance [18]. Firstly, the gas flow of *kth* pipeline connected to node *i* and *j* can be expressed by:

$$f_k = K_g s_{ij}\sqrt{s_{ij}(pr_i^2 - pr_j^2)} \tag{1}$$

$$K_g = 7.57 \times 10^{-4} \times \frac{T_n}{p_n}\sqrt{\frac{{D_g}^5}{\chi_g S_g T_g L_g Z_g}} \tag{2}$$

where pr_i and pr_j are pressure of node i and j; s_{ij} is used to describe the direction of gas flow, set +1 if the $pr_i > pr_j$, otherwise set -1; K_g is comprehensive pipe parameters; D_g and L_g are the diameter and length of the pipeline; χ_g is friction factor; Z_g is compression coefficient; T_g is average temperature; S_g is gas specific gravity.

A certain number of compressor stations are necessary to compensate pressure loss in the gas network, the energy consumption in horsepower of kth compressor H_k is [19]:

$$H_k = B_k f_k \left[\left(\frac{\pi_j}{\pi_i}\right)^{Z_{ki}^{(\frac{\alpha-1}{\alpha})}} - 1\right] \tag{3}$$

$$\tau_k = \alpha_k + \beta_k H_k + \gamma_k H_k^2 \tag{4}$$

where B_k, Z_k and α are parameters of the compressor; τ_k is the gas consumption by the gas turbine connected to the compressor k; α_k, β_k and γ_k are consumption coefficients of the compressor k.

The gas flow balance equation in a matrix form is shown:

$$(A + U)f + \omega - T\tau = 0 \tag{5}$$

where A is branch-nodal incidence matrix; U is the compressors and nodes connection matrix; f is the vector of gas flow; ω is the vector of nodal injection flow; the matrix T and vector τ are compressors matrix and gas consumption by compressors.

B. HEATING NETWORK

The heating network consists of a supply network and a return network, which are identical topological structures. The steady-state hydraulic and thermal models are used to model heating network in this paper. The hydraulic model determines the mass flow rates going through heat pipelines [20].

$$A\dot{m} = \dot{m}_q \tag{6}$$

$$BK_h|\dot{m}|\dot{m} = 0 \tag{7}$$

$$K_h = \frac{8Lf}{D^5\rho^2\pi^2 g} \tag{8}$$

where A is network incidence matrix; B is loop incidence matrix; $\dot{m}$ is vector of mass flow rate; K_h is vector of heat resistance coefficient.

The thermal model determines the supply and return temperatures of heat nodes. Equ. (9) presents the relationship among heat power, mass flow rates and temperatures; Equ. (10) presents temperature loss alone the pipe; Equ. (11) presents ideal heat water mixture process [21].

$$\Phi = C_p \dot{m}_q (T_s - T_o) \tag{9}$$

$$T_{end} = (T_{start} - T_a)\, e^{-\lambda L / C_p \dot{m}} + T_a \tag{10}$$

$$\left(\sum \dot{m_{out}}\right) T_{out} = \sum (\dot{m_{in}} T_{in}) \tag{11}$$

where Φ is vector of nodal heat power; C_p is the specific heat ratio; T_s and T_o are vector of supply and outlet temperatures of heat nodes; T_{start} and T_{end} are start and end temperatures of the heat pipe; λ is the heat transfer coefficient; L is the length of the heat pipe; T_a is the ambient temperature; $\dot{m_{out}}$, T_{out}, $\dot{m_{in}}$, T_{in} are mass flow rates and temperatures going out and into the mixture node, respectively.

C. ELECTRICAL NETWORK

The classical AC power flow formulation is used to model electrical network.

$$\Delta P_i = P_i^{sp} - V_i \sum_{j \in i} V_j \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}\right) \quad \forall i = 1, 2, \ldots, (N_e - 1) \tag{12}$$

$$\Delta Q_i = Q_i^{sp} - V_i \sum_{j \in i} V_j \left(G_{ij} sin\theta_{ij} - B_{ij} cos\theta_{ij}\right) \quad \forall i = 1, 2, \ldots, (N_e - N_{e,PV} - 1) \tag{13}$$

where P_i^{sp} and Q_i^{sp} are specific injected active and reactive power; V_i and θ_i are magnitude and angle of voltage at bus i, and $\theta_{ij} = \theta_i - \theta_j$; G_{ij} and B_{ij} are the real and imaginary part of related bus admittance matrix. N_e and $N_{e,PV}$ are the total number of electrical buses and PV buses. The centralized slack bus is adopted in this paper.

D. ENERGY CONVERSION FACILITIES

E. COMBINED HEAT AND POWER (CHP) PLANTS

CHP is a clean and efficient approach to generating electric and heat power from a single fuel source (e.g., natural gas). The amount of consumed gas by CHPs is [6]:

$$f_{CHP} = \frac{3600}{LHV} \left(\frac{P_{CHP} + \Phi_{CHP}}{\eta_{CHP}}\right) \tag{14}$$

where P_{CHP} and Φ_{CHP} are active power and heat power generated by CHPs, and $\Phi_{CHP} = C_m P_{CHP}$, C_m is heat-to-power ratio; η_{CHP} is the efficiency of CHPs; LHV is lower heating value of the natural gas.

F. GAS-POWERED GENERATIONS

Heat rate is employed to indicate the efficiency of gas-power generations. The characteristics of its input gas and output power is shown:

$$f_{GG} = \frac{1}{LHV} (a_{GG}(P_{GG})^2 + b_{GG} P_{GG} + c_{GG} + \left| d_{GG} sin\left[e_{GG}\left(P_{GG,min} - P_{GG}\right)\right]\right|) \tag{15}$$

where P_{GG} and $P_{GG,min}$ are produced active power and its lower limit; a_{GG}, b_{GG}, c_{GG}, d_{GG}, e_{GG} are parameters of heat rate relate to gas-power generations.

G. BOILERS

Two kinds of boilers are discussed as follows. Gas boilers and electric boilers generate heat by consuming gas and electricity:

$$P_{EB} = \frac{\Phi_{EB}}{\eta_{EB}} \tag{16}$$

$$f_{GB} = \frac{\Phi_{GB}}{\eta_{GB} LHV} \tag{17}$$

where P_{EB}, f_{EB} are power and gas consumption; Φ_{EB}, Φ_{GB} are heat power generation of electric and gas boilers; η_{EB}, η_{GB} are efficiency of electric and gas boilers.

III. UNCERTAINTY IN MULTI-ENERGY FLOW PROBLEM

A. PROBABILISTIC UNCERTAINTY MODELLING

1) WIND TURBINE GENERATION

The probabilistic model of wind turbine generation is composed of wind speed model and generation model. Wind speeds vary greatly due to seasonal, climatic and geographical differences, Weibull distribution is adopted to describe wind speeds variation in this paper [3]:

$$f(v) = \frac{c}{k} (\frac{v}{c})^{k-1} exp\left[-(\frac{v}{c})^k\right] \tag{18}$$

where k and c are the shape and scale coefficients, respectively. The wind power output can be expressed with the correlation between wind speeds and wind generation:

$$P_{WT}(v) = \begin{cases} 0, & 0 \leq v < v_{ci} \ or \ v_{co} \leq v; \\ P_{rated} \dfrac{(v - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \leq v < v_r; \\ P_{rated} & v_r \leq v < v_{co}, \end{cases} \tag{19}$$

where v_{ci}, v_{co} and v_r mean cut in, cut out and rated speed of wind generation; P_{rated} is rated power of wind generation.

2) ELERTRICAL, GAS AND HEAT LOADS

Generally, the characteristics of uncertainty forecasts of various loads (e.g., electricity, gas, heat) can be taken as the normal probability distribution function (PDF) [11]:

$$f(L) = \frac{1}{\sqrt{2\pi}\sigma_L} exp\left[-\frac{(L - \mu_L)^2}{2\sigma_L^2}\right] \tag{20}$$

where L represents electrical loads or gas loads or heat loads in different sub-network; σ and μ are mean and standard deviation of corresponding energy loads.

B. POSSIBILISTIC UNCERTAINTY MODELING

1) PIPELINE PARAMETERS IN GAS AND HEATING NETWORKS

During the practical modeling process, there is usually devoid of the complete and accurate information of parameters in gas and heating networks due to their complex structures. For instance, the resistance coefficient of the gas network K_g in (2), of the heating network K_h in (8), show uncertainty, which are regarded as crisp values in the conventional multi-energy flow calculation. In fact, these values cannot be directly measured, and they will be affected by some factors such as the age of the pipeline, pipe diameter, pipe flow rate and so forth. In this part, it assumed that no statistical data of pipe parameters is available. Set a predicted value of the pipeline parameter K_{sp}, and a pipeline parameters' fluctuation rate of κ_u, the parameters of pipelines K_p are modeled by triangular membership function as follows:

$$K_p = [1-\kappa_u, 1, 1+\kappa_u] \times K_{sp} \tag{21}$$

where $1-\kappa_u$ and $1+\kappa_u$ stand for the lower and upper bounds of the support, K_{sp} is the core of fuzzy number.

2) RELATED PARAMETERS OF ENERGY CONVERSION FACILITIES

In the previous multi-energy flow calculation, the related parameters of energy facility devices are usually taken several representative values as their crisp values. However, these parameters also shows uncertainty since they will fluctuate within a certain range in light of multiple conversion techniques, operating conditions and calculation methods. Firstly, the performance characteristics of CHPs using various technologies are different, and generally the range of values of their related parameters can be given. For instance, according to Ref. [22], the overall CHP efficiency for microturbine-based CHP systems is $55\% - 80\%$, while for gas-turbine-based CHP systems, it is $66\% - 71\%$. Similarly, their typical power to heat ratios are $0.5 - 0.7$ and $0.6 - 1.1$, respectively. Besides, the conversion efficiency of boilers, which can be divided into electric boilers and gas boilers, also indicates uncertainty [23]. Moreover, the gas flow consumption of gas-fired generation and CHPs has relation with the lower heating value (LHV) varied from 35.40 to 39.12 MJ/m^3 [24], which results in the uncertainty as well. Therefore, these related parameters P^{dev} which are inaccurate or susceptible to subjective experience are assumed to be represented by triangular membership functions as follows:

$$P^{dev} = \left[\xi_{min}^{dev}, \xi_u^{dev}, \xi_{max}^{dev}\right] \times P_{sp}^{dev} \tag{22}$$

where P_{sp}^{dev} is the predicted parameter value of the energy facility device, ξ_{min}^{dev}, ξ_u^{dev}, ξ_{max}^{dev} are the minimum, the most likely, and maximum coefficient of the P_{sp}^{dev}.

IV. HYBRID POSSIBILISTIC-PROBABILISTIC UNCERTAINTY ALGORITHM

A. 2M+1 POINT ESTIMATE METHOD WITH NATAF TRANSFORMATION

2M+1 point estimate method (PEM), also known as three-point estimate method, has advantages of obtaining the low order moments of the output random variables accurately with low computational burden [10]. However, input variables are strictly required to be independent of each other in this method. In the actual MEC systems, there are correlation among the renewable energy generation, electrical, gas and heat loads. Through 2M+1 PEM with Nataf transformation, the correlation of random variables can be processed, and the random variables can be accurately simulated. The specific steps are summarized as follows:

Step 1) Get the correlation matrix C_X of input random variables vector X (e.g. wind-turbine generation and energy loads), ρ is the non-diagonal element of C_Z, representing correlation coefficient of related random variables. Calculate the non-diagonal correlation efficient ρ_0 in correlation matrix C_Z of standard normal distribution vector Z according to semiempirical formulation in [25]:

$$\rho_0 = h\rho \tag{23}$$

where h is conversion coefficient.

Step 2) Decompose C_Z by Cholesky decomposition into a lower triangular matrix L:

$$C_Z = LL^T \tag{24}$$

Step 3) Construct the matrix S_Z of random variables Z in independent standard normal spaces through 2M+1 PEM. Compute the location by (25)(26)(27) and weight by (28) of the variable Z_l.

$$Z_{l,k} = \mu_{Z_l} + \zeta_{l,k}\sigma_{Z_l}, \quad k = 1, 2, 3 \tag{25}$$

$$\zeta_{l,k} = \frac{\lambda_{Z_l,3}}{2} + (-1)^{3-k}\sqrt{\lambda_{Z_l,4} - \frac{3}{4}\lambda_{Z_l,3}^2} \tag{26}$$

$$\lambda_{Zl,i} = \frac{\int_{-\infty}^{\infty}(Z_l - \mu_{Z_l})f_{Zl}dZ_l}{(\sigma_{Zl})^i} \tag{27}$$

$$\omega_{l,k} = \frac{(-1)^{3-k}}{\zeta_{l,k}(\zeta_{l,1} - \zeta_{l,2})}, \quad \omega_{l,3} = \frac{1}{m} - \frac{1}{\lambda_{Z_l,4} - \lambda_{Z_l,4}^2} \tag{28}$$

where the location $Z_{l,k}$ is the kth value of Z_l; μ_{Z_l}, σ_{Z_l} are the mean value and standard deviation of Z_l; $\zeta_{l,k}$ and $\omega_{l,k}$ are the standard location and weight; $\lambda_{Zl,i}$ and f_{Zl} are the ith moment and the probability density function of Z_l.

Step 4) Transform the matrix S_Z acquired by step 3) into the vector Y in original space by means of inverse Nataf transformation.

$$S_Z = L^{-1}Y \tag{29}$$

Step 5) On the basis of isoprobabilistic transformation principle, the initial random variable X can be obtained by:

$$\begin{cases} \Phi(Y_i) = F(X_i) \\ X_i = F^{-1}(\Phi(Y_i)) \end{cases} \tag{30}$$

where F and Φ are the cumulative probability distribution function of the vector X and Y.

B. POSSIBILITY THEORY

1) PRELIMINARY

Usually, there are not enough data to construct reliable probabilistic distributions in MEC systems, which leads to the formulation of possibility theory based on the fuzzy set approach. Denote $A \subseteq U$ as a fuzzy set of elements and give a possibility distribution $\pi(x)$, which maps the universe U into [0, 1]. It must be mentioned that when $\pi(x) = 0$, the membership degree of 0, means that x is an impossible event and when $\pi(x) = 1$, the membership degree of 1, means that x is a possible event and may be occurred. Here, the possibility measure $\Pi(A)$ and necessity measure $N(A)$ of the event occurrence $(x \in A)$ are defined.

$$\Pi(A) = 1 - N(A^C) = sup\,\{\pi(x)|x \in A\} \tag{31}$$

$$N(A) = 1 - \Pi(A^C) = inf\,\{1 - \pi(x)|x \notin A\} \tag{32}$$

where A^C is the complement of A. Fuzzy numbers are a specific type of fuzzy sets represented by the membership functions. Triangular fuzzy shape are frequently used in practice, which can be defined by:

$$M(x; m_1, m_2, m_3) = \begin{cases} \dfrac{x - m_1}{m_2 - m_1}, & if\ m_1 < x \le m_2 \\ \dfrac{m_3 - x}{m_3 - m_2}, & if\ m_2 < x \le m_3 \\ 0, & otherwise \end{cases} \tag{33}$$

2) FUZZY ARITHMETIC

Currently, there are two mathematical approaches available to implement fuzzy arithmetic: α-cut approach and extension principle approach, where α-cut approach is frequently applied in fuzzy power flow due to its simplicity. A α-cut of a fuzzy set M_d is a classical set M_α, which contains all the elements in U with a membership value in M_d greater or equal to α, that is,

$$M_\alpha = \left\{x \in U|\mu_{M_d} \ge \alpha, \alpha \in [0, 1]\right\} \tag{34}$$

The specific procedures of α-cut approach can be found in [26]. However, it should be recoginized that this method leads to overestimation of uncertainty in the resulting fuzzy numbers. To reduce this overestimation, the extension principle approach with product t-norms [27] is firstly utilized to solve uncertainty in HPPMEF calculation. Fig.1 illustrates an example of the resulting fuzzy numbers solved by product t-norms and α-cut, it can be observed that the membership value for each point of the support using α-cut method is larger than the membership value using product t-norms, which result in reducing overestimation of uncertainty.

The extended fuzzy addition and multiplication with product t-norms will be introduced below. The extended fuzzy subtraction and division can be achieved according to $M \ominus N = M \oplus (-1) \times N$ and $M \oslash N = M \otimes (1)/N$. Assuming

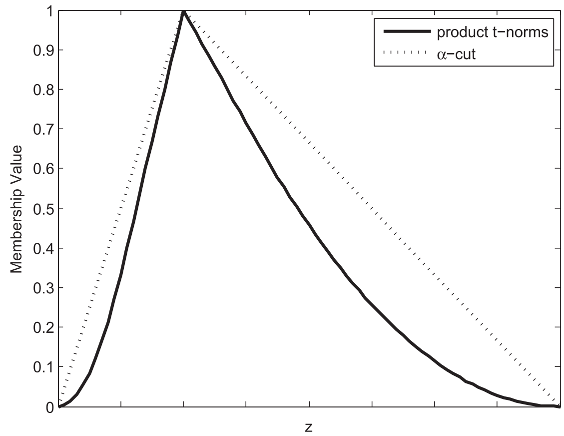

FIGURE 1. Fuzzy calculation with different methods.

there are two triangular fuzzy numbers $M(x; m_1, m_2, m_3)$ and $N(x; n_1, n_2, n_3)$, where:

$$M(x; m_1, m_2, m_3) = \begin{cases} \overline{\alpha_m x} + \overline{\beta_m}, & if\ m_1 \le x \le m_2 \\ \underline{\alpha_m x} + \underline{\beta_m}, & if\ m_2 \le x \le m_3 \\ 0, & otherwise \end{cases} \tag{35}$$

$$N(x; n_1, n_2, n_3) = \begin{cases} \overline{\alpha_n x} + \overline{\beta_n}, & if\ n_1 \le x \le n_2 \\ \underline{\alpha_n x} + \underline{\beta_n}, & if\ n_2 \le x \le n_3 \\ 0, & otherwise \end{cases} \tag{36}$$

The mathematical form of extended fuzzy addition using product t-norms is presented as follows:

$$T(z) = M(x) \oplus N(y) = \sup_{z=x+y}\ (M(x) \times N(y)) \tag{37}$$

Proposition 1: In the increasing part of the support of the resulting fuzzy number, where each discrete point $z = t \in [m_1 + n_1, m_2 + n_2]$. Firstly, let

$$\theta_1 = max(m_1, t - n_2) \tag{38}$$

$$\theta_2 = min(m_2, t - n_1) \tag{39}$$

$$\begin{cases} x_r^1 = \dfrac{c}{2} - \dfrac{\overline{\beta_m}\overline{\alpha_n} - \overline{\alpha_m}\overline{\beta_n}}{2 \times \overline{\alpha_m}\overline{\alpha_n}}, \\ y_r^1 = c - m_r^1 = \dfrac{c}{2} + \dfrac{\overline{\beta_m}\overline{\alpha_n} - \overline{\alpha_m}\overline{\beta_n}}{2 \times \overline{\alpha_m}\overline{\alpha_n}} \end{cases} \tag{40}$$

Then, the value of $T(t)$ can be calculated as follows:

$$T(t) = \begin{cases} M(x_r) \times N(y_r), & if\ \theta_1 \le x_r^1 \le \theta_2 \\ M(\theta_2) \times N(c - \theta_2), & if\ \theta_2 < x_r^1 \\ M(\theta_1) \times N(c - \theta_1), & if\ x_r^1 < \theta_1 \end{cases} \tag{41}$$

Proposition 2: In the decreasing part of the support of the resulting fuzzy number, where each discrete point $z = t \in [m_2 + n_2, m_3 + n_3]$. Firstly, let

$$\theta_3 = max(m_2, t - n_3) \tag{42}$$

$$\theta_4 = min(m_3, t - n_2) \tag{43}$$

$$\begin{cases} x_r^2 = \dfrac{c}{2} - \dfrac{\beta_m\alpha_n - \alpha_m\beta_n}{2 \times \alpha_m\alpha_n}, \\ y_r^2 = c - m_r^2 = \dfrac{c}{2} + \dfrac{\beta_m\alpha_n - \alpha_m\beta_n}{2 \times \alpha_m\alpha_n} \end{cases} \tag{44}$$

Then, the value of $T(t)$ can be calculated as follows:

$$T(t) = \begin{cases} M(x_r^2) \times N(y_r^2), & if\ \theta_3 \le x_r^2 \le \theta_4 \\ M(\theta_4) \times N(c - \theta_4), & if\ \theta_4 < x_r^2 \\ M(\theta_3) \times N(c - \theta_3), & if\ x_r^2 < \theta_3 \end{cases} \tag{45}$$

Then, the mathematical form of extended fuzzy multiplication using product t-norms is presented as follows:

$$T(z) = M(x) \otimes N(y) = \sup_{z=x\times y} (M(x) \times N(y)) \tag{46}$$

Proposition 3: In the increasing part of the support of the resulting fuzzy number, where each discrete point $z = t \in [m_1n_1, m_2n_2]$. Firstly, let

$$\theta_1 = max(m_1, t/n_2) \tag{47}$$

$$\theta_2 = min(m_2, t/n_1) \tag{48}$$

$$\begin{cases} x_r^1 = \sqrt{\dfrac{\overline{\beta_m}\overline{\alpha_n}}{\overline{\alpha_m}\beta_n} \times c}, \\ y_r^1 = \dfrac{c}{x_r^1} = \sqrt{\dfrac{\overline{\beta_n}\overline{\alpha_m}}{\overline{\alpha_n}\beta_m} \times c} \end{cases} \tag{49}$$

Then, the value of $T(t)$ can be calculated as follows:

$$T(t) = \begin{cases} M(x_r^1) \times N(y_r^1), & if\ \theta_1 \le x_r^1 \le \theta_2 \\ M(\theta_2) \times N(\frac{c}{\theta_2}), & if\ \theta_2 < x_r^1 \\ M(\theta_1) \times N(\frac{c}{\theta_1}), & if\ x_r^1 < \theta_1 \end{cases} \tag{50}$$

Proposition 4: In the decreasing part of the support of the resulting fuzzy number, where each discrete point $z = t \in [m_2n_2, m_3n_3]$. Firstly, let

$$\theta_3 = max(m_2, t/n_3) \tag{51}$$

$$\theta_4 = min(m_3, t/n_2) \tag{52}$$

$$\begin{cases} x_r^2 = \sqrt{\dfrac{\beta_m\underline{\alpha_n}}{\underline{\alpha_m}\beta_n} \times c}, \\ y_r^2 = \dfrac{c}{x_r^2} = \sqrt{\dfrac{\beta_n\underline{\alpha_m}}{\underline{\alpha_n}\beta_m} \times c} \end{cases} \tag{53}$$

Then, the value of $T(t)$ can be calculated as follows:

$$T\ (t) = \begin{cases} M(x_r^2) \times N(y_r^2), & if\ \theta_3 \le x_r^2 \le \theta_4 \\ M(\theta_4) \times N(\frac{c}{\theta_4}), & if\ \theta_4 < x_r^2 \\ M(\theta_3) \times N(\frac{c}{\theta_3}), & if\ x_r^2 < \theta_3 \end{cases} \tag{54}$$

The proof of above 4 propositions can be found in Ref. [27].

C. DEMPSTER-SHAFER EVIDENCE THEORY

Dempster-Shafer (D-S) evidence theory is a systematic theory to tackle multiple uncertain information [28]. Here, the basic concept related to the D-S evidence theory will be introduced. D-S evidence theory is an uncertainty theory based on the identification framework Θ, of which the subset recorded as a power set 2^Θ, is all possible outcomes of the uncertain problem. A is any subset of the set 2^Θ, denoted as $A \subseteq 2^\Theta$. Define the mass function m as a mapping of the set to [0, 1], which satisfies [28]:

$$\begin{cases} m(\varnothing) = 0 \\ \sum_{A\subset\Theta} m(A) = 1 \end{cases} \tag{55}$$

where $m(A)$ is the basic probability assignment function of event A. During the data fusion process, the trust degree of the final result can be represented by belief $Bel(A)$ and plausibility $Pl(A)$.

$$Bel(A) = \sum_{B\subseteq A} m(B) \tag{56}$$

$$Pl(A) = \sum_{B\bigcap A\neq\varnothing} m(B) = 1 - Bel(\overline{A}) \tag{57}$$

where $Bel(A)$ and $Pl(A)$ are the trust degree for the condition that A is true and not-false, indicating the minimum and maximum probability for the occurence of the event A.

When there are multiple sources of data, these data can be fused into a more reliable basic probability distribution through synthetic rules to consistently describe the output uncertainty. For the output obtained by joint possibilistic and probabilistic input, the belief and plausibility measure can be expressed by [17]:

$$Bel(A) = \sum_{i=1}^{2k+1} p_i N_i(A) \tag{58}$$

$$Pl(A) = \sum_{i=1}^{2k+1} p_i \Pi_i(A) \tag{59}$$

where p_i is the sample probability of the probabilistic variable vector.

D. HYBRID POSSIBILISTIC-PROBABILISTIC UNCERTAINTY ALGORITHM FOR UNCERTAIN ENERGY FLOW CALCULATION

The general mathematic description of hybrid possibilistic-probabilistic multi-energy flow (HPPMEF) problem in MEC systems is summarized as:

$$\begin{cases} Y_e = F_e(X_e, X_g, X_h, \widetilde{X}_e, \widetilde{X}_g, \widetilde{X}_h) \\ Y_g = F_g(X_e, X_g, X_h, \widetilde{X}_e, \widetilde{X}_g, \widetilde{X}_h) \\ Y_h = F_h(X_e, X_g, X_h, \widetilde{X}_e, \widetilde{X}_g, \widetilde{X}_h) \end{cases} \tag{60}$$

where nonlinear transformation function F_e, F_g, F_h are electrical, gas and heat equation mentioned in section II; X_e, X_g, X_h are probabilistic variables, e.g., wind generation, electrical, gas, and heat loads; $\widetilde{X}_e$, $\widetilde{X}_g$, $\widetilde{X}_h$ are possibilistic variables, e.g., parameters of gas and heating pipelines and coupling units; Y_e, Y_g, Y_h are output variables, e.g., the magnitude and angle of voltage at each bus, the power flow of each electrical line, the pressure at each gas node, the temperature at each heat node, the flow at each gas or heat pipeline and so on.

Algorithm 1 HPPMEF Assessment

Begin: Input data of MEC systems.
for $j = 1 : 2m + 1$
1. Sample jth probabilistic variables X_e, X_g, X_h based on (23)-(30), set $\nu = 0$.
2. Calculate possibilistic variables $\widetilde{X}_e$, $\widetilde{X}_g$, $\widetilde{X}_h$ by product t-norms based on (37)-(54).
3. Set $\alpha = K\nu$.
4. Get the $\alpha-$cut set of the obtained possibilistic results by step 2.
5. Calculate Y_e, Y_g, Y_h based on (60).

if $\alpha = 1$
if $j = 2m + 1$
Compute $Bel(Y)$ and $Pl(Y)$ measures based on (58)(59), output the results.
else
Return to step 1.
end if
else
$\nu = \nu + 1$, return to step 2.
end if; end for.

For clarity, the proposed HPPMEF assessment algorithm is outlined in algorithm 1.

Here some tips should be noticed, 1) K is the step size of the α-cut method and can be divisible by 1; 2) Newton-Raphson technique is utilized during the process of HPPMEF calculation in this paper.

V. CASE STUDIES

In this section, the effectiveness of the proposed method for uncertainty assessment in multi-energy systems is validated by two cases. All simulations have been conducted on MATLAB utilizing an Intel Core i5 3.20 GHz PC with 8 GB RAM.

A. CASE 1: N6-H7-E9 COUPLED NETWORKS

The proposed approach is first applied to an integrated MEC system consisted of a 6-node natural gas network, a 7-node heating network, and a modified IEEE 9-bus electrical network [29], the configuration and interdependencies of which are shown in Fig.2. In this case, a gas-fired generation, two wind farms, and a CHP plant are separately connected to the electrical bus 1, 2 and 3. Meanwhile, the heating system has 1 CHP plant, 1 gas boiler, and 1 electric boiler as its three heat sources. Besides, a moto-compressor is placed between gas node 1 and 2. Gas node 3 provides gas supply for the CHP plant, while gas node 6 offers gas supply to the gas-fired generation and the gas boiler at the same time.

The crisp parameters associated with this small MEC system can be found in Ref. [29]. To assess the uncertainty of this system, some probabilistic and possibilistic parameters are considered as follows. Firstly, the energy loads and wind generations are assumed as probabilistic uncertain variables

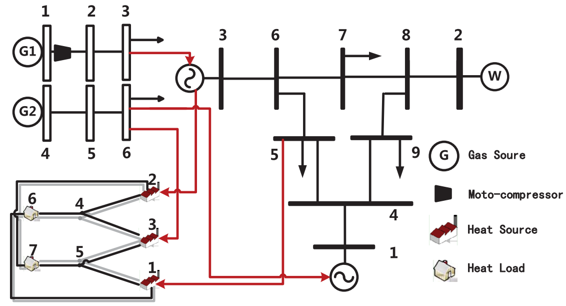

FIGURE 2. Schematic of the N6-H7-E9 MEC system.

modeled by the normal PDF and the Weibull PDF, respectively. For energy loads, their mean values equal to the crisp values in Ref. [29], the standard values equal to 5% of the mean values. For wind generations, the rated capacity is 100MW, the cut-in, rate, and cut-out speeds of two wind farms are assumed to be 3, 13 and 25 m/s. The correlated coefficients of energy loads and wind generations are: $\rho_{EE} = \rho_{GG} = \rho_{HH} = 0.9$, $\rho_{WW} = 0.8$, $\rho_{EG} = \rho_{EH} = \rho_{GH} = 0.5$, where the subscript label E, G, H, W mean electrical loads, gas loads, heat loads, and wind generation, respectively. Furthermore, it is assumed that the pipeline parameters in gas and heating networks, and related parameters of couple units are modeled as possibilistic uncertain variables by the fuzzy membership function presented in Table 1, taking the crisp value in Ref. [29] as their predicted value.

In this part, five approaches are implemented to investigate and compare their technical performance to assess uncertainties in MEC systems, and they are described as follows:

Approach 1: it is based on Monte Carlo.

Approach 2: it is based on 2M+1 PEM.

Approach 3: it is based on Monte Carlo, product t-norms plus α-cut, and evidence theory.

Approach 4: it is based on Monte Carlo, α-cut, and evidence theory.

Approach 5: namely the proposed approach in this paper, it is based on 2M+1 PEM, product t-norms plus α-cut, and evidence theory.

Table 2 shows typical uncertain multi-energy flow results of the proposed approach, the approach 1~4, where MCS with 5000 iterations has been carried out. It can be seen that the approach 1 and 2 can only handle pure probabilistic input, indicating that 2M+1 PEM can get proper results as MCS in MEC systems. When there is probabilistic and possibilistic input, the results of the hybrid approaches: approach 3~5 have an upper and lower range, their CPU times and samples are presented in Table 3. From Table 2 and Table3, it can be observed that the performance of the proposed approach can provide good results and faster computation speed compared with approach 3 and 4.

Then, to illustrate the performance of uncertainty overestimation of approaches 5, Fig.3-5 separately compare the cumulative distribution function (CDF), plausibility, and belief of the pressure of gas node 3, mass flow of heat pipe 1-5, and voltage magnitude of bus 5 under the proposed

TABLE 1. Parameters of possibilistic uncertain variables.

Possibility distribution	K_g	K_h	C_m	η_{CHP}	η_{EB}	η_{GB}	LHV
$\pi(x) = 0\,(min)$	0.85	0.85	0.909	0.66	0.92	0.85	35.4
$\pi(x) = 1$	1.00	1.00	1.266	0.685	0.95	0.88	37.26
$\pi(x) = 0\,(max)$	1.15	1.15	1.667	0.71	0.98	0.91	39.12

TABLE 2. Typical uncertain multi-energy flow results and their relative errors.

Type of input	Output variables	Mean value		Standard value	
		MCS	2M+1 PEM	MCS	2M+1 PEM
Pure probabilistic	V_9	1.0208	1.0222	0.0028	0.0024
	π_6	12.1228	12.1435	0.1036	0.0842
	m_5	416.5854	415.4875	4.5694	3.0385
	T_{s5}	89.3811	89.3749	0.0057	0.0046
	T_{r5}	39.8633	39.8607	0.0010	0.0015
Both probabilistic and possibilistic	V_{9_min}	1.0192	1.0219	0.0019	0.0009
	π_{6_min}	11.0578	11.4217	0.4227	0.1263
	m_{5_min}	413.8461	409.5060	6.2138	3.0470
	T_{s5_min}	89.2905	89.2849	0.0352	0.0053
	T_{r5_min}	39.8419	39.8407	0.0078	0.0012
	V_{9_max}	1.0215	1.0228	0.0014	0.0006
	π_{6_max}	12.5641	12.8390	0.2699	0.0610
	m_{5_max}	417.7809	413.4605	7.1294	3.0300
	T_{s5_max}	89.4700	89.4658	0.0266	0.0040
	T_{r5_max}	39.8820	39.8810	0.0059	0.0009

TABLE 3. CPU times.

Approaches	Case1		Case 2	
	CPU time (s)	Samples	CPU time (s)	Samples
Approach 3	696.675	5000	16958.530	7000
Approach 4	411.406	5000	12057.921	7000
Proposed approach	27.541	19	205.706	83

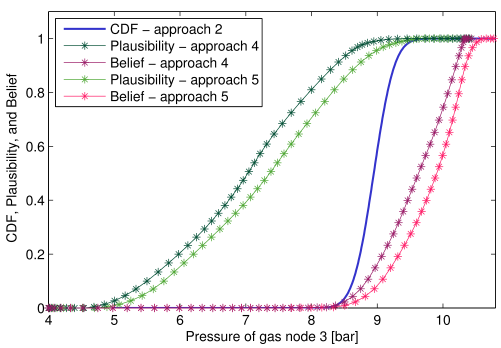

FIGURE 3. The cumulative probability distribution, plausibility, and belief of pressure of gas node 3 in the case 1.

approach, the approach 2 and 4. It can be found that when $pr_3 = 8.8048\,bar$ in Fig.3, its probability equals to 0.8147 calculated by approach 2 considering only probabilistic uncertainty. On this basis, considering additional possibilistic uncertainty, its belief and plausibility calculated by approach 4 are 0.0875 and 0.9803, which mean the trust degree for $pr_3 = 8.8048\,bar$ is true and not false. It is

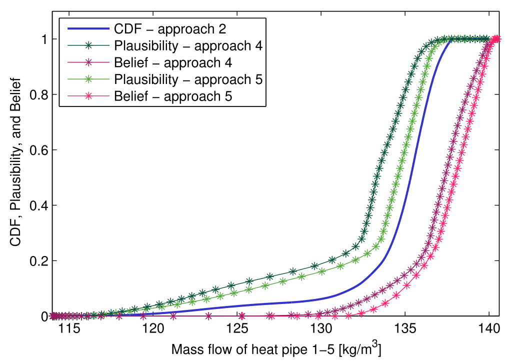

FIGURE 4. The cumulative probability distribution, plausibility, and belief of mass flow of heat pipe in the case 1.

worth noting that when it comes to the results of the proposed approach, the belief and plausibility are 0.0411 and 0.9412, indicating uncertainties overestimation of pressure of gas node 3 is reduced according to Ref. [14]. Here, the rate of uncertainty reduction is defined as: $(BP_{pa} - BP_{a4}) \times 100\%/BP_{a4}$, where the BP_{pa} and BP_{a4} mean the belief or plausibility calculated by the proposed approach and approach 4, respectively. The scopes for the rate of uncertainty reduction calculated from Fig.3 are [0%,69.431%] (for plausibility) and [0%,57.428%] (for belief) for pressure of gas node 3. The above shows: the proposed method not only can assess the uncertain range of state variables, but it also can reduce the uncertainties overestimation, and further avoid the optimistic assessment for uncertainties in MEC systems compared with approach 2 and 4.

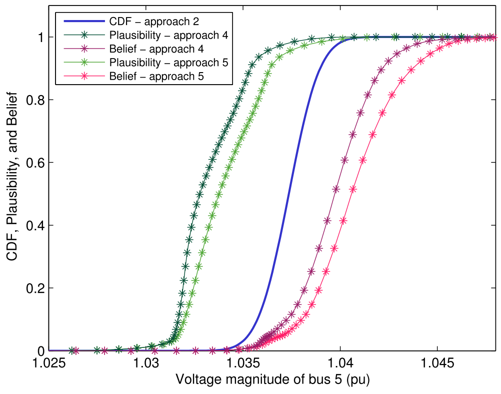

FIGURE 5. The cumulative probability distribution, plausibility, and belief of pressure of electrical bus 5 in the case 1.

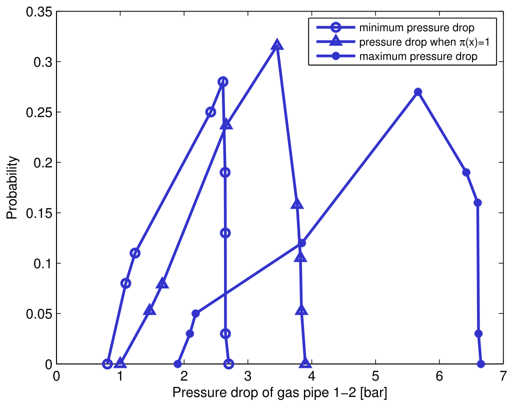

FIGURE 6. The PDF of membership function parameters of the pressure drop of gas pipe 1-2 in the case 1.

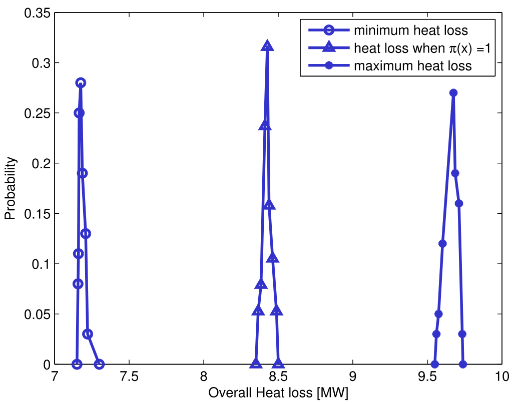

FIGURE 7. The PDF of membership function parameters of the overall heat loss in the case 1.

The similar conclusion can be reached based on the Fig.4 and Fig.5.

Additionally, there is another way to represent the uncertainty of such a situation: associating specific membership functions to the output variables and probabilistically represent its parameters [16]. Therefore, this paper also illustrates the uncertainties of the pressure drop of gas pipe 1-2, overall heat loss, and overall power loss in Fig.6-8. To illustrate,

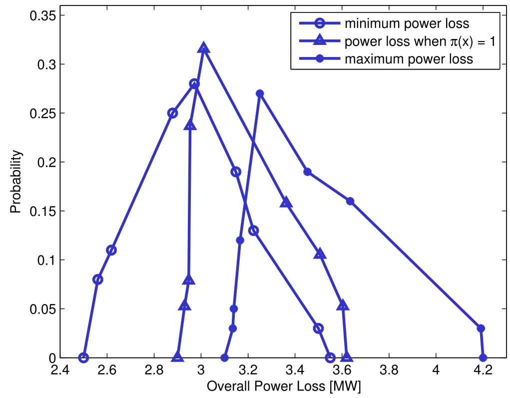

FIGURE 8. The PDF of membership function parameters of the overall power loss in the case 1.

the probability of the parameters of the overall power loss membership function shown in Fig.8 is explained. It can be seen that the the range of minimum power loss is [2.5,3.55] with the possibility [0,0.28]; the range of the maximum power loss is [3.1,4.2] with the possibility [0,0.27]; the range of the power loss when $\pi(x) = 1$ is [2.9,3.62] with the possibility [0,0.32].

B. CASE 2: N20-H14-E30 COUPLED NETWORKS

This case is composed of a 20-node natural gas network, a 14-node heating network, and a modified IEEE 30-bus electrical network, where further analysis is implemented to verify the proposed method. For generation in electrical network, there are 2 gas-fired generation in bus 1 and 2, 2 wind farms in bus 8, 4 CHP plants in bus 7, 14, 17, 23 and other generators are coal-powered. In the heating network, there are 15 pipelines and 9 heat sources including CHP plants and boilers. Note that the gas boiler placed at heat node 1 is assumed as the slack node in the heating network. Besides, 2 gas sources, 4 gas storages and 2 moto-compressors driven by electricity are installed in the gas network.

The structure of this complex MEC system is presented in Fig.9, its correlated crisp data and specific configuration can be found in Ref. [10]. The values of the possibilistic and probabilistic uncertain variables are set identically with uncertainties in the case 1 presenting in Table 1. Similarly, MCS with 7000 samples of approach 3 is contrasted with the proposed approach. Fig. 10 compares their cumulative probability distribution, plausibility and belief. It indicates that the accuracy of the proposed method is well within the expected level. Again, Table 3 displays the efficiency of the proposed approach in the way of CPU time and samples compared with approach 3 and 4.

Then, typical uncertainty assessment including the results of the pressure of gas node 4, mass flow of heat pipe 9-10, and voltage of bus 17 are depicted in Fig.11-Fig.13. To illustrate, the coupled electrical bus 17 is analyzed as follows. It can be observed that when $V_{17} = 1.045$V, the plausibility of the proposed approach is 0.858, which is lower than the plausibility of approach 4: 0.975; when $V_{17} = 1.049$V,

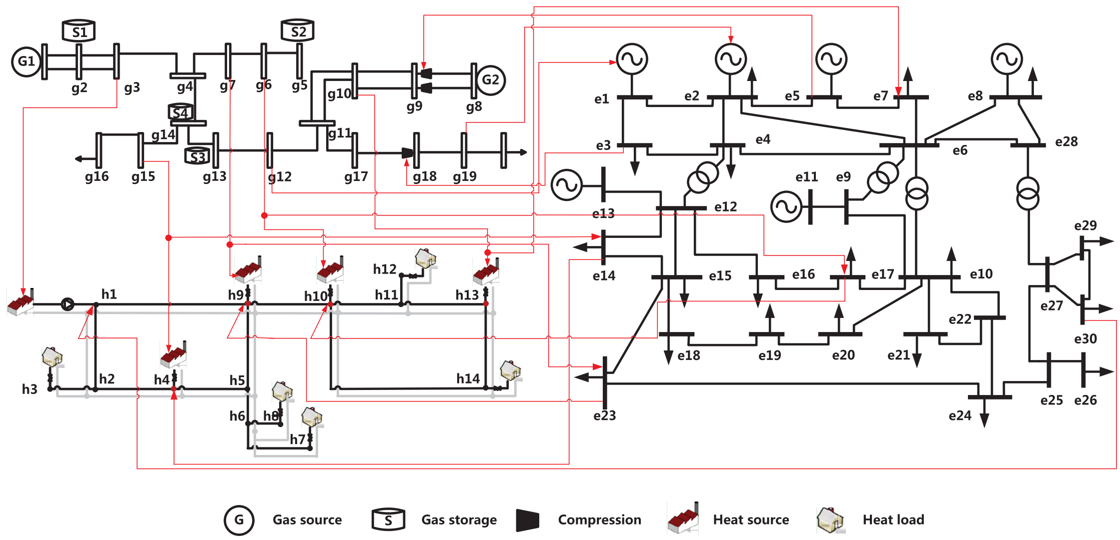

FIGURE 9. Schematic of the N20-H14-E30 MEC system.

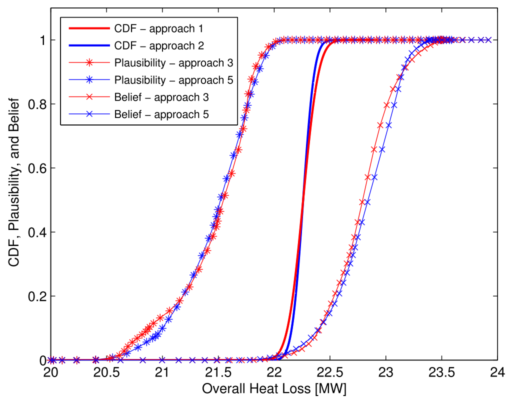

FIGURE 10. Comparison of plausibility, belief, pure probabilistic measures of the overall heat losses obtained by different approaches.

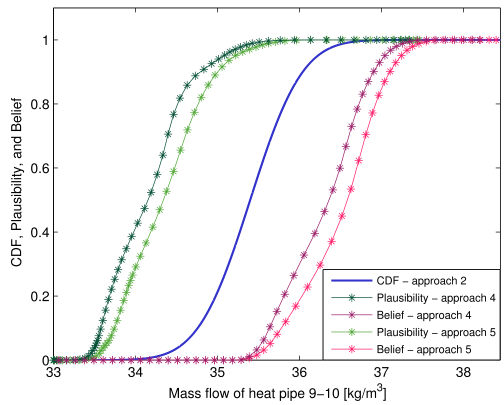

FIGURE 12. The cumulative probability distribution, plausibility, and belief of mass flow of heat pipe 9-10 in the case 2.

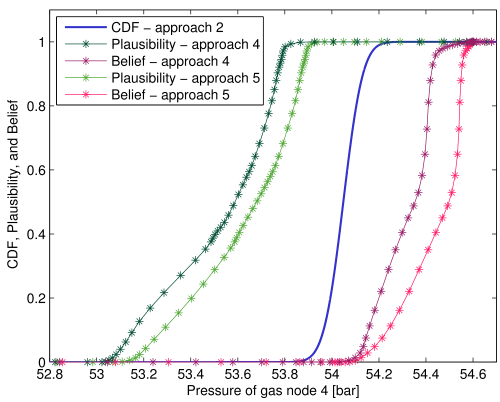

FIGURE 11. The cumulative probability distribution, plausibility, and belief of pressure of gas node 4 in the case 2.

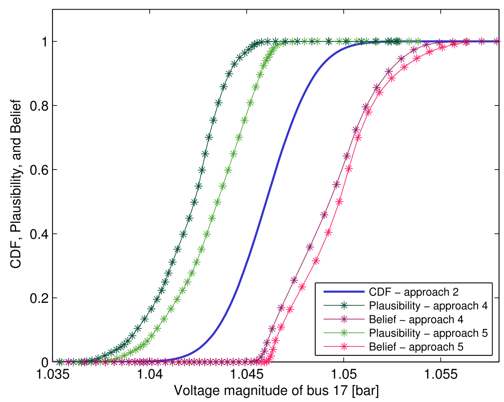

FIGURE 13. The cumulative probability distribution, plausibility, and belief of voltage magnitude of bus 17 in the case 2.

the belief of the proposed approach is 0.4033, which is still lower than belief of approach 4: 0.4588. These mean that the uncertainties overestimation is reduced. The scopes for the rate of uncertainty reduction calculated from Fig.13 are [0%,87.303%] (for plausibility), and [0%,89.651%] (for belief) for voltage magnitude of electrical bus 17.

Similar conclusions can be drawn according to Fig.11 and Fig.12. Therefore, the practicability and effectiveness of the proposed method have been verified through both accuracy and execution time criteria. Besides, the presented results have shown the proposed method can be applied in the complex MEC systems to assess its uncertainty, and it has advantages of computationally efficient and more accurate than other hybrid approaches.

VI. CONCLUSION

This paper has proposed a hybrid possibilistic-probabilistic energy flow assessment approach for multi-energy carrier (MEC) systems. The more realistic MEC systems have been modeled by simultaneously considering the correlated probabilistic uncertainties (e.g., wind generations, energy loads) and possibilistic uncertainties (e.g., pipe parameters in energy networks, related parameters of coupled units). Two case studies have demonstrated the practicability and effectiveness of the proposed method through different comparisons. These results have led to the conclusion that the high computational efficiency can be realized and uncertainty overestimation can be reduced by the proposed method, which help operators and planners to evaluate the technical performance of MEC systems better.

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