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BLOCK CHAIN BASED ENERGY TRADING BETWEEN DISTRICT ENERGY SYSTEMS CONSIDERING the UNCERTAINTIES

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ABSTRACT

As a high-efficiency and low-carbon energy supply mode, district energy systems (DESs) have gained rapid development recently. This paper proposes a framework for energy trading among DESs, with the aim of exploiting the synergies and complementary advantages of various energy demand profiles in DESs. Blockchain technology is utilized to facilitate energy trading. The distributed algorithm based stochastic decision-making process is developed to determine the energy trading, including the transaction quantities and prices. A chance-constrained programming model is developed for dealing with the uncertainties. The illustration of the technique is provided based on a test system.

Keywords: district energy systems, energy trading, blockchains, chance-constrained programming, distributed algorithm

NONMENCLATURE

Abbreviations	
DES	District energy system
CHP	Combined heat and power
Symbols	
t	Time step
P_{ct}	Electric power of CHP unit *c*
H_{ct}	Heat power of CHP unit *c*
H_{at}	Heat power of auxiliary boiler
P_{wt}^{avi}	Power capacity of wind turbine w
P_{wt}	Power output of wind turbine w
H_{bt}	Heat demand of building *b*
P_{bt}	Electric demand of building *b*

1. INTRODUCTION

In the last decades, the fast-growing energy consumption has raised concerns over supply difficulties, exhaustion of energy resources and heavy environmental impacts all over the world [1]. Under such circumstances, there has been intense interest in the development of energy-efficient technologies and systems. District energy systems (DESs) have aroused a wide interest of academic and engineering for its ability of supplying thermal energy to buildings while reducing peak demand, annual energy use, and total greenhouse gas emissions [2]. DESs use a central energy plant, which is usually a combined heat and power (CHP) plant [3], to produce thermal power and then distribute them through underground pipes to local buildings [4]. Moreover, DESs may also include the distributed renewable energy generation, such as wind power or solar power, to supply the electrical loads. As a consequence, DESs contribute significantly to the decarbonization of the building sectors.

Recently, the optimal operation of the DES has been studied. References [5] and [6] developed a mixed-integer linear programming (MILP) model to optimally design and operate a DES in a limited urban area with interconnected buildings via a heat distribution network. A district energy management strategy was devoted to monitor and control district power consumptions to satisfy customer comfort and preferences at minimum cost [7]. Some studies exploited the flexibility of CHP units for improving the DES operation. Authors in [8] presented the opportunities for increasing the flexibility of CHP units using electric boilers and heat storage tanks. Reference [9] presented a model that determined the theoretical maximum flexibility of a CHP system coupled with a thermal energy storage solution.

In previous studies, DESs are operated independently with each other. Restricted by their relatively limited scale, DESs usually do not participate in the centralized energy markets. In such a situation, DESs may face the mismatch between the supply and demand and lack of operational flexibility.

This paper develops an energy sharing and trading framework for the connected DESs based on the blockchain and smart contract technologies. In the framework, the energy surplus can be traded between the DESs. In this way, the synergies and complementary advantages of various load profiles in different DESs can be exploited. Moreover, DESs can be standby to each other and therefore the operational reliability of the DESs can be improved.

Energy trading between the DESs is formulated as a collaborative decision-making problem. Each DES determines how much energy it wants to purchase or sell to minimize the total operation cost. Moreover, the optimal operation of each DES is formulated as a chance-constrained programming problem with the consideration of the uncertainties about the renewable energies and energy demand. Then, an iterative-based distributed algorithm is used to solve the collaborative optimization problems of the DESs. Finally, the energy trading between the DESs can be determined. The energy transaction information is broadcasted to every DESs. During the operation phase, the transactions will be executed and cleared.

2. BLOCKCHAIN BASED ENERGY TRADING

2.1 Introduction of district energy systems

DESs are used to satisfy comprehensive energy demands for different types of loads in an industrial park, hospitals, military bases, a cluster of commercial buildings, universities, and other similar settings [10]. A DES usually consists of a CHP unit, auxiliary boiler, distributed renewable energy resources and the energy networks for supplying the local buildings [11]. The CHP-based DES considered in this paper is illustrated in Fig. 1, which includes CHP plant, auxiliary boilers and wind power representing distributed renewable energies. Moreover, it is assumed multiple DESs are connected with each other through electricity transmission lines, allowing the energy flow between DESs.

2.2 Blockchain and smart contract

Blockchain technology is utilized to facilitate energy trading between the DESs. Blockchain is an emerging technology for decentralized computation and data storage, secured by a combination of cryptographic signatures and a distributed consensus mechanism. As shown in the bottom half of Fig. 1, a blockchain is composed of a chain of data packages (blocks) [12]. Each block comprises multiple transactions at a time step *t*. The blockchain is extended by each additional block and hence represents a complete ledger of the transaction history. In addition to the transactions, each block contains a timestamp, the hash value of the previous block (''parent''), and a nonce, which is a random number for verifying the hash [13].

The idea of energy trading between DESs based on blockchain technology can be illustrated as:

- DESs determine how much energy they want to purchase or sell at time *t* in advance based on the forecasted supply and demand conditions;
- a collaborative decision-making process is launched for matching buy and sell contracts, and the quantity and price of each transaction are confirmed in this step;
- the block *t* recording the concluded transactions for time *t* is generated and the blockchain is extended.
- At time *t*, the operators of the DESs will read the information from blockchains and execute the transactions.

Take the DESs in Fig. 1 as an example, DES1 will deliver $P_{1\text{-}2t}$ of electricity to DES2 and supply $P_{1\text{-}3t}$ of electricity to DES3 according to the concluded transactions. Moreover, the transactions will be settled through the smart contracts, which are self-executing contracts with the terms of the agreement between buyer and seller being directly written into lines of code [14]. In this case, DES1 will receive the payment of $P_{1-2t}\cdot\rho_{1-2t}+P_{1-3t}\cdot\rho_{1-3t}$ at time *t*.

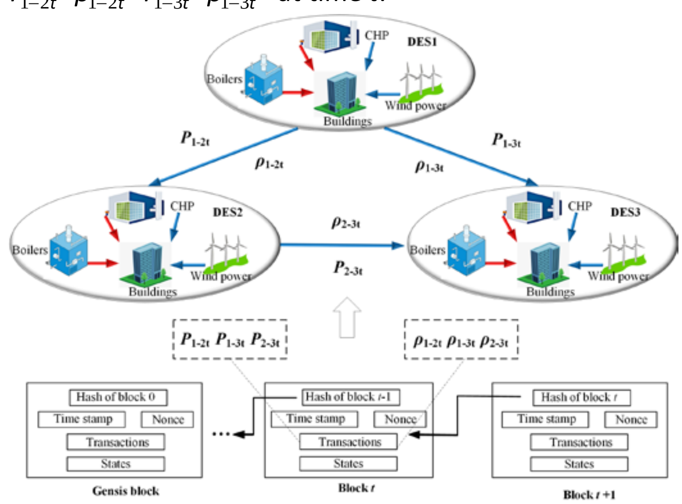


Fig 1 Blockchain based energy trading among DESs.

3. COLLABORATIVE DECISION-MAKING PROCESS

This section introduces the collaborative decision-making process for determining the transactions, including the quantities and prices. First, the chance-constrained programming for each DES is developed which tries to satisfy the buildings energy demands with minimum costs while considering the uncertainties. Then, the collaboration between the DESs is formulated as a collaborative decision-making process, which optimizes the energy flow between the DESs, based on which the transactions are concluded.

3.1 Chance-constrained programming for DES

In this subsection, an individual optimal operation problem of the DES is formulated without the consideration of energy exchange with other DESs. In this case, DES operator schedules the CHP plant, auxiliary boilers and wind power to meet the buildings energy demands. Notice that there are several uncertainties need to be considered in the DES optimization. Indeed, neither the power consumption or wind power can be exactly predicted [15]. The uncertainties related to the electricity demand and wind power will influence the DES operation.

For handling the demand and wind power uncertainties, the DES optimization is formulated as a chance-constrained stochastic programming problem [16],[17]. The objective function of the DES optimization problem is shown in (1):

$$\min \sum_{c=1}^{NC} F_c\left(P_{ct}, H_{ct}\right) + F_a\left(H_{at}\right) + \gamma_w \sum_{w=1}^{Nw}\left(P_{wt}^{avi} - P_{wt}\right) \quad (1)$$

As shown in (1), the objective function includes operating costs of the CHP plant F_c and auxiliary boiler F_a and the penalty cost for the wind power curtailment with γ_w denoting the penalty rate.

The optimization problem needs to consider the following constraints:

$$m_{it} = \sum\nolimits_{b=1}^{Nb} m_{bt} \quad (2)$$

$$S_{bt} = (S_{it} - T_{ot})e^{-hl/c_w \cdot m_{it}} + T_{ot}$$
$$E_{bt} = (E_{it} - T_{ot})e^{hl/c_w \cdot m_{it}} + T_{ot} \quad (3)$$

$$H_{at} + \sum\nolimits_{c=1}^{Nc} H_{ct} = H_{it} = m_{it} c_w (S_{it} - E_{it}) \quad (4)$$

$$H_{bt} = m_{bt} c_w (S_{bt} - E_{bt}) \quad (5)$$

$$H_{bt}^{\mathrm{loss}} = k_b s_b \left(T_{bt} - T_{ot}\right) + c_b \left(T_{bt} - T_{ot}\right) n \quad (6)$$

$$c_b \frac{T_{bt} - T_{bt-1}}{\Delta t} = H_{bt} - H_{bt}^{\mathrm{loss}} \quad (7)$$

$$\overline{T_{bt}} \le T_{bt} \le \underline{T_{bt}} \quad (8)$$

where m_{bt} denotes water mass flow to the building *b;* m_{it} denotes the aggregated heat water mass flow of DHS *i;* S_{bt} and E_{bt} denotes the supply and return water temperature to building *b,* respectively*;* S_{jh} and E_{jh} denotes the supply and return water temperature from DHS *i*, respectively; T_{ot} denotes the ambient temperature; c_w denotes the specific heat of water; *h* and *l* denotes the heat transfer coefficient and length of the heat pipeline, respectively; k_b denotes the heat transfer coefficient with outside; s_b and c_b respectively denote the surface area and heat capacity of the building *b*; *n* denotes the air exchange time; T_{bt} denotes the indoor temperature of the building *b*.

Equations (2)-(4) denote the heat power distribution constraints in the DES; equations (5)-(8) denote the thermal dynamic model of buildings [18].

Because of the demand and wind power uncertainties, the electric power balance constraint (9) has a stochastic characteristic. Using the expected values of the random variables and applying the chance constraint technique, the corresponding stochastic constraint is formulated by:

$$\sum\nolimits_{c=1}^{Nc} P_{ct} + \sum\nolimits_{w=1}^{Nw} P_{wt} = \sum\nolimits_{b=1}^{Nb} P_{bt}^{*} \quad (9)$$

$$\Pr\left\{\sum\nolimits_{c=1}^{Nc}\left(P_{ct} + R_{ct}\right) + \sum\nolimits_{w=1}^{Nw} P_{wt}^{avi} \ge \sum\nolimits_{b=1}^{Nb} P_{bt}\right\} \ge 1 - \mathrm{LOLP}_t \quad (10)$$

$$R_{ct} \le P_c^{\max} - P_{ct}; R_{ct} \le \upsilon_c \cdot \Delta t \quad (11)$$

Equation (9) represents the electric power balance constraint where the expected values of wind power and demand are considered; equation (10) restricts the loss of load probability (LOLP_t) to achieve the required level; equation (11) provides the limit of the operating reserves of CHP plant R_{ct} which is constrained by the maximum electric power output $P_c^{\max}$ and the ramping rate υ_c.

In this paper, the wind power forecast error at time *t* is modeled as a Gaussian variable with a zero mean and a standard deviation of σ_{wt}. Similarly, the electricity load forecast error at time *t* is modeled as a Gaussian variable with a zero mean and a standard deviation of σ_{bt}.

The probability distribution functions (PDFs) of wind power and demand are respectively expressed as:

$$P_{wt}^{avi} = P_{wt}^{*} + \Delta P_{wt},\ \Delta P_{wt} \in N\left(0, \sigma_{wt}\right) \quad (12)$$

$$P_{bt} = P_{bt}^{*} + \Delta P_{bt},\ \Delta P_{bt} \in N\left(0, \sigma_{bt}\right) \quad (13)$$

where P^*_{bt} and P^*_{wt} denote the forecast for electricity load and wind power generation, respectively.

Then, the chance constraint expressed in (10) is converted into the equivalent deterministic constraint based on the PDFs of wind power and demand. The equivalent deterministic constraint is shown as (14):

$$\sum_{c=1}^{Nc}\left(P_{ct}+R_{ct}\right)+\sum_{w=1}^{Nw}P_{wt}^{avi} \geq \sum_{b=1}^{Nb}P_{bt}+\mathrm{Z}_{\mathrm{LOLPt}}\left[\sum_{w=1}^{Nw}\left(\sigma_{wt}\right)^2+\sum_{b=1}^{Nb}\left(\sigma_{bt}\right)^2\right] \quad (14)$$

In (14), $\mathrm{Z}_{\mathrm{LOLPt}}$ denotes the inverse process of probability calculating, which is used to find a value x* that satisfies

$$\Pr\left\{x\leq x^*\right\}\geq\left[\sum_{w=1}^{Nw}\left(\sigma_{wt}\right)^2+\sum_{b=1}^{Nb}\left(\sigma_{bt}\right)^2\right] \quad (15)$$

where x follows a Gaussian variable with a zero mean and a standard deviation of $\sqrt{\sum_{w=1}^{Nw}\left(\sigma_{wt}\right)^2+\sum_{b=1}^{Nb}\left(\sigma_{bt}\right)^2}$.

3.2 Energy transactions between DESs

This subsection describes the collaborative decision-making process for determining the energy transactions between DESs.

Considering the energy trading, the shared variables, i.e. the transaction power between the DESs, should be considered. In this paper, the pseudo generation/load model is used to deal with shared variables between the DESs [19]. Suppose that the power $P_{i\text{-}jt}$ is transferred from the DES *i* to DES *j*. Then, the energy trading is modeled as a pseudo electric demand from the perspective of DES *i* and as a pseudo generator from the perspective of DES *j*. In this way, the optimization problems of DESs are separated from each other.

With the consideration of energy transactions, the optimization problems of DESs need to be modified. First, a set of augmented Lagrangian penalty functions are added to the objective functions of the optimization problems denoting the impacts of pseudo generator/load. Using these penalty function as well as penalty multipliers, each DES can individually solve its own local optimal operation problem. The modified objective function of DES *i* is expressed as:

$$\min\sum_{c=1}^{NC}F_c\left(P_{ct},H_{ct}\right)+F_a\left(H_{at}\right)+\gamma_w\sum_{w=1}^{Nw}\left(P_{wt}^{avi}-P_{wt}\right) + \sum_{j=1,\ j\neq i}^{Nd}\left(\alpha_{i\text{-}jt}\left(P^*_{i\text{-}jt}-P_{i\text{-}jt}\right)+\left\|\beta_{i\text{-}jt}\circ\left(P^*_{i\text{-}jt}-P_{i\text{-}jt}\right)\right\|_2^2\right) \quad (16)$$

where $\alpha_{i\text{-}jt}$ and $\beta_{i\text{-}jt}$ are the penalty multipliers; the symbol $\circ$ represents the Hadamard product; $P^*_{i\text{-}jt}$ denotes the pre-scheduled transaction power while $P_{i\text{-}jt}$ denotes the transaction power need to be optimized.

The power balance constraint and equivalent deterministic constraint are also modified as:

$$\sum_{c=1}^{Nc}P_{ct}+\sum_{w=1}^{Nw}P_{wt}=\sum_{b=1}^{Nb}P^*_{bt}-\sum_{j\neq i}^{Nd}P_{i\text{-}jt} \quad (17)$$

$$\sum_{c=1}^{Nc}\left(P_{ct}+R_{ct}\right)+\sum_{w=1}^{Nw}P_{wt}^{avi}-\sum_{j\neq i}^{Nd}P_{i\text{-}jt} \geq \sum_{b=1}^{Nb}P_{bt}+\mathrm{Z}_{\mathrm{LOLPt}}\left[\sum_{w=1}^{Nw}\left(\sigma_{wt}\right)^2+\sum_{b=1}^{Nb}\left(\sigma_{bt}\right)^2\right] \quad (18)$$

The transaction power is restricted by the tie-line capacity, which is expressed as:

$$P_{i\text{-}jt}\leq\overline{P_{i\text{-}j}} \quad (19)$$

The iterative solution procedure is used to solve this collaborative decision-making process and determine the transaction power $P_{i\text{-}jt}$. This algorithm is briefly explained as follows:

- Set the iteration index *s*=1 and choose initial values for $P^{*s-1}_{i\text{-}jt}$ $\alpha^{s-1}_{i\text{-}jt},\beta^{s-1}_{i\text{-}jt}$;
- Solve the optimal scheduling problem for each DES with the variable $P^s_{i\text{-}jt}$ and the values of $P^{*s-1}_{i\text{-}jt}$ from the previous iteration.
- Check the following necessary-consistency (20) and sufficient (21) stopping criteria. If they are not satisfied, go to next step; otherwise, the converged optimal result is obtained and the solution procedure stops.

The necessary-consistency condition and sufficiency are expressed as (20) and (21), respectively:

$$P_{i\text{-}jt}+P_{j\text{-}it}\leq\varepsilon_1\ \forall i,\forall j,\forall t \quad (20)$$

Sufficiency condition:

$$\left|f_i^s-f_i^{s-1}\right|\Big/f_i^s\leq\varepsilon_2\ \forall i,\forall t \quad (21)$$

where f_i^s denotes the value of the objective function;

- Set s=s+1 and update the values of multipliers, and return to step 2.

Solving the collaborative decision-making process, the power of transactions between the DESs can be determined. Then, the prices are evaluated as follows.

As discussed above, the optimal operation problems of DESs are formulated as nonlinear optimization programming represented by (16)-(19), and (2)-(8). The problems can be solved with the interior point method (IPM). Moreover, the shadow prices corresponding to constrint (17) at the optimal solution denote the marginal electricity cost of the DESs on real time. It is assumed that the marginal electricity cost for DHS *i* and

DHS j are ρ_{it} and ρ_{jt}, respectively. Then, the clearing price for transaction $P_{i\text{-}jt}$ is set as:

$$\rho_{i\text{-}jt} = \left(\rho_{it} + \rho_{jt}\right)/2 \tag{22}$$

Actually, ρ_{it} should be equal to ρ_{jt} if the tie-line capacity is not bounded. In this case, we have:

$$\rho_{i\text{-}jt} = \rho_{it} = \rho_{jt} \tag{23}$$

4. COLLABORATIVE DECISION-MAKING PROCESS

4.1 System and parameters

Three connected DESs are considered, which supply energy to the residential, commercial and industrial buildings, respectively. The electric and heat demand profiles for the three DESs are shown in Fig. 2 [20].

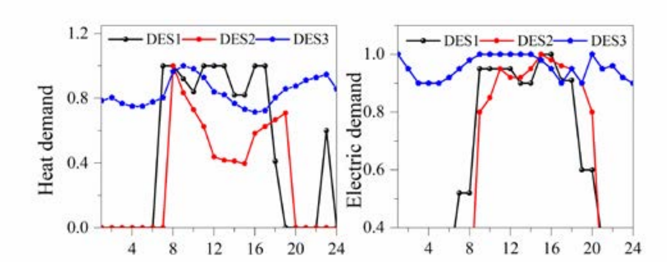
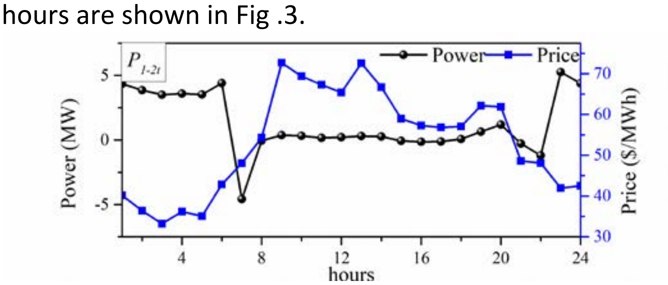


Fig. 2 Demand profiles for the three DESs.

The basic data are derived based on the real DES project in Hallstahammar, Sweden. The CHP plant is sized to supply 12MW of power and 25MW of thermal energy from the condenser. The installed capacity of wind power is set as 4MW. The capacity of gas-fired auxiliary boiler is set as 5MW. The maximum electric demand and heat demand are 10MW and 20MW, respectively. The cost parameters of CHP plant are set as $a_p = a_h = 0.5; b_p = b_h = 40; c_p = c_h = 0$. The cost functions of auxiliary boilers are set as $F_a\left(H_{at}\right) = 60H_{at}$.

4.2 Simulation results

The transactions between the three DESs are determined based on the proposed technique. The transaction power and corresponding prices over the 24 hours are shown in Fig .3.



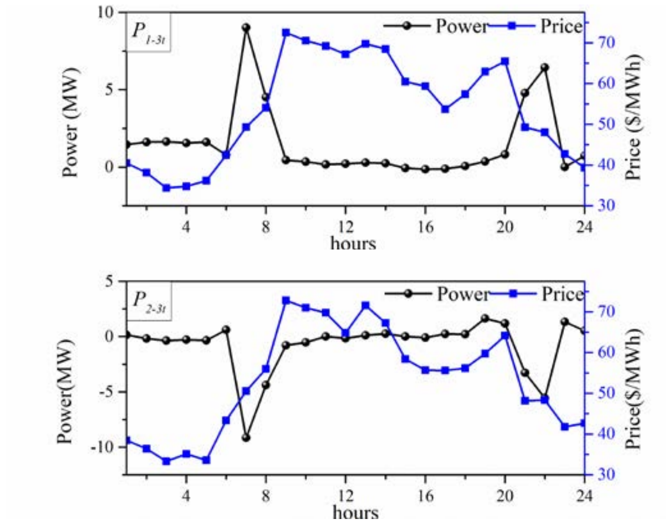


Fig. 3 Energy trading between the DESs over 24 hours.

As we can see from Fig. 3, the transactions are frequent and sizable. The transaction prices are also variable, which are determined by the demand and supply conditions in the DESs.

To illustrate the benefits of energy trading, two scenarios are modeled with scenario 1 denoting the non-trading scenario and scenario 2 denoting the with-trading scenario. First, the two scenarios are compared in term of daily operation cost ($) as shown in Table I.

Table I Summary of the comparisons in term of cost

Scenarios	Scenario 1	Scenario 2
DES1	3.14×10^4	3.07×10^4
DES2	1.35×10^4	1.06×10^4
DES3	1.81×10^4	1.73×10^4

As shown in Table I, the operation costs in the three DESs all decrease in Scenario 2 compared with Scenario 1. Averagely, the operation cost can decrease by 7.5% with the consideration of energy trading. The simulation results in the two scenarios are also compared in term of wind power integration. Without the consideration of energy trading, the mismatch between wind power and demand may lead to wind power curtailment. As shown in Fig. 4, wind power curtailment in DES2 and DES3 in Scenario1. In Scenario2, the energy surplus can be traded and therefore the wind power can be fully utilized.

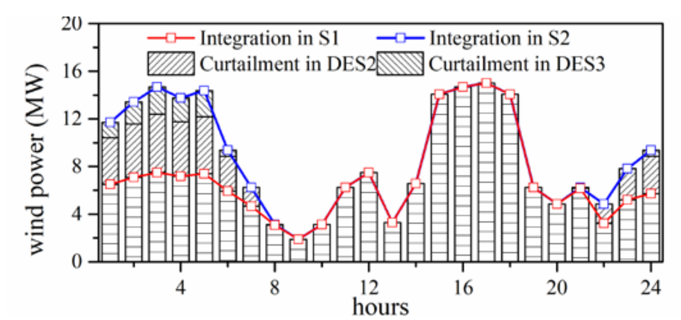


Fig. 4 Comparisons in term of wind power integration.

CONCLUSION

The framework for energy trading among DESs is developed based on the blockchains technology. Stochastic chance-constrained programming and distributed algorithm are applied to determine the transaction quantities and prices. Evidenced by the simulation results, the energy trading contributes to the operation cost saving and wind power integration.

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