Distributionally Robust Collaborative Dispatch of Integrated Energy Systems with DNE Limits Considering Renewable and Contingency Uncertainties

Xiaotong Ji[1], Fan Xiao[2], Dan Liu[2,*], Ping Xiong[2], Mingnian Zhang[3]
[1]State Grid Hubei Electric Power CO., LTD.,
Wuhan, China
[2]State Grid Hubei Electric Power Research Institute,
Wuhan, China
[3]State Grid Huanggang Electric Power CO., LTD.,
Huanggang, China
tonyji7@hotmail.com; xiao103fan@163.com; [*]dannyliu6@hotmail.com; 498236317@qq.com; 805328112@qq.com

***Abstract*—Collaborative optimisation of system reserves and utilisation of renewable energy is an efficient approach to achieving robust optimal dispatch of integrated energy systems (IES). However, conventional robust dispatch methods are often too conservative and lack the ability to consider uncertainties such as renewable energy and contingency probabilities. To address these limitations, this paper proposes a distributionally robust dispatch model that co-optimises reserves and do-not-exceed (DNE) limits while considering these uncertainties. First, a deterministic optimisation model of IES is established with a minimum operational cost objective and security constraints. Next, a two-stage robust collaborative optimisation framework of IES is built, based on the Wasserstein measure, with random equipment faults represented by an adjustable ambiguity set. Finally, to overcome the computational challenges associated with robust approaches, duality theory and Karush-Kuhn-Tucker (KKT) conditions are used to convert the formulation into a mixed integer linear programming (MILP) model. The Simulation results on the modified IEEE 33-bus system demonstrate the effectiveness of the proposed model and solution methodology.**

***Index Terms*—Renewable energy integration; Integrated energy systems; Distributionally robust optimisation; Do-not-exceed limits; Combined heat and power; Uncertainty.**

I. INTRODUCTION

With the advancement of renewable energy generation and green energy consumption, the increasing penetration of renewable energy has become an emerging trend for future power systems [1]–[3]. However, the inherent uncertain nature of renewable generation can pose an immense challenge to the safe and stable operation of integrated energy systems (IES). The combined heat and power (CHP) unit has the characteristics of quick start & stop, which can effectively mitigate the fluctuation of renewable output. Therefore, the CHP units, considered as the coupling elements to facilitate the renewable energy consumption in the IES, have raised increasing attention.

On this background, many researchers have proposed approaches to handle the uncertainty of renewable energy, such as stochastic programming (SP) [4], [5] and robust optimisation (RO) [6]–[8]. The authors in [9] proposed a stochastic programming method using probabilistic scenarios to deal with the uncertainty of wind power. This method relies on obtaining the probability distributions of the wind power forecast error in a priori, but the accuracy and rationality are difficult to verify. The authors in [10] established a scheduling model based on the interval optimisation method, but interval representation of dispatch decisions is not easy to use for practical implementations. Despite the merits of SP and RO methods, the following three problems remain unsettled:

1. The decision-making results obtained by RO can be too conservative, while the probability distribution of renewable energy is difficult to accurately estimate;
2. The uncertainty of contingency events, such as equipment and line outages, is not considered in the dispatch model, which may affect the stability of system operations;
3. Considering the renewable energy as non-dispatchable resources, it is too costly to balance the power-load mismatches by regulating other dispatchable resources, especially in the case of high proportion of renewable integration.

To address the first challenge, the distributionally robust optimisation (DRO) is applied because it can combine the probabilistic distribution information of uncertain parameters and the technical bounds of uncertainty. DRO quantifies an

Manuscript received 4 December, 2022; accepted 28 March, 2023.
This research was supported by the Science and Technology Project of State Grid Corporation of China under Grant No. 4000-202122070A-0-0-00.

ambiguity set to represent distribution information, which is particularly useful given limited datasets and could provide less conservative results than traditional RO [11]. The authors in [12] established an ambiguity set for wind power constrained by combined conditions of the l_1- and l_∞-norm, where dispatch decisions of electric-gas coupled systems are made in the worst-case scenario. In [13], the wind power prediction error is assumed to follow the normal distribution, and its mean and variance are characterised by the uncertainty set in the form of a polyhedron. In [14], statistical values of the mean and covariance matrix of the wind power forecast error were obtained to solve the scheduling results under the worst probability distribution, which satisfies the given moment information obtained from the sampling set. Instead of restricting to a specific distribution type, the authors in [15] utilised the moment information of the wind power output, which is incorporated into the piecewise linear model, but the spatial-temporal correlation of neighbouring wind farms is not considered. The authors in [16] presented a two-stage DRO model, which quantifies the renewable consumption rate by an affinely adjustable mechanism, to jointly optimise power dispatch outputs and spinning reserves.

In terms of the second challenge, in [17], the *N-k* criterion was used to quantify the operating reserves of the system for possible contingencies, such as equipment failure and line outages. The authors in [18] adopted a heuristic rule that reserve requirements are set as a percentage of the expected renewable output and load. However, a critical concern is whether the committed reserve is deliverable or not when congested issues occur. For this reason, a stochastic programming method was presented to optimise the spinning reserves within an acceptable risk level. In [19], the operational flexibility of the system was enhanced by employing reserve margins through an offline training algorithm. This offline approach eliminated the real-time computational challenge of stochastic programming. In [20], a distributionally robust framework was constructed by capturing the distribution of fault events in an interval ambiguity set. However, in-depth analysis and research is yet to be done on how to fully account for the combined impact of both contingency and renewable uncertainty.

The concept of do-not-exceed (DNE) limit can effectively tackle the third challenge and has been widely adopted and incorporated in the optimal dispatch model of renewable integrated systems. The DNE limit is defined to allow an acceptable range of renewable energy output power to ensure the safety of system operations. This provides a clear guide on the use of renewable energy and measures the maximum capacity of the system to accommodate renewable power. In [21], the rate of consumption of renewable energy is obtained based on the dispatch results given, but this is not the best strategy to coordinate the renewable power and the generation units, which can underestimate the ability of the system to adapt to renewable energy. The DNE limit is presented in [22] without accounting for the renewable power curtailment and load reduction, and a stringent renewable energy control is adopted. In recent years, many studies have advocated for optimising the power dispatch output and the DNE limit simultaneously. In [23], an adjustable RO model is established to jointly optimise the DNE limit and the power scheduling strategy. In [24], an affine policy rule is proposed for an RO dispatch model, in which the specific coefficients are optimised to quantify the DNE limit, as well as the power dispatch level of the generation units.

To address the research gap mentioned above, we have implemented a robust cooperative optimal dispatch approach for IES. The primary contributions of this study can be outlined as follows.

1. A two-stage distributionally robust framework is proposed as an alternative to the traditional robust or stochastic methods, which can result in dispatch outcomes that are either excessively radical or overly conservative. In our approach, the reserves of IES and the DNE limit are co-optimised, leading to improved utilisation of renewable energy generation.
2. An adjustable ambiguity set is established to effectively address the uncertainty associated with both the continuous output of renewable energy and the discrete probability of contingencies.
3. Various techniques are employed including absolute value linearisation, duality theory, and Karush-Kuhn-Tucker (KKT) conditions to transform the dispatch model into a manageable mixed integer linear programming (MILP) problem that can be solved directly by commercial solvers.

The following sections of this paper are arranged as follows. In Section II, we present the mathematical formulation of the deterministic optimal dispatch model of IES. Section III outlines the distributionally robust framework that considers uncertainties arising from renewable energy and contingencies. Section IV presents the numerical results of the proposed method in the test case using different scenarios. Lastly, in Section V, we conclude this paper.

II. DETERMINISTIC OPTIMAL DISPATCH MODEL OF IES

The goal of the optimal dispatch model of IES is to minimise the operational cost by considering the fuel cost, start-up cost, no-load cost, and spinning reserve cost of the unit. It is noted that the CHP unit is kept ON during the period and threfore there is no start-up cost for the CHP unit [25]

$$\min f = \sum_{t\in\mathcal{T}}\Bigg[\sum_{g\in\mathcal{G}} C_g\left(p_{gt}^{G}\right) + \sum_{h\in\mathcal{H}} C_h\left(p_{ht}^{\mathrm{CHP}}\right) + \sum_{g\in\mathcal{G}} c_g^{u} u_{gt} + \\ + \sum_{g\in\mathcal{G}} c_g^{U} r_{gt}^{U} + \sum_{g\in\mathcal{G}} c_g^{D} r_{gt}^{D} + \sum_{h\in\mathcal{H}} c_h^{U} r_{ht}^{U} + \sum_{h\in\mathcal{H}} c_h^{D} r_{ht}^{D}\Bigg], \quad (1)$$

where:

$$C_g\left(p_{gt}^{G}\right) = a_g\left(p_{gt}^{G}\right)^2 + b_g\left(p_{gt}^{G}\right) + c_g x_{gt}, \quad (2)$$

$$C_h\left(p_{ht}^{\mathrm{CHP}}\right) = c_{gas}\, p_{ht}^{\mathrm{CHP}} \big/ \eta^{\mathrm{CHP}} Q_{gas}, \quad (3)$$

which is subject to the following constraints:

$$x_{gt}, u_{gt}, v_{gt} \in \{0,1\} \qquad \forall t \in \mathcal{T},\ g \in \mathcal{G}, \quad (4)$$

$$x_{gt} - x_{g,t-1} = u_{gt} - v_{gt} \quad \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{5}$$

$$P_g^{\min} x_{gt} \le p_{gt}^G \le P_g^{\max} x_{gt} \quad \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{6}$$

$$\left(t_{g,t-1}^{\mathrm{ON}} - T_g^{\mathrm{ON}}\right)\left(x_{g,t-1} - x_{gt}\right) \ge 0 \ \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{7}$$

$$\left(t_{g,t-1}^{\mathrm{OFF}} - T_g^{\mathrm{OFF}}\right)\left(x_{gt} - x_{g,t-1}\right) \ge 0 \ \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{8}$$

$$-R_g^D x_{gt} - S_g^D v_{gt} \le p_{gt}^G - p_{g,t-1}^G \le$$
$$\le R_g^U x_{gt} + S_g^U u_{gt} \ \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{9}$$

$$0 \le r_{gt}^U \le \min\begin{Bmatrix} p_{g,t-1}^G - p_{gt}^G + R_g^U \\ P_g^{\max} x_{gt} - p_{gt}^G \end{Bmatrix} \forall t \in \mathcal{T},\ g \in \mathcal{G}, \tag{10}$$

$$0 \le r_{gt}^D \le \min\begin{Bmatrix} p_{gt}^G - p_{g,t-1}^G + R_g^D \\ p_{gt}^G - P_g^{\min} x_{gt} \end{Bmatrix} \forall t \in \mathcal{T}, g \in \mathcal{G}, \tag{11}$$

$$P_h^{\min} \le p_{ht}^{\mathrm{CHP}} \le P_h^{\max} \quad \forall t \in \mathcal{T},\ h \in \mathcal{H}, \tag{12}$$

$$-R_h^D \le p_{ht}^{\mathrm{CHP}} - p_{h,t-1}^{\mathrm{CHP}} \le R_h^U \ \ \forall t \in \mathcal{T},\ h \in \mathcal{H}, \tag{13}$$

$$0 \le r_{ht}^U \le \min\begin{Bmatrix} p_{h,t-1}^{\mathrm{CHP}} - p_{ht}^{\mathrm{CHP}} + R_h^U \\ P_h^{\max} - p_{ht}^G \end{Bmatrix} \forall t \in \mathcal{T},\ h \in \mathcal{H}, \tag{14}$$

$$0 \le r_{ht}^D \le \min\begin{Bmatrix} p_{ht}^{\mathrm{CHP}} - p_{h,t-1}^{\mathrm{CHP}} + R_h^D \\ p_{ht}^{\mathrm{CHP}} - P_h^{\min} \end{Bmatrix} \forall t \in \mathcal{T},\ h \in \mathcal{H}, \tag{15}$$

$$0 \le p_{wt} \le P_W^f \quad \forall t \in \mathcal{T},\ w \in \mathcal{W}, \tag{16}$$

$$H_{ht}^{\mathrm{CHP}} = \gamma^{\mathrm{CHP}} p_{ht}^{\mathrm{CHP}} \ \ \forall t \in \mathcal{T},\ h \in \mathcal{H}, \tag{17}$$

$$H_t^{\mathrm{EB}} = H_t^{\mathrm{EBD}} + H_t^{\mathrm{HST},in} \quad \forall t \in \mathcal{T}, \tag{18}$$

$$H_t^{\mathrm{EB}} = \eta^{\mathrm{EB}} p_t^{\mathrm{EB}} \quad \forall t \in \mathcal{T}, \tag{19}$$

$$H_{\min}^{\mathrm{EB}} \le H_t^{\mathrm{EB}} \le H_{\max}^{\mathrm{EB}} \quad \forall t \in \mathcal{T}, \tag{20}$$

$$Q_t - Q_{t-1} = \eta_{\mathrm{char}} H_t^{\mathrm{HST},in} - H_t^{\mathrm{HST},out} / \eta_{\mathrm{dis}} \quad \forall t \in \mathcal{T}, \tag{21}$$

$$0 \le H_t^{\mathrm{HST},in} \le V^{\mathrm{HST},in} \times I_t \quad \forall t \in \mathcal{T}, \tag{22}$$

$$0 \le H_t^{\mathrm{HST},out} \le V^{\mathrm{HST},out} \times \left(1 - I_t\right) \ \forall t \in \mathcal{T}, \tag{23}$$

$$Q_{\min} \le Q_t \le Q_{\max} \quad \forall t \in \mathcal{T}, \tag{24}$$

$$\sum\nolimits_{g \in \mathcal{G}} p_{gt}^G + \sum\nolimits_{h \in \mathcal{H}} p_{ht}^{\mathrm{CHP}} + \sum\nolimits_{w \in \mathcal{W}} p_{wt} =$$
$$= \sum\nolimits_{n \in \mathcal{N}} p_{nt}^D + p_t^{\mathrm{EB}} \ \ \forall t \in \mathcal{T}, \tag{25}$$

$$\sum\nolimits_{h \in \mathcal{H}} H_{ht}^{\mathrm{CHP}} + H_t^{\mathrm{EBD}} + H_t^{\mathrm{HST},out} = \sum\nolimits_{n \in \mathcal{N}} H_{nt}^D \quad \forall t \in \mathcal{T}, \tag{26}$$

$$-T_l \le \sum\nolimits_{n \in \mathcal{N}} F_{l,n} \left(\sum\nolimits_{g \in \mathcal{G}_n} p_{gt}^G + \sum\nolimits_{h \in \mathcal{H}_n} p_{ht}^{\mathrm{CHP}} + \sum\nolimits_{w \in \mathcal{W}_n} p_{wt} - p_{nt}^D \right) \le$$
$$\le T_l \ \ \forall t \in \mathcal{T}, l \in \mathcal{L}, \tag{27}$$

where (2) and (3) represent the operational costs of conventional thermal and CHP units. Constraints (4) and (5) link the start-up u_{gt} and shut-down v_{gt} binary variables to the binary commitment variables x_{gt}. Constraint (6) enforces the minimum and maximum generation capacity limits. Constraints (7) and (8) enforce the minimum up- and down-time requirements. Constraint (9) enforces ramp-up and -down limits. Constraints (12)–(15) are, respectively, the electric output constraint, the ramp rate constraint, and the spinning reserve constraint for CHP units. Constraint (16) enforces the output limits of the renewable power plant. Equation (17) couples the electric and heat output of the CHP units. Constraints (18)–(20) enforce the operational constraints of the electric boiler. Constraints (21)–(24) enforce the charge/discharge and state of charge (SOC) limits of the heat storage tank. Equations (25) and (26) are the constraints of power and heat balance at the system level. Constraint (27) enforces the limits of the transmission line.

III. DISTRIBUTIONALLY ROBUST OPTIMISATION METHOD FOR OPTIMAL DISPATCH OF IES

A. Uncertainty Modelling of Renewable Energy

In this section, an ambiguity set characterising renewable power based on the Wasserstein measure is presented, where the empirical distribution of renewable output is used as a reference to estimate its actual probability density function. Given the historical sampled dataset $\left[w_1', w_2', ..., w_N'\right]$, the empirical distribution $\mathbb{P}_N$ is a stepwise function, which can be expressed as follows

$$\mathbb{P}_N = \begin{cases} 0, & w < w_1', \\ \dfrac{k}{N}, & w_k' \le w < w_{k+1}' \left(k = 1, \cdots, N-1\right), \\ 1, & w \ge w_N'. \end{cases} \tag{28}$$

According to the law of large numbers, it is proven that the reference distribution will finally converge to the real distribution with increasing input data. The set of ambiguities for the forecast renewable power can be defined as

$$\mathcal{P}\left(P_w\right) := \left\{ \mathbb{P} \in \mathcal{R}(\Xi) \middle| \, \mathbb{E}_{\mathbb{P}}\left[W\left(\mathbb{P}, \mathbb{P}_N\right)\right] \le \varepsilon \right\}, \tag{29}$$

where

$$W\left(\mathbb{P}, \mathbb{P}_N\right) = \inf_{\rho}\left(\int d\left(w, \tilde{w}\right) \rho\left(dw, d\tilde{w}\right)\right), \tag{30}$$

where $\mathcal{P}(\cdot)$ is the Wasserstein ball with centred distribution $\mathbb{P}_N$ and radius ε, $d\left(w, \tilde{w}\right) = \left\| w - \tilde{w} \right\|_2$ is the Euclidean distance between w and $\tilde{w}$, and $\rho\left(dw, d\tilde{w}\right)$ is the joint probability density function of $\mathbb{P}$ and $\mathbb{P}_N$.

B. Uncertainty Modelling of Contingencies

In this section, we also present an adjustable uncertainty set Ω to characterise the contingency probability of both the generation/CHP unit and line outages. The contingency probability of units or lines being shut down in the system can be expressed as

$$\begin{cases} \rho_{gt} \approx r_g^{ORR} u_{gt}, \\ \rho_{lt} \approx r_l^{ORR}, \end{cases} \tag{31}$$

where

$$\begin{cases} r_g^{ORR} = 1 - e^{-r_g^{FOR}} \tau \approx r_g^{FOR} \tau, \\ r_l^{ORR} = 1 - e^{-r_l^{FOR}} \tau \approx r_l^{FOR} \tau. \end{cases} \tag{32}$$

Taking the example of the failure of the generator set, if we utilise the interval to describe the failure probability of the generators, its possible probability value $\tilde{\rho}_{c,t}$ will be located in the interval $\left[\underline{\rho}_{c,t}, \overline{\rho}_{c,t}\right]$, which can be expressed as a combination of a bounded continuous variable and an auxiliary variable:

$$\tilde{\rho}_{c,t} = \rho_{c,t} + \hat{\rho}_{c,t}\nu_{c,t}, \tag{33}$$

$$\begin{cases} \rho_{c,t} = \left(\bar{\rho}_{c,t} + \underline{\rho}_{c,t}\right)/2, \\ \hat{\rho}_{c,t} = \left(\bar{\rho}_{c,t} - \underline{\rho}_{c,t}\right)/2, \\ -1 \le \nu_{c,t} \le 1, \end{cases} \tag{34}$$

$$\sum_{c\in\Omega} \tilde{\rho}_{c,t} = 1, \tag{35}$$

where $\rho_{c,t}$ and $\hat{\rho}_{c,t}$ are the midpoint and radius of the interval, respectively.

According to (33) and (35), we get

$$\sum_{c\in\Omega} \rho_{c,t} + \sum_{c\in\Omega} \hat{\rho}_{c,t}\nu_{c,t} = 1. \tag{36}$$

Combined with the above formulas, the comprehensive set of ambiguity of the contingency probability can be further expressed as

$$\Omega = \left\{ \begin{matrix} \sum_{c\in\Omega} \rho_{c,t} + \sum_{c\in\Omega} \hat{\rho}_{c,t}\nu_{c,t} = 1 \\ \sum_{c\in\Omega} \left|\nu_{c,t}\right| \le \Gamma_t^{\mathrm{C}} \\ \sum_{t\in\mathcal{T}} \left|\nu_{c,t}\right| \le \Gamma_t^{\mathrm{T}} \\ -1 \le \nu_{c,t} \le 1 \end{matrix} \right\}, \tag{37}$$

where Γ_t^C and Γ_t^{T} are introduced to control the size of the ambiguity set, which represents the conservativeness of the system. Considering the probability of contingency, the unit and system constraints (6), (12), (25)–(27) can be further expressed as:

$$p_{gt}^G - r_{gt}^D \le p_{gt,c}^G \le p_{gt}^G + r_{gt}^U, \tag{38}$$

$$p_{ht}^{\mathrm{CHP}} - r_{ht}^D \le p_{ht,c}^{\mathrm{CHP}} \le p_{ht}^{\mathrm{CHP}} + r_{ht}^U, \tag{39}$$

$$\begin{aligned} &\sum\nolimits_{g\in\mathcal{G}} p_{gt,c}^G + \sum\nolimits_{h\in\mathcal{H}} p_{ht,c}^{\mathrm{CHP}} + \sum\nolimits_{w\in\mathcal{W}} p_{wt,c} = \\ &= \sum\nolimits_{n\in\mathcal{N}} \left(p_{nt}^D - p_{nt,c}^D\right) - p_{t,c}^{\mathrm{EB}}, \end{aligned} \tag{40}$$

$$\sum\nolimits_{h\in\mathcal{H}} H_{ht,c}^{\mathrm{CHP}} + H_{t,c}^{\mathrm{EBD}} + H_{t,c}^{\mathrm{HST},out} = \sum\nolimits_{n\in\mathcal{N}} H_{nt}^D, \tag{41}$$

$$-T_l \le \sum\nolimits_{n\in\mathcal{N}} F_{l,n,c} \left(\sum\nolimits_{g\in\mathcal{G}_n} \left(\begin{matrix} p_{gt,c}^G + \sum\nolimits_{h\in\mathcal{H}_n} p_{ht,c}^{\mathrm{CHP}} + \\ \sum\nolimits_{w\in\mathcal{W}_n} p_{wt,c} - \left(p_{nt}^D - p_{nt,c}^D\right) \end{matrix} \right) \right) \le T_l. \tag{42}$$

C. Optimal Dispatch Model Incorporating the DNE Limit

When incorporating the DNE limit into the aforementioned optimal dispatch model, the goal of the power system is to adjust the power for rescheduling so that the accommodated power of renewable energy can meet the DNE limit. Assume that the system uncertainty at time *t* is ξ_t, which satisfies $\xi_t \in \left[\underline{\xi}_t, \bar{\xi}_t\right]$. Then the corresponding power adjustment of thermal and CHP units are $\tilde{p}_{gt,c}^G\left(\xi_t\right) = p_{gt,c}^G + \Delta p_{gt}^G\left(\xi_t\right)$ and $\tilde{p}_{ht,c}^{\mathrm{CHP}}\left(\xi_t\right) = p_{ht,c}^{\mathrm{CHP}} + \Delta p_{ht}^{\mathrm{CHP}}\left(\xi_t\right)$, respectively. Constraints (38)–(42) can be further expressed as:

$$\begin{cases} P_g^{\min} x_{gt} \le \tilde{p}_{gt,c}^G\left(\xi_t\right) \le P_g^{\max} x_{gt}, \\ p_{gt}^G - r_{gt}^D \le \tilde{p}_{gt,c}^G\left(\xi_t\right) \le p_{gt}^G + r_{gt}^U, \\ P_h^{\min} \le \tilde{p}_{ht,c}^{\mathrm{CHP}}\left(\xi_t\right) \le P_h^{\max}, \\ p_{ht}^{\mathrm{CHP}} - r_{ht}^D \le \tilde{p}_{ht,c}^{\mathrm{CHP}}\left(\xi_t\right) \le p_{ht}^{\mathrm{CHP}} + r_{ht}^U, \end{cases} \tag{43}$$

$$\begin{aligned} &\sum\nolimits_{g\in\mathcal{G}} \tilde{p}_{gt,c}^G\left(\xi_t\right) + \sum\nolimits_{h\in\mathcal{H}} \tilde{p}_{ht,c}^{\mathrm{CHP}}\left(\xi_t\right) + \sum\nolimits_{w\in\mathcal{W}} \left(\tilde{p}_{wt,c} + \xi_{wt}\right) = \\ &= \sum\nolimits_{n\in\mathcal{N}} \left(p_{nt}^D - p_{nt,c}^D\right) - \tilde{p}_{t,c}^{\mathrm{EB}}, \end{aligned} \tag{44}$$

$$\sum\nolimits_{h\in\mathcal{H}} \tilde{H}_{ht,c}^{\mathrm{CHP}} + \tilde{H}_{t,c}^{\mathrm{EBD}} + \tilde{H}_{t,c}^{\mathrm{HST},out} = \sum\nolimits_{n\in\mathcal{N}} H_{nt}^D, \tag{45}$$

$$-T_l \le \sum\nolimits_{n\in\mathcal{N}} F_{l,n,c} \left(\left(\sum\nolimits_{g\in\mathcal{G}_n} \begin{matrix} \tilde{p}_{gt,c}^G\left(\xi_t\right) + \sum\nolimits_{h\in\mathcal{H}_n} \tilde{p}_{ht,c}^{\mathrm{CHP}}\left(\xi_t\right) + \\ + \sum\nolimits_{w\in\mathcal{W}_n} \left(\tilde{p}_{wt,c} + \xi_{wt}\right) - \left(p_{nt}^D - p_{nt,c}^D\right) \end{matrix} \right) \right) \le T_l. \tag{46}$$

D. Formulation of a Two-Stage Distributionally Robust Optimal Dispatch Model

In general, this paper presents a two-stage distributionally robust optimal dispatch model of spinning reserves and DNE limits in IES considering the uncertainty of renewable energy and system contingencies. The two-stage decision-making structure can be rewritten in the following min-max-min form

$$\begin{aligned} &\min \sum_{t\in\mathcal{T}} \left[\sum_{g\in\mathcal{G}} C_g^G\left(p_{gt}^G, u_{gt}, r_{gt}^U, r_{gt}^D\right) + \sum_{h\in\mathcal{H}} C_h^{\mathrm{CHP}}\left(p_{ht}^{\mathrm{CHP}}, r_{ht}^U, r_{ht}^D\right) \right] + \\ &+ \max_{\tilde{\rho}_{c,t} \in \left[\underline{\rho}_{c,t}, \bar{\rho}_{c,t}\right]} \min \sum_{t\in\mathcal{T}} \sum_{c\in\Omega} \tilde{\rho}_{c,t} RC \end{aligned} \tag{47}$$

s.t. (4)–(27), (31)–(46) and (48)–(51).

Due to the quadratic form of the operation cost in the objective function, we could alternatively use the piecewise linear expression to approximate the quadratic function for computational tractability.

The objective function of the second stage is to minimise the regulation cost of the unit:

$$RC = \sum_{t\in\mathcal{T}} \left[\sum\nolimits_{g\in\mathcal{G}} c_g^G \omega_{gt,c}^G \left|\Delta p_{t,c}^G\right| + \sum\nolimits_{h\in\mathcal{H}} c_h^{\mathrm{CHP}} \omega_{ht,c}^{\mathrm{CHP}} \left|\Delta p_{t,c}^{\mathrm{CHP}}\right| \right], \tag{48}$$

$$\begin{cases} \xi_t = \Delta p_{t,c}^G + \Delta p_{t,c}^{\mathrm{CHP}}, \\ \tilde{p}_{gt,c}^G = p_{gt,c}^G - \omega_{gt,c}^G \Delta p_{t,c}^G, \\ \tilde{p}_{ht,c}^{\mathrm{CHP}} = p_{ht,c}^{\mathrm{CHP}} - \omega_{ht,c}^{\mathrm{CHP}} \Delta p_{t,c}^{\mathrm{CHP}}, \end{cases} \tag{49}$$

$$\begin{cases} \xi_t = \xi_{wt}, \\ \xi_{wt} = \sum\nolimits_{w\in\mathcal{W}} \left(p_{wt,c} - p_{wt,c}^f\right), \end{cases} \tag{50}$$

$$\begin{cases} \sum_{t\in\mathcal{T}} \sum_{g\in\mathcal{G}} \sum_{c\in\Omega} \omega_{gt,c} = 1, \\ 0 \le \omega_{gt,c} \le 1. \end{cases} \tag{51}$$

E. Model Transformation

The two-stage distributionally robust dispatch model constructed in the above section can be rewritten in a compact form as follows

$$\min_x \boldsymbol{c}^{\mathrm{T}} \boldsymbol{x} + \sup_{p\in\mathcal{P}} \min \sum_{t\in\mathcal{T}} \sum_{c\in\Omega} \tilde{\rho}_{c,t} RC, \tag{52}$$

where $\boldsymbol{c}^{\mathrm{T}}$ is the coefficient vector of the linearised first-stage objective function in formula (47). $\boldsymbol{x}$ is the decision variable of the first stage. Let $\min RC = T(c,t)$, detailed expression of the second stage can be further expanded as

$$\begin{aligned}&\sup_{p\in\mathcal{P}}\sum_{t\in\mathcal{T}}\sum_{c\in\Omega}\rho_{c,t}T(c,t)=\\&=\sup_{p\in\mathcal{P}}\left\{\sum_{t\in\mathcal{T}}\left(\sum_{c\in\Omega}\rho_{c,t}+\sum_{c\in\Omega}\hat{\rho}_{c,t}v_{c,t}\right)T(c,t)\right\}.\end{aligned} \tag{53}$$

Because there exist absolute values in the set of ambiguities (37) that represent system faults, we introduce two new auxiliary variables for linearisation. Thus, the set of ambiguities (37) can be transformed into

$$\Omega=\left\{\begin{array}{l}\sum_{c\in\Omega}\rho_{c,t}+\sum_{c\in\Omega}\hat{\rho}_{c,t}\left(v_{c,t}^{+}-v_{c,t}^{-}\right)=1\\\sum_{c\in\Omega}\left(v_{c,t}^{+}+v_{c,t}^{-}\right)\leq\Gamma_t^{\mathrm{C}}\\\sum_{t\in\mathcal{T}}\left(v_{c,t}^{+}+v_{c,t}^{-}\right)\leq\Gamma_t^{\mathrm{T}}\\0\leq v_{c,t}^{+},v_{c,t}^{-}\leq1\end{array}\right\}. \tag{54}$$

Robust constraints can be reformulated by using linear programming duality. The dual form can be obtained by introducing the auxiliary variables π_t^1, π_t^2, π_c^3, $\pi_{c,t}^4$, and $\pi_{c,t}^5$ as follows

$$\min_{\boldsymbol{x}}\left[\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x}+\sum_{t\in\mathcal{T}}\left(\begin{array}{l}\left(1-\rho_{c,t}\right)\pi_t^1+\Gamma_t^C\pi_t^2+\\+\sum_{c\in\Omega}\Gamma_t^{\mathrm{T}}\pi_c^3+\sum_{t\in\mathcal{T}}\sum_{c\in\Omega}\left(\pi_{c,t}^4+\pi_{c,t}^5\right)\end{array}\right)\right] \tag{55}$$

s.t.

$$\begin{cases}\hat{\rho}_{c,t}\pi_t^1+\pi_t^2+\pi_c^3+\pi_{c,t}^4\geq\hat{\rho}_{c,t}T(c,t),\\-\hat{\rho}_{c,t}\pi_t^1+\pi_t^2+\pi_c^3+\pi_{c,t}^5\geq-\hat{\rho}_{c,t}T(c,t),\\\pi_t^1\in\mathbb{R},\ \ \pi_t^2,\pi_c^3,\pi_{c,t}^4,\pi_{c,t}^5\geq0.\end{cases} \tag{56}$$

The maximisation problem of formula (53) is transformed into the equivalent minimisation problem (55) via duality theory. However, due to the complexity of $T(c,t)$ in (56), the reformulated optimisation problem still cannot be directly solved. The term $T(c,t)$ can be refirstwritten in a compact form as follows:

$$\begin{cases}\min f(x)\\\text{s.t. } h_k\left(x,\zeta_s\right)=d_k,\\\qquad g_j\left(x,\zeta_s\right)\leq e_j.\end{cases} \tag{57}$$

After solving (57), the upper bound of the worst-case scenario and the objective function in the set of ambiguities can be found. This problem can be solved by using Karush-Kuhn-Tucker (KKT) conditions as follows:

$$\begin{cases}\nabla f\left(x^*\right)+\sum_k\tau_k\nabla\left[h_k\left(x^*,\zeta_s\right)-d_k\right]+\sum_j\mu_j\nabla\left[g_j\left(x^*,\zeta_s\right)-e_j\right]=0,\\h_k\left(x^*,\zeta_s\right)-d_k=0,\\\mu_j\left[g_j\left(x^*,\zeta_s\right)-e_j\right]\leq0,\\\mu_j\geq0,\end{cases} \tag{58}$$

where τ_k and μ_j are the Lagrange multipliers. Once the KKT conditions are applied, the entire optimisation problem is transformed into a single-level mixed integer linear programming (MILP) model, which can be directly solved by commercial solvers such as CPLEX and Gurobi.

IV. CASE STUDY

A. Case Study Setup

The integrated test energy system is illustrated in Fig. 1, which consists of an IEEE 33-bus power distribution network and a modified 33-bus heating network.

It generally contains 3 CHP units, 2 energy storage systems (ESS), 2 electricity boilers (EB) and 2 heat storage tanks (HST), 1 wind farm and 1 solar photovoltaic (PV) plant. Detailed information on the topological structure and load data can be found in [26]. The CHP unit (CHP 1) with flexible and adjustable energy conversion ratio is considered a slack bus. Various cost coefficients and energy prices can be derived from [27]. The confidence interval of the Wasserstein ball is set to 95 % and the control parameters are set as $\Gamma_t^{\mathrm{C}}=10$, $\Gamma_t^{\mathrm{T}}=10$. To investigate the influence of renewable and load uncertainty on the dispatch results, we assume that the fluctuation range covers 20 % of the forecasted value, which is shown in Fig. 2. The proposed MILP model is solved by GAMS/CPLEX on a desktop computer with a quadcore 3.6 GHz processor and 12 GB memory.

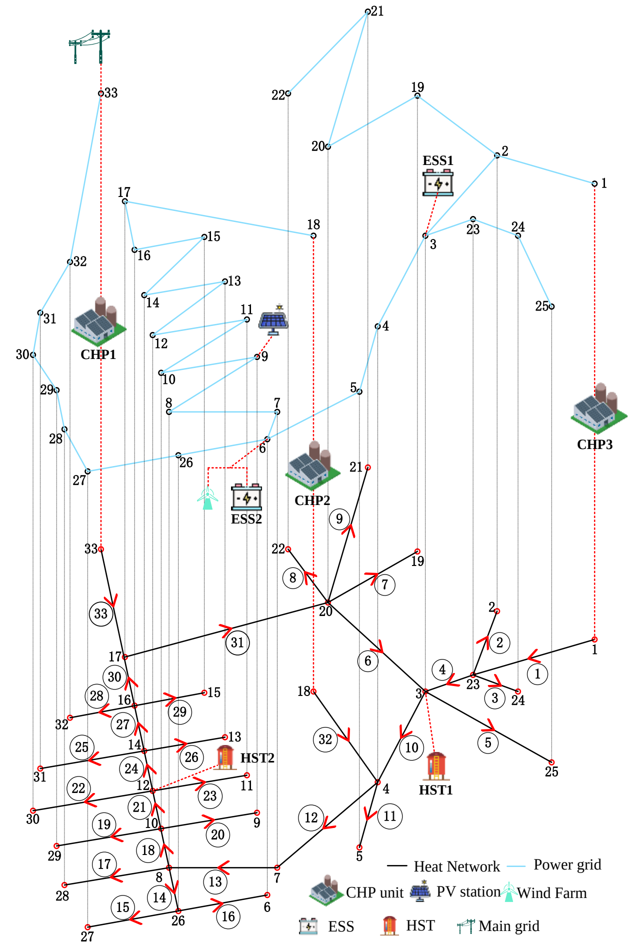

Fig. 1. Single-line diagram of the integrated electric and heat system for the case study.

For comparison, in this paper, three scenarios are set for analysis to verify the effectiveness and reliability of the proposed model:

– Case 1: The distributionally robust optimal dispatch model of IES without considering the uncertainty of the probability of the contingency and the limit of the DNE, which is named “DROD”;

– Case 2: The distributionally robust optimal dispatch model of IES considering the uncertainty of the probability of contingency but without accounting for the limit of the DNE, which is named “DROD-CP”;

– Case 3: The distributionally robust optimal dispatch model of IES collaboratively considering both the uncertainty of the probability of contingency and the DNE limit, which is named “DROD-CP-DNE”.

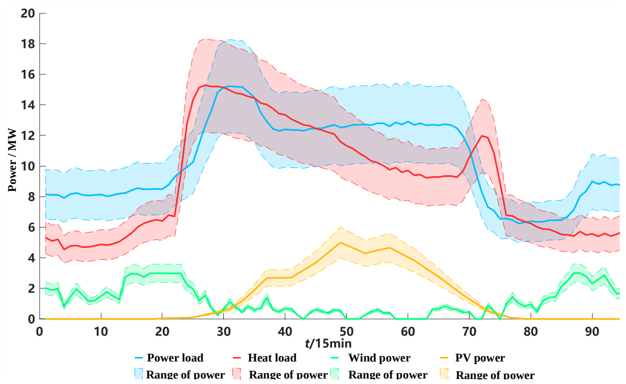

Fig. 2. Uncertainties of renewable energy and load with fluctuation range covering 20 % of the forecast value.

B. Analysis of Numerical Results

The expected system spinning reserves (up and down reserves), renewable energy utilisation ratio (wind farm and PV plant), and load-serving ratio under the three cases are compared and analysed. The numerical results under the three scenarios are given in Table I.

TABLE I. COMPARISONS OF THE DISPATCH RESULTS UNDER DIFFERENT CASES.

	Exp. Total Cost [$/day]	Exp. Renewable Utilisation Ratio [%]	Exp. Load-Serving Ratio [%]	Exp. Spinning Reserves [MWh/day]
Case 1	2784.65	76.64	92.18	750.98
Case 2	2612.93	84.65	95.30	796.12
Case 3	2558.84	94.79	98.71	785.59

It can be seen that, when considering the uncertainty of system faults, the overall spinning reserve capacity of the DROD-CP and DROD-CP-DNE model is higher than that of the DROD model. This is because when there is an unexpected equipment failure in the system, the DROD-CP and DROD-CP-DNE models will increase the demand for spinning reserve capacity and improve the utilisation ratio of renewable energy, while ensuring that the demand of the system stays as stable as possible. If equipment failure is neglected as in the DROD model, when the system encounters an emergency shutdown, it will result in load shedding or renewable curtailment, and thus the DROD model has the lowest load-serving ratio. For the DROD-CP-DNE model, the DNE limit is further incorporated into the DROD-CP model, which further enhances the utilisation ratio of renewable power in the system.

Figures 3 and 4 outline the detailed results of the energy dispatch of Case 3 in the power distribution network. The centred optimal dispatch values of versatile resources are given in Fig. 3, while the maximum power variation around the centred values is shown in Fig. 4 in the presence of uncertainties. It can be seen from the figure that there is no amount of wind and PV power curtailment in the proposed dispatch scheme, which shows that the DROD-CP-DNE model can ensure the effective absorption of renewable energy and provide reliable energy supply for users under the influence of the uncertainty of renewable generation and contingencies.

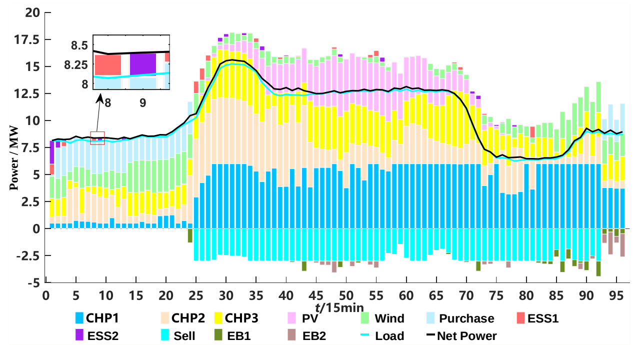

Fig. 3. Centred dispatch results of power system.

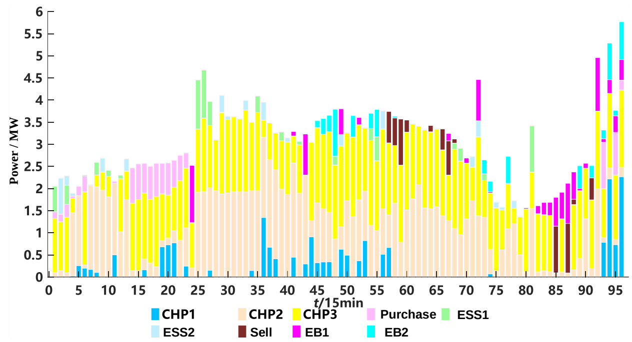

Fig. 4. Maximum variation of dispatch results for power system.

Figures 5 and 6 illustrate the centred dispatch results as well as its maximum amount of variation for the heat network. Since CHP 2 is more economical than CHP 1, and CHP 3, it takes up the majority part to supply the heat load, while CHP 1 only maintains the minimum thermal output. Moreover, since the power load is larger than the heat load for most of the time, the CHP unit with flexible and adjustable energy conversion ratio (CHP 1) should be responsible for consuming the extra electric load.

Furthermore, the power capacity of the maximum allowable wind power access for the system is analysed under the three scenarios, and the relevant simulation results are statistically presented in Fig. 7.

Figure 7 presents the allowable range of access to wind power for a wind farm. As depicted, the DROD-CP-DNE model allows for a wider range of wind power access compared to the DROD-CP and DROD models. This is because the DROD-CP model takes into account the randomness of equipment failure, resulting in an increased demand for renewable energy and indirectly allowing for a greater amount of wind power to be connected to the system compared to the DROD model. Furthermore, the DROD-CP-DNE model considers the wind power absorption rate based on the DROD-CP model, thus improving the system's ability to cope with uncertainty of wind power and further expanding the allowable range of access to wind power.

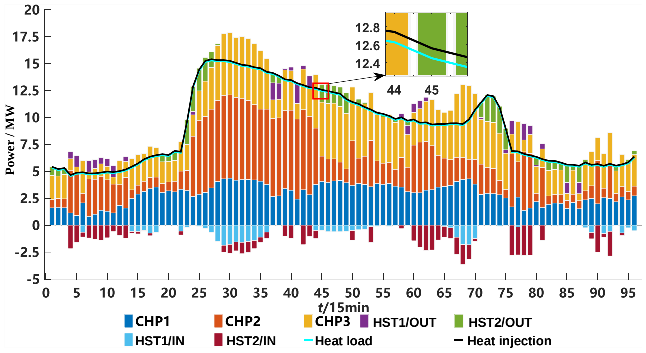

Fig. 5. Centred dispatch results of the heat system.

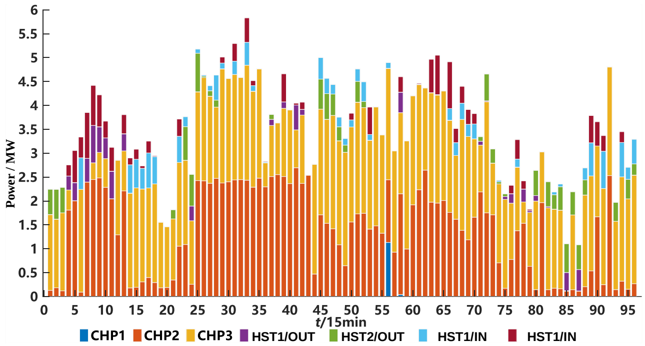

Fig. 6. Maximum variation of dispatch results for the heat system.

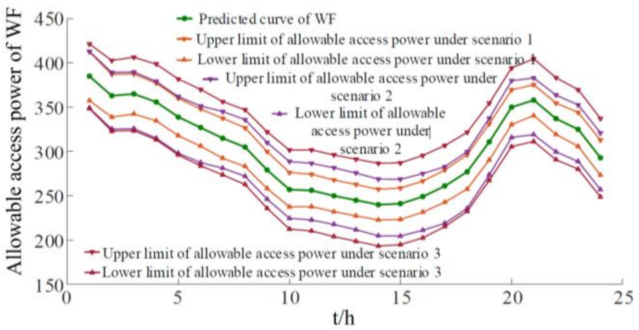

Fig. 7. Maximum allowable access to wind power under different scenarios.

To study the impact on system operation under different control parameters Γ_t^{T}, we mainly focus on Case 3, the DROD-CP-DNE model, and relevant experimental results are shown in Table II with increasing value of Γ_t^{T}. For a small value of $\Gamma_t^{\mathrm{T}} = 5$, which means that the number of allowable equipment failures is small, the total cost and spinning reserves are the lowest of all, showing the operation results are economical. With the increase of Γ_t^{T}, the conservatism of the proposed model is enhanced, leading to a consistent increase of the operating cost of the system, and the renewable consumption power is also increased. Therefore, the reliability and economics of the model can be controlled by adjusting the parameters.

TABLE II. COMPARISONS OF THE RESULTS UNDER DIFFERENT Γ_t^{T}.

	$\Gamma_t^{\mathrm{T}} = 5$	$\Gamma_t^{\mathrm{T}} = 10$	$\Gamma_t^{\mathrm{T}} = 15$	$\Gamma_t^{\mathrm{T}} = 20$
Total cost ($)	2512.55	2558.84	2580.70	2654.26
Spinning reserves (MW)	778.26	785.59	796.73	814.48
Renewable utilisation ratio (%)	93.84	94.79	96.16	97.82

V. CONCLUSIONS

In this paper, a distributionally robust cooperative optimal dispatch model for spinning reserve and DNE limits of IES is presented considering the uncertainty of renewable energy and system contingencies. Using Wasserstein measure theory, an adjustable ambiguity set of both renewable power and system/equipment faults is developed. Furthermore, given the day-ahead generation cost and real-time regulation cost, a two-stage distributionally robust optimal dispatch model is formulated and transformed into a single-level mixed integer linear problem (MILP) using duality theory and KKT conditions. The simulation results of the modified IEEE-33 test system are verified and the concluding remarks are summarised as follows:

1. By accounting for the system contingency uncertainty, the distributionally robust cooperative model can simultaneously optimise the spinning reserves, improve the utilisation rate of renewable energy, and enhance the robustness of the system;
2. The proposed collaborative optimisation model can greatly broaden the feasible range of renewable energy integration into the system by co-optimising the do-not-exceed limits, thereby achieving a more favourable trade-off between the overall operation cost and the utilisation of renewable power;
3. The reliability and economy of the system can be adapted by tuning the adjustable parameters of the ambiguity set of contingency probability;

It should be noted that the computational complexity of the proposed distributionally robust optimal model is not investigated in this paper. Future work will focus on the solution efficiency of the proposed model for large-scale integrated energy systems.

NOMENCLATURE

Parameters

a_g, b_g, c_g	Generation cost coefficient
c_g^u	Start-up cost coefficient
c_g^U, c_g^D	Up and down reserve cost coefficient for thermal units
c_h^U, c_h^D	Up and down reserve cost coefficient for CHP units
c_{gas}	Cost of natural gas purchase
η^{CHP}	Conversion efficiency of the CHP unit
Q_{gas}	High calorific value of natural gas
$P_g^{\min} / P_g^{\max}$	Min/Max power output of the generator g

$T_g^{\mathrm{ON}} / T_g^{\mathrm{OFF}}$	Min up/down times of generator *g*
R_g^U / R_g^D	Ramp up/down rates of generator *g*
S_g^U / S_g^D	Ramp rates when generator *g* turns on/shuts down
$P_h^{\min} / P_h^{\max}$	Min/Max power output of the CHP unit *h*
R_h^U / R_h^D	Ramp up/down rates of CHP unit *h*
P_W^f	Predicted power of renewable energy
p_{nt}^D	Power load at time *t*
γ^{CHP}	Electrothermal conversion ratio of the CHP unit
η^{EB}	Electrothermal conversion ratio of the electric boiler
$H_{\min}^{\mathrm{EB}} / H_{\max}^{\mathrm{EB}}$	Min/Max power output of electric boiler
H_{nt}^D	Thermal load at time *t*
$\eta_{\mathrm{char}} / \eta_{\mathrm{dis}}$	Heat absorption/release efficiency of the heat storage tank
$V^{\mathrm{HST},in} / V^{\mathrm{HST},out}$	Charging/discharging rate of heat storage tank
$Q_{\min} / Q_{\max}$	Min/Max heat storage capacity
T_l	Limit of the transmission capacity of line *l*
r_g^{ORR} / r_l^{ORR}	Outage replacement rate of unit/line
r_g^{FOR} / r_l^{FOR}	Forced outage rate of unit/line
τ	Lead time
$F_{l,n}$	Generation load transfer factor

Indices and Sets

$\mathcal{G}_n$	Set of generators at bus *n*
$\mathcal{G}$	Set of generators in the system
$\mathcal{N}$	Set of buses
$\mathcal{H}$	Set of CHP units
$\mathcal{L}$	Set of transmission lines
$\mathcal{T}$	Set of time periods

Variables

u_{gt} / v_{gt}	Start-up/shut-down variables at time *t*
p_{gt}^G	Active power of generator *g* at time *t*
$t_{g,t-1}^{\mathrm{ON}} / t_{g,t-1}^{\mathrm{OFF}}$	Start-up/shut-down duration time at *t*-1
r_{gt}^U / r_{gt}^D	Up/down spinning reserve of generator *g*
p_{ht}^{CHP}	Scheduled power of the CHP unit *h*
r_{ht}^U / r_{ht}^D	Up/down spinning reserve of CHP unit *h*
p_{wt}	Scheduled power of renewable energy
p_t^{EB}	Power consumption of electric boiler
H_{ht}^{CHP}	Heat output of a CHP unit *h*
H_t^{EB}	Electrothermal conversion power of the electric boiler
H_t^{EBD}	Direct heating power of the electric boiler
$H_t^{\mathrm{HST},in} / H_t^{\mathrm{HST},out}$	Input/output power of heat storage tank
Q_t	Heat storage capacity of heat storage tank
$\rho_{c,t}$	Contingency probability of the system
$p_{gt,c}^G$	Active power of generator *g* in fault scenario
$p_{ht,c}^{\mathrm{CHP}}$	Scheduled power of the CHP unit *h* under a fault scenario
$p_{t,c}^{\mathrm{EB}}$	Power consumption of electric boiler under fault scenario
$p_{nt,c}^D$	Load shedding at bus *n* under fault scenario
$H_{ht,c}^{\mathrm{CHP}}$	Heat output of CHP unit *h* under fault scenario
$\omega_{gt,c}^G / \omega_{ht,c}^{\mathrm{CHP}}$	Participation factor of thermal/CHP unit
$\Delta p_{t,c}^G / \Delta p_{t,c}^{\mathrm{CHP}}$	Adjusted power of the thermal/CHP unit

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] S. Zhang, P. Huang, and Y. Sun, "A multi-criterion renewable energy system design optimization for net zero energy buildings under uncertainties", *Energy*, vol. 94, pp. 654–665, 2016. DOI: 10.1016/j.energy.2015.11.044.

[2] M. R. Elkadeem, A. Younes, S. W. Sharshir, P. E. Campana, and S. Wang, "Sustainable siting and design optimization of hybrid renewable energy system: A geospatial multi-criteria analysis", *Applied Energy*, vol. 295, art. 117071, 2021. DOI: 10.1016/j.apenergy.2021.117071.

[3] Z. Guo, P. Pinson, S. Chen, Q. Yang, and Z. Yang, "Chance-constrained peer-to-peer joint energy and reserve market considering renewable generation uncertainty", *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 798–809, 2021. DOI: 10.1109/TSG.2020.3019603.

[4] T. Ding *et al.*, "Multi-stage distributionally robust stochastic dual dynamic programming to multi-period economic dispatch with virtual energy storage", *IEEE Transactions on Sustainable Energy*, vol. 13, no. 1, pp. 146–158, 2022. DOI: 10.1109/TSTE.2021.3105525.

[5] M. A. Velasquez, N. Quijano, A. I. Cadena, and M. Shahidehpour, "Distributed stochastic economic dispatch via model predictive control and data-driven scenario generation", *International Journal of Electrical Power & Energy Systems*, vol. 129, art. 106796, 2021. DOI: 10.1016/j.ijepes.2021.106796.

[6] L. Wang, C. Jiang, K. Gong, R. Si, H. Shao, and W. Liu, "Data-driven distributionally robust economic dispatch for distribution network with multiple microgrids", *IET Generation, Transmission & Distribution*, vol. 14, no. 24, pp. 5712–5719, 2020. DOI: 10.1049/iet-gtd.2020.0861.

[7] S. Nojavan, A. Akbari-Dibavar, A. Farahmand-Zahed, and K. Zare, "Risk-constrained scheduling of a CHP-based microgrid including hydrogen energy storage using robust optimization approach", *International Journal of Hydrogen Energy*, vol. 45, no. 56, pp. 32269–32284, 2020. DOI: 10.1016/j.ijhydene.2020.08.227.

[8] X. Zhu, B. Zeng, H. Dong, and J. Liu, "An interval-prediction based robust optimization approach for energy-hub operation scheduling considering flexible ramping products", *Energy*, vol. 194, art. 116821, 2020. DOI: 10.1016/j.energy.2019.116821.

[9] A. Khoshrou and E. J. Pauwels, "Short-term scenario-based probabilistic load forecasting: A data-driven approach", *Applied Energy*, vol. 238, pp. 1258–1268, 2019. DOI: 10.1016/j.apenergy.2019.01.155.

[10] A. M. Jasim, B. H. Jasim, H. Kraiem, and A. Flah, "A multi-objective demand/generation scheduling model-based microgrid energy management system", *Sustainability*, vol. 14, no. 16, p. 10158, 2022. DOI: 10.3390/su141610158.

[11] D. Kuhn, P. M. Esfahani, V. A. Nguyen, and S. Shafieezadeh-Abadeh, "Wasserstein distributionally robust optimization: Theory and applications in machine learning", in *Operations Research & Management Science in the Age of Analytics*. Informs, 2019, pp. 130–166. DOI: 10.1287/educ.2019.0198.

[12] P. Li, M. Yang, and Q. Wu, "Confidence interval based distributionally robust real-time economic dispatch approach considering wind power accommodation risk", *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 58–69, 2021. DOI: 10.1109/TSTE.2020.2978634.

[13] Z. Shi, H. Liang, and V. Dinavahi, "Data-driven distributionally robust chance-constrained unit commitment with uncertain wind power",

IEEE Access, vol. 7, pp. 135087–135098, 2019. DOI: 10.1109/ACCESS.2019.2942178.

[14] X. Zheng, K. Qu, J. Lv, Z. Li, and B. Zeng, “Addressing the conditional and correlated wind power forecast errors in unit commitment by distributionally robust optimization”, *IEEE Transactions on Sustainable Energy*, vol. 12, no. 2, pp. 944–954, 2021. DOI: 10.1109/TSTE.2020.3026370.

[15] X. Xu, Z. Yan, M. Shahidehpour, Z. Li, M. Yan, and X. Kong, “Data-driven risk-averse two-stage optimal stochastic scheduling of energy and reserve with correlated wind power”, *IEEE Transactions on Sustainable Energy*, vol. 11, no. 1, pp. 436–447, 2020. DOI: 10.1109/TSTE.2019.2894693.

[16] A. Ratha, A. Schwele, J. Kazempour, P. Pinson, S. Shariat Torbaghan, and A. Virag, “Affine policies for flexibility provision by natural gas networks to power systems”, *Electric Power Systems Research*, vol. 189, art. 106565, 2020. DOI: 10.1016/j.epsr.2020.106565.

[17] A. Bagheri and C. Zhao, “Distributionally robust reliability assessment for transmission system hardening plan under $N-k$ security criterion”, *IEEE Transactions on Reliability*, vol. 68, no. 2, pp. 653–662, 2019. DOI: 10.1109/TR.2019.2893138.

[18] A. Papavasiliou, S. S. Oren, and R. P. O’Neill, “Reserve requirements for wind power integration: A scenario-based stochastic programming framework”, *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2197–2206, 2011. DOI: 10.1109/TPWRS.2011.2121095.

[19] M. Hedayati-Mehdiabadi, K. W. Hedman, and J. Zhang, “Reserve policy optimization for scheduling wind energy and reserve”, *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 19–31, 2018. DOI: 10.1109/TPWRS.2017.2707568.

[20] Y. Chen, W. Wei, F. Liu, and S. Mei, “Distributionally robust hydro-thermal-wind economic dispatch”, *Applied Energy*, vol. 173, pp. 511–519, 2016. DOI: 10.1016/j.apenergy.2016.04.060.

[21] J. Zhao, T. Zheng, and E. Litvinov, “Variable resource dispatch through do-not-exceed limit”, *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 820–828, 2015. DOI: 10.1109/TPWRS.2014.2333367.

[22] H. Li, Z. Wan, and H. He, “Constrained EV charging scheduling based on safe deep reinforcement learning”, *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2427–2439, 2020. DOI: 10.1109/TSG.2019.2955437.

[23] M. Poursoltani and E. Delage, “Adjustable robust optimization reformulations of two-stage worst-case regret minimization problems”, *Operations Research*, vol. 70, no. 5, pp. 2906–2930, 2022. DOI: 10.1287/opre.2021.2159.

[24] P. Li, Q. Wu, M. Yang, Z. Li, and N. D. Hatziargyriou, “Distributed distributionally robust dispatch for integrated transmission-distribution systems”, *IEEE Transactions on Power Systems*, vol. 36, no. 2, pp. 1193–1205, 2021. DOI: 10.1109/TPWRS.2020.3024673.

[25] W. Gu, J. Wang, S. Lu, Z. Luo, and C. Wu, “Optimal operation for integrated energy system considering thermal inertia of district heating network and buildings”, *Applied Energy*, vol. 199, pp. 234–246, 2017. DOI: 10.1016/j.apenergy.2017.05.004.

[26] X. Qin, X. Shen, Y. Guo, Z. Pan, Q. Guo, and H. Sun, “Combined electric and heat system testbeds for power flow analysis and economic dispatch”, *CSEE Journal of Power and Energy Systems*, vol. 7, no. 1, pp. 34–44, 2021. DOI: 10.17775/CSEEJPES.2020.02810.

[27] Z. Bao, Q. Zhou, Z. Yang, Q. Yang, L. Xu, and T. Wu, “A multi time-scale and multi energy-type coordinated microgrid scheduling solution—Part I: Model and methodology”, *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2257–2266, 201. DOI: 10.1109/TPWRS.2014.2367127.