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Multi-party stochastic energy scheduling for industrial integrated energy systems considering thermal delay and thermoelectric coupling

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HIGHLIGHTS

- The multi-party stochastic energy scheduling in IIES is studied.
- A decentralized decision support system with stochastic utility model is built for IUs.
- A stochastic game is designed to formulate the interaction among uncertain IUs.
- A solution algorithm with Markov decision process and iterative method is designed.
- A comparison between multiple stochastic and deterministic scenarios is provided.

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ABSTRACT

Multi-dimensional stochastic factors challenge the interactive energy scheduling of the industrial integrated energy system (IIES). Previous research focuses on either deterministic energy scheduling or individual stochastic scheduling while neglecting complicated interactions among uncertain parties, which brings the research gaps about stochastic multi-party's interaction. In this regard, a multi-party stochastic energy scheduling approach in IIES is proposed based on the stochastic game. A decentralized decision support system is considered, and a stochastic utility model is designed for decentralized IUs with multi-dimensional stochastic factors from photovoltaic (PV) production and IIES parameters, enabling them to participate in the multi-energy scheduling with their own strategies. A stochastic game model is developed considering the thermoelectric coupling and the IUs' interaction. The co-decision mechanism, recognizing different transfer times of electrical and thermal energy, is built based on the state transition within the game. Moreover, a distributed solution algorithm that includes the Markov decision process and iterative method is designed to address the problem of the "curse of dimensionality" arising from multiple stochastic factors. Finally, case studies with realistic data from an industrial park in Guangdong Province, China, are designed to show the effectiveness of the proposed approach, which enhances IUs' profits by 9.4% and fits flexible load strategies and price strategies. The decentralized system can also reduce the computation time by 70.1% compared to the centralized system. Through analyzing different number of scenarios and intervals for PV generation, electrical and thermal load, the conclusion has obtained that increase the number of scenarios has a negative effect on IUs' decision, but increase the number of load intervals contributes to more specific results and higher utility.

1. Introduction

As an industrial user (IU) is a high energy consumer, like process IU, energy optimization is an integral part of its daily operation, aiming at maximizing production profits and minimizing energy consumption costs [1]. Moreover, an IU usually consumes both thermal and electrical energy, resulting in an industrial integrated energy system (IIES) with tight thermoelectric coupling [2]. In addition, with the expansion in the industrial scale and the increase in the energy consumption, an efficient way for mitigating the energy crisis concern is to deploy distributed energy resources (DER) within the IUs [3], such as photovoltaic (PV) panels, combined heat and power (CHP) units, and combined cold, heat, and power (CCHP) units.

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Nomenclature

Abbreviations

IU	Industrial user.
IIES	Industrial integrated energy system.
CHP	Combined heat and power.
DER	Distributed energy resources.
PV	Photovoltaic.
MDP	Markov decision process.
SO	System operator.
CVaR	Conditional value at risk.
STN	State-task network.
ECU	Electrical comprehensive uncertainties.
TCU	Thermal comprehensive uncertainties.
TLF	Thermal load following.
ELF	Electrical load following.
NE	Nash Equilibrium.

Parameters and variables

ξ	Coupling ratio of thermal and electrical energy in industrial users (IUs).
γ	Thermal-to-electrical energy ratio in combined heat and power (CHP).
β	Ratio of electricity consumption to the thermal energy production for CHP units.
T_{delay}	Delay of thermal energy compared with electrical energy (h).
ε_t	Heat loss coefficient.
h, H	Index and total number of time slot.
i, N	Index and total number of IUs.
v, V	Index and total number of PV generations.
j, J	Index and total number of load intervals.
X, Y	Number of electrical and thermal load demands.
k, K	Index and total number of load demands, $K = X \bullet Y$.
N_s, N_b	Total number of sellers and buyers.
$R_{e,i,h,x}$, $R_{t,i,h,y}$	Probability that the electrical and thermal load generation falls in this level.
$\mathscr{R}_{e,i,h}$, $\mathscr{R}_{t,i,h}$	Set of electrical and thermal probability.
$E_{i,h,v}$	PV generation (kWh).
$R_{PV,i,h,v}$	The probability that the PV generation level falls in this interval.
$L_{i,h,j,x}$	Electrical load level, which belongs to the set $\mathscr{L}_{i,h,j}$ (kWh).
$fL_{i,h}$,$sL_{i,h}$	Fix electrical load and flexible electrical load (kWh).
$HL_{i,h,j,y}$	Thermal load level, which belong to the set $\mathscr{HL}_{i,h,j}$ (kWh).
$fHL_{i,h}$,$sHL_{i,h}$	Fix thermal load and flexible thermal load (kWh).
$\theta_{i,h,j}$	Set of IU's load demands in the interval j (kWh).
$\varphi_{i,h}$	Set of IU's load strategies (kWh).
$DL_{i,h,j,v,k}$	Net electrical load (kWh).
$TL_{h,j,y}$	Thermal production of CHP units (kWh).
$EL_{h,j,y}$	Electricity generation of the CHP units (kWh).
$pr_{b,h,j,v,k}$	Dynamic electricity purchasing price (CNY/kWh).
$pr_{s,h,j,v,k}$	Dynamic electricity selling price (CNY/kWh).
$\mathscr{P}_{b,h,j}$, $\mathscr{P}_{s,h,j}$	Set of dynamic electricity purchasing and selling prices (CNY/kWh).
$pr_{t,h,j,y}$, $\mathscr{P}_{t,h,j}$	Dynamic thermal price, and the set for the prices (CNY/kWh).
a_e, b_e	Parameters of electrical cost function (CNY/kWh and CNY).
$a_{t,h,1}$, $a_{t,h,3}$	Parameters of thermal prices function (CNY/kWh and CNY).

Function

$F_{i,h,j}(\theta_{i,h,j}, E_{i,h,v})$	IU's total utility that includes electrical and thermal uncertainties, as well as PV uncertainties.
$f_{i,h,j,v}(\theta_{i,h,j,k}, E_{i,h,v})$	Expected utility under a PV generation scenario v.
$g_{i,h,j,v,k}(\theta_{i,h,j,k}, E_{i,h,v})$	Instantaneous utility for each possible load demand k under a PV generation scenario v.
$C(L_{i,h,j,x})$	Electricity cost function.
$C_{SO,h,j,y}(TL_{h,j,y}, EL_{h,j,y})$	Operation cost of CHP unit.

There are two multi-energy scheduling categories for IUs in IIES: 1) studies without uncertainties, and (ii) studies with uncertainties. The former category primarily focuses on optimizing multi-party DERs and loads with coupled multi-energy aspects, accounting for different transfer time of electrical and thermal energy. The uncertain DERs generation and other stochastic factors of IIES are supposed as a constant. Whereas, uncertainties and fluctuations of DER outputs and other key IIES parameters could easily make the deterministic energy scheduling solution suboptimal or even infeasible. For example, actual PV outputs may deviation from the deterministic solution, leading to significant supply and demand imbalance [4]. Therefore, considering the stochastic factors among the multi-energy scheduling in IIES will become the main direction in the future.

Most literature on multi-energy scheduling on IIES, as we will see in the next section, mainly considers single stochastic factors in each IU, like DER's uncertainties [5], and system operators (SOs) are generally considered, then the system structure is generally built as a centralized way, which doesn't consider IUs iteration with stochastic factors [6]. However, it is stressed that there are multi-dimensional stochastic factors for an IU from PV generation and other key IIES parameters. Besides, the multi-energy scheduling for the IUs in the IIES is a multi-party profit-competed problem, which requires the iterations among individual IU [7]. These two factors further complicate the multi-energy scheduling in IIES which presents difficulties for the centralized system structure to formulate the multi-dimensional stochastic factors in the multi-energy scheduling with multi-party's interactions [8]. To conclude, there are two challenges: (i) How to formulate IU's participation in the energy scheduling while considering thermoelectric coupling as well as multi-dimensional stochastic factors for each IU in the industrial production process and IU's characteristic; and (ii) How to design a profit-related multi-energy scheduling plan for the multi-party operation while considering the effect of stochastic factors and different transfer time of electrical and thermal energy in the IIES.

To address the aforementioned difficulties and supplement the research gap, a decentralized decision support system is proposed for IUs to participate in the multi-party energy scheduling. Based on the decentralized decision support system, the multi-dimensional stochastic factors of each IU can be considered in the energy scheduling process, and IUs can get their energy scheduling strategies individually based on their own characteristics. Besides, due to the superior performance of the game theory in dealing with multi-party profit-related interactions, the non-cooperative type game is adopted to schedule the profit-competed IUs' strategy. We start from the multi-dimensional stochastic factors, consider thermoelectric coupling and thermal delay, as well as many possible thermal and electrical load demands of interactive IUs under an uncertain environment. The widely used static game theory, such as Nash game, Stackelberg game, is not suitable to be used. Therefore, the formulation is based on a richer class of games, namely stochastic games [9], to capture the stochastic multi-energy interaction. This is a new energy scheduling approach and has not been reported, as far as we know. The contributions of the paper are as follows:

(1). A decentralized decision support system is proposed for IUs with multi-dimensional stochastic factors and interactive characteristic. In the system, a stochastic utility model is built for each IU, which enables them to participate in the multi-energy scheduling with their own strategies. The multi-dimensional stochastic factors from DERs and IUs' industrial production process are distributedly considered, as well as many possible load demand according to the PV uncertainties. The thermal delay and thermoelectric coupling are also incorporated in the decentralized system.
(2). A stochastic game model is proposed for multi-energy scheduling among multiple profit-driven parties, where the interactions of IUs with multi-dimensional stochastic factors is formulated via dynamic processes. A co-decision mechanism based on state transitions within the game is provided to address different transfer time of electrical and thermal energy, and a distributed solution algorithm with the Markov decision process (MDP) and iterative method is designed to address the problem of "curse of dimensionality" arisen from the stochastic factors.

The remainder of the paper is organized as follows: We discuss the relate literature on multi-energy scheduling in IIES in Section 2 followed by a description of the considered system framework and basic characteristic in Section 3. The IUs and system operator (SO)'s model is formulated in Section 4. The iteration of stochastic IUs is formulated as a stochastic game in Section 5, where we also analyze the properties of the game and designed a distributed solution algorithm. Case study are discussed in Section 6, and some concluding remarks are contained in Section 7.

2. Literature review

Recently, there has been considerable research effort to understand the multi-energy scheduling in IIES. This is mainly because the energy scheduling for IIES is a challenging task, in observing complications of thermoelectric coupling, different transfer time of electrical and thermal energy [7], as well as fluctuation and intermittence of DERs and other key IIES parameters [10].

The literature can be divided into two general categories: (i) studies without considering uncertainties, and (ii) studies considering stochastic factors. In the first category, the multi-energy scheduling for IUs usually accompanies with many interactions relationship to get the optimal solution [11]. As the superior performance in dealing with multi-party profit-related interactions, game theory is widely used to study the optimal schedule. The interactions between IUs and upper operators are usually existed, and the Stackelberg game is one of major frameworks to model the interactions, such as between IUs and CHPs unit owner [12] and between IIES operator and urban manager [13], which realizes the distributed autonomy and centralized coordination of IIES. The phenomenon of thermoelectric coupling and thermal delay, which is caused by the different transfer time of electrical and thermal energy, is considered in the game formulation [7]. The interaction among IUs is also existed. Nash game provides a feasible way to formulate their interaction [14]. To maintain a certain level of users' anonymity, a two-stage game model and a generalized Nash game model with thermal comfort are built for suppliers and IUs [14,15]. Energy management for IUs in IES can also be studied by a cooperative perspective, building cooperative game model for energy hub to coordinate IU community [16]. The cooperative game also introduces to formulate the cooperative alliance, then processing the energy trading among them under the consideration of virtual energy storage [17].

In addition to the IUs, another important entity in IIES is CHP (and CCHP), which generally affords the thermal energy demand and meets partial electrical energy demand [7]. The research for CHP system is mainly focus on the optimal output and industrial use of CHP/CCHP units, some of them considering the thermal energy storage system to co-optimized their scheduling strategies [18], some of others incorporate the DER supply and regional hydropower plants to evaluate the influence of local DER on the production planning of CHP system [19]. The economic profitability is also an important issue that can be improved through the scheduling of CHP units, where the mathematical model is generally built as mix integer linear programming [20].

For the second category, as we discussed in the Introduction, the uncertainties from DERs and other key IIES parameters are crucial for the multi-energy scheduling and become the main direction in the future. Most literature have focused on the uncertainties problem and multiply methods have been adopted such as: scenario based stochastic modeling method, robust optimization, fuzzy theories, and conditional value at risk (CVaR). These methods generally solve the problems in a centralized manner. The scenario based stochastic optimization is implemented by the centralized aggregators, which builds the cost minimization model based on the multiple scenarios generated through from electricity price and solar PV uncertainties [21]. The multi-stage scenario tree generation method is proposed to minimize the comprehensive cost based on the conditional generative adversarial network-random forest-Markov chain [22]. Stochastic optimal operation model is formulated based on scenario generation and reduction for the heat, gas, and electric delivery system, which helps the centralized operators to schedule the system with minor cost [5]. A two-stage stochastic optimization approach is proposed to maximize the expected revenue of the community microgrid companies as well as enhance the reliability of the system [23]. Robust optimization has the characteristics of simple modeling and strong anti-interference, which consider the optimal solution of the worst scenarios in all the uncertain scenarios [6]. A two-stage robustly coordinated operation method is proposed to achieve the optimal profits for the multi-energy microgrid operator, and the load uncertainties are modeled as uncertainty sets for the operator [24]. The reserve is also co-optimized with multi-energy through an adaptive robust model to minimize the total system cost in a centralized way under the worst-case realization [25]. The industrial use of centralized CHP system is usually scheduled together with the renewable energy, storage system, and electric vehicles, and the robust optimization is adopted to deal with the future pricing uncertainties [26]. To face the supply and demand side uncertainties in IIES with CHP and renewable power, manufacturing and non-manufacturing loads in industrial production is scheduled based on the robust optimization and CVaR [27]. Robust optimization also provides a solution to conquer the challenges of increased operating cost and energy supply deficiency caused by DERs' uncertainties through forming a multi-timescale coordinated adaptive approach [28]. Also, the similar robust coordinated optimization method is designed to explore the quantitative impact of thermal inertia under the thermal inertia uncertainties [29]. Besides, the CVaR can also be incorporated in the fuzzy model, to resolve the sudden absence of distributed energy resources and power failures [30]. The CVaR can also be used to consider the PV uncertainties, then reflecting the CVaR value in the game formulation, which enables a static game process without considering the uncertainties [16]. Other uncertainties solving methods are also used in IIES multi-energy scheduling, like a powerful probabilistic tool named 2 m + 1 point estimate strategy is presents for energy flow analysis of an IIES.

Aforementioned literature mostly focuses on the centralized system structures, where the centralized operators, such as aggregators [21], industrial multi-energy microgrids operators [28], and hub managers [16], are responsible for the energy scheduling through the column-and-constraint generation algorithm [28], Matlab-ANSYS co-simulations method [29], and game theory [16,30]. With the increasing number of users, centralized system structure faces the problem of processing massive users' data, which facilitates the appearance of decentralized system structure. In the decentralized system structure, IUs with various scheduling and preference can be individually considered, and the uncertainties from IU's characteristic can be deal with by setting the fuzzy rules [31], or be tackled by the CHP with fuzzy load duration curves

[32]. However, current decentralized system structure can only consider the stochastic factors of each IU [21,24,30,31], rather than their interactions. Although some research considers entities' interactions under a decentralized manner, their interactions are modeled as a two-stage static game framework as the uncertainties are deal with in the former stages [16].

Based on the aforementioned points, it is obvious that there still exist research gaps to build a decentralized system structure that can consider multi-dimensional stochastic factors during the IUs' interactions. In this regard, unlike the discussed literature, this paper investigates the decentralized decision support system with a stochastic game model, where the dynamic multi-party's interactions with stochastic factors can be captured. The stochastic game theory is first proposed by L. Shapley in 1953 [9], which includes five elements: game player, state, action, state transition probability, and utility. Different from the static games, such as the Nash game, with only one kind of stage and one state, the stochastic game is a kind of dynamic game with multi-stage, and different stages have different states. As the game dynamically implements in different stages, the work here dynamically models the multi-dimensional stochastic factors, which will change the states in different stages with the state transition probability. Besides, we also consider the thermoelectric coupling and thermal delay, as well as many possible thermal and electrical load demands of interactive IUs under the interactive uncertain environment.

3. System framework and basic characteristics

3.1. Structure for the decentralized decision support system

A detailed structure of the decentralized decision support system is shown in Fig. 1, which includes IUs and SO. Most IUs have both electrical and thermal demands, as well as PV panels to cover part of the electrical energy needs. A CHP unit, which is controlled by the SO to provide both electrical and thermal energy, consists of microturbines, heating and waste-heat recovery systems, and auxiliary boilers. In terms of electrical energy, an IU can purchase electrical energy from other IUs. While if PV production of an IU is greater than its electrical demand, it can sell excessive electricity to other IUs for profit; the SO maintains electrical energy balance. On the other hand, IUs' thermal energy demand is satisfied by CHP units. The SO also determines the selling and purchasing prices of electrical energy as well as purchasing prices of thermal energy.

IUs conduct the multi-energy scheduling independently through the user energy management system (UEMS), where the electrical/thermal demand are optimized according to the price signal transmitted by the SO. Under the decentralized decision support system structure, IUs can participate in the stochastic energy scheduling based on their own strategies. Besides, the system can provide decentralized computing resources, like UEMS, to reduce the computation burden in the centralized operators. With these advantages, the IUs' multi-dimensional stochastic factors can be considered into the IUs' interactions. The reason is that it can overcome the difficulties that there are massive data from stochastic scenarios required to be transmitted, and the scenarios will be exponential increased if solving in a centralized method.

3.2. Process industry with thermal delay and thermoelectric coupling

A process industrial contains multiple operation with the characteristic of continuity of each operation. Typical process industrial have a stable-state process that can be employed in iron and steel plants, chemical plants, and pharmaceutical factories [33]. The production process of a process industry can be expressed in a state-task network (STN) form. A STN is composed of multiple operations, like the evaporation and concentration, oxidation distillation, and condensation in chemical plants, each of which has multiple material use, products, as well as thermal and electrical equipment. An STN representation of a detailed process industry is shown in Fig. 2.

Specifically, Fig. 2 shows two critical factors of a process industry:

(1). ***Thermoelectric Coupling***: Operations of electrical and thermal equipment are tightly connected with each other. Indeed, the normal operation of thermal equipment is generally accompanied by an electrical energy consumption, resulting in the thermoelectric coupling in IUs (denoted as ξ). For example, a distillation tower in a chemical plant requires a control panel that runs on electrical energy. The thermoelectric coupling also exists in the SO. A CHP unit produces thermal energy to satisfy thermal demands of IUs, while electrical energy is a byproduct based on the thermal-to-electrical energy ratio γ of the CHP.

(2). ***Thermal Delay***: The electricity and thermal networks support the electrical and thermal demands of IUs in the IIES. Electrical demands are satisfied in real time (i.e., $h1 = h2$) by the electricity network, as electricity production, transmission, and consumption are carried out almost simultaneously. In comparison, the thermal energy is always supplied with a time delay (i.e., $h1 =$

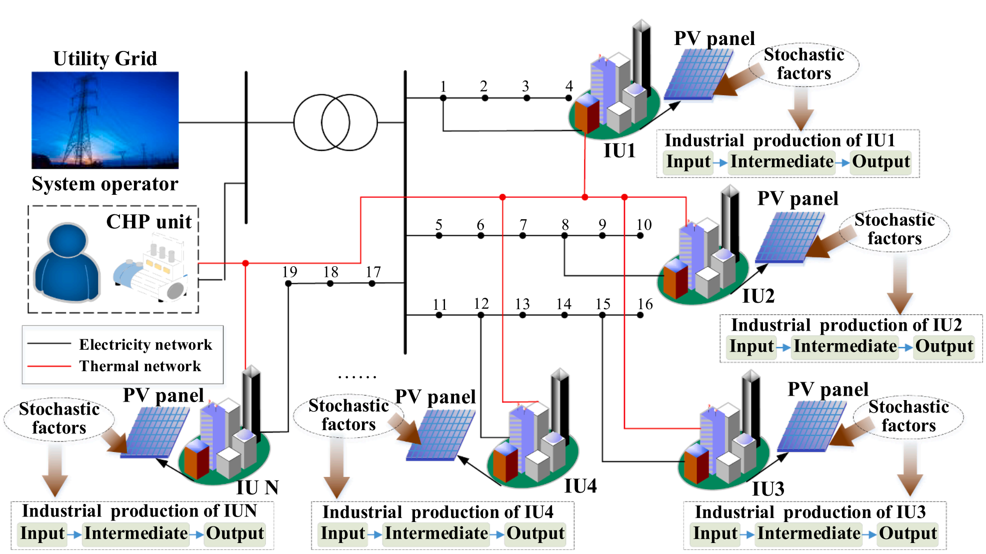

Fig. 1. Structure of the decentralized decision support system in IIES.

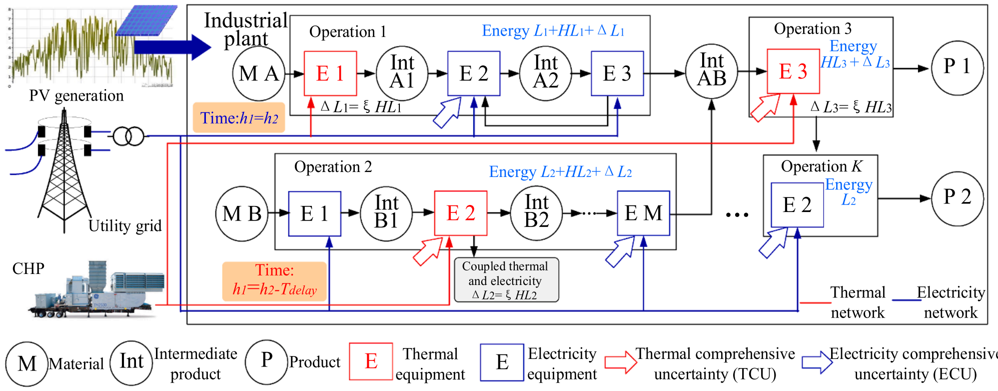

Fig. 2. STN of process IUs composed of thermal delay, thermoelectric coupling, and stochastic factors.

$h2 - T_{delay}$). The transmission time delay depends on physical characteristics and operating conditions of heating pipes in the thermal network that connect heat sources and thermal loads, e.g., energy loss, pipe size, frictional resistance, and temperature [7].

The difference in the transfer time of thermal and electrical energy complicates the energy scheduling in IIES. Specifically, electricity demand and generation are balanced instantaneously, while a thermal demand to be satisfied by the CHP units in one time slot shall be prepared T_{delay} slots ahead of time, i.e., have the coupling effect in time horizon. Therefore, because thermal states of the current time slot and T_{delay} hours ahead are coupled and IUs also present tight thermoelectric coupling, the electrical states of the current time slot and T_{delay} hours ahead are also coupled.

3.3. Multi-party interactions with multi-dimensional stochastic factors

The multi-party interaction is shown in Fig. 3. With the built decentralized decision support system, IU will transmit their thermal and electric load strategies that obtained from their own decision process to other IUs and the SO, then other IU can decide their strategies and SO will calculate the prices signals. Specifically, because energy prices depend on load consumption levels of all IUs and affect each IU's load strategies, the IU's load strategies have interactive influence during the decision-making process, as well as the stochastic factors.

Fig. 3 also shows the influence of multi-dimensional stochastic factors on the decision-making process. The uncertain PV generation in the source side is caused by the fluctuation and variation of solar irradiation. Therefore, all IUs suffer the same PV uncertainties. This uncertainty is processed by the scenario generation, each scenario includes PV generation and corresponding occurrence probability. All the scenarios can be described by a probability measure, which can be expressed as follows:

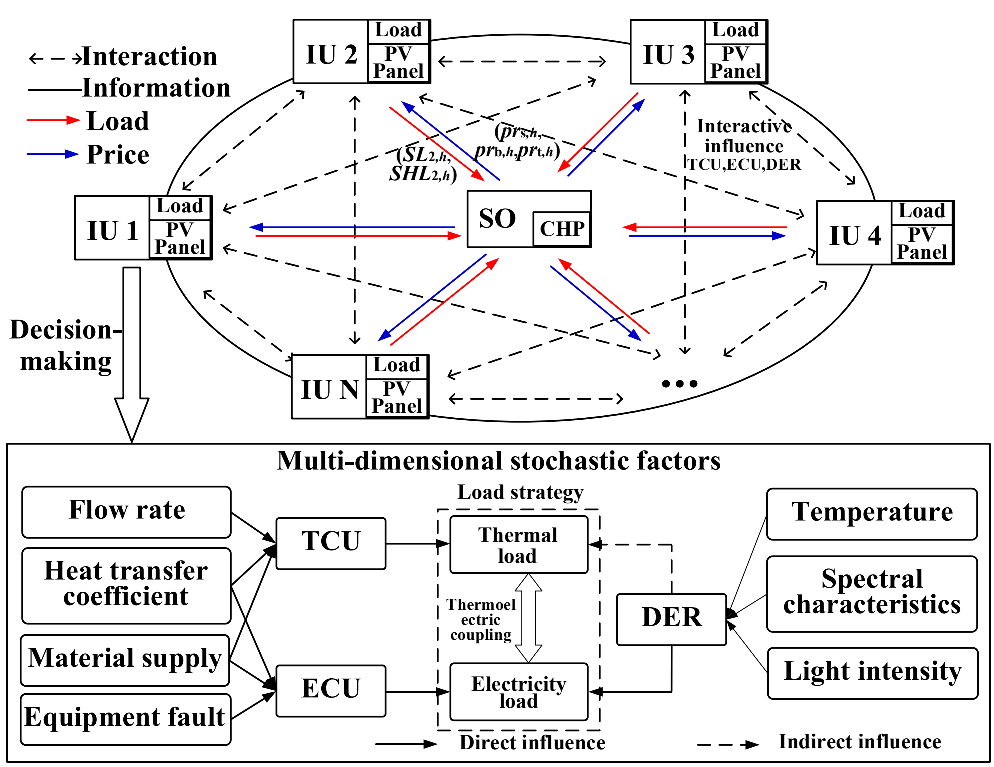

Fig. 3. Multi-dimensional stochastic factors of IUs in IIES.

$$\eta_{PV,h} \sim \mathbb{R}\left(\mathrm{E_{i,h}}, \mathscr{R}_{\mathrm{PV,i,h}}\right), \mathscr{R}_{\mathrm{PV,i,h}} := \left\{\mathrm{R_{PV,i,h,v}}, \mathrm{v} \in \mathrm{V}\right\}, \tag{1}$$

where $\mathbb{R}(\bullet)$ is the probability measure, which can be derived by leveraging statistical information from historical PV generation data, the method to get $\mathbb{R}(\bullet)$ is based on polynomial interpolation or fitting.

The industrial production of process IUs also introduces uncertainties, which can be classified into three categories [34]: (i) inherent uncertainty of the production process, such as thermodynamic constant, pipe condition, flow rate, etc.; (ii) external uncertainty of the production system, resulting from the material supply, product requirements, and prices of raw material; (iii) random uncertainty, such as equipment failure and manual operation errors. If the equipment is out of service, the material may stay unused, and the profit may not be acquired. Thus, all the factors are related to the production process and the normal equipment operation, and have influence on the production cost, product, and energy consumption. To this end, two types of comprehensive uncertainties related to the industrial production are considered, including the electrical comprehensive uncertainties (ECU) associated with electrical equipment and the thermal comprehensive uncertainties (TCU) associated with thermal equipment.

The ECU and TCU are processed by the interval partition and consider the thermal and electrical load as a discrete type. Because of the uncertainties, each load interval contains multiple possible thermal and electrical load demands and corresponding probabilities. These uncertainties transfer thermal and electrical load to random variables that also follow certain probability measures, obtained from historical production-related data by polynomial interpolation or fitting method. These random variables can be expressed as follows:

$$\eta_{e,i,h} \sim \mathbb{Z}\left(L_{i,h}, \mathscr{R}_{e,i,h}\right), \mathscr{R}_{e,i,h} := \left\{R_{e,i,h,x}, x \in X\right\} \tag{2}$$

$$\eta_{t,i,h} \sim \mathbb{C}\left(\mathrm{HL_{i,h}}, \mathscr{R}_{\mathrm{t,i,h}}\right), \mathscr{R}_{\mathrm{t,i,h}} := \left\{\mathrm{R_{t,i,h,y}}, \mathrm{y} \in \mathrm{Y}\right\}, \tag{3}$$

where $\mathbb{Z}(\bullet)$ and $\mathbb{C}(\bullet)$ are the probability measures calculated with the statistical data of electrical and thermal equipment, respectively.

Both the ECU and TCU would impact the energy scheduling decision-making process due to the thermoelectric coupling. Specifically, the TCU is reflected in the IU's thermal load; The electrical load, which is coupled with the thermal load $L = \xi \bullet \mathrm{HL}$, is affected by both TCU and ECU. Therefore, both ECU and TCU are embodied in the load profile, and eventually affect the energy scheduling. Additionally, uncertain PV outputs impact the IUs' net load and affect the load scheduling in combination with ECU and TCU, showing the influence of the interacted multi-dimensional stochastic factors on the decision-making process.

$$g_{i,h,j,v,k}\left(\theta_{i,h,j,k}, E_{i,h,v}\right) = \begin{cases} PR_{i,h,j,k} - pr_{b,h,j,v,k} \cdot DL_{i,h,j,v,k} - pr_{t,h,j,v,k} \cdot HL_{i,h,j,y}, DL_{i,h,j,v,k} \leq 0 \\ PR_{i,h,j,k} - pr_{s,h,j,v,k} \cdot DL_{i,h,j,v,k} - pr_{t,h,j,v,k} \cdot HL_{i,h,j,y}, DL_{i,h,j,v,k} > 0 \end{cases}, \tag{9}$$

4. System model

4.1. Stochastic utility model for decentralized IUs

Each of electrical and thermal loads consists of a fixed component and a flexible component. Fixed loads require highly reliable supply, with fixed energy consumption time and quantity. On the other hand, the time and quantity of a flexible load can be adjusted during the decision-making process. The IUs' production is determined by the electrical and thermal loads, and IUs can be electrical energy sellers or buyers depending on the available PV production. Therefore, the IUs' profit is determined by the electrical load, thermal load, and PV production, with the given purchasing price $pr_{b,h}$, selling price $pr_{s,h}$, and thermal price $pr_{t,h}$. Each IU implement their multi-energy scheduling individually according to their own utility model, where the load strategies (including thermal and electrical load strategies) are considered as discrete variables (corresponding to multiple intervals j), and multiple possible thermal and electrical load demands (denoted as $k, k \in K$) are included in each interval. The thermal and electrical load demands are assumed to belong to independent set $\mathscr{L}_{i,h,j}$ and $\mathscr{HL}_{i,h,j}$, and the set of IU's load demands in the interval j are defined as:

$$\theta_{i,h,j} := \left\{\theta_{i,h,j,k} \middle| \left(L_{i,h,j,x}, HL_{i,h,j,y}\right) \in \mathscr{L}_{i,h,j} \times \mathscr{HL}_{\mathrm{i,h,j}}\right\} \tag{4}$$

where $\times$ is the Cartesian product, and K number of elements are included in the set, i.e., $K = X \bullet \mathrm{Y}$.

Then the set of IU's load strategies (interval) can be expressed as:

$$\varphi_{i,h} := \left\{\theta_{i,h,j}, j \in J\right\} \tag{5}$$

The stochastic utility model for decentralized IUs is expressed as follows:

$$F_{i,h,j}\left(\theta_{i,h,j}, E_{i,h,v}\right) = \sum_{v \in V} p_{PV,i,h} \bullet \mathrm{f_{i,h,j,v}} \tag{6}$$

$$f_{i,h,j,v}\left(\theta_{i,h,j,k}, E_{i,h,v}\right) = \sum_{k \in K} \pi_{i,h,k} \bullet \mathrm{g_{i,h,j,v,k}}, \tag{7}$$

$$\pi_{i,h,k} = \left\{R_{e,i,h,x} \bullet \mathrm{R_{t,i,h,y}} \middle| \mathscr{R}_{\mathrm{e,i,h}} \times \mathscr{R}_{\mathrm{t,i,h}}\right\}, \tag{8}$$

The reflection of stochastic factors on the stochastic utility model is explained in Fig. 4. There are two expectation forms to reflect the stochastic factors. The first is the IU's total utility $F_{i,h,j}$ that reflects the PV uncertainties, and the second is the expected utility $f_{i,h,j,v}$ under a PV generation scenario v that reflect the ECU and TCU. The total utility in a load interval j includes the expected utility $f_{i,h,j,v}$ in all PV generation scenarios with occurrence probabilities, as (6) shows. $g_{i,h,j,v,k}$ is the instantaneous utility of a possible load demand k in a load interval j and PV generation scenario v. The expected utility is calculated as (7) shows with all the instantaneous utility $g_{i,h,j,v,k}$ and corresponding probability in a load interval j.

The instantaneous utility is a deterministic utility, and the model for seller (i.e., $DL_{i,h,j,v,k} > 0$) and buyer (i.e., $DL_{i,h,j,v,k} \leq 0$) are expressed as follows:

$$PR_{i,h,j,k} = kn_{i,h} \ln\left(1 + L_{i,h,j,k}\right) + km_{i,h} \ln\left(1 + HL_{i,h,j,k}\right), \tag{10}$$

$$L_{i,h,j,x} = fL_{i,h,j,x} + sL_{i,h,j,x}, \tag{11}$$

$$HL_{i,h,j,y} = fHL_{i,h,j,y} + sHL_{i,h,j,y}, \tag{12}$$

$$DL_{i,h,j,v,k} = L_{i,h,j,x} + \xi HL_{i,h,j,y} - E_{i,h,v}, \tag{13}$$

where $kn_{i,h}$ and $km_{i,h}$ are respectively the constant preference parameters of electricity and thermal energy of IU i at time h; $ln(\bullet)$ is the natural logarithm function, which is widely used in economics to model user preferences in the decision-making process [35]; $DL_{i,h,j,v,k}$ depends on the electrical load $L_{i,h,j,x}$, thermal load$HL_{i,h,j,y}$, PV production $E_{i,h,v}$.

The IUs' utilities consist of three components: production utility, electricity trading utility, and thermal energy cost. The production utility is first terms in (9) $PR_{i,h,j,k}$, which reflects the electricity

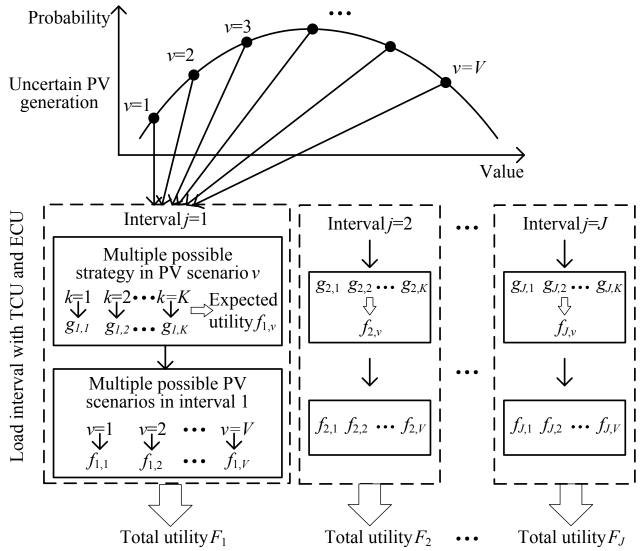

Fig. 4. Reflection of stochastic factors on the stochastic utility model.

consumption. Based on whether IU is a buyer or a seller, the utility for trading electricity with other IUs is either $pr_{b,h,j,v,k}\cdot DL_{i,h,j,v,k}$ or $pr_{s,h,j,v,k}\cdot DL_{i,h,j,v,k}$. The role is determined by $DL_{i,h,j,v,k}$, i.e., the buyer pays the purchasing cost if $DL_{i,h,j,v,k} > 0$, and the seller receives a profit if $DL_{i,h,j,v,k} \le 0$. The utility of trading thermal energy is $pr_{t,h,j,v,k}\cdot HL_{i,h,j,y}$. The cost is due to the IUs' inability to generate thermal energy and the necessity to purchase it from the SO.

Adjustment capabilities of the flexible electrical and thermal loads are limited by their lower and upper bounds:

$$sL_{i,h,min} \le sL_{i,h} \le sL_{i,h,max}, \tag{14}$$

$$sHL_{i,h,min} \le sHL_{i,h} \le sHL_{i,h,max}, \tag{15}$$

where $sL_{i,h,min}$ and $sL_{i,h,max}$ are respectively the lower and upper bounds of the flexible electrical load of IU i at time h; $sHL_{i,h,min}$ and $sHL_{i,h,max}$ are those for the flexible thermal load.

4.2. Prices model of the SO

The dynamic purchasing price $pr_{b,h}$, selling price $pr_{s,h}$, and thermal price $pr_{t,h}$ are set by the SO to help the IUs' energy scheduling. The dynamic electrical prices (including purchasing and selling prices) are calculated based on the electrical cost function, which considers the effect of IU's load consumption and the profit of SO. According to [36], a quadratic polynomial model is used to represent the electrical cost function:

$$C\left(L_{i,h,j,x}\right) = a_e\cdot\left(\sum_{i\in N} L_{i,h,j,x}\right)^2 + b_e\cdot\sum_{i\in N} L_{i,h,j,x} \tag{16}$$

The parameters a_e and b_e are determined by the SO based on some related influencing factors of the electricity cost, such as generator types, fuel prices, SO's profit margins. Based on the electrical cost function, the electrical prices model can be obtained:

$$pr_{b,h,j,v,k} = a_e\sum_{i\in N} DL_{i,h,j,v,k} + b_e, DL_{i,h,j,v,k} > 0, pr_{b,h,j,v,k} \in \wp_{b,h,j} \tag{17}$$

$$pr_{s,h,j,v,k} = -a_e\sum_{i\in N} DL_{i,h,j,v,k} - b_e, DL_{i,h,j,v,k} \le 0, pr_{b,h,j,v,k} \in \wp_{s,h,j} \tag{18}$$

In terms of thermal energy, the CHP units generates thermal and electrical energy simultaneously. In the thermal load following (TLF) mode, the CHP is mainly used to generate thermal energy, with electrical energy as a byproduct. In the electric load following (ELF) mode, it is mainly used to generate electrical energy. This study focuses the CHP in the TLF mode. The thermal energy generated by the CHPs is based on the thermal demand of the IUs.

$$TL_{h,j,y} = \sum_{i\in N} \varepsilon_t\cdot HL_{i,h-T_{delay},j,y}, \tag{19}$$

$$EL_{h,j,y} = \gamma\cdot TL_{h,j,y}, \tag{20}$$

$$\gamma = \frac{(1-\lambda-\lambda_{loss})}{\lambda}\cdot\sigma_{heat}, \tag{21}$$

where $HL_{i,h-T_{delay},j,y}$ is thermal load of IU i at time $(h-T_{delay})$, and time delay T_{delay} depends on physical characteristics of the thermal network; λ, λ_{loss}, and σ_{heat} are power generation efficiency, heating loss coefficient, and heating coefficient of CHP, respectively.

The operation cost of CHP units for SO is formulated as a quadratic function of heat production and electricity generation based on [37,38].

$$C_{SO,h,j,y}\left(TL_{h,j,y}, EL_{h,j,y}\right) = a_{t,h,1}\bullet \mathrm{TL}_{\mathrm{h,j,y}}^2 + \mathrm{a_{t,h,2}}\bullet \mathrm{EL}_{\mathrm{h,j,y}}^2 + \mathrm{a_{t,h,3}}\bullet \mathrm{TL_{h,j,y}} + \mathrm{a_{t,h,4}}\bullet \mathrm{EL_{h,j,y}} + \mathrm{a_{t,h,5}}\bullet \mathrm{TL_{h,j,y}}\bullet \mathrm{EL_{h,j,y}} \tag{22}$$

where $C_{SO,h,j,y}\left(TL_{h,j,y}, EL_{h,j,y}\right)$ is the operation cost of CHP units.$a_{t,h,1}$, $a_{t,h,2}$, $a_{t,h,3}$, $a_{t,h,4}$, and $a_{t,h,5}$ are the parameters, and decided by the characteristic of CHP units, price of natural gas, and low heating value of natural gas.

Because the CHP units operates in the TLF mode, the operation cost is based on the thermal production.

$$C_{SO,h,j,y}\left(TL_{h,j,y}\right) = a_{t,h,1}\bullet \mathrm{TL}_{\mathrm{h,j,y}}^2 + \mathrm{a_{t,h,3}}\bullet \mathrm{TL_{h,j,y}} \tag{23}$$

According to the operation cost model of CHP units, the thermal price model can be obtained by taking the derivative of the cost function.

$$pr_{t,h,j,y} = a_{t,h,1}\bullet \mathrm{TL_{h,j,y}} + \mathrm{a_{t,h,3}}, \mathrm{pr_{t,h,j,y}} \in \wp_{\mathrm{t,h,j}} \tag{24}$$

5. Stochastic game model and solution algorithm

5.1. Stochastic game model among IUs

The IUs participation in IIES is to maximize their utility. It is similar to a multiagent profit-related problem and studied via game theory [11]. The interaction between the IUs can be formulated as a non-cooperative game, in which SO is the middleman to provide the dynamic prices $pr_{b,h}$, $pr_{s,h}, pr_{t,h}$, and the IUs are the game players with the strategies of load distribution $L_{i,h}$, $sHL_{i,h}$. The interaction relationships are expressed as Fig. 3.

However, the multi-dimensional stochastic factors would impact their load strategies due to interactions and the tight coupling of thermal and electrical energy, then the states (i.e., includes dynamic purchasing prices, selling prices, and thermal prices) are affected. The state in each stage (i.e., time slot) will also be different and updated from previous stages because the prices are dynamically updated with the load strategies under the influence of multi-dimensional stochastic factors. Besides, the thermal delay couples the state of a certain time slot and T_{delay} time slots after it, resulting in the states in current time slot affected by the previous time slots. An independent review of each IU's stochastic factors cannot accurately reflect their interactions and cannot dynamically update states during the decision-making process. Therefore, a dynamic gaming process with the states transition is formulated as stochastic game model:

$$\Psi = \langle N, \boldsymbol{S}_h, \boldsymbol{A}_h, \boldsymbol{\rho}_h\left(A_{i,h,j}|S_{i,h-1,j}\right), F_i \rangle, \tag{25}$$

$$S_{i,h,j} = \left\{\nu_{b,h,j}, \nu_{s,h,j}, \nu_{t,h,j}\right\}, S_{i,h,j} \in \boldsymbol{S}_h, \tag{26}$$

$$A_{i,h,j} = \left\{\theta_{i,h,j}\right\}, A_{i,h,j} \in \boldsymbol{A}_h, \tag{27}$$

$$\rho_{i,h,j} = \mathbb{p}\left\{S_{i,h-1,j}, A_{i,h,j}\right\}, \rho_{i,h,j} \in \boldsymbol{\rho}_h \tag{28}$$

$$\max_{\rho_{i,h,j}} F_i\left(\rho_{i,h,j}\right) = \sum_{h=1}^{H} \sum\nolimits_{j=1}^{J} \rho_{i,h,j} \bullet \mathrm{F}_{\mathrm{i,h,j}} \tag{29}$$

$$\text{s.t.} \sum\nolimits_{j=1}^{J} \rho_{i,h,j} = 1, \forall h \in H, \forall i \in N \tag{30}$$

where subscript h is the index of stages in the game. Note that in this paper the state index is consistent with the time index. $\mathbb{p}\{\bullet\}$ is the probability measure over the state and load strategy.

(1). N is the set of IUs that represent the game players.
(2). $\boldsymbol{S}_h$ is the states' set of the game, which updates with the game stages and each state describes the dynamic purchasing prices, selling prices, and thermal prices at certain time slot.
(3). $\boldsymbol{A}_h$ is the set of strategies of the game, and each strategy includes flexible electrical and thermal loads of IUs. The state changes as the game stage process and the strategy are applied, and $S_{i,h,j}$ is determined by strategy $A_{i,h,j}$ and the previous state $S_{i,h-1,j}$. The strategy set includes J number of possible strategies, and each strategy is associated with a probability. Besides, there are K number of possible load demands in a load interval under the ECU and TCU.
(4). $\boldsymbol{\rho}_h\left(A_{i,h,j}|S_{i,h-1,j}\right)$ is the state transition probability, which is a conditional probability according to the definition of the stochastic game and determined by the load strategies and previous state [9]. A map is existed in the state transition probability and load strategy, in which the state transition probability implicates the probability of a chosen strategy. Therefore, choose the optimal load strategies equivalent to determine the state transition probability of each load strategy.
(5). F_i is the IUs' utility when participating in the game, which is determined by the IU's stochastic utility model (6–13). The utility is the sum of all the time slots for the day-ahead energy scheduling with different transfer time. During the game process, each IU maximizes their utility by optimizing the state transition probabilities under different load strategies.

Fig. 5 shows the game process that includes the coupled thermal and electrical energy in each stage. There are interactions between each IU, and SO serves as a middleman to provide the dynamic electrical and thermal prices during IUs' interaction. The state transition occurs as the game develops, and they are supported by the probability distribution of the state transition probability and the strategies of IUs. IUs develop their strategies in each stage by maximizing their own profits F_i. Affected by the dynamic prices, the optimal load strategies will be determined under the consideration of multi-dimensional stochastic factors.

Thermal delay has significant impact on the stochastic game process, as thermal energy of the IU's previous stage will affect the thermal prices of SO in the following stages. The reason is that as the physical characteristics of the thermal network induce certain thermal delays, thermal generation and transmission have to be prepared T_{delay} hours in advance to meet thermal demand of the current hour, which consequently influences thermal prices over T_{delay} hours. Because the natural gas for thermal energy generation is used in the generation time slot, so that the previous thermal energy affects the parameter $a_{t,h,1}$ of the prices function (24), then reflecting in the current thermal prices. The parameter is calculated by:

$$a_{t,h,1} = a_{t,h,1,0} \frac{TL_{i,h-1,y}}{TL_{i,h,y}} \tag{31}$$

where parameters with subscript "0" is the initial value in each time slot.

In comparison, the electrical energy is generated and priced within the same time slot because of the instantaneous electricity generation and consumption without significant delays. Besides, the multi-dimensional stochastic factors and state change probability have influence on the IU's load strategies at each stage, then the states (i.e., dynamic prices) will also be affected. Therefore, under the influence of thermal delay and stochastic factors, the game stage will continuously change and the states in each stage will be affected by previous states

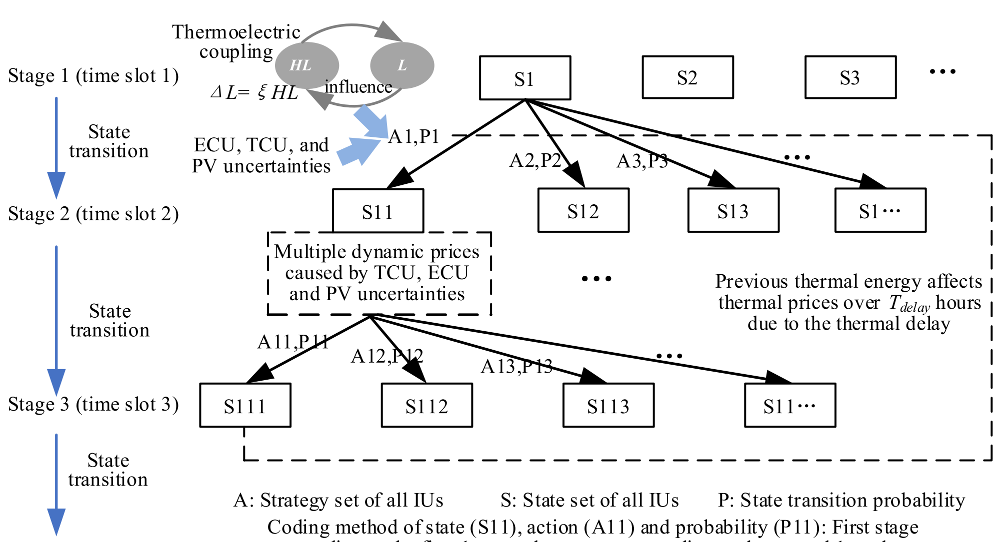

Fig. 5. Stochastic game process.

and dynamically updated during the game process.

5.2. Nash equilibrium (NE) of stochastic game model

The equilibrium of the stochastic game is referred to as NE, which is defined as follows:

Definition:. *A set of optimal strategies* $A_{i,j}^{*} = \left\{\theta_{i,h,j}^{*} | h = 1, 2, \cdots H\right\}$ *of player i is the NE, if and only if the strategy of player i is the optimal strategy of the combination of other players' strategy, which satisfy the following expression*:

$$F_i\left(A_{1,j}^{*}, \cdots, A_{i,j}^{*}, \cdots A_{N,j}^{*}\right) \geq F_i\left(A_{1,j}^{*}, \cdots, A_{i-1,j}^{*}, A_{i,j}^{*}, A_{i+1,j}^{*}, \cdots A_{N,j}^{*}\right), \forall i \in N, \quad (32)$$

The solving process will follow the MDP if all the IUs in each stage can be regarded as a cluster. The MDP following the optimality principle of dynamic programming, i.e., the sub-result of the optimal results is always optimal and called as 'without aftereffect' [39]. Therefore, the equilibrium in the whole stages can be acquired by the segmented optimization in each stage if each stage can get the equilibrium solution. Only the optimal strategies of previous stage should transmit to the next stage, so that the solution space can be limited within J^N. To realize the MDP, each IU should reach the NE in each stage. Therefore, the following theorem can be obtained:

Theorem:. *The unique NE always exists in each stage of the proposed stochastic game* Ψ.

Proof:. *Two aspects is required for the proof.* (*i*) *The strategy set of each IU is nonempty, compact, and convex*; (*ii*) *The utility model is always concave for each IU* [40,41]. *It is obvious that the strategy set is nonempty, compact, and convex. To show the concavity and convexity of IU's utility function in each load interval j, the Hessian matrix with respect to* $A_{i,h,j}$ *is expressed as*:

$$HM = \begin{bmatrix} \dfrac{-kn_{i,h}}{\left(1 + L_{i,h,j}\right)^2} & 0 \\ 0 & \dfrac{-km_{i,h}}{\left(1 + HL_{i,h,j}\right)^2} \end{bmatrix} \quad (33)$$

The Hessian matrix is negative definite with respect to $A_{i,h,j}$*, and the utility model should be maximized during the decision-making process, thus,* $f_{pr,i,h,j}$ *is a strictly concave function and* ***Theorem*** *is proved.*

5.3. Solution algorithm for the proposed method

Because of the multi-dimensional stochastic factors, solving the game will face the problem of "curse of dimensionality", which exists in two aspects: (i) in a stage and (ii) inter stages. The first part is because each IU has J possible load strategies (i.e., intervals), which will cause J possible states, and N IUs will have J^N possible load strategies and states because of the profit-related characteristic. If simultaneously consider all IU's strategies, the number of states will exponential growth with the strategies J and IUs N in one stage. The second part is because the J^N possible state in current stage will indicate J^{2N} possible states in the next stage because the solution in next stage is affected by the previous stage, i.e., the thermal prices are affected by the previous thermal energy. For H stage, there will be number of J^{NH} states. Therefore, the problem of curse of dimensionality makes the game cannot be directly solved by the centralized solution algorithm.

The game is solved in a decentralized way, in which the IUs' optimal strategies in one stage are firstly obtained, and optimal state change probabilities of each IU are also got, then transferring the next stage. In each stage, each IU separately decides their strategies, and updates their strategies through their iteration. Affected by each IUs strategies, the dynamic prices serve as the intermediary to connect each iteration in the decision-making process. Through the decentralized method, the J^{NH} solution space can be reduced to $H \times J^N$ in H stage, and the J^N solution space can be reduced to $J \times N \times iter_h$ in one stage, where $iter_h$ is the number of iterations require to reach the equilibrium. Therefore, by adopting the decentralized solution algorithm, the final solution spaces of the proposed stochastic game model can be reduced to $H \times J \times N \times iter_h$, enabling to directly solve the problem.

The detailed decentralized solution method combined with MDP and iterative process is expressed as follows:

Algorithm 1: Decentralized solution method for the game Ψ

---

1. Set the parameters a_e, b_e, λ, λ_{loss}, γ, σ_{heat}, $a_{t,h,1,0}$, and $a_{t,h,3}$ for the SO, $kn_{i,h}$, $km_{i,h}$, and ξ for IUs, the probability distributions of thermal, electrical, and PV uncertainties, and the iterative index *Itermax*.
2. Perform the IUs' optimization in one time slot and conduct the state transition based on MDP.

For h = 1:H
  Optimize the IUs' profit by decentralized method in time slot h.
  Input the initial load information, load demand with probability distribution, and load interval with probability distribution of IU i in time slot h.
  The thermal price parameter $a_{t,h,1}$ is calculated by (31) based on the thermal load information in time slot *h-1*.
  For iter = 1:Itermax
    For i = 1:N
      For j = 1:J
        According to the load interval j of IU i and load information of other IUs, calculate the electrical prices $pr_{b,h,j,v,k}$, $pr_{s,h,j,v,k}$, and thermal price $pr_{t,h,j,y}$ by (8–9), (15).
        Calculate the utility $F_{i,h,j,iter}$ in interval j under all the PV generation scenarios by (6).
      End for j
      Obtain the maximum utility, and the corresponding load interval is the optimal load strategy for IU i in time slot h.
    End for i
    Update the electricity load strategy and thermal load strategy of IUs in time slot h.
    If $\sum_{i=1}^{N} F_{i,h,j,iter} - F_{i,h,j,iter-1} \leq 1e^{-3}$
      Break;
    End if
  End for iter
  Acquire the state transition probability via (28–30), and implement the state transition.
End for h

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6. Case study

6.1. Basic data

A prototype IIES with four IUs and one SO in an industrial park in Guangdong Province, China, is used in this study. Fig. 6 shows the decentralized system structure. Two types of process IUs are included, i.e., an electroplate factory and a chemical plant, and each IU equips with a PV panel. Historical load and PV generation data were recorded by the

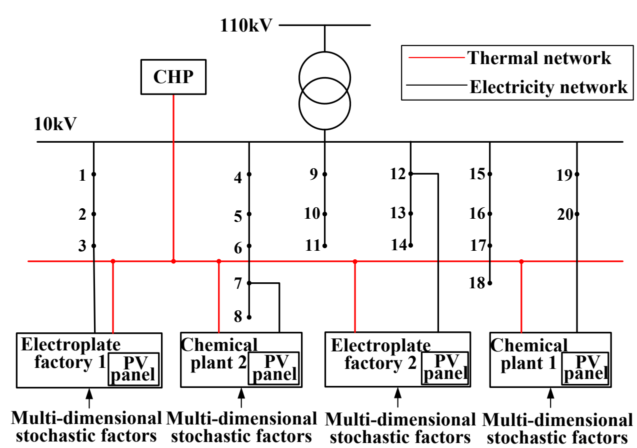

Fig. 6. Decentralized structure of the test system.

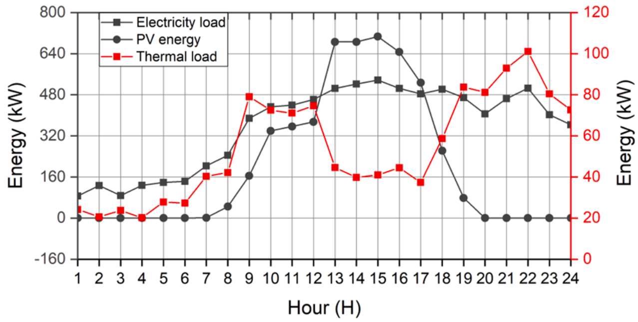

Fig. 7. Electrical load, PV energy, and thermal load of IU.

Table 1
Parameters and initial values (^{0}) of the proposed framework.

Parameter	Value	Parameter	Value	Parameter	Value
λ_{loss}	0.05	a_e	0.0021CNY/kWh	σ_{heat}	1
λ	0.4	b_e	0.302CNY	$kn_{i,h}$	100CNY/kWh
T_{delay}	1	$a_{t,h,1,0}$	0.01CNY/kWh	$km_{i,h}$	15CNY/kWh
ξ	0.5	$a_{t,h,3}$	0.05CNY	ε_t	1

smart meters installed in individual IUs. The initial data of the hourly electrical net load and thermal load are presented in Fig. 7. The parameters of the process industry and the CHP units are set based on the realistic thermal load and electrical load data and corresponding reference [7,12,42], as shown in Table 1. Suppose the number of electrical load interval and thermal load interval for each IU is 5, which is based on each IU's total load range and load difference in different time slots. The initial state transition probability follow the uniform distribution. The number of possible PV generation scenario is 10, and the number of scenarios in a electrical and thermal load interval is respective 4 and 3. Therefore, there are 250 scenarios for an IU.

6.2. Results of dynamic pricing and load strategies

Three cases are designed to demonstrate effectiveness of the proposed decentralized system with stochastic game model for multi-energy scheduling in IIES: (1) Initial cases without any energy scheduling method ("Initial"), (2) Non-cooperation game without stochastic factors ("Deterministic"), (3) Stochastic game with multi-dimensional stochastic factors of decentralized IIES ("Stochastic game"). Moreover, it is noted that the Non-cooperative game in Deterministic scenarios is conducted based on the centralized system structure that IU should transmit their information to the centralized solver, while the Stochastic game for IUs with multi-dimensional stochastic factors is based on the decentralized decision system.

6.2.1. Dynamic prices of the SO

Fig. 8 compares the optimal electricity purchasing and selling prices and thermal prices of the SO in the Stochastic game and the Deterministic cases. The price is calculated by the boundary value of load interval.

The prices are determined by the SO and affected by the IUs' load distribution. In time slots 0–7 and 20–24, the purchasing and selling prices are almost keep unchanged, especially the deterministic scenario. The reason is that no PV production is available in those time slots, so that all IUs serve as buyers, optimizing their load strategy to the similar values to get maximum profit. The dynamic prices are friendly to IUs in time slots 8–19. Specifically, for the buying prices, in time slots 9–18 when the PV production reaches the highest level, SO reduces the purchasing prices to stimulate IUs purchasing energy, increasing the buyer's profit. For the selling prices, in time slots 9–16, SO slightly reduces the selling prices to avoid selling too much energy to increase the local consumption of PV production. It can be seen that the purchasing prices are always higher than the selling prices, preventing IUs from buying and selling energy at the same time.

The thermal prices increase with the thermal energy according to (24). In time slots 9–18 with higher PV production, the thermal prices are higher because the thermoelectrical coupling results in the increase thermal consumption of IUs in those time slots. The thermal prices also remain at a higher level in time slots 19–24, producing higher profit for the SO resulted from the peak thermal load requirements. The thermal price valley in time slot 17 is resulted from the low thermal load level in time slot 16.

Although the distribution of prices is similar in the Stochastic and Deterministic cases, some fluctuations exist. The comparison between the Stochastic game and Deterministic cases demonstrates that uncertainties will increase the fluctuations in all time slots. For time slots 1–7 and 19–24 with no PV production, the fluctuations are caused by the ECU and TCU, while for the time slots 9–17, the fluctuation also resulted by the PV uncertainties. The reason is that considering the multi-dimensional stochastic factors can obtained multiple possible load demands and PV generations, enlarging the solution space of electrical and thermal prices, so that the boundary value indicating violent fluctuations.

6.2.2. IU's load strategies

Fig. 9 shows the IUs' hourly electricity load strategies for all cases. The electricity net loads in time slots 1–9 and 9–18 is higher than the initial load, and in peak time slots 19–24 are decreased. Although the purchasing is relatively high in time slots 1–9, the electricity load is increased. One of the reasons is that the thermal loads at these time slots are increased, the increased electrical loads resulted by the thermo-electric coupling. Another reason is that the increasing electricity load led to a higher utility for IUs based on the utility model (9). In time slots 9–18, the valley electricity load is increased due to the lower purchasing

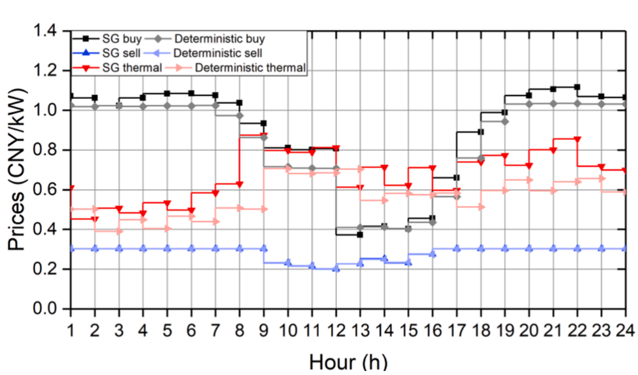

Fig. 8. SO's pricing strategy.

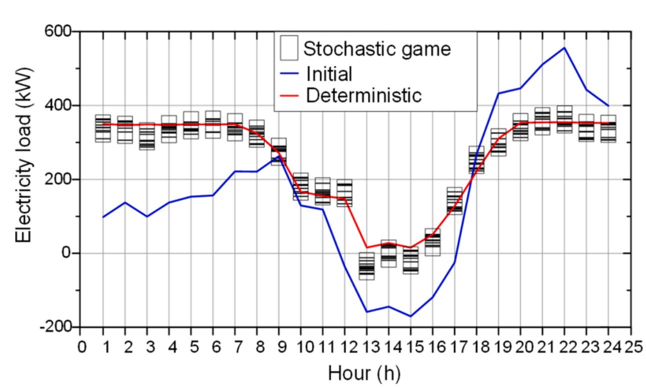

Fig. 9. Electricity net load of IU in three cases.

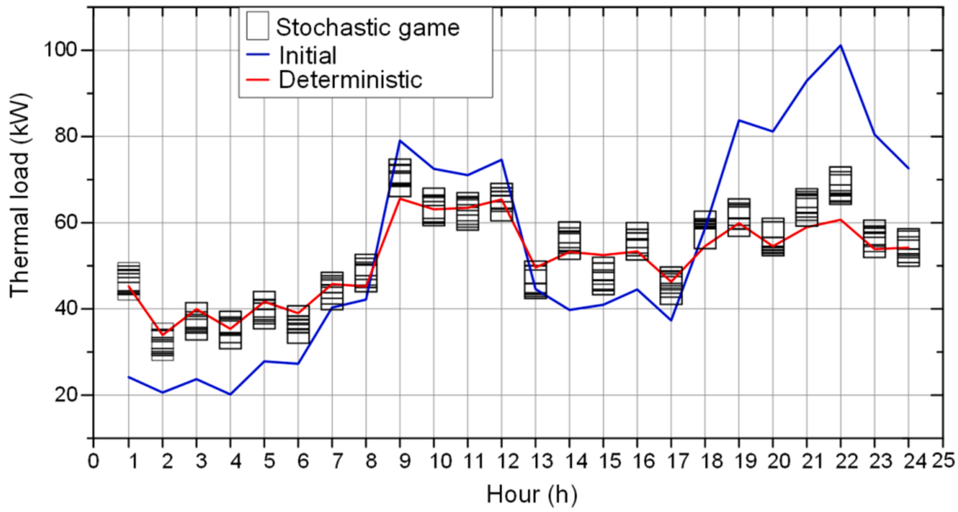

Fig. 10. Thermal load of IU in three cases.

prices, selling prices, and higher PV production. Contrary to time slots 1–9, the electricity load in time slots 19–24 is decreased for keeping their utilities. That is because the purchasing prices are relatively higher, and the decreased thermal load also has influence due to the thermo-electrical coupling.

The thermal load strategies in the three cases are shown in Fig. 10. The optimal thermal load distribution with and without the consideration of stochastic factors are both flatted in all time slots. The thermal load peak in time slots 19–24 is reduced, while the thermal load valley in time slots 1–8 and 13–17 is increased. An increase in thermal prices, as shown in Fig. 7, results in a thermal load decrease, which can be understood based on (9).

Figs. 9 and 10 also show that, the load profile of the Stochastic game is more volatile than those derived from the Initial and Deterministic cases. Specifically, for the electricity load, deterministic case can render the load close to 0 in time slots 13–15 with high PV production, however, when considering the stochastic factors, the load distribution presents the fluctuation characteristic. The reason is that the multiple possible occurrence scenarios are included in the load strategies as an interval form, enlarging the range of load adjustment. For the thermal load, the fluctuations are evenly distributed at all time slots because the simple trading process for thermal load and slight influence of PV production, i.e., each IU can only buy thermal energy from CHP units, and the energy is greatly determined by the thermal prices. Although the fluctuation is different in Stochastic game and Deterministic cases, the trends are similar for both thermal and electrical load.

6.2.3. *Utility with and without the uncertainties of IUs*

Fig. 11 shows the hourly utility of IUs in the three cases. As illustrated in the figure, the utilities of the two optimization cases are higher than that of the Initial case, and the largest one is the summation of the utilities in the Stochastic game with 41, 212 CNY. The utility and the corresponding optimal strategies are obtained by comprehensively considering the uncertainty of PV generation, ECU, and TCU. The utility increases during the time slots 1–8 with higher load consumption and time slots 19–24 with lower load consumption, because the profit of IUs is determined by both the energy trading and the process industrial production. Utility of the Stochastic game case is higher than Deterministic case in almost all hours. But in time slots 1–8, and 19–24 with no PV generation, the utility of the Stochastic game case is not much different from that of the Deterministic case, only slightly increases. The utility of the Stochastic game case is much higher than that of the Deterministic case in time slots 9–18 with high PV generation. The reason is that there are multi-dimensional stochastic factors from load and PV generation at the time, which affects the load strategy, while the Deterministic case cannot deal with the uncertainty so that has a worse utility.

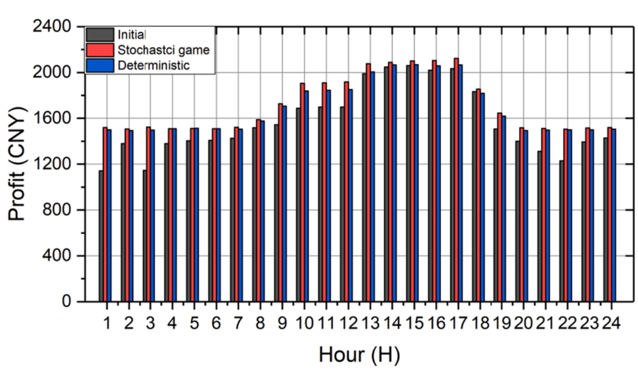

Fig. 11. Profit of IU.

6.3. *Computation time for the centralized and decentralized system*

The stochastic game model for multi-energy scheduling in IIES is developed based on the decentralized decision system, which is difficult to be solved with centralized method, as mentioned in Sec. II and Sec. V. C. In this section, the computation time of the centralized decision system for the Deterministic case [16], and the decentralized decision system for the Stochastic game case are compared and shown in Table 2. It is clear that the computation time under the decentralized system is shorter than that of the centralized system. The reason is that the massive data from stochastic scenarios will result in "curse of dimensionality" in the centralized solver, and the solution space would be exponential increased, so does the computation time. Moreover, the computation time of the centralized system will be longer with the increasing number of IUs. However, not only can the proposed decentralized system realize the interaction among IUs with multi-dimensional stochastic factors, but also IUs can independently make decision, which reduces the computation time by discrete processing and distributed iterative method. Besides, the short computation time

Table 2
Computation time of centralized and decentralized system.

Solution algorithm	Centralized	Decentralized
Computation time (s)	5.36	1.58

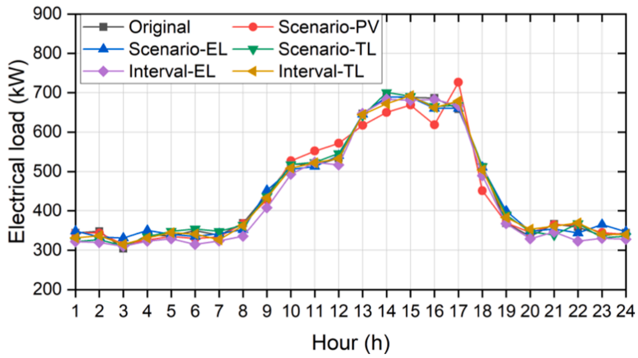

Fig. 12. IUs' electrical load in different intervals and scenarios.

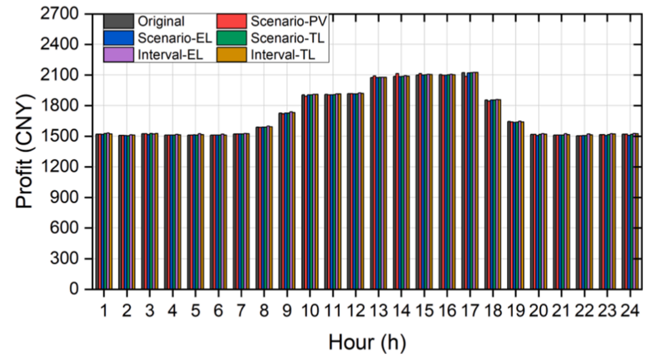

Fig. 14. IU's profit in different intervals and scenarios.

can also be maintained by increasing the number of solvers when the number of IU increases.

6.4. Analysis of scenarios and intervals of the proposed method

Five cases are designed to analyze the effectiveness of the proposed approaches on uncertain multi-energy scheduling in IIES: (1) Doubled the number of PV generation scenarios to 20 ("Scenario-PV"), (2) Set 10 scenarios in an electrical load interval ("Scenario-EL"), (3) Set 6 scenarios in a thermal load interval ("Scenario-TL"), (4) Increase the number of electrical load interval to 10 ("Interval-EL"), (5) Increase the number of thermal load interval to 10 ("Interval-TL"). Besides, set original case that keep the number of scenarios and intervals unchanged ("Original').

Fig. 12 shows the optimal electrical load of the five cases and the original case. For convenience, the electrical load interval is expresses as the median value of the interval. It is clear that the trend of electrical load is similar in all cases, but differences are still existed in each case. Comparing the Scenario-PV case with the Original case, the electrical load is higher during the time slots 7–13 and 17–18, lower during time slots 14–16. The reason is that the increased scenarios of PV generation intensity the uncertainties and fluctuate the IUs' load strategies.

The comparison results of Scenario-EL and Interval-EL show that increase the number of scenarios in an electrical load interval has relatively little influence on the IUs' electrical load strategy, while increase the number of intervals for electrical load makes a difference to the IUs' electrical load strategy. The reason is that more intervals indicating more specific load strategies, increasing IUs' decision flexibility for flatting load strategies. The load interval is expressed as an expectation form, so that the scenarios have slightly influence on the IUs' decision. The results of Scenario-TL and Interval-TL shows the optimal electrical load strategy is affected slightly by thermal load scenarios and intervals, a little difference arise from the thermoelectric coupling.

The thermal load strategies in the six cases are shown in Fig. 13.

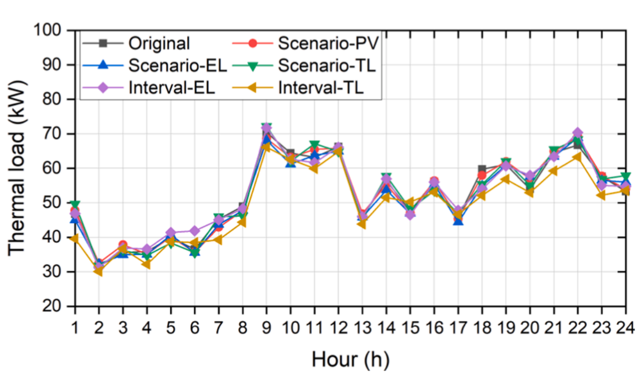

Fig. 13. IU's thermal load in different intervals and scenarios.

Similar to Fig. 12, the interval's median values are used to express the thermal load strategy. It is evident that the trend of thermal load in the five cases is similar to that in the original case. Besides, the influence of increasing the number of thermal load intervals and scenarios on Scenario-TL and Interval-TL is similar to that in the electrical load, i.e., IUs' decision flexibility enhances with the intervals' number and result in flat load strategies, while scenarios' number have slight influence. For the Scenario-PV, Scenario-EL, and Interval-EL, due to the thermoelectric coupling and the relationship of electrical load and PV generation, the thermal load strategies in these cases are a little bit different from that in the Original case, but the variations are slight.

Fig. 14 shows the hourly utility of IUs in the six cases. It is shown that in the Scenario-PV, the total utility 41,184 CNY is lower than that in the Original case. This phenomenon indicates that the intensified PV uncertainties fluctuate IU's load strategies then reduce IUs' utility. The utility in Scenario-EL and Scenario-TL also decreases. The reason is that the load uncertainties is intensified by the increased scenarios, similar to the condition of PV generation scenarios, which slightly affects IU's strategies, then reduces IU's utility. However, the utility is enhanced through increasing intervals' number, e.g., in Interval-EL with 41,385 CNY and Interval-TL with 41,288 CNY. That is because more intervals indicate more specific load strategies, which increases IUs' decision flexibility then increases their utility.

6.5. Practical feasibility and convergence of solution algorithm

Interfaces can be designed in UEMS for IUs to collect their PV generation data, thermal and electrical load data. Based on these data, the discrete probabilities can be obtained. Then the multi-dimensional stochastic factors can be considered in the modeling process using these probabilities. As the proposed stochastic game model requires the iteration between IUs and the transmission of load and prices signals, it is expected that a few bytes of data shall be bidirectionally exchanged. Based on the wireless communication channels in private 4G/5G network with Virtual Private Network (VPN), the information sharing is realized through the equipment support of SO and IUs' UEMS. The process method of stochastic factors and decentralized solution algorithm is proposed based on the decentralized IIES framework, which solves the problem of curse of dimensionality in the stochastic game model and obtains the optimal strategy in a short time. The proposed decentralized solution algorithm is implemented in MATLAB 2018a, and solved on a computer with Intel Core i5-8250 CPU 1.60 GHz, 16 G memory. The computation time is illustrated in Table 3 with different numbers of IUs. It is shown that the computation time increases with the

Table 3
Computation time with the number of IUs.

Number of IUs	4	8	16	32	64
Computation time (s)	1.58	3.64	8.18	17.92	41.62

number of IUs, but the growth rate is similar to a constant. That is because the computation complexity of the decentralized solution algorithm is *O(n)* determined by the iterations among IUs. The short computation time reflects the small computation cost. Besides, the decentralized system structure with multiple smart terminals in IUs provides the chance of parallel computation, which implements the iterations based on individual IUs' smart terminals. Thus, the proposed approach is scalable to face the increase of IUs' number.

7. Discussion

In this section, the performance of the proposed decentralized IIES framework, multi-party stochastic energy scheduling approach and decentralized solution algorithm is validated based on the comparison between the obtained results.

Firstly, the influence of considering multi-dimensional stochastic factors on multi-energy scheduling are analyzed through the decentralized decision support system with stochastic game model. The uncertainties come from PV output, electrical load and thermal load of IUs' industrial production process. In the comparison of results from the Deterministic case and Stochastic game case, it can be concluded that the multiple possible occurrence scenarios considered in the Stochastic game case enlarge the range of load adjustment and the solution space of prices, for facing the uncertainties of PV outputs and IUs' industrial production process. Besides, the utility of IUs increases from 40,537 CNY to 41,212 CNY due to the optimal and flexible load strategies.

Secondly, although centralized system structure has been applied in multiple cases [16,21,28], it cannot be used to deal with the interactions between IUs with multi-dimensional stochastic factors. However, the proposed decentralized solution algorithm can reduce the solution space of the stochastic multi-energy scheduling, i.e., from J^{NH} to $H \times J \times N \times iter_h$, while shortening the computation time by nearly 70.1% compared to the centralized system. Besides, the parallel computation can be realized by the decentralized system, which can also resolve the scalability problem, as we expressed in Sec. V. E. Therefore, the decentralized decision support system with the stochastic game model provides the feasible method for the interaction of stochastic IUs, and deal with the problem of high solution space and long computation time.

Thirdly, the influence of PV uncertainties, the number of scenarios and intervals of load strategies on the stochastic energy scheduling are analyzed. In terms of the PV outputs, it affects the final load strategies by influencing the netload and prices. Therefore, the fiercely fluctuating PV output will lead to volatile load strategies, as shown in Figs. 12 and 13. Besides, the intensified PV uncertainties decrease the utility of IUs. The more scenarios of load strategies make the load uncertainty more severe, which has little influence in the final load strategies, but similar to fiercely fluctuating PV output also decrease the utility. That is, the more the stochastic factors fluctuate, the more it reduces the IUs' utility. The number of intervals for load strategies reflects the degree of subdivision for stochastic factors in electrical load and thermal load. Moreover, more load intervals contribute to higher utility, which is shown in Fig. 14.

8. Conclusion

This paper proposes a decentralized decision system for the multi-energy scheduling in IIES, in which the multi-dimensional stochastic factors of IUs and the co-decision mechanism for the thermal load and electrical load is considered by stochastic game model. Numerical results are obtained through the MDP and solution algorithm, which deliver the optimal dynamic prices, load strategies, and profits. The load and pricing strategies have an interactive influence, and they are also affected by the PV generation and thermoelectric coupling. The influence of multi-dimensional stochastic factors is illustrated through the comparison of three designed cases. By considering the state transition in the game model, the multi-dimensional stochastic factors can be reflected into the dynamic game process, which better fit flexible load and price strategies then enhances 9.4% profits for IUs as compared to other cases. Besides, considering more scenarios increases the uncertainties and against IUs' decision, while dividing more intervals increases IUs' decision flexibility then enhances IU's profit. Through the analysis of computation time, it is concluded that the decentralized system has a better solution performance in the proposed stochastic game model. However, some limitations of this work lie in the application environment, which requires modern grid infrastructures and may hinder the application in some places. Future research would explore the relation among the industry product, industrial production process, and energy scheduling. Then consider stochastic factors from IUs' subjective decision, and investigate the approaches to further improve computational performance of the IIES scheduling problem.

CRediT authorship contribution statement

Liudong Chen: Conceptualization, Methodology, Software, Writing – original draft. **Nian Liu:** Conceptualization, Methodology, Supervision, Funding acquisition. **Chenchen Li:** Conceptualization, Methodology, Software, Writing – original draft. **Lei Wu:** Supervision, Writing – review & editing. **Yubing Chen:** Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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