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Authors
Dai, Xuemei
Li, Yaping
Zhang, Kaifeng
et al.

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A robust offering strategy for wind producers considering uncertainties of demand response and wind power

Xuemei Dai[a], Yaping Li[b], Kaifeng Zhang[a,*], Wei Feng[c,*]

[a]Key Laboratory of Measurement and Control of CSE, School of Automation, Southeast University, No. 2 Sipailou Road, Nanjing 210096, China
[b]Power Automation Department China EPRI, Nanrui Road, Nanjing 210096, China
[c]Energy Technologies Area, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

Abstract

This paper proposes a risk-constrained decision-making approach for a wind power producer participating in the day-ahead market. In the developed model, a flexible demand response trading scheme between the wind power producer and different customers is employed. Through the proposed demand response mechanism, the wind power producer is able to trade demand response resource internally with different customers, and then trade energy externally with the market to increase the expected profit and the wind energy utilization. The uncertainties in the wind power and demand response are modeled by using the information gap decision theory approach from risk averse (robust) and risk-seeking (opportunistic) perspectives. The objective of the robust model is to maximize the robust level while satisfying the desired profit, whereas the opportunistic model aims to evaluate the possibility of achieving windfall profits with favorable uncertainties. The over-all offering strategy problem is modeled as a bi-objective mixed integer nonlinear programming, which is linearized by proper techniques and solved efficiently by using the normal boundary in-tersection technique. Simulation results show that utilizing demand response resource to mitigate wind power deviations can increase a wind power producer's profit and reduce potential risks. In addition, the results demonstrate that the proposed bi-objective optimization approach enables the wind power producer to select appropriate offering decisions with respect to uncertainties.

Keywords: Offering strategy, wind power producer, demand response, information gap decision theory, day-ahead market

1. Introduction

1.1. Aims and background

In recent years, renewable energy technologies, especially wind power, have grown widely to decrease environmental pollution and promote energy efficiency[1]. However, the variability and limited predictability of wind power may impose significant challenges to the power system. The latest statistics of China's National Energy Administration show that, in the first three quarters of 2019, the curtailed capacity of wind reached 12.8 terawatt (TW). The national average wind power

*Corresponding author
Email addresses: kaifengzhang@seu.edu.cn (Kaifeng Zhang), weifeng@lbl.gov (Wei Feng)

Nomenclature

Sets

t	Index of time period
i	Index of blocks of the load reduction/increase DR curve
k	Index of blocks of the load reduction/increase DR price curve
j	Index of DR customers

Parameters

M	Sufficiently large number
λ_t^{DA}	Day-ahead electricity price at time t ($\$/MWh$)
$\lambda_{t,k}^{LR}/\lambda_{t,k}^{LI}$	Upper bound of the kth load reduction/increase DR price at time t ($\$/MWh$)
$\varphi_{t,k}^{LR}/\varphi_{t,k}^{LI}$	Constant correspond to the kth load reduction/increase DR price at time t
P_t	Forecasted load demand at time t (MWh)
ψ_{LR}/ψ_{LI}	Load reduction/increase participation factor
λ_t^{WP}	Contracted price between the WPP and consumers at time t ($\$/MWh$)
P_t^w	Forecasted wind production at time t (MWh)
P_t^{aw}	Wind maximum capacity at time t (MWh)

Variables

$P_{t,i}^{LR}/P_{t,i}^{LI}$	Load reduction/increase of the ith interval of the DR quantity curve at time t (MWh)
P_t^D	Power traded in the day-ahead market at time t (MWh)
$u_{t,i,j}^{LR}/u_{t,i,j}^{LI}$	Binary variable shows whether the DR curve is selected by the WPP
D_t	Net power demand at time t (MWh)
$\alpha_{robust}^{wind}/\alpha_{robust}^{DR}$	Robust index of the wind/DR
$\alpha_{opportunity}^{wind}$	Opportunity index of the wind
$\alpha_{opportunity}^{DR}$	Opportunity index of the DR
PF^{DET}	Deterministic profits of the WPP ($)
PF^{robust}	Robust profits of the WPP ($)
$PF^{opportunity}$	Opportunity profits of the WPP ($)

generation curtailment was 4.2%, and in Xinjiang, nearly 15.4% of wind generation was curtailed [2]. If the situation is not improved, wind curtailment may become an obstacle to the development of wind power. Therefore, it is essential to make efforts to facilitate wind power integration and better exploit the economic profits of wind energy.

1.2. Literature review

Coordinated operation of wind power with other flexible resources such as energy storages [3], electric vehicles [4] or demand response (DR) [5] is considered to be an effective method to mitigate wind fluctuations and reduce imbalance costs. Due to the development of smart grid technologies, DR has received increasing attention, and it is regarded to be a promising approach to mitigate wind power variability[6]. For example, it can help reduce demand during times of low energy production and increase demand during periods when higher amounts of energy is offered [7]. Recently, much research has been conducted on how wind power producers (WPPs) can best integrate DR resources[8]. In [9], a study was conducted to develop a stochastic-based decision-making framework for WPPs in the day-ahead (DA) market. It showed that the joint operation of WPP and DR aggregators could increase the expected benefits and alleviate the uncertainty risk related to wind outputs. Ref.[10] proposed an optimal bidding strategy for WPPs participating in the DA market, and various DR contracts between the WPP and DR aggregators were set to maximize WPP profits. Ref.[11] developed the new Demand Response eXchange (DRX) market to handle the variability of renewable energy. In [12], both upward and downward demand side resources were employed in the DRX market to counterbalance the deviations of renewable energy.

When optimizing the WPP bidding strategies that consider DR, the abovementioned research is mainly focused on the DR aggregators, such as setting specific DR contracts for DR aggregators. However, little attention has been paid to the interaction between WPPs and DR customers in a competitive market. As active participants in the electricity market, commercial, industrial and residential consumers will be able to adjust energy consumption and actively trade it with WPPs based on their characteristics and preferences. According to the latest U.S. Energy Information Administration (EIA) statistics, more than 8 million residential customers, 900,000 commercial customers and 60,000 industrial customers participated in DR programs in 2018 [13]. In 2019, different types of DR programs were employed to integrate renewable energy in China, and a growing number of customers were enrolled in DR programs to gain the expected benefits [14]. Under this context, it has become important to design a flexible DR trading mechanism between WPPs and customers to optimize the electricity procurement decisions of both sides.

In addition to the wind power generation uncertainty mentioned before, the uncertainty caused by demand response, like the random behaviour of DR customers, also can have impacts on WPP profits[15]. It is difficult for a WPP to decide submitting strategies under uncertainties since the day-ahead market closes (i.e. 12 pm in the prior day) several hours earlier than the beginning of real-time operation. In this regard, various uncertainty modeling methods have been proposed, such as the stochastic programming (SP) [16], robust optimization (RO) [17], fuzzy mathematics (FM) [18] and information gap decision theory (IGDT) [19]. Stochastic programming is often cited as the most popular approach to optimize bidding strategies under uncertainties[20]. The main idea of the SP method is to characterize the uncertain variables by means of a probability distribution and employ a number of scenarios to represent the possible realizations of uncertain variables. In [21], the SP approach was adapted to optimize the bidding strategy of a WPP, which incorporated the uncertainties related to wind output and market prices. However, the performance of the SP method is restricted by the high computational complexity resulting from a large number of scenarios. The RO approach models random variables by uncertainty intervals and optimizes the worst-case scenario over an uncertainty interval[22]. Ref.[23] proposed a two-stage robust framework to derive the optimal bidding strategies for WPPs while considering the uncertainty of wind power generation. However, the applicability of RO is limited by its conservativeness. Fuzzy mathematics characterizes random variables through fuzzy membership functions[24]. Ref.[18] applied the fuzzy method for optimizing the offering strategy of a virtual power plant (VPP) that included renewable energy and demand response. However, it is difficult to select an appropriate fuzzy membership function representing the uncertainty parameter like wind power in practice.

To date, the IGDT approach has been applied to power system problems, such as the optimal scheduling of GenCos [25] and renewable power plants [26], as well as decision-making for DR aggregators [27], microgrid operators [28] and distribution network operators [29]. Compared to the SP, RO or FM, IGDT requires no information on the probability distribution, a fixed uncertainty set with explicit boundaries or an appropriate membership function of uncertain variables. It aims to maximize the uncertainty interval while a certain economic expectation can be attained. Moreover, with robustness and opportunistic functions, the IGDT can provide risk-averse or risk-seeking strategies according to the decision makers' risk preference[30]. In Ref.[27], a robust self-scheduling model for DR aggregators was developed, while both uncertainties of consumers and market prices were modeled through IGDT. Ref.[28] proposed an optimal bidding strategy for the microgrids in joint day-ahead energy and reserve markets. The uncertainties related to market prices and load consumption were considered and modeled by the IGDT method. In Ref.[29], an IGDT-based three-phase optimal power flow is proposed to optimize switch decisions for distribution network operators while considering the uncertainty of load demand.

In view of the above, however, limited research has been carried out to develop a risk-constrained WPP offering strategy that is optimized through the IGDT approach and hedged against uncertainties associated with wind power output and demand response. Moreover, few studies have been conducted on the trading mechanism between WPPs and DR customers. Table 1 summarizes the comparison between different literature in the field of WPP offering strategies; "*" represents "considered" and "-" represents "not considered".

Table 1 Comparison between the existing methods and the proposed method

Reference	Uncertainty Parameter				Uncertainty Modelling			
	Price	Load	Wind	DR	SP	RO	Fuzzy	IGDT
[3, 4]	*	-	*	-	*	-	-	-
[6]	*	*	*	-	*	-	-	-
[16]	*	-	-	-	*	-	-	-
[18]	-	-	*	-	-	-	*	-
[20]	*	-	*	-	-	*	-	-
[21]	*	-	*	-	*	-	-	-
[23]	-	-	*	-	-	*	-	-
This Paper	-	-	*	*	-	-	-	*

1.3. Contribution

This paper proposes a risk-constrained framework to develop an optimal WPP offering strategy in the DA market. As shown in Fig.1, an internal market (between the WPP and DR customers) is developed to optimize the participation of the WPP in the external market (the ISO market). In the internal market, a flexible DR trading scheme between the WPP and different customers is developed, which helps to mitigate the deviation of wind power generation and thus increases WPP's profit. Furthermore, the IGDT approach is used to evaluate multiple uncertainties (i.e. wind production and demand response) and find a flexible and robust offering strategy.

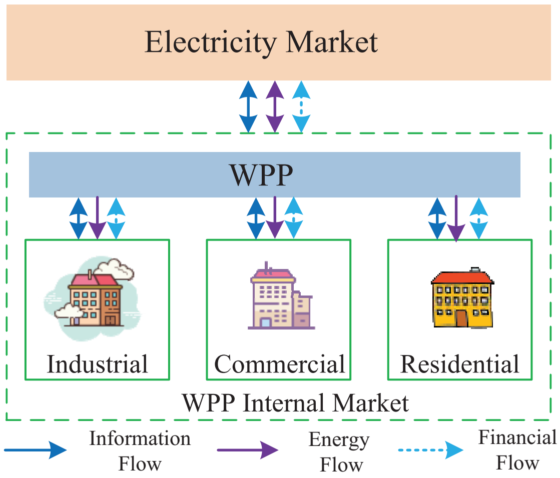


Fig. 1: The schematic diagram of the WPP

Overall, the main contributions of the paper are summarized as follows:

1. A flexible DR trading scheme between the WPP and DR customers is proposed to enhance the flexibility of the WPP participating in the market and to maximize expected profits. Different customers are allowed to submit load reduction or load increment offers according to their characteristics and preferences. Each offer consists of the quantity of reduced/increased capacity and corresponding desired prices.
2. An IGDT-based decision-making model for the WPPs is formulated that simultaneously considers the uncertainties from variable wind power and random DR customers' participation behavior. The proposed IGDT-model allows for controlling the robustness of the optimal solution based on the decision maker's economic expectations and risk preference. That is, minimum profits of a risk-averse WPP can be achieved under unfavorable variations of uncertainties with the robust IGDT model, whereas windfall profits of the risk-seeking WPP can be achieved under favorable uncertainties with the opportunistic IGDT model.
3. The proposed risk-constrained bidding strategy is formulated as a mixed integer nonlin-ear programming problem that considers the impacts of different uncertainties. To solve this problem, we transform the model into a bi-objective mixed integer linear programming (MILP), which can be solved efficiently using the normal boundary intersection (NBI) technique.

1.4. Paper organization

The rest of the paper is organized as follows. Section 2 provides the detailed description of the problem; Section 3 presents the risk-constrained offering strategy model for the WPP participating in day-ahead market; Case studies and results are shown in Section 4 and in Section 5, some relevant conclusions are drawn.

2. Problem description

2.1. Electricity market framework

Fig.2 presents the timeline considered in this paper. The day-ahead market of Day D closes at 12:00 pm on Day D-1. Thus, WPPs have to submit their hourly offer for Day D no later than 12:00 p.m. on Day D-1. To maximize WPPs' profit, an internal market (between the WPP and DR customers) is developed to optimize the participation of the WPP in the external market (the ISO market). In the internal market, customers are allowed to submit offers to the WPP for their flexible loads. After collecting all the curves of the DR offers, the WPP runs an internal market to determine its involvement in the external market. The specific trading framework of the offering strategies is illustrated in Fig.3. As shown in Fig.3, a two-stage decision-making process is deployed.

In the first stage, the uncertainties of the problem, i.e., variable wind output and random behaviour of DR customers, are neglected. The aim of the WPP is to maximize its economic benefits. In this regard, a flexible DR trading scheme between the WPP and DR customers is deployed. It allows different consumers to submit day-ahead DR offers to reduce or increase load demand. Then, with the information of predicted demands, wind output and market price, the WPP optimizes the proposed model to determine the accepted DR offer and desired energy bids for buying/selling electricity in the day-ahead market. Note that the WPP is assumed to act as a price taker; i.e., its bids would not affect the market clearing price. Thus, it only needs to submit power bid quantities instead of bidding curves to the market.

In the second stage, a risk-constrained IGDT-based optimization model is developed to manage the risk related to wind power and DR uncertainties. In addition, both robust and opportunistic functions are employed to offer different offering strategies regarding uncertainties. For example, the uncertainty resources may lead to an unfavorable condition and minimum profits can be attained through a risk-averse strategy. On the contrary, the uncertainty resources may be useful, and higher profits can be pursued based on a risk-seeking offering strategy.

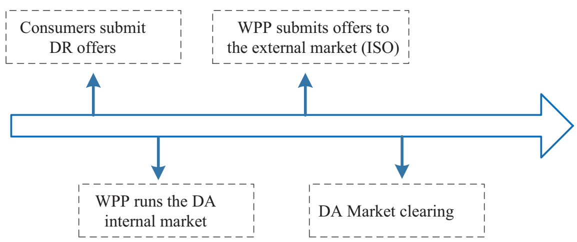


Fig. 2: The timeline of the proposed method

2.2. DR trading mechanism

The wind power operator is assumed to serve different types of customers, such as residential, commercial and industrial. The customers pay the WPP for the energy that they use based on the predetermined price λ_t^{WP} and get rewards from adjusting their flexible loads to lower or higher consumption levels. Through the proposed mechanism, the customer is allowed to submit offers to the WPP for its flexible loads. Each offer specifies the amount of demand that the customer is willing to curtail or increase for different rewards or electricity prices.

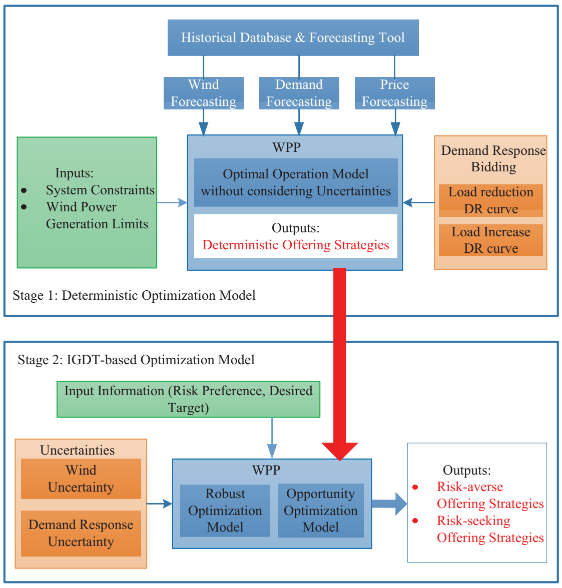


Fig. 3: The schematic of proposed wind offering strategies

The load reduction based DR curve is shown in Fig.4, where the amount of load reduction $P_{t,i}^{LR}$ increases with higher rewards $\lambda_{t,k}^{LR}$. Fig.5 illustrates the load increase based DR curve, where the amount of increased load $P_{t,i}^{LI}$ decreases with higher prices $\lambda_{t,k}^{LI}$. Each price bound of DR curves is defined as the day-ahead electricity price λ_t^{DA} multiplied by predetermined constants $\varphi_{t,k}$, which is formulated as follows:

$$\lambda_{t,k}^{LR} = \varphi_{t,k}^{LR} \lambda_t^{DA} \tag{1}$$

$$\lambda_{t,k}^{LI} = \varphi_{t,k}^{LI} \lambda_t^{DA} \tag{2}$$

In addition, the values of $P_{t,i}^{LR}$ and $P_{t,i}^{LI}$ are defined as the forecasted customer demand of P_t multiplied by DR participation factor ψ, which is formulated as Eqs.(3)-(4). The DR participation factor denotes the willingness of consumers to participate in the DR and ranges between 0 and 1.

$$P_{t,i}^{LR} = \psi_{LR} P_t \tag{3}$$

$$P_{t,i}^{LI} = \psi_{LI} P_t \tag{4}$$

After collecting all the curves of the DR offers, the WPP runs an internal market to determine its involvement in the DR trading scheme.

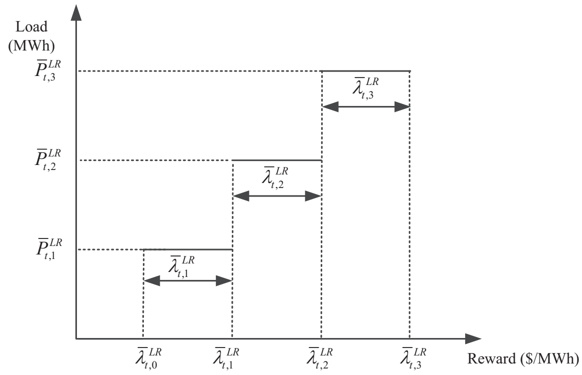


Fig. 4: Diagram of load reduction curve

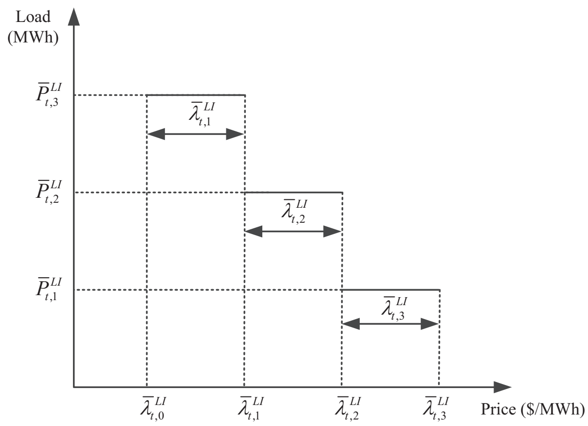


Fig. 5: Diagram of load increase curve

2.3. Uncertainty characterization

This paper considers two major sets of uncertainties: (1) wind power generation and (2) DR consumer's participation factor.

To deal with the uncertainties from wind power production and demand response, the IGDT approach is employed. Specifically, these uncertainties are modeled by the envelope bound uncertainty method as shown in Eqs.(5),(6) and (7):

$$U\left(\alpha, P_t^w\right)=\left\{\begin{array}{l} P_t^w:\left|\frac{P_t^w-\tilde{P}_t^w}{\tilde{P}_t^w}\right| \leq \alpha ; \alpha \geq 0 \\ P_t^w \in\left[\tilde{P}_t^w-\alpha \tilde{P}_t^w, \tilde{P}_t^w+\alpha \tilde{P}_t^w\right] ; \forall t \end{array}\right\} \tag{5}$$

$$U\left(\alpha, \psi_t\right)=\left\{\begin{array}{l} \psi_t:\left|\frac{\psi_t-\tilde{\psi}_t}{\tilde{\psi}_t}\right| \leq \alpha ; \alpha \geq 0 \\ \psi_t \in\left[\tilde{\psi}_t-\alpha \tilde{\psi}_t, \tilde{\psi}_t+\alpha \tilde{\psi}_t\right] ; \forall t \end{array}\right\} \tag{6}$$

$$\hat{\alpha}=\left\{PF^{IGDT}\left(P_t^w, \psi_t, \beta\right) \leq|1 \pm \beta| PF^{DET}\left(P_t^w, \psi_t\right) ;\right\} \tag{7}$$

In the above formulation, $\tilde{P}_t^w$ $(\tilde{\psi}_t)$ and P_t^w (ψ_t), respectively, denote the forecasted wind power output (forecasted demand response participation factor) and actual output (actual demand response participation factor). The term α denotes the uncertainty parameter, and it is optimized to ensure a specified economic target as stated in Eq.(7). PF^{IGDT} and PF^{DET} denote the optimized values of the IGDT-based and deterministic model, respectively. The uncertainty budget (UB) β is defined to control the expected level of the objective function. When β is set to zero, the uncertainty formulation is converted to the nominal deterministic model.

3. Day-ahead optimization model

In this section, the detailed formulation of the day-ahead offering strategy model is presented. First, a deterministic optimization model is built without considering uncertainties. Then the IGDT-based optimization approach is developed to evaluate the risks associated with the uncertainties of wind and demand response. The IGDT method is flexible to control the uncertainty level of the problem, and it has a moderate computation cost.

3.1. Deterministic offering strategy model

In the deterministic day-ahead model, the main purpose of the WPP is to maximize its expected profit. The mathematic formulation of the problem is presented in the following.

$Maximize\ PF$

$$\begin{aligned} PF=\sum_{t=1}^{T}\big(\lambda_t^{DA} P_t^{D}- & \sum_{i=1}^{I} \sum_{j=1}^{J} P_{t,i,j}^{LR} \lambda_{t,i,j}^{LR} u_{t,i,j}^{LR}+ \\ & \sum_{i=1}^{I} \sum_{j=1}^{J} P_{t,i,j}^{LI} \lambda_{t,i,j}^{LI} u_{t,i,j}^{LI}+\lambda_t^{WP} D_t \end{aligned} \tag{8}$$

Subject to:

$$P_t^w = D_t + P_t^D \tag{9}$$

$$\varphi_{t,k}^{LR}\lambda_t^{DA}u_{t,i,j}^{LR} \le \lambda_{t,i,j}^{LR} \le \varphi_{t,k+1}^{LR}\lambda_t^{DA}u_{t,i,j}^{LR} \tag{10}$$

$$\varphi_{t,k}^{LI}\lambda_t^{DA}u_{t,i,j}^{LI} \le \lambda_{t,i,j}^{LI} \le \varphi_{t,k+1}^{LI}\lambda_t^{DA}u_{t,i,j}^{LI} \tag{11}$$

$$\lambda_t^{LR} = \sum_i^I \sum_j^J \lambda_{t,i,j}^{LR} \tag{12}$$

$$\lambda_t^{LI} = \sum_i^I \sum_j^J \lambda_{t,i,j}^{LI} \tag{13}$$

$$\sum_i^I \sum_j^J u_{t,i,j}^{LR} + \sum_i^I \sum_j^J u_{t,i,j}^{LI} \le 1 \quad \forall t \tag{14}$$

$$u_{t,i,j}^{LR} \in \{0,1\} \tag{15}$$

$$u_{t,i,j}^{LI} \in \{0,1\} \tag{16}$$

$$P_t^w \le P_t^{aw} \tag{17}$$

$$D_t = \sum_i^I \sum_j^J L_{t,i,j} - \sum_i^I \sum_j^J P_{t,i,j}^{LR}u_{t,i,j}^{LR} + \sum_i^I \sum_j^J P_{t,i,j}^{LI}u_{t,i,j}^{LI} \tag{18}$$

The first term in (8) represents the profit of WPP from trading energy in the market. The second and third terms represent the total cost of rewarding customers for load reduction (LR) and increase (LI), respectively. The LR includes the cost of rewarding consumers to reduce the load and the loss of revenue from not selling the reduced energy. The LI denotes an increase in the WPP's revenue from selling energy to consumers at a price lower than the day-ahead market price. The last term accounts for the WPP revenue from selling net energy to consumers at a predetermined price. Note that the fuel cost of wind generation is considered to be zero.

Equation (9) ensures the energy balance of the WPP; namely, the total energy traded in the market and the net load of customers is equal to the total generation produced by the WPP at each time. The aggregated DR curves are mathematically formulated as (10)-(16), where (10)-(13) denote the prices for the each block of DR curves; (14) indicates that only one type of DR scheme can be chosen at each time period; (15)-(16) are included to define $u_{t,i,j}^{LR}$ and $u_{t,i,j}^{LI}$ as binary variables, and $u_{t,i,j}^{LR}$ ($u_{t,i,j}^{LI}$) is equal to 1 if the WPP accepts the load curtailment (load increase). Otherwise, $u_{t,i,j}^{LR}$ ($u_{t,i,j}^{LI}$) is 0. Equation (17) enforces that the wind generation is less than the available wind power production at each time. The net load demand after taking part in the DR scheme is expressed as (18).

3.2. IGDT-based offering strategy model

For a price-taker wind power producer, the uncertainty model of wind output and demand response is important and should be considered since it directly impacts the WPP's revenue. In this section, the IGDT-based optimization models regarding the wind power and demand response uncertainties are mathematically formulated in the robust and opportunistic functions through (19)-(34).

1) Robust IGDT-based model

max α_{robust}^{wind}

subject to:

$$PF^{robust} \geq \left(1 - \beta_{robust}^{wind}\right) PF^{DET} \tag{19}$$

$$\left(1 - \alpha_{robust}^{wind}\right) P_t^w = D_t + P_t^D \tag{20}$$

$$(10) - (18) \tag{21}$$

max α_{robust}^{DR}

subject to:

$$PF^{robust} \geq \left(1 - \beta_{robust}^{DR}\right) PF^{DET} \tag{22}$$

$$P_{t,i}^{LR} = \left(1 - \alpha_{robust}^{DR}\right) \psi_{LR} P_t \tag{23}$$

$$P_{t,i}^{LI} = \left(1 - \alpha_{robust}^{DR}\right) \psi_{LI} P_t \tag{24}$$

$$P_t^w = D_t + P_t^D \tag{25}$$

$$(10) - (18) \tag{26}$$

2) Opportunistic IGDT-based model

min $\alpha_{opportunity}^{wind}$

subject to:

$$PF^{opportunity} \geq \left(1+\beta_{opportunity}^{wind}\right) PF^{DET} \tag{27}$$

$$\left(1+\alpha_{opportunity}^{wind}\right) P_t^w = D_t + P_t^D \tag{28}$$

$$(10)-(18) \tag{29}$$

min $\alpha_{opportunity}^{DR}$

subject to:

$$PF^{opportunity} \geq \left(1+\beta_{opportunity}^{DR}\right) PF^{DET} \tag{30}$$

$$P_{t,i}^{LR} = \left(1+\alpha_{opportunity}^{DR}\right) \psi_{LR} P_t \tag{31}$$

$$P_{t,i}^{LI} = \left(1+\alpha_{opportunity}^{DR}\right) \psi_{LI} P_t \tag{32}$$

$$P_t^w = D_t + P_t^D \tag{33}$$

$$(10)-(18) \tag{34}$$

In the above formulation, the robust function aims to determine the maximal level of uncertainty α_{robust} that the system can tolerate. Uncertainty budget constraints (19) and (22) limit the targeted profits, which indicates that the risk-averse revenue PF^{robust} should be higher than $(1-\beta_{robust}) PF^{DET}$, where the parameters PF^{robust} and PF^{DET} represent the risk-averse and deterministic revenue, respectively. Eqs.(20) and (23-25) impose constraints of forecasted wind generation and DR results. In the opportunistic function, the objective is to evaluate the minimum uncertainty level $\alpha_{opportunity}$, which should be satisfied to attain the windfall profit $(1+\beta_{opportunity}) PF^{DET}$.

Note that the presented IGDT-based offering strategy model is a mixed integer nonlinear programming problem because of the multiplication of continuous variable α^{DR} and binary variables $u_{t,i,j}$ in Eqs.(22,25) and (30,33). To linearize the nonlinear formulation, the Big-M linearization technique is employed in this paper [31]. It can be formulated as follows:

$$z = \alpha^{DR} u_{t,i,j} \tag{35}$$

where

$$\begin{aligned} & z \leq M\alpha^{DR} \\ & z \geq -M\alpha^{DR} \\ & z - \alpha^{DR} \leq M\left(1-u_{t,i,j}\right) \\ & z - \alpha^{DR} \geq -M\left(1-u_{t,i,j}\right) \end{aligned} \tag{36}$$

3.3. Bi-objective IGDT-based offering strategy model

In this section, IGDT-based optimization models that simultaneously consider wind power and demand response uncertainties are formulated as a bi-objective mixed integer linear programming problem. To solve this problem, this paper employs the normal boundary intersection (NBI) method considering a certain uncertainty budget [29]. The robust and opportunistic models corresponding to uncertainties are formalized in (37) and (38), respectively.

$$\max\ \left(\alpha_{robust}^{wind}, \alpha_{robust}^{DR}\right)$$

subject to:

$$\begin{aligned}
&\left(1-\alpha_{robust}^{wind}\right) P_t^w = D_t + P_t^D \\
&PF^{robust} \geq \left(1-\beta_{robust}\right) PF^{DET} \\
&P_{t,i}^{LR} = \left(1-\alpha_{robust}^{DR}\right) \psi_{LR} P_t \\
&P_{t,i}^{LI} = \left(1-\alpha_{robust}^{DR}\right) \psi_{LI} P_t \\
&(10)-(18)
\end{aligned} \tag{37}$$

$$\min\ \left(\alpha_{opportunity}^{wind}, \alpha_{opportunity}^{DR}\right)$$

subject to:

$$\begin{aligned}
&\left(1+\alpha_{opportunity}^{wind}\right) P_t^w = D_t + P_t^D \\
&PF^{opportunity} \geq \left(1+\beta_{opportunity}\right) PF^{DET} \\
&P_{t,i}^{LR} = \left(1+\alpha_{opportunity}^{DR}\right) \psi_{LR} P_t \\
&P_{t,i}^{LI} = \left(1+\alpha_{opportunity}^{DR}\right) \psi_{LI} P_t \\
&(10)-(18)
\end{aligned} \tag{38}$$

In summary, the flowchart for the proposed offering strategies of the WPP is shown in Fig.6. Firstly, forecast the data of wind power output, DA market price, load consumption and DR customer participation factors for offering day. Then based on the developed DR trading mechanism, consumers submit load reduction or load increment offers to the internal market. After collecting all the curves of the demand response offers, the WPP solves the deterministic optimization problem to determine accepted DR offers and generate deterministic energy bids. Next, considering the uncertainty associated with wind power and demand response, the WPP solves the day-ahead IGDT-based optimization problem to derive risk-constrained bidding strategies. Finally, the WPP submits appropriate energy bids to the market before the gate closure, i.e., 12:00 pm of the day before.

4. Case study

In this section, the developed IGDT-based risk constrained decision-making approach is assessed to show the performance of the proposed method. The simulation is performed on a personal computer system with an 8 GB memory and a 2.6 GHz CPU speed. The algorithm is programmed by YALMIP and solved through CPLEX. The case study is carried out on a week (13 November 2019-19 November 2019). The forecasted wind power output, load consumptions and electricity price are taken from the California market [32]. Three types of consumer data, including residential,

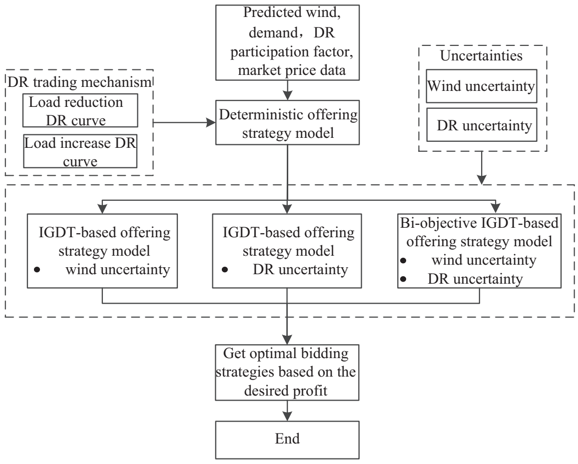
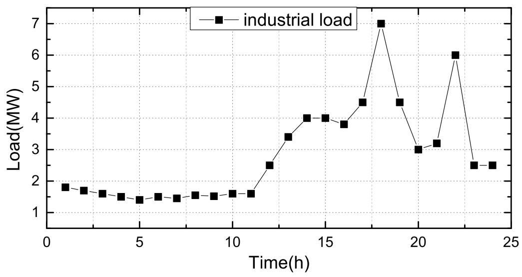
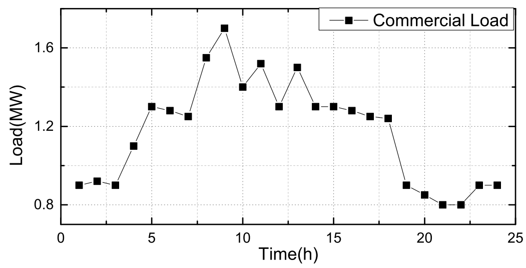


Fig. 6: The flowchart of the proposed strategy

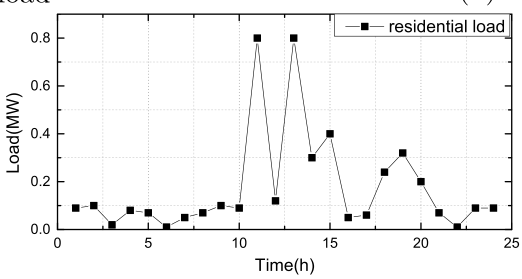
commercial and industrial consumers, are considered. The participation parameters of customers are based on the "Demand Response Bids" in the PJM website [33] and are presented in Table 2. With the first day of the week (13 November of 2019) as an example, the predicted sample load profiles are taken from Ref.[20] and presented in Fig.7. Based on the proposed DR trading mechanism in Section 2.2, an example of submitted load reduction offers for different consumers, including quantities and prices, is presented in Fig.8 and Fig.9. In addition, Fig.10 and Fig.11 show the sample load increment offers. The contracted price between the WPP operator and customers is set to \$34.27/$megawatt - hour(MWh)$.



(a)Industrial load

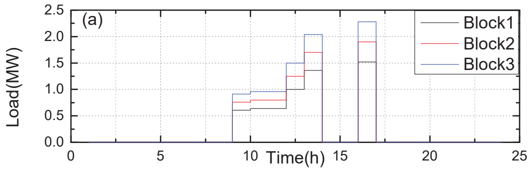


(b)Commercial load

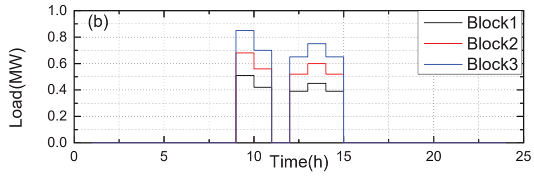


(c)Residential load

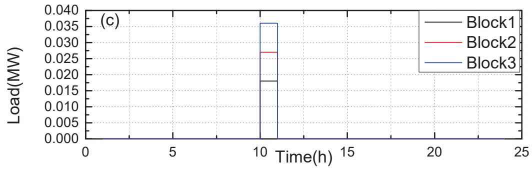
Fig. 7: Forecasted demand of sample loads



(a)Industrial load

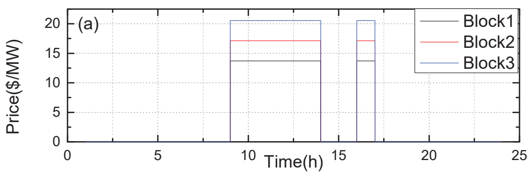


(b)Commercial load

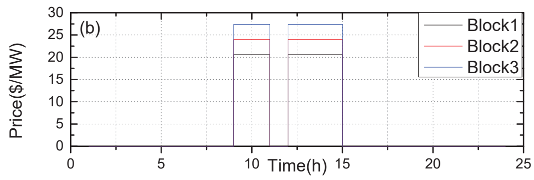


(c)Residential load

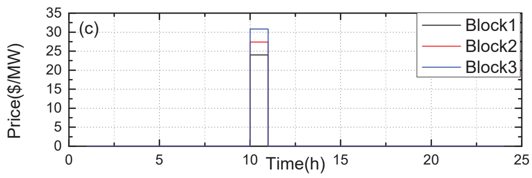
Fig. 8: Load reduction offer quantities for sample loads



(a)Industrial load

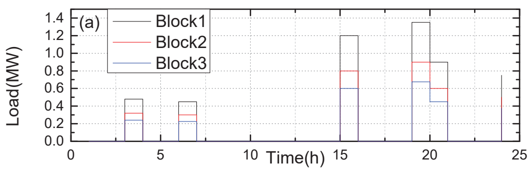


(b)Commercial load

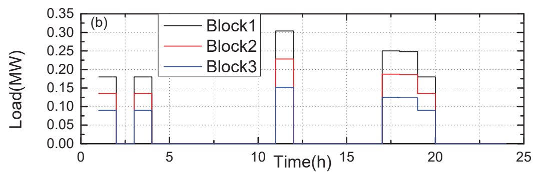


(c)Residential load

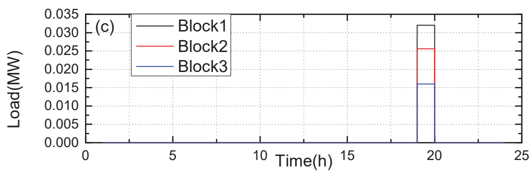
Fig. 9: Load reduction offer prices for sample loads



(a)Industrial load

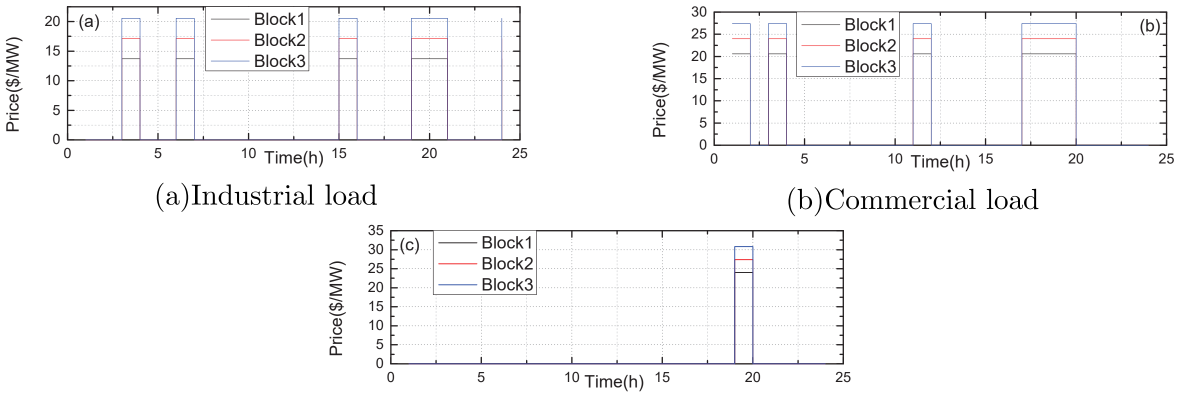


(b)Commercial load



(c)Residential load

Fig. 10: Load increment offer quantities for sample loads



(a)Industrial load

(b)Commercial load

(c)Residential load

Fig. 11: Load increment offer prices for sample loads

Table 2 DR data of customers

Block i		LRDR 1	LRDR 2	LRDR 3	LIDR 1	LIDR 2	LIDR 3
Industrial Customer	Participation Factor ψ	0.4	0.5	0.6	0.3	0.2	0.15
	Price Factor φ	0.4	0.5	0.6	0.4	0.5	0.6
Commercial Customer	Participation Factor ψ	0.3	0.4	0.5	0.2	0.15	0.1
	Price Factor φ	0.6	0.7	0.8	0.6	0.7	0.8
Residential Customer	Participation Factor ψ	0.2	0.3	0.4	0.1	0.08	0.05
	Price Factor φ	0.7	0.8	0.9	0.7	0.8	0.9

4.1. Deterministic results

In this section, the results of cases without uncertainty are shown, where the expected values of wind power productions and customer participation factors are perfectly known. In addition, to show the effect of the DR trading mechanism on the expected benefit of the WPP, two cases are studied:

Case 1: Deterministic case without considering DR

Case 2: Deterministic case considering DR

The total expected profits of the WPP with and without enabling the DR trading mechanism in the test week are compared in Table 3. The results show that, in contrast with Case 1, WPP's revenue increases in Case 2. For instance, compared to Case 1 on November 13, the WPP's total profit in Case 2 increases $7138 (8.9%). The main reason for the increasing profits is that the proposed DR scheme could help smooth the consumers' load profile. Specifically, through the proposed DR mechanism, the WPP could reduce customers' electricity consumption at hours with a wind power shortage, while the wind energy would not be wasted during surplus wind power hours, which is beneficial to the WPP. The power traded in the DA market on November 13 and November 16 is respectively plotted in Fig.12 and Fig.13. It turns out that, the offering quantity of Case 2 increases during peak periods due to the participation of DR. Therefore, the DR trading mechanism is profitable since it enables the WPP to trade its energy flexibly.

Table 3 Comparison results of total expected profits of the WPP

Day of Week		11/13	11/14	11/15	11/16	11/17	11/18	11/19
Expected Profit($)	Case 1	72869	45882	57987	74049	48258	52398	62309
	Case 2	80007	50599	63173	77430	53898	57911	69144

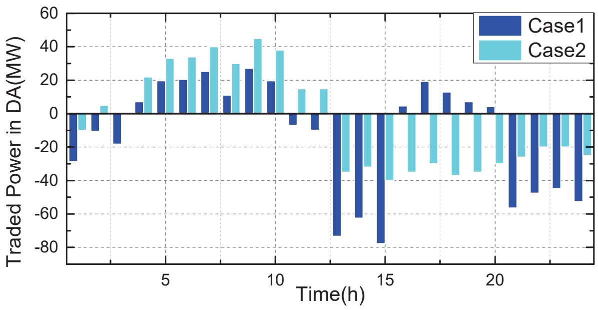


Fig. 12: Traded power of WPP on November 13, 2019

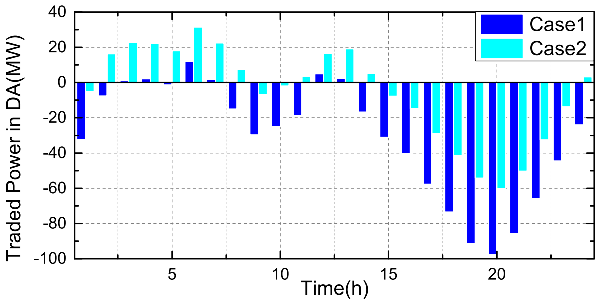


Fig. 13: Traded power of WPP on November 16, 2019

4.2. IGDT results

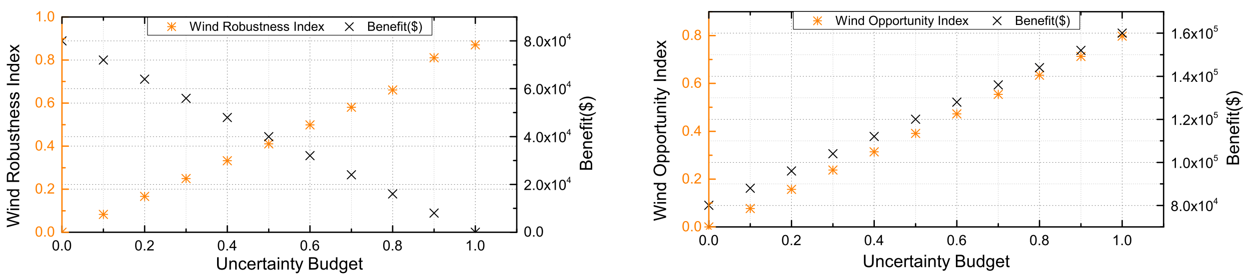
In this section, we focus on the first and last days of the week (November 13 of 2019 and November 19 of 2019) to better show the results. Based on the deterministic results, the IGDT-based approach is employed to evaluate the impacts of uncertainties on the WPP's revenue. In this regard, three more cases are considered:

Case 3: The wind power production is assumed to be uncertain, while the participation factors are known.

Case 4: The wind power production is assumed to be perfectly known, while participation factors are uncertain.

Case 5: Both uncertainties related to wind power and participation factors are studied.

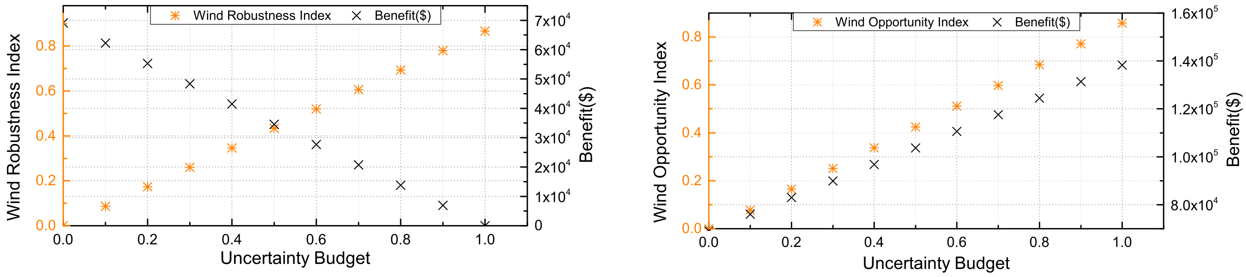
The robust and opportunity optimization framework regarding uncertainties has been solved based on Eqs.(19-34). Fig.14(a) presents the variations of the wind robustness index versus the daily benefit on November 13 of 2019. Each robustness index represents a tolerable uncertainty horizon for the corresponding payoff expectation. For instance, the desired minimum benefit \$72,006.3 is guaranteed if the deviations of wind fluctuations does not exceed 8.31%. This implies that, when actual wind generation is within this robustness horizon, the attained benefit would be larger than or equal to \$72,006.3. According to Eqs.(19-21), the total profit can be reduced by decreasing the wind power production. It can be seen from Fig.14(a) that the wind robustness value increases from 0 to 0.8708, while the day-ahead benefit decreases from \$80,007 to \$0. It indicates that lower benefit results have a stronger ability to deal with undesirable deviation in wind uncertainty. This is reasonable, since the optimal uncertainty index of the proposed model (i.e., the maximum the uncertainty level) would increase with the increase of the uncertainty budget. Analogously, in the opportunity strategy, the total benefit will increase with increasing penetration of wind power production. The changes of the day-ahead revenue versus the wind opportunity index on November 13 are illustrated in Fig.14(b). It can be observed that the wind opportunity index varies from 0 to 0.7981 when the benefit increases from \$80,007 to \$160,014. It turns out that a higher desirable uncertainty horizon can lead to greater benefits. Similarly, the variations of wind robust index and opportunity index are plotted in Fig.15 for November 19. Fig.15(a) shows that the wind robust index increases from 0 to 0.8665 when the expected profit is decreased from \$69144 to \$0. From Fig.15(b), it can be seen that the wind opportunity index varies from 0 to 0.8578 while the expected profit increases from \$69144 to \$138288.



(a)Variations of wind robustness index

(b)Variations of wind opportunity index

Fig. 14: Variations of wind uncertainty index and daily benefit on November 13 (Case 3)



(a)Variations of wind robustness index (b)Variations of wind opportunity index

Fig. 15: Variations of wind uncertainty index and daily benefit on November 19 (Case 3)

For a detailed analysis, wind power fluctuations for a certain economic target are shown in Fig16. While for PF^{IGDT} = \$72006.3, the corresponding uncertainty level is 0.0831. It means that the wind forecast error should be less than 8.31% to get expected economic revenue. In other words, if actual wind power fall into the robust range (yellow area), the attained benefit would be larger than or equal to \$72006.3. Similarity, for a certain economic expectation, i.e. PF^{IGDT} = \$88007.7, the corresponding uncertainty level is 0.0766. It indicates that, when realized wind power are within this opportunity range (blue area), a maximum revenue \$88007.7 is possibly obtained.

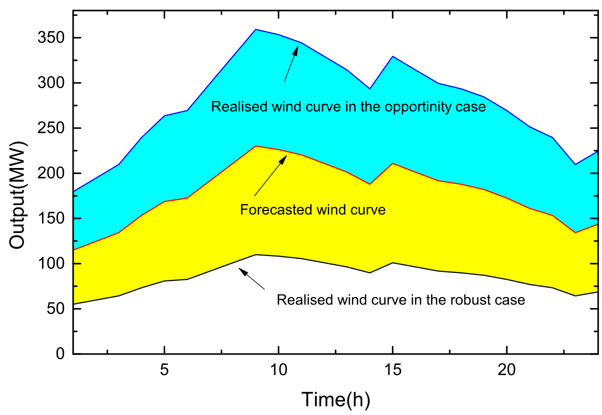
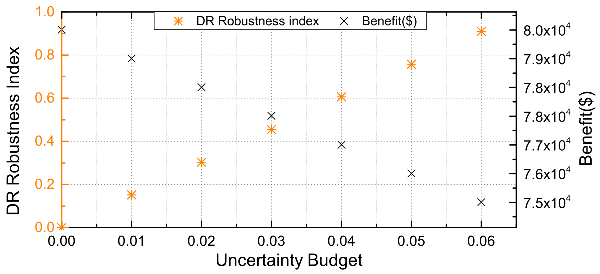


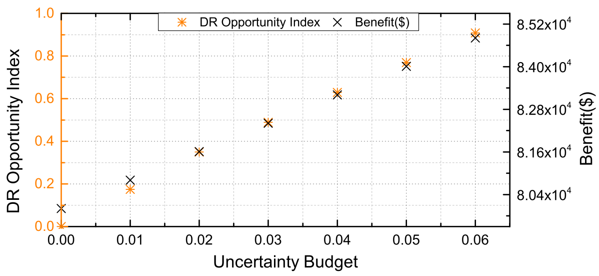
Fig. 16: Wind curves for different cases

The robust and opportunistic results pertaining to the demand response uncertainty on November 13 are depicted in Fig.17. The corresponding results on November 19 are plotted in Fig.18. In the robust model, the benefit is expected to reduce as the customer participation factor decreases. From Fig.17(a), it can be observed that when UB reaches 0.06, the declining trend of the profit function is saturated and has no change, due to the supply-demand balance constraint and economical limitations of the system. At this point, the total benefit and highest DR robustness index are \$75206.58 and 0.9097, respectively. Analogously, in the opportunistic case, the growing trend of the benefit function is saturated when the DR opportunity index is equal to 0.9087. A comparison between Case 3 and Case 4 indicates that the wind uncertainty index changes in a wider range as compared to the DR uncertainty index. The results on November 19 show that, compared to Case 3, the highest robustness value of case 4 is increased by 6.9%. It demonstrates that the uncertainty on demand response impacts the WPP offering strategy less than it does the wind power uncertainty.

Using these results, the WPPs can optimize their decisions in the DA market. In the robust case, the objective of WPP is to choose a risk-averse bidding strategy to handle the uncertainty. For example, the WPP can make appropriate decisions based on the results presented in Fig.18(a). If the WPPs choose the energy bids for $PF^{IGDT} = \$69144$, they will get the highest profits when the realized DR results are equal to the forecasted values. However, this strategy leads to the biggest risk caused by uncertainty. Conversely, if the WPPs decide the bids for $PF^{IGDT} = \$68452.56$, they will obtain less profits with lower risk. In the opportunistic case, the WPP aims to choose a risk-seeking bidding strategy to attain a higher revenue. Fig.18(b) shows that a higher economic target will incur higher risks related to uncertainty. The results can help the WPPs make appropriate decisions based on the trade-off between the risk of uncertainty and profits.

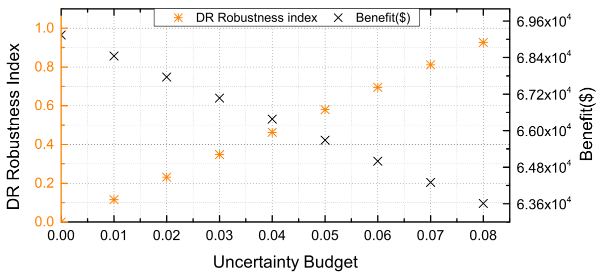


(a)Variations of DR robustness index

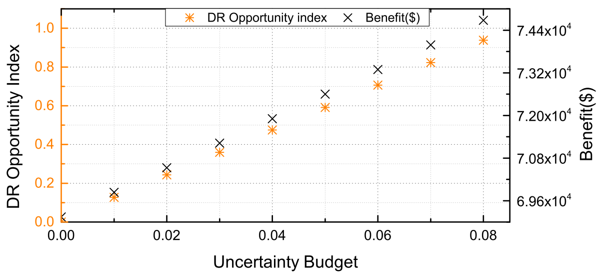


(b)Variations of DR opportunity index

Fig. 17: Variations of DR uncertainty index and daily benefit on November 13 (Case 4)



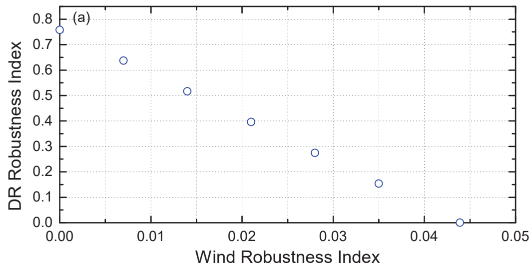
(a)Variations of DR robustness index



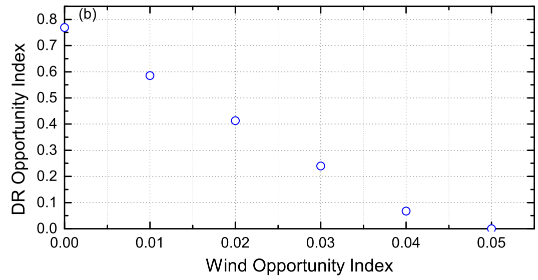
(b)Variations of DR opportunity index

Fig. 18: Variations of DR uncertainty index and daily benefit on November 19 (Case 4)

The bi-objective IGDT-based problems regarding both wind and DR uncertainties are solved based on (37) and (38). The UBs in robust and opportunistic structures are set to be 0.05. The Pareto front is obtained using the NBI method. The results of case 5 on November 13 and November 19 are depicted in Fig.19 and Fig.20. As shown in Fig.19, the wind robustness can increase to 0.0439 while the DR robustness decreases to 0. On the contrary, the DR robustness can increase to 0.7581 while the wind robustness decreases to 0. Analogously, in the opportunistic case, the wind opportunity index varies from 0 to 0.05 while the DR opportunity index decreases from 0.7689 to 0. This tendency is true, since the revenue of WPP is influenced by uncertainties from both wind energy and demand response. It also can be observed from Fig.20 that the wind uncertainty index increases with the decreases in DR uncertainty index. When a higher level of risk is considered in the former, the WPP can tolerate a lower risk level from the latter with the same expected profit.

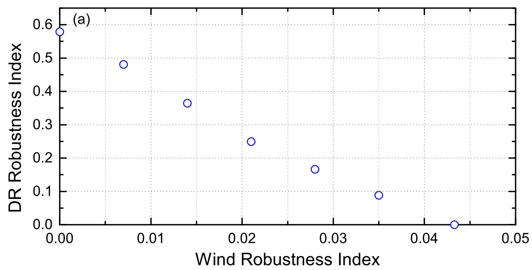


(a)Optimal Pareto front for robust case

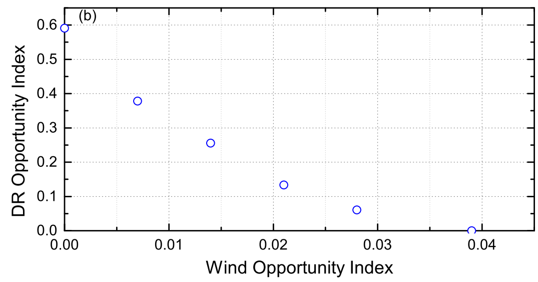


(b)Optimal Pareto front for opportunistic case

Fig. 19: Optimal Pareto front result on November 13



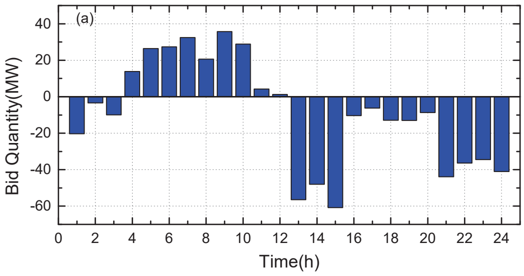
(a)Optimal Pareto front for robust case



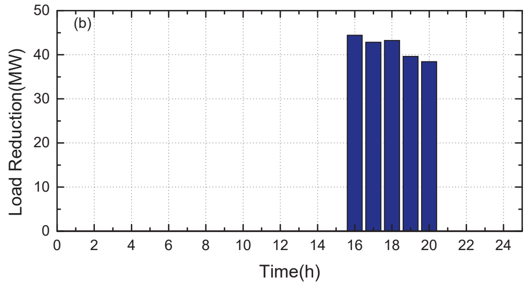
(b)Optimal Pareto front for opportunistic case

Fig. 20: Optimal Pareto front result on November 19

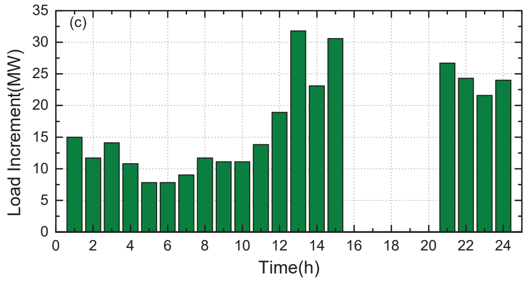
The most preferred solution is selected by using the fuzzy decision-making approach [20]. For a detailed analysis, the day-ahead results including offering quantities, total reduced and increased loads on November 13 are shown in Fig.21 and Fig.22, respectively. The corresponding results on November 19 are plotted in Fig.23 and Fig.24, respectively. Note that the positive bids represent the WPP selling energy to the market, while negative bids indicate that the WPP is purchasing energy from the market. As shown in Fig.21 (a) and Fig.22 (a), it turns out that risk-averse WPPs purchase more power from the market during times of high prices than risk-seeking ones. The reason is that risk-averse decision makers tend to buy the required energy from sources with less uncertainty. It can be observed from Fig.21 (b) and Fig.22 (b) that the maximum reductions occur during the peak market price period. Similarly, most of the increased loads occur at the low market price time. By comparing Fig.21 and Fig.22, it can be seen that, risk-seeking WPPs buy more DR resources than the risk-averse ones, especially in high price periods (i.e., 5 pm-7 pm). This is because buying energy from DR customers and trading it in the market increases the risk for risk-averse WPPs and thus, they tend to avoid this practice. It also can be observed from Fig.23 and Fig.24 that the maximum reductions occur during the peak market price period. Similarly, most of the increased loads occur at the low market price time.



(a)WPP bid quantities in the robust case

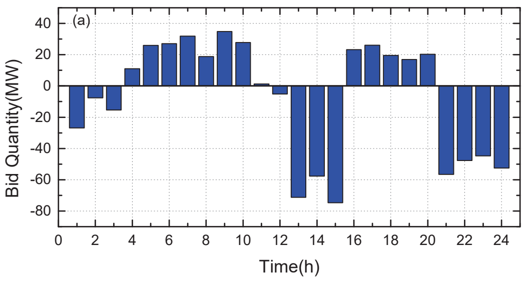


(b)Total load reductions in the robust case

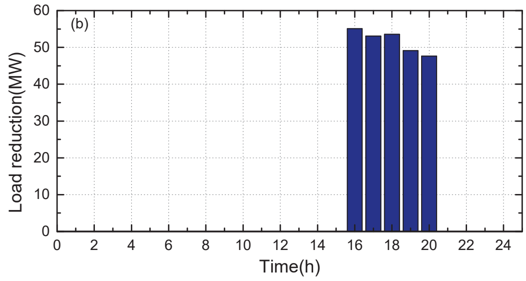


(c)Total load increments in the robust case

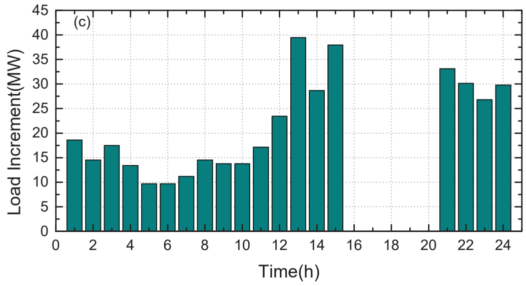
Fig. 21: Day-ahead results in the robust case (November 13 of 2019)



(a)WPP bid quantities in the opportunistic case

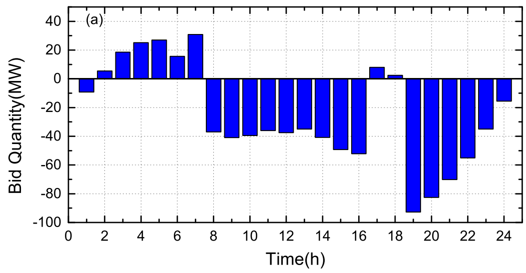


(b)Total load reductions in the opportunistic case

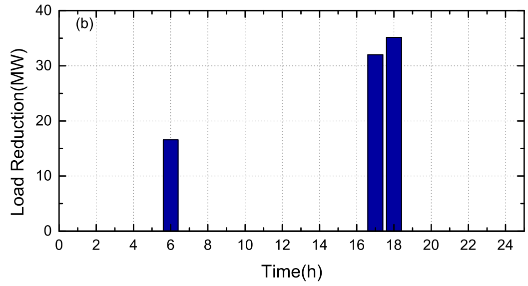


(c)Total load increments in the opportunistic case

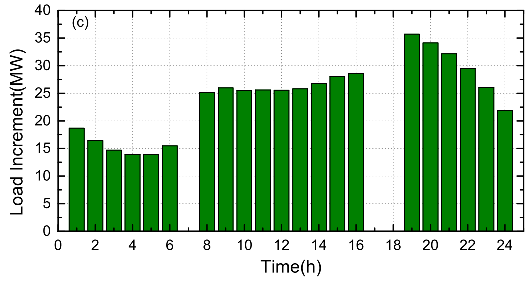
Fig. 22: Day-ahead results in the opportunistic case (November 13 of 2019)



(a)WPP bid quantities in the robust case

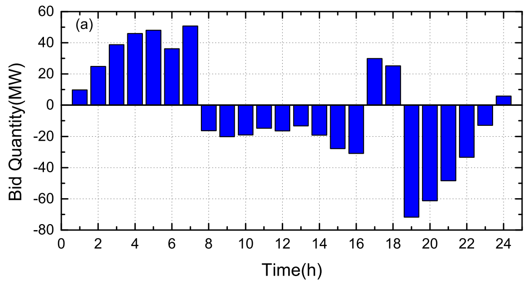


(b)Total load reductions in the robust case

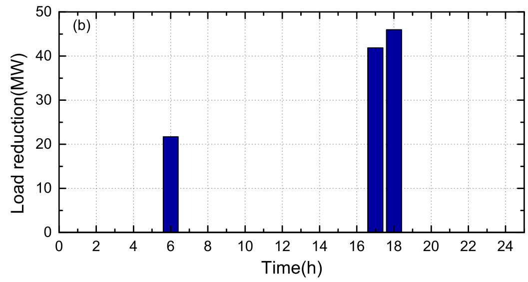


(c)Total load increments in the robust case

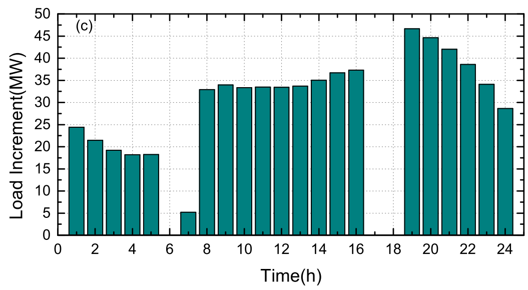
Fig. 23: Day-ahead results in the robust case (November 19 of 2019)



(a)WPP bid quantities in the opportunistic case



(b)Total load reductions in the opportunistic case



(c)Total load increments in the opportunistic case

Fig. 24: Day-ahead results in the opportunistic case (November 19 of 2019)

4.3. Model validation

In this subsection, in order to verify the IGDT-based results, the Monte Carlo (MC) method-ology is deployed to solve the bidding strategy problem. First, with the first day of the week

(13 November of 2019) as an example, 1000 random scenarios are generated using the Gaussian probability density function for wind power. Concerning to the DR uncertainty, random scenarios are generated by multiplying the forecasted participation factors by fixed coefficients that range from 0.8 to 1.2.

The histograms of the generated scenarios for the wind and DR uncertainties are shown in Figs.25 and Fig.26. Comparing the IGDT-based results with the MC, it is seen that WPP bidding strategies with different uncertainty budgets (UBs) can be economic, conservative or opportunistic. For example, in Fig.25, $Robust - UB = 0.03$ leads to an economic strategy, while $Robust - UB = 0.28$ can result a conservative decision. Similarly, the strategies with $Opportunistic - UB = 0.05$ and $Opportunistic - UB = 0.25$ are economic and opportunistic. In addition, strategies with larger UBs yield to more conservative or opportunistic decisions. For instance, in Fig.26, the strategy with Robust-UB equals to 0.02 is economic (closer to the MC average value), while the strategy with Robust-UB equals to 0.06 can be a conservative decision (higher distances from the MCS average values).

Overall, based on the robust and opportunity functions, different WPPs could make desirable offering decisions regarding their risk preferences and benefit targets. In the opportunistic strategy, the higher UBs lead to higher risk levels and greater profits, while in the robust strategy, the higher UBs lead to lower profits and more robust decisions. If the WPP chooses a risk-averse strategy, the results obtained from the robustness model can be utilized. On the other hand, if the WPP takes a risk-taking strategy, the results related to the opportunity function will be helpful.

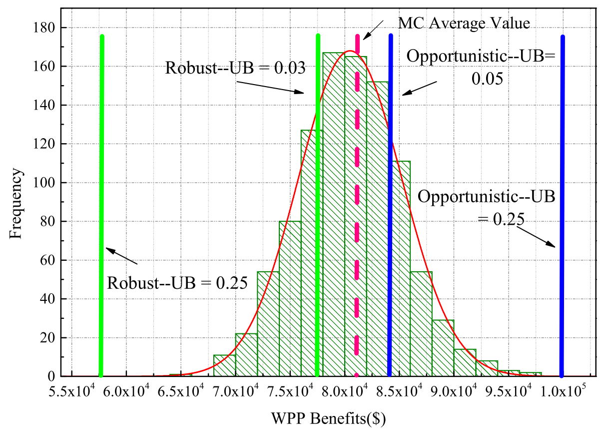


Fig. 25: WPP benefits using MC and IGDT considering wind uncertainty

5. Conclusion

In this paper, a decision-making model for a wind power producer in the day-ahead market is presented. In the proposed model, a flexible demand response scheme is developed to model electricity trading between the wind power producer and demand response customers. Through the trading mechanism, customers submit load reduction or increment offers to the wind power producer at favorable prices. And then, the wind power producer decides its involvement in the DR trading and submits offers to the market to maximize its profit. Furthermore, the uncertainties pertaining to wind generation and demand response are applied by the information gap decision

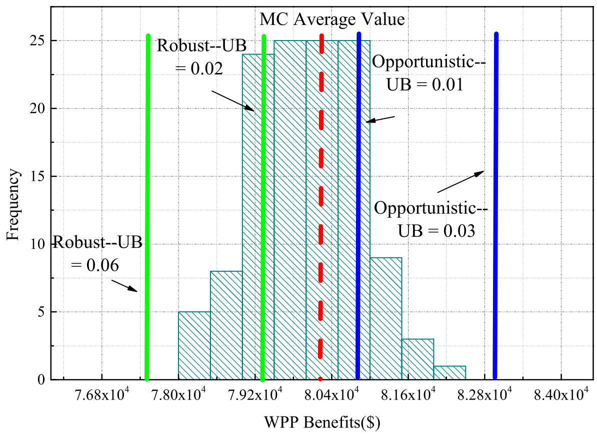


Fig. 26: WPP benefits using MC and IGDT considering DR uncertainty

theory resulting in a robustness/opportunity function. The case studies verify the effectiveness of the proposed model and methodology. The key findings of the paper can be summarized as follows.

1) Employing a demand response trading mechanism between the wind power producer and demand response customers can improve the wind power producers profit and reduce the related risks. Through the proposed demand response scheme, the wind power producer is able to purchase demand response resources at peak price times, to mitigate the deviations of its production. On the other hand, the wind power producer can sell energy to demand response consumers at off-peak times in order to achieve higher profits.

2) The offering strategies are affected by uncertainties of both wind power and demand response. For a certain economic target, when a higher risk of wind power uncertainty is taken into account, the decision maker can only tolerate a lower risk level from demand response, and vice versa.

3) By utilizing the proposed risk-constrained information gap decision theory approach, the wind power producer can select a desired strategy according to its risk preference. More specifically, the robust model enables a risk-averse wind power producer to attain a minimum profit under unfavorable uncertainty, while the opportunistic model can help a risk-seeking wind power producer achieve a windfall profit by taking advantage of favorable uncertainty.

In future work, we plan to study the decision-making strategies from both the wind power producers and consumers perspectives. The optimization of wind power producers participating in joint energy and ancillary services markets may also be studied in the future research. Moreover, we plan to explore the uncertainties in distribution/transmission networks.

Acknowledgements

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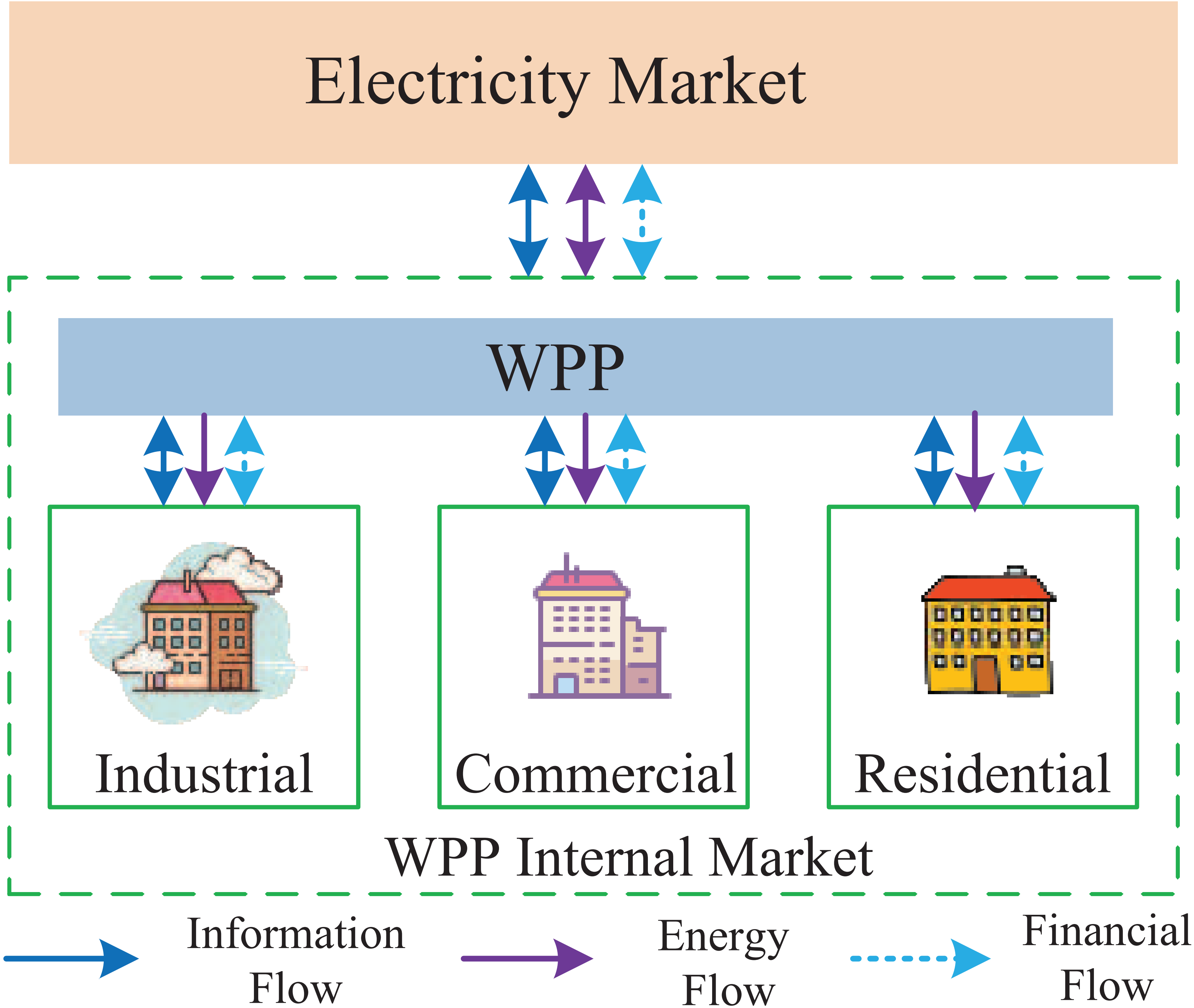
figure 1



Electricity Market
WPP
Industrial
Commercial
Residential
WPP Internal Market
Information Flow
Energy Flow
Financial Flow

figure 2

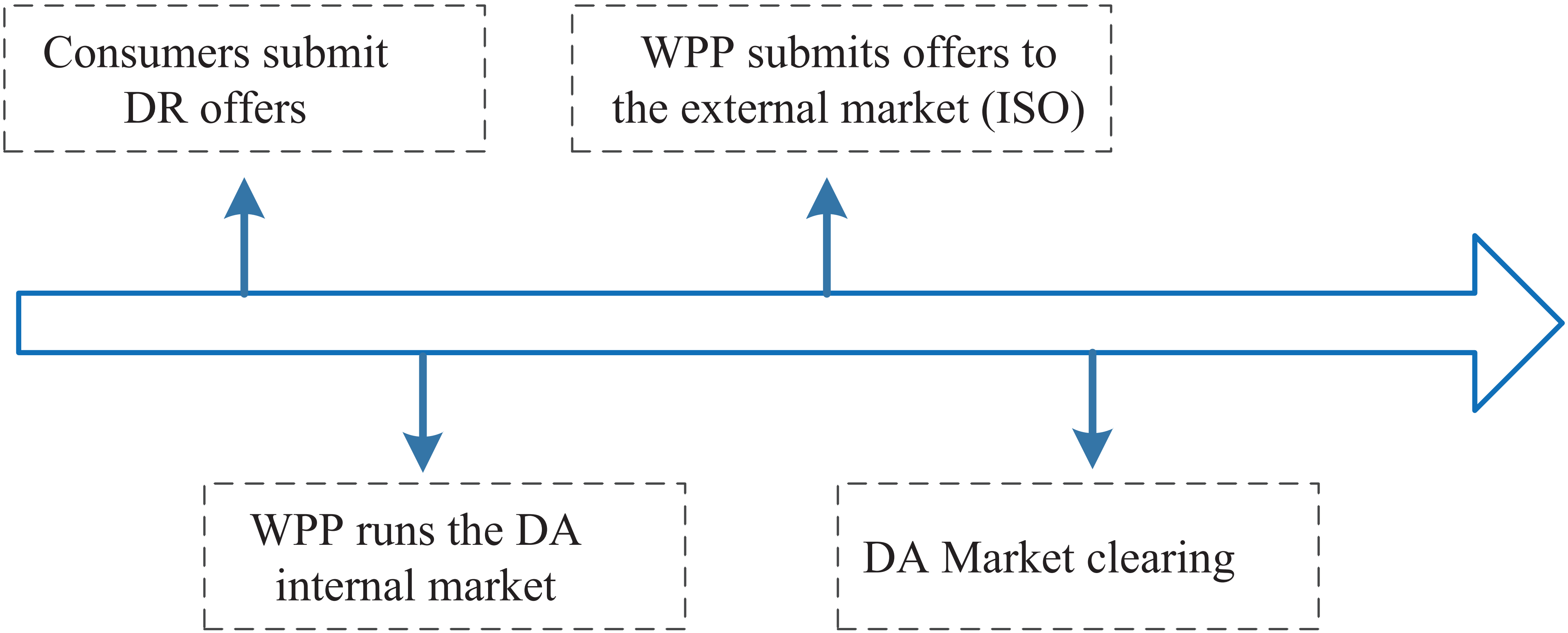
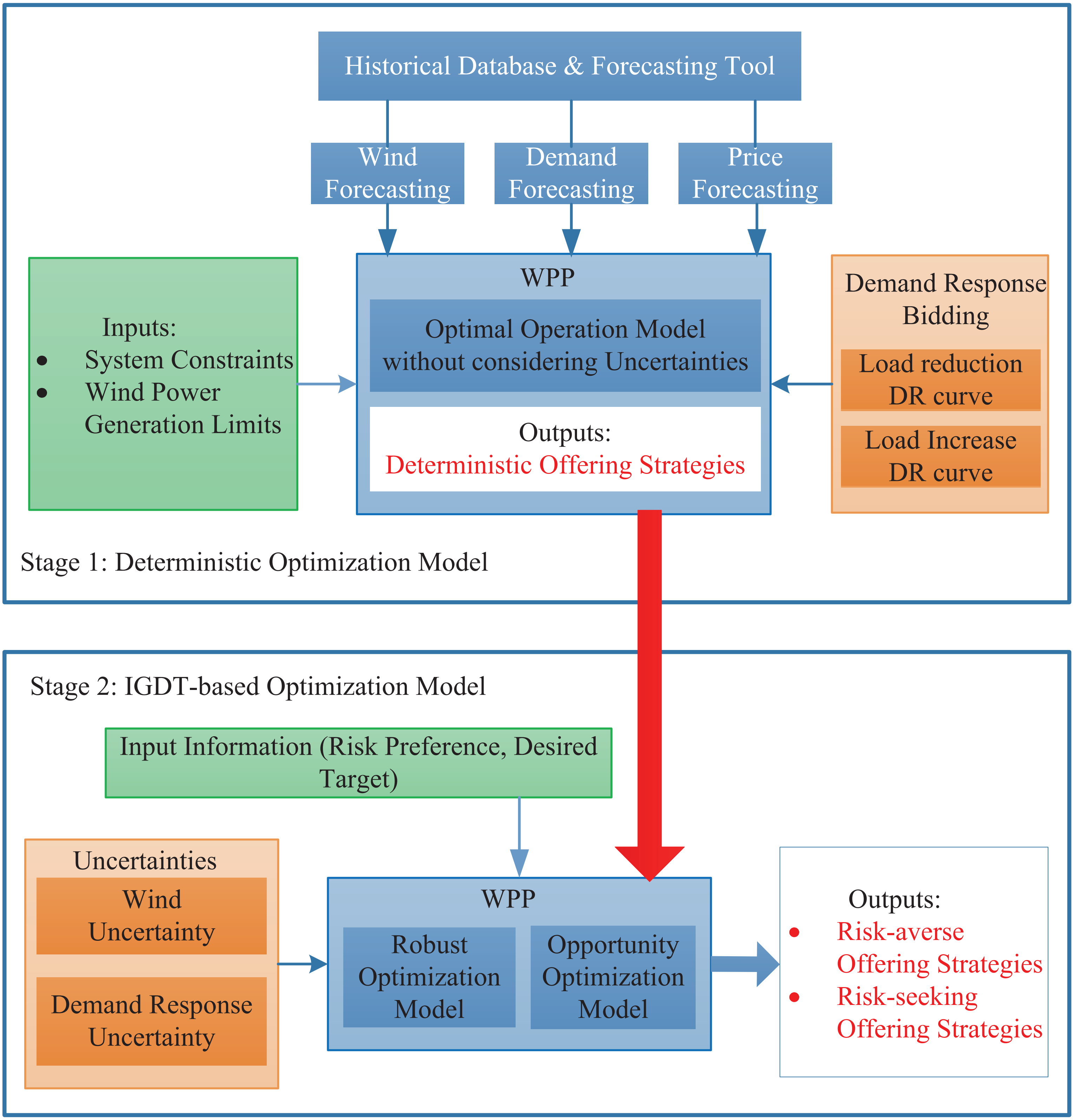
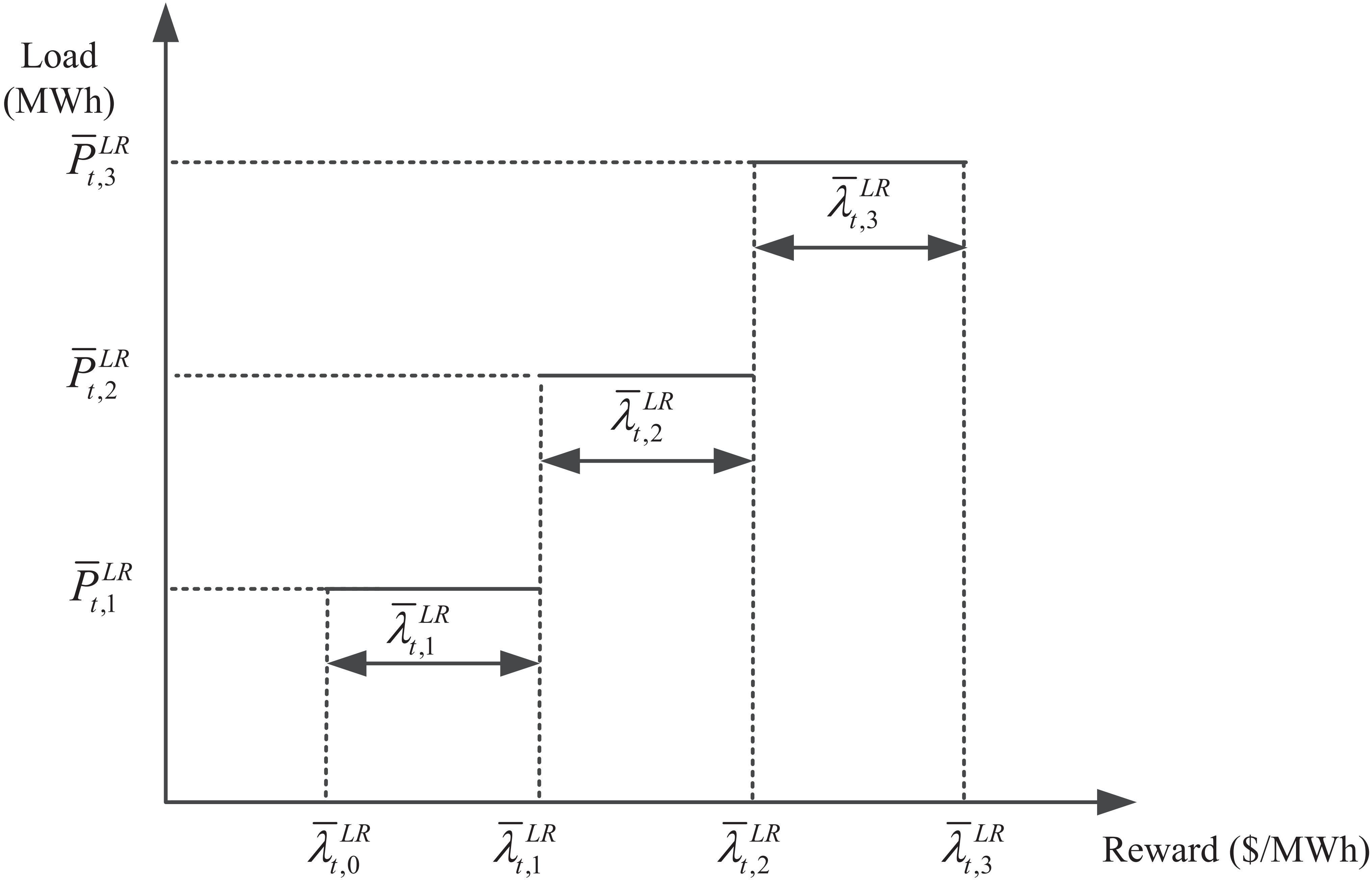

Consumers submit DR offers
WPP submits offers to the external market (ISO)
WPP runs the DA internal market
DA Market clearing

figure 3



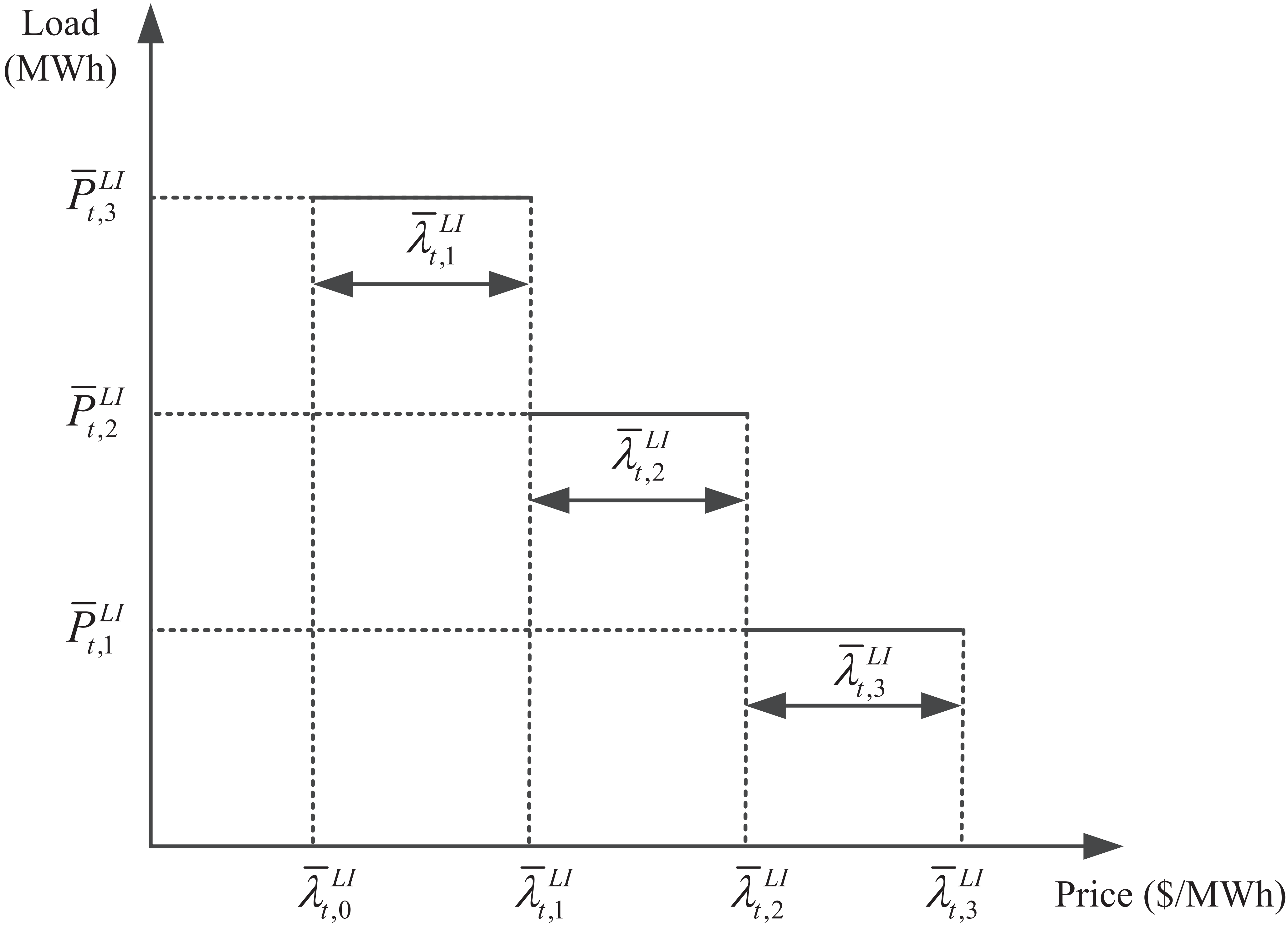
Historical Database & Forecasting Tool
Wind Forecasting
Demand Forecasting
Price Forecasting
Inputs:
• System Constraints
• Wind Power Generation Limits
WPP
Optimal Operation Model without considering Uncertainties
Outputs:
Deterministic Offering Strategies
Demand Response Bidding
Load reduction DR curve
Load Increase DR curve
Stage 1: Deterministic Optimization Model
Stage 2: IGDT-based Optimization Model
Input Information (Risk Preference, Desired Target)
Uncertainties
Wind Uncertainty
Demand Response Uncertainty
WPP
Robust Optimization Model
Opportunity Optimization Model
Outputs:
• Risk-averse Offering Strategies
• Risk-seeking Offering Strategies

figure 4



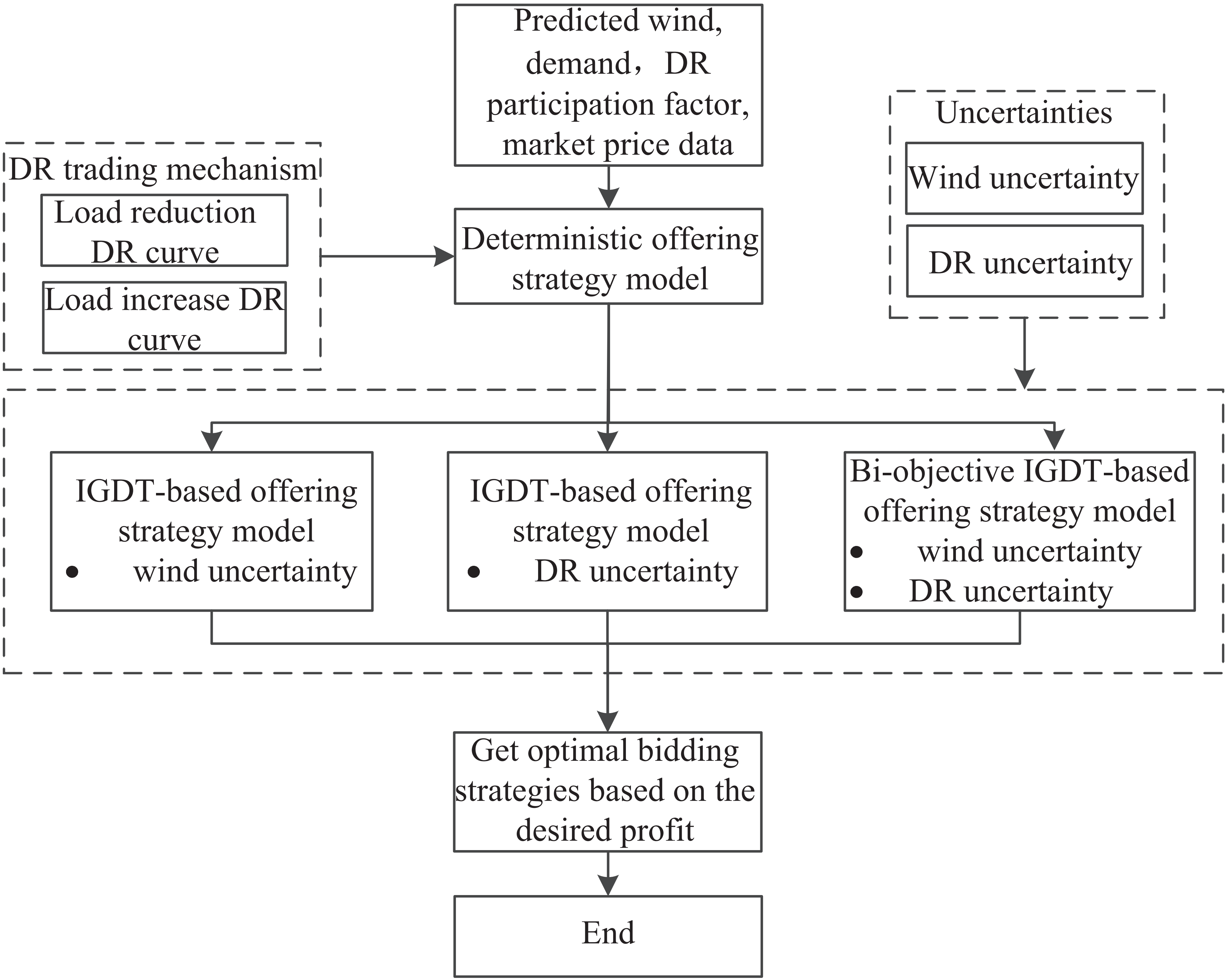
Load
(MWh)
$\overline{P}_{t,3}^{LR}$
$\overline{P}_{t,2}^{LR}$
$\overline{P}_{t,1}^{LR}$
$\overline{\lambda}_{t,3}^{LR}$
$\overline{\lambda}_{t,2}^{LR}$
$\overline{\lambda}_{t,1}^{LR}$
$\overline{\lambda}_{t,0}^{LR}$
$\overline{\lambda}_{t,1}^{LR}$
$\overline{\lambda}_{t,2}^{LR}$
$\overline{\lambda}_{t,3}^{LR}$
Reward ($/MWh)

figure 5



Load (MWh)
$\overline{P}_{t,3}^{LI}$
$\overline{P}_{t,2}^{LI}$
$\overline{P}_{t,1}^{LI}$
$\overline{\lambda}_{t,1}^{LI}$
$\overline{\lambda}_{t,2}^{LI}$
$\overline{\lambda}_{t,3}^{LI}$
$\overline{\lambda}_{t,0}^{LI}$
$\overline{\lambda}_{t,1}^{LI}$
$\overline{\lambda}_{t,2}^{LI}$
$\overline{\lambda}_{t,3}^{LI}$
Price ($/MWh)

figure 6



Predicted wind, demand， DR participation factor, market price data
DR trading mechanism
Load reduction DR curve
Load increase DR curve
Deterministic offering strategy model
Uncertainties
Wind uncertainty
DR uncertainty
IGDT-based offering strategy model
• wind uncertainty
IGDT-based offering strategy model
• DR uncertainty
Bi-objective IGDT-based offering strategy model
• wind uncertainty
• DR uncertainty
Get optimal bidding strategies based on the desired profit
End

figure 7a

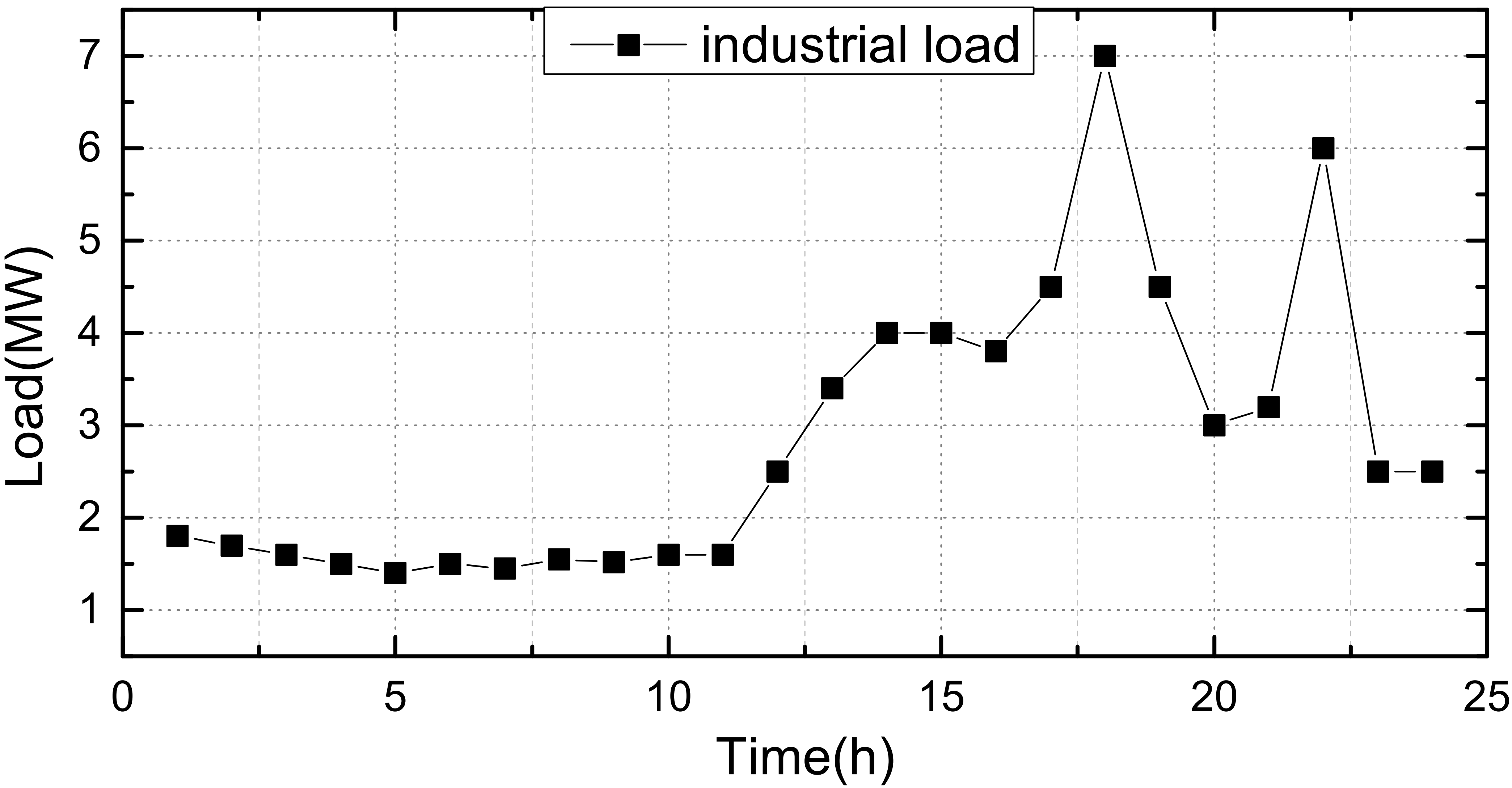


figure 7b

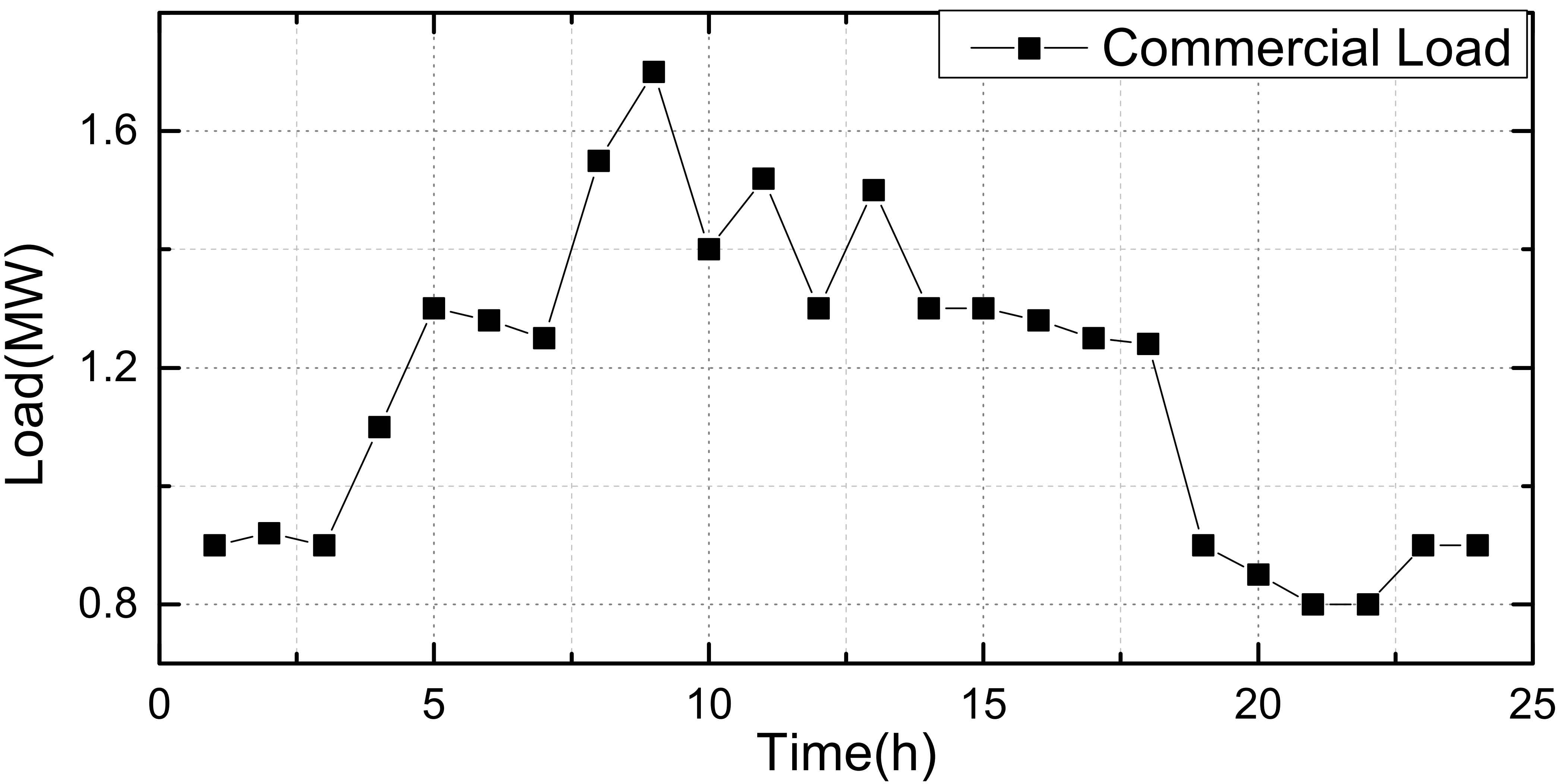


figure 7 c

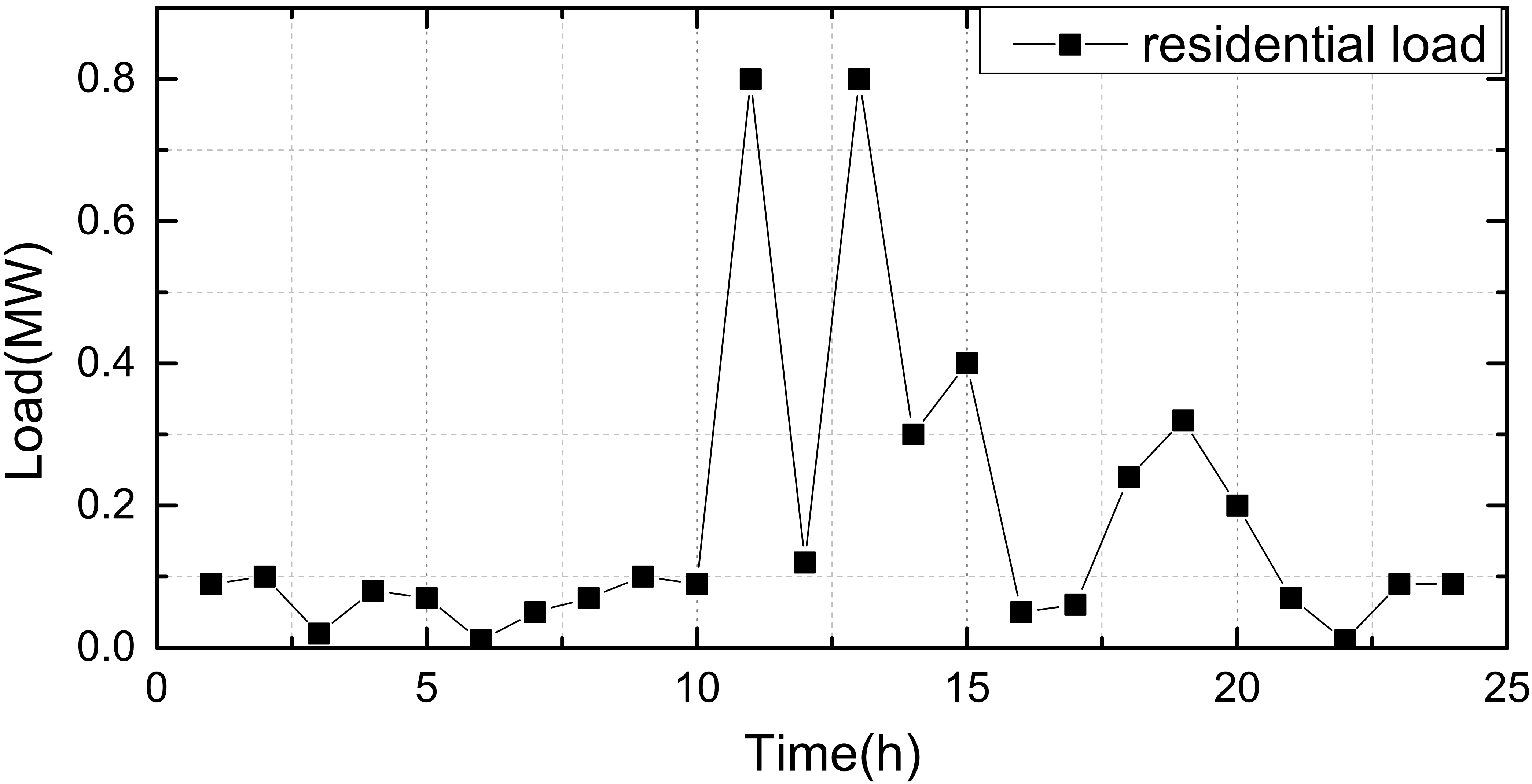


figure 8 a

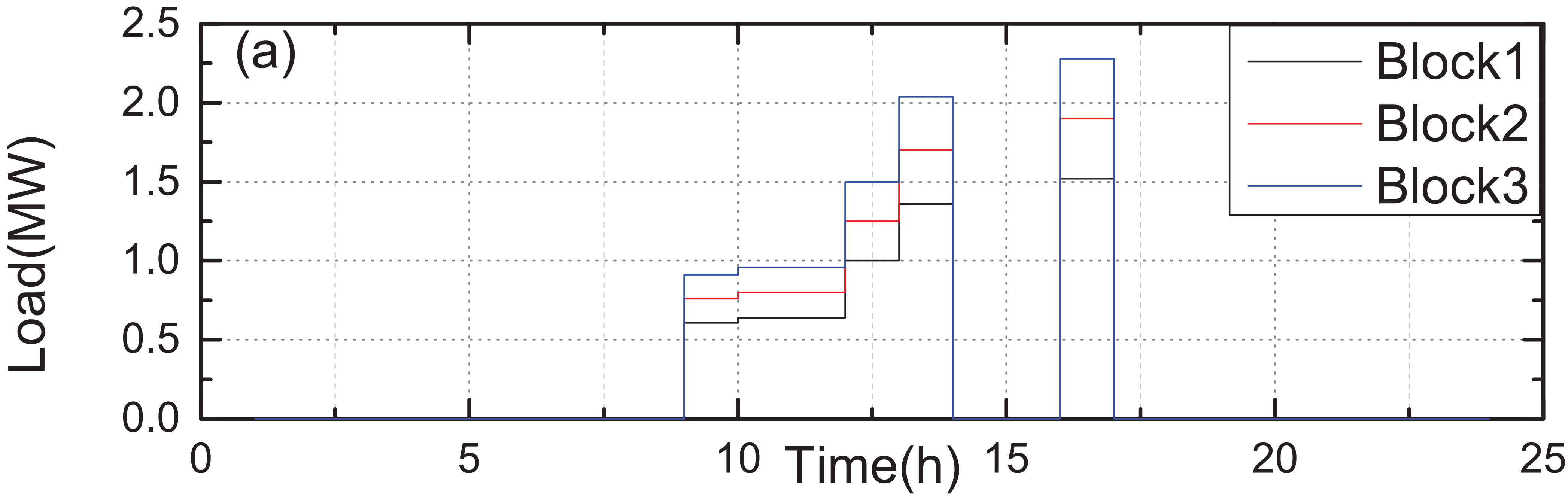

(a)
Block1
Block2
Block3
Load(MW)
Time(h)
0.0
0.5
1.0
1.5
2.0
2.5
0
5
10
15
20
25

figure 8 b

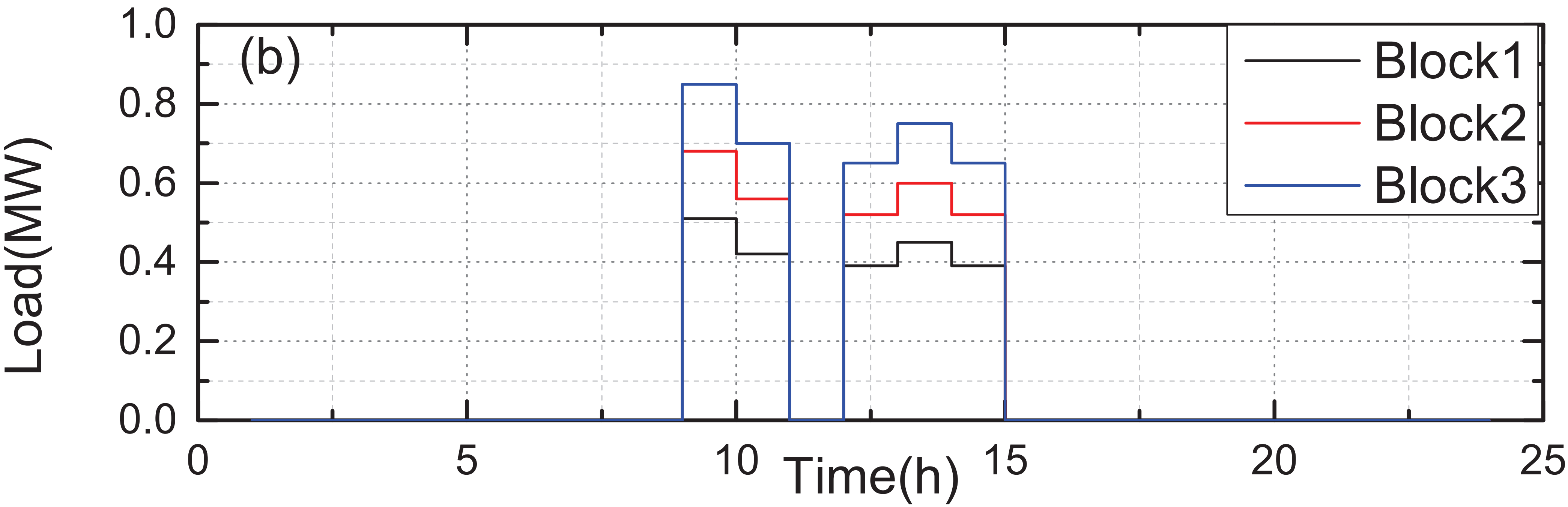

(b)
Block1
Block2
Block3
Load(MW)
Time(h)
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25

figure 8 c

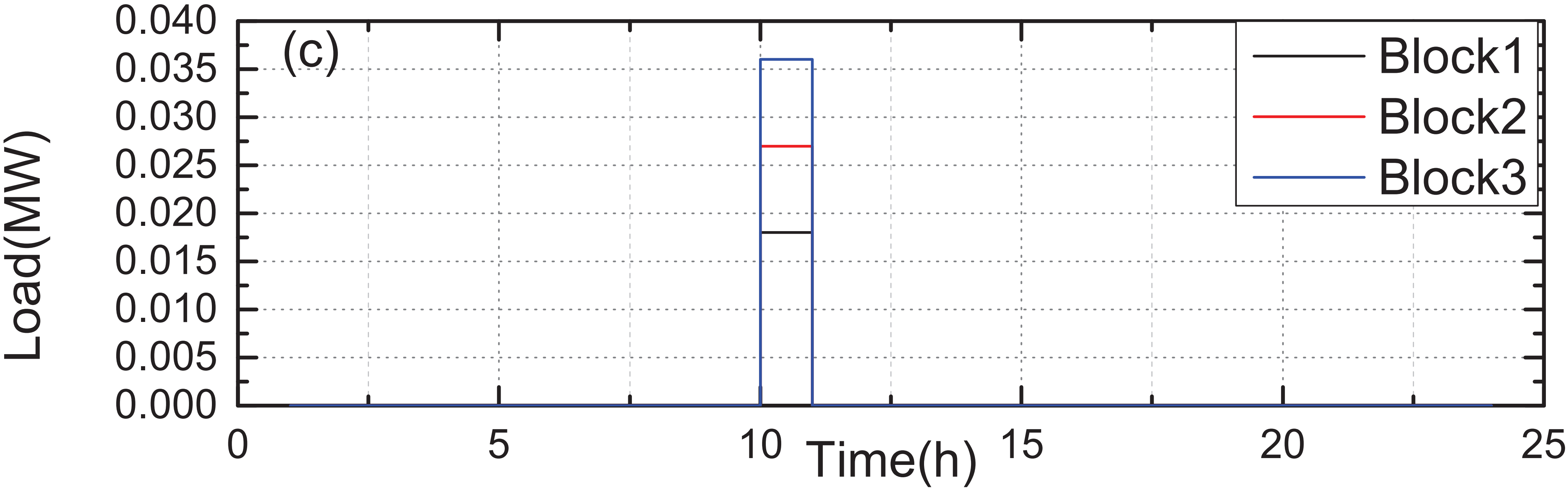

(c)
Block1
Block2
Block3
Load(MW)
Time(h)
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
5
10
15
20
25

figure 9 a

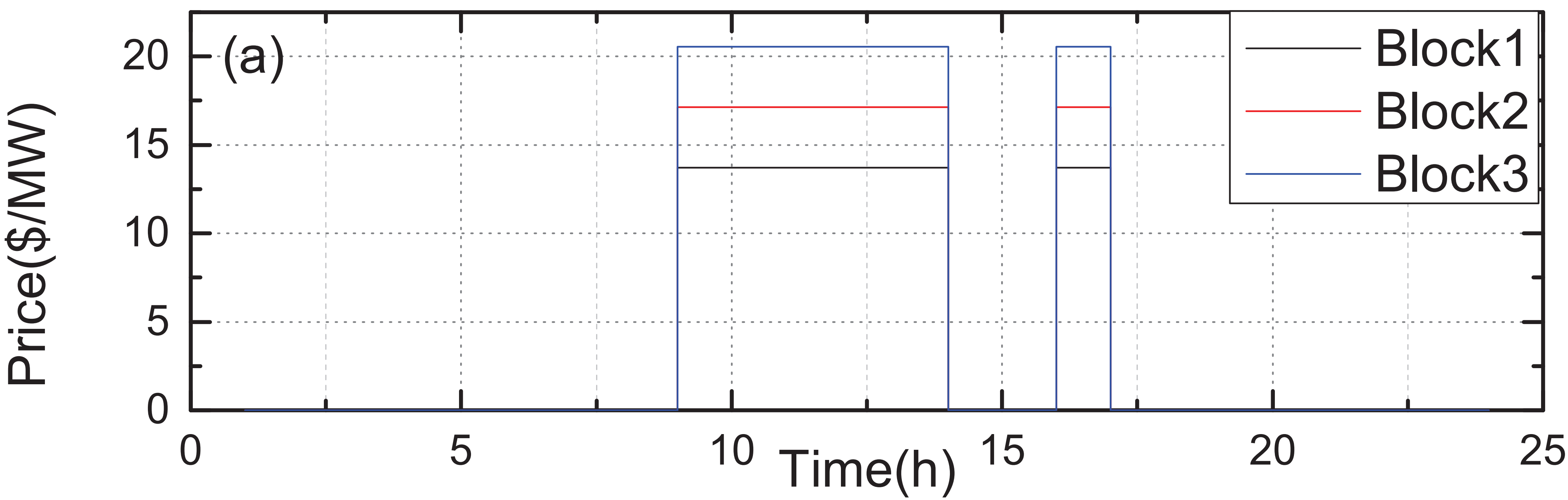


figure 9 b

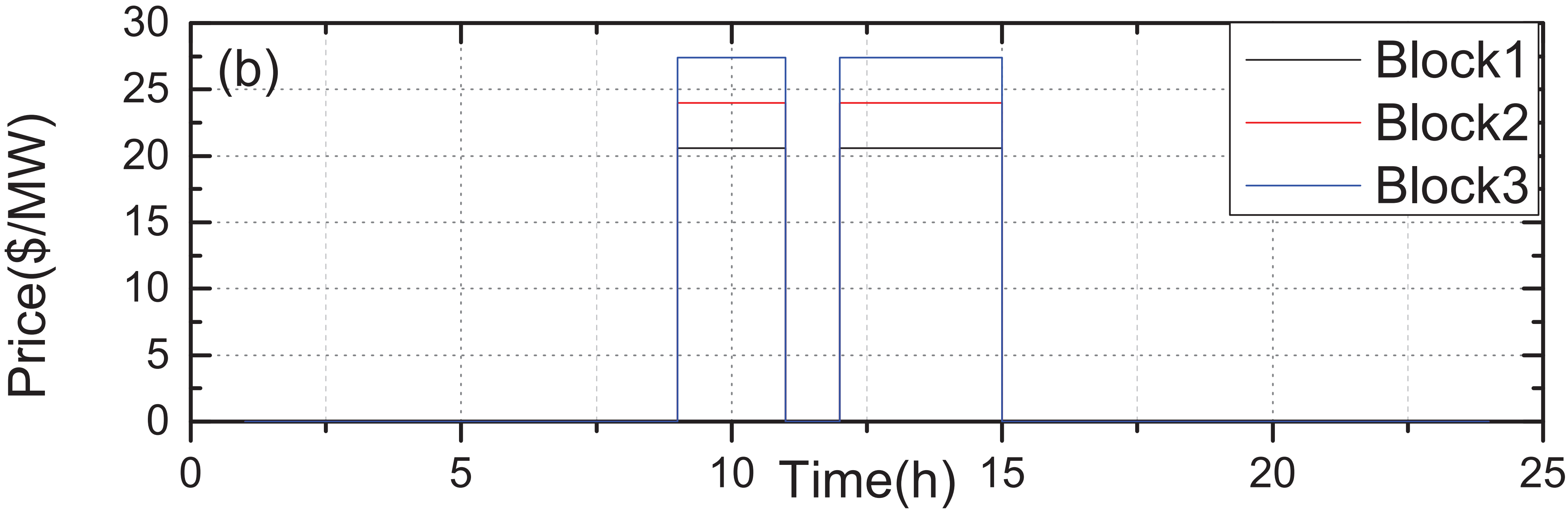


figure 9 c

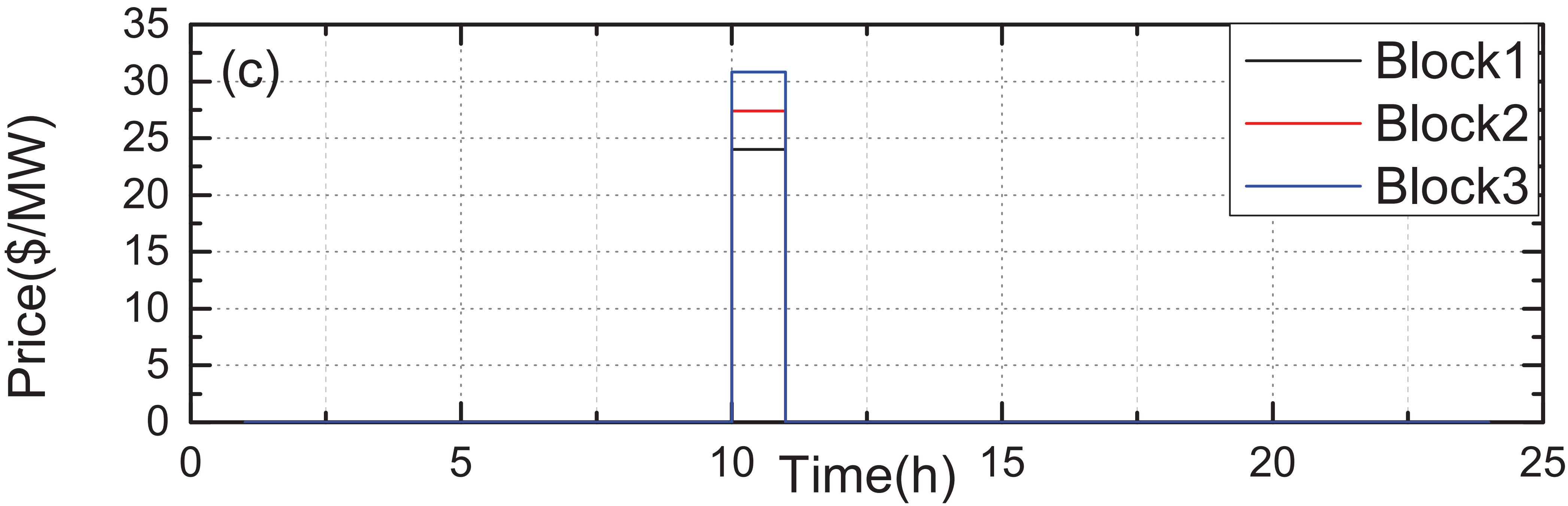


figure 10 a

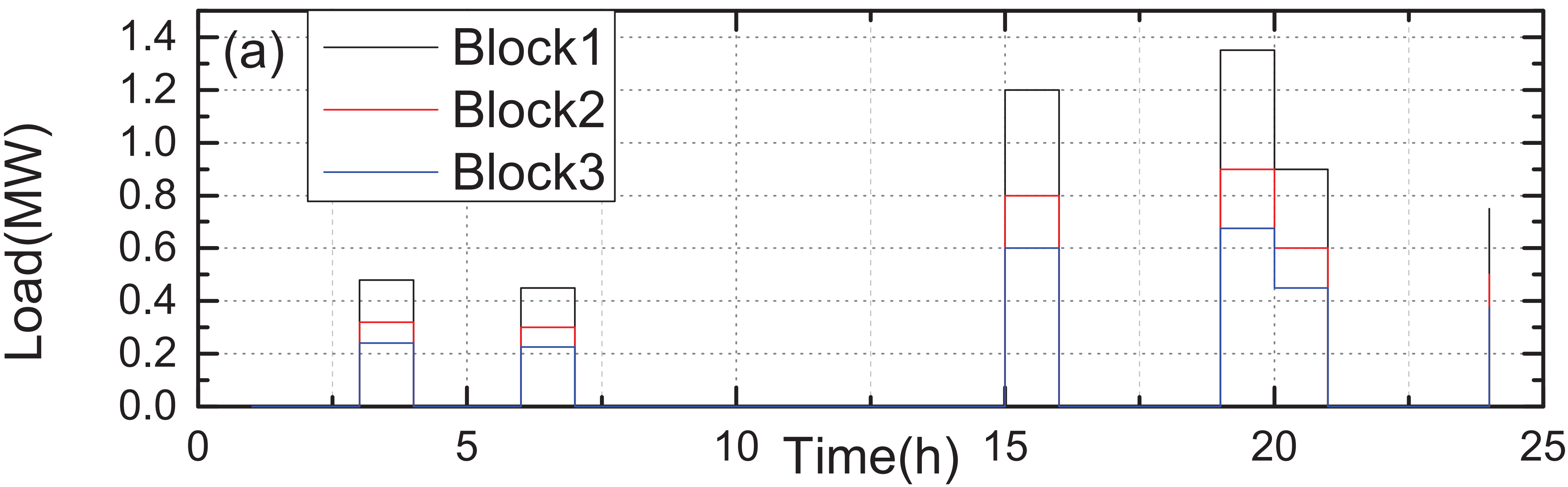
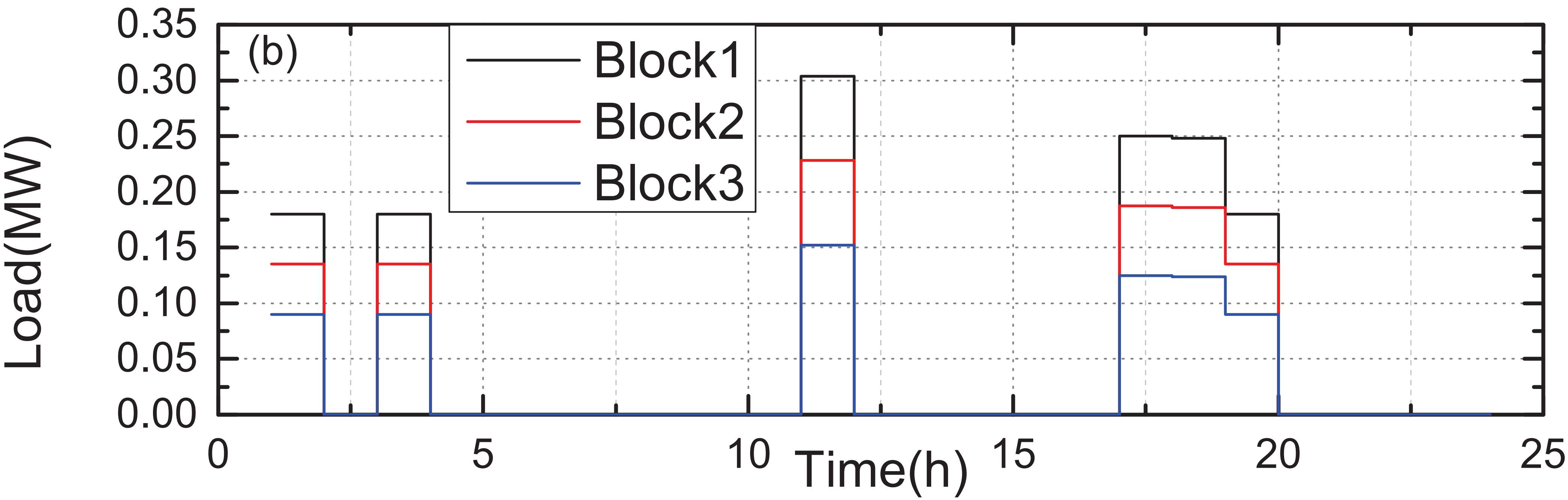

(a)
Block1
Block2
Block3
Load(MW)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
Time(h)

figure 10 b



(b)
Block1
Block2
Block3
Load(MW)
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
5
10
15
20
25
Time(h)

figure 10 c

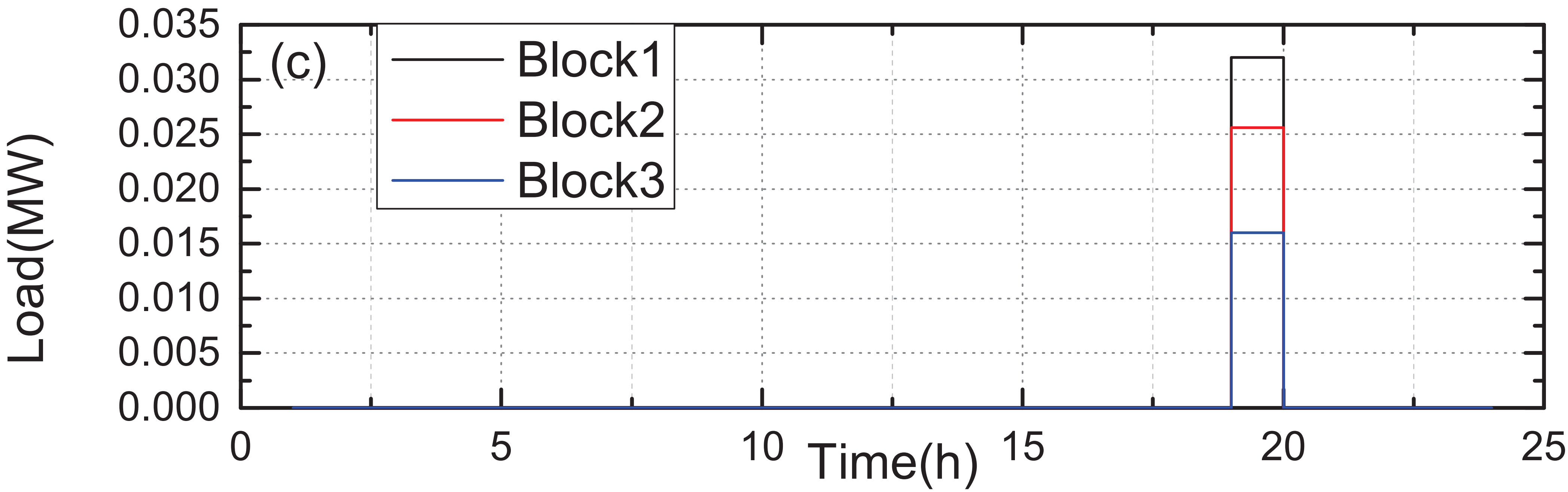

(c)
Block1
Block2
Block3
Load(MW)
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
5
10
15
20
25
Time(h)

figure 11 a

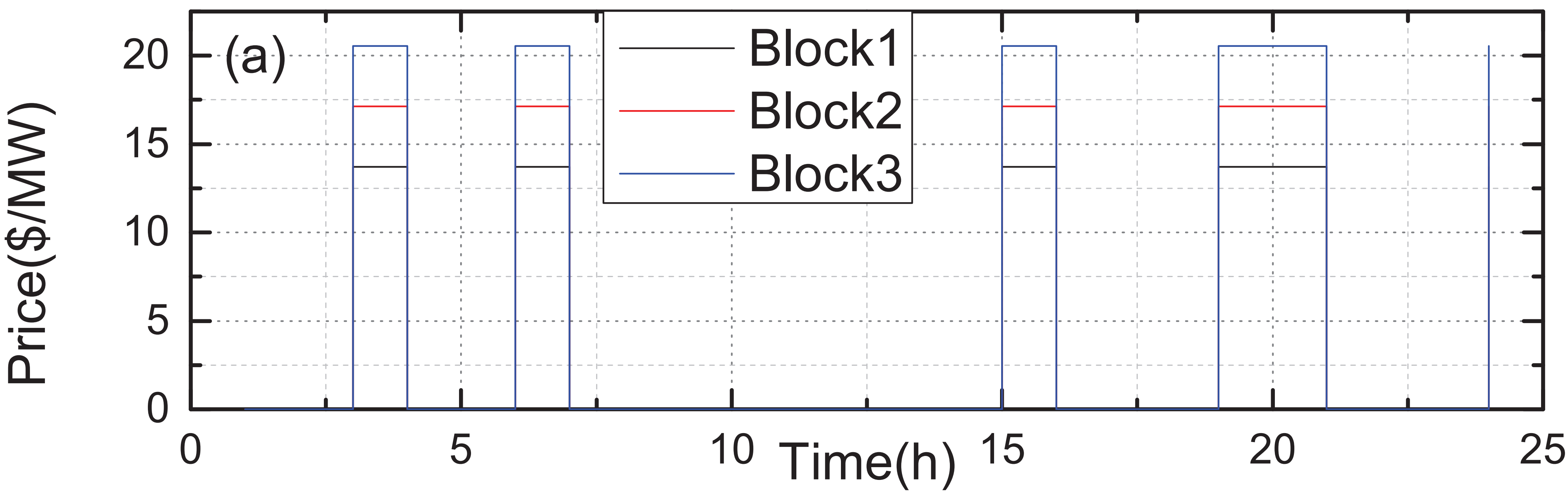
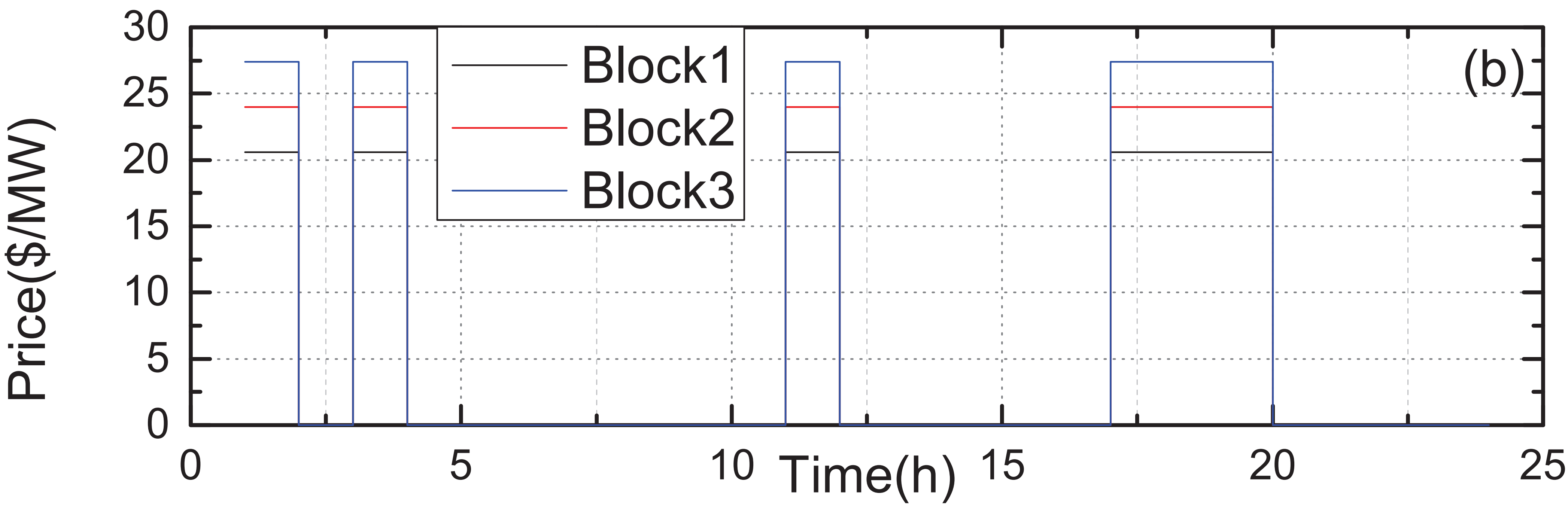


figure 11 b



30
25
20
15
10
5
0
Price($/MW)
0
5
10
15
20
25
Time(h)
Block1
Block2
Block3
(b)

figure 11 c

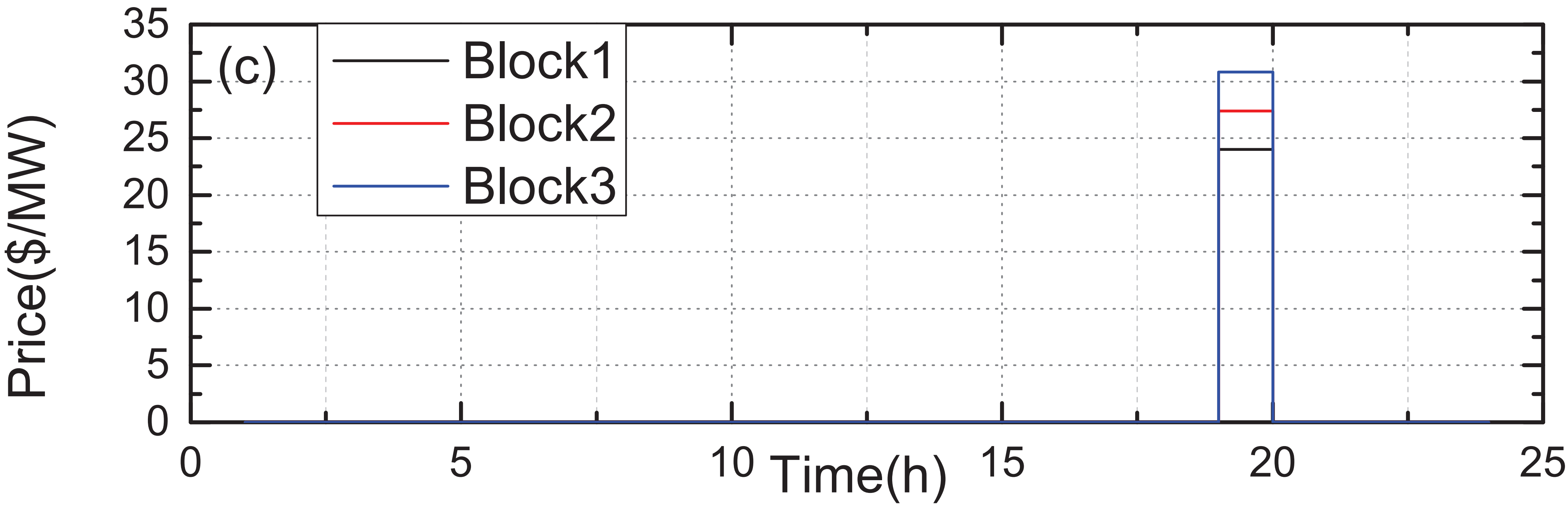
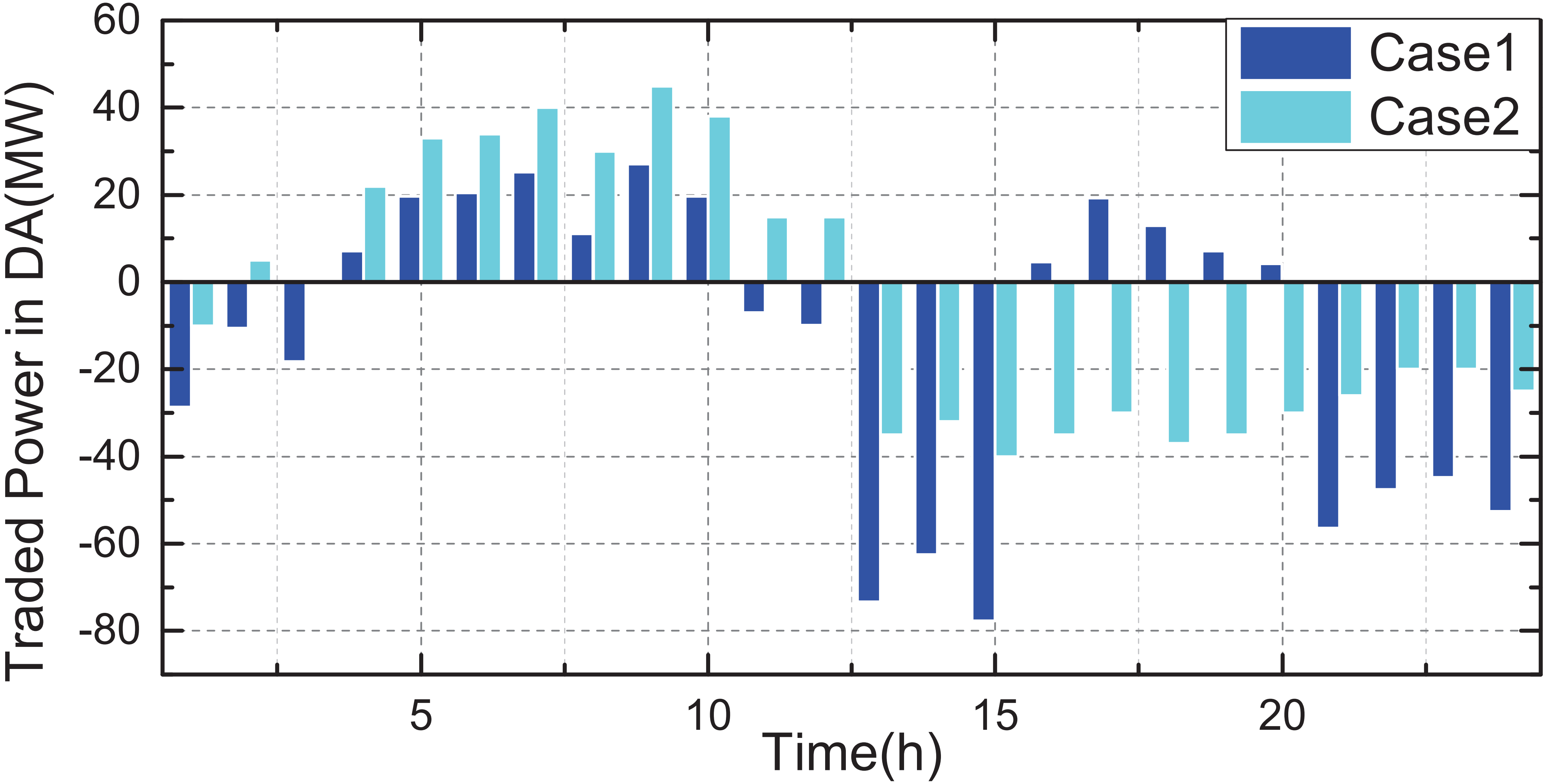
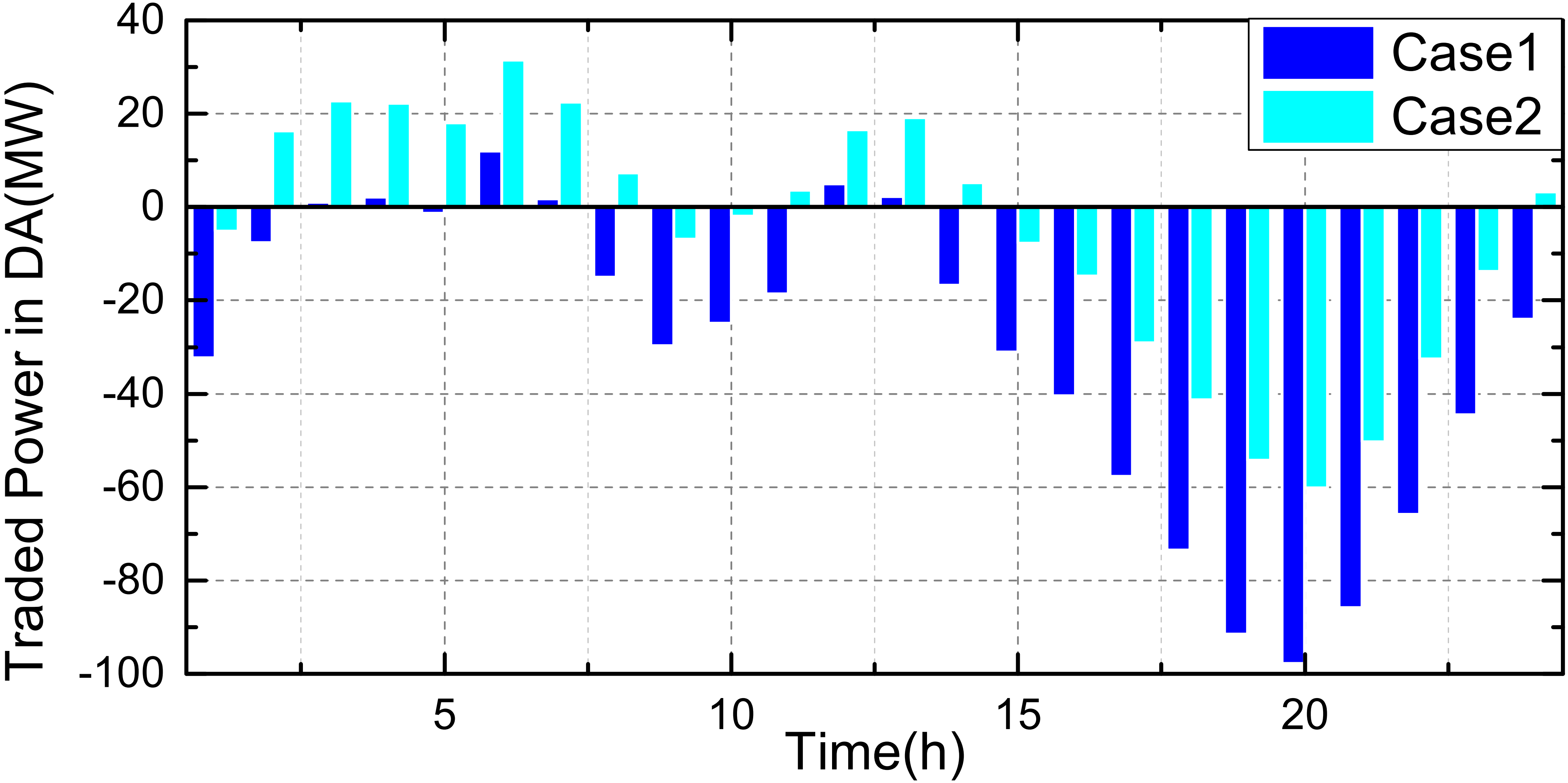

(c)
Block1
Block2
Block3
Price($/MW)
Time(h)
0
5
10
15
20
25
30
35
0
5
10
15
20
25

figure 12



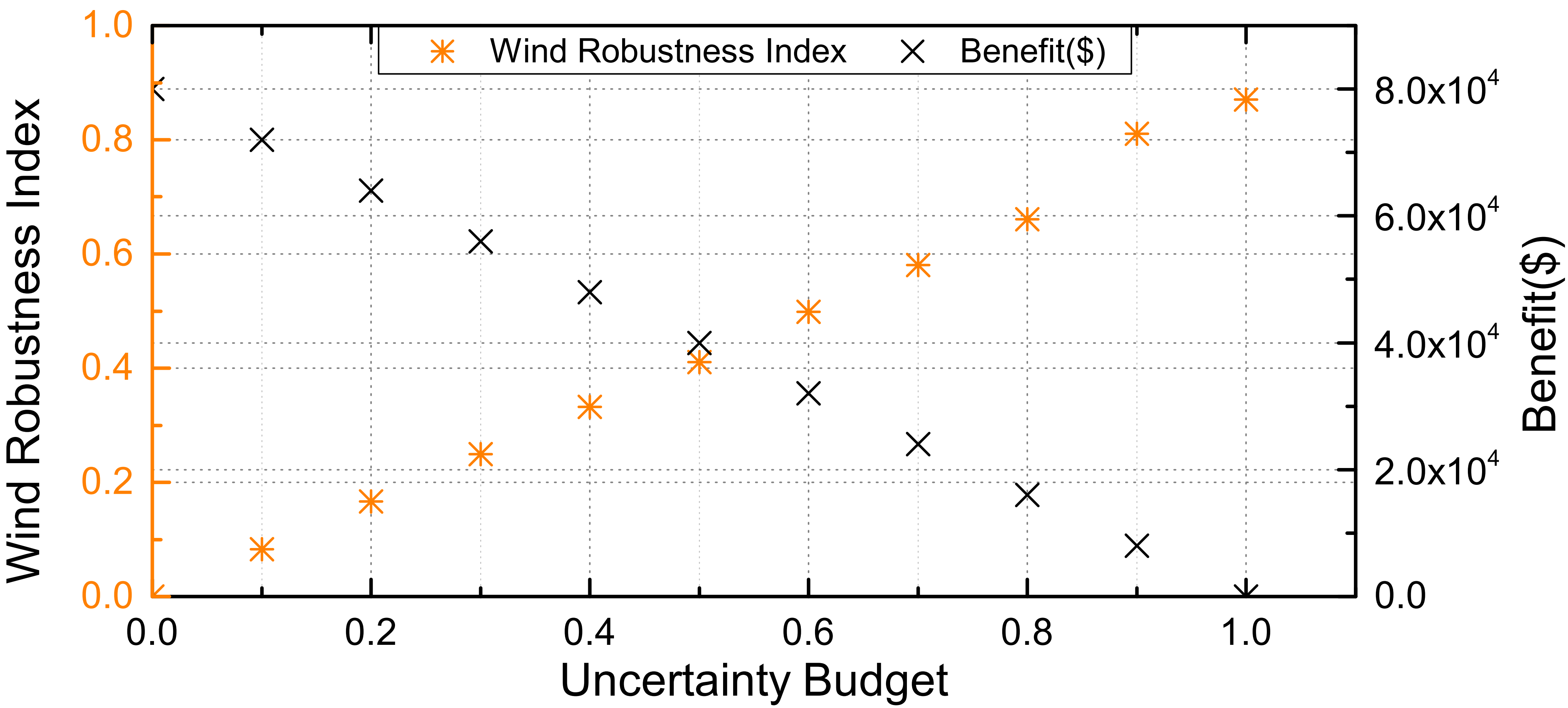
Case1
Case2
Traded Power in DA(MW)
60
40
20
0
-20
-40
-60
-80
5
10
15
20
Time(h)

figure 13



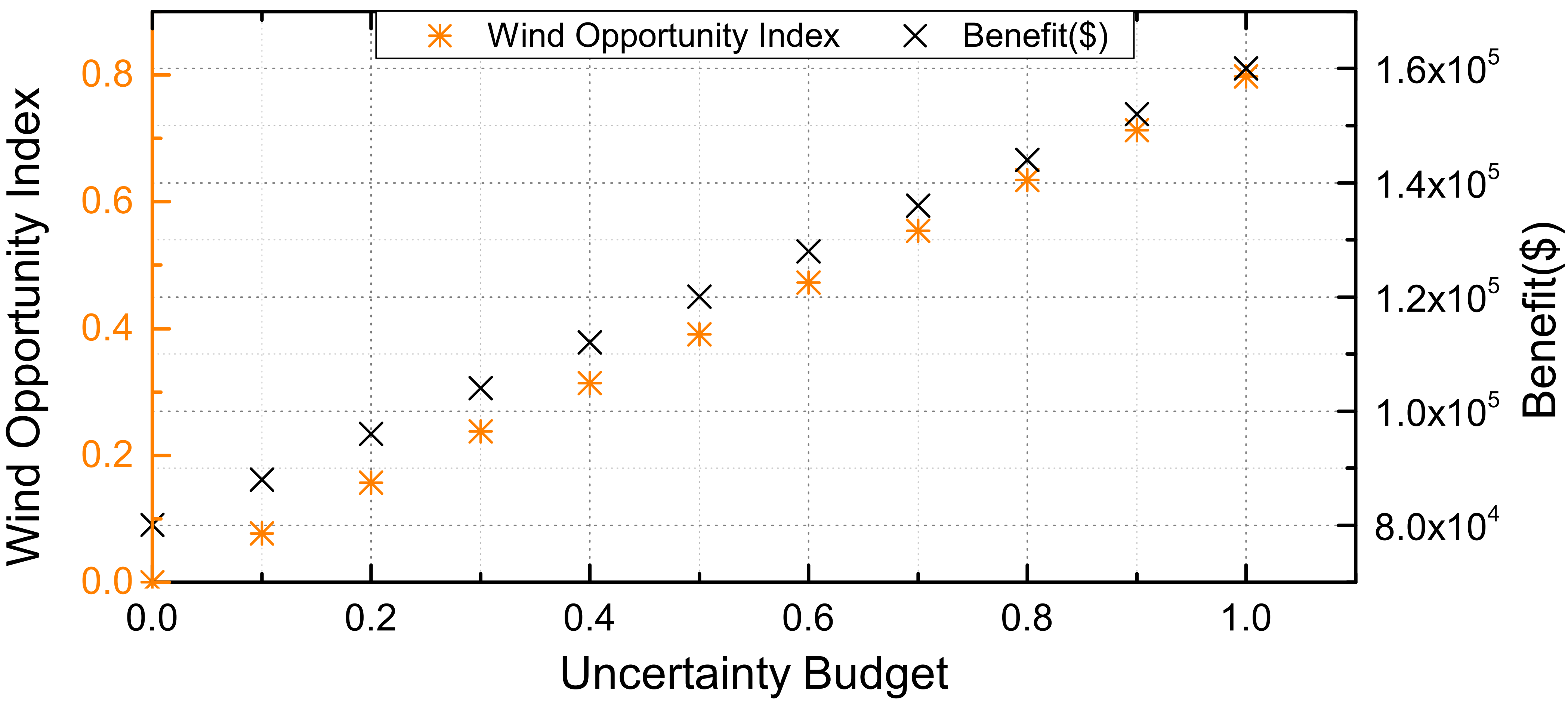
Traded Power in DA(MW)
40
20
0
-20
-40
-60
-80
-100
5
10
15
20
Time(h)
Case1
Case2

Figure 14 a



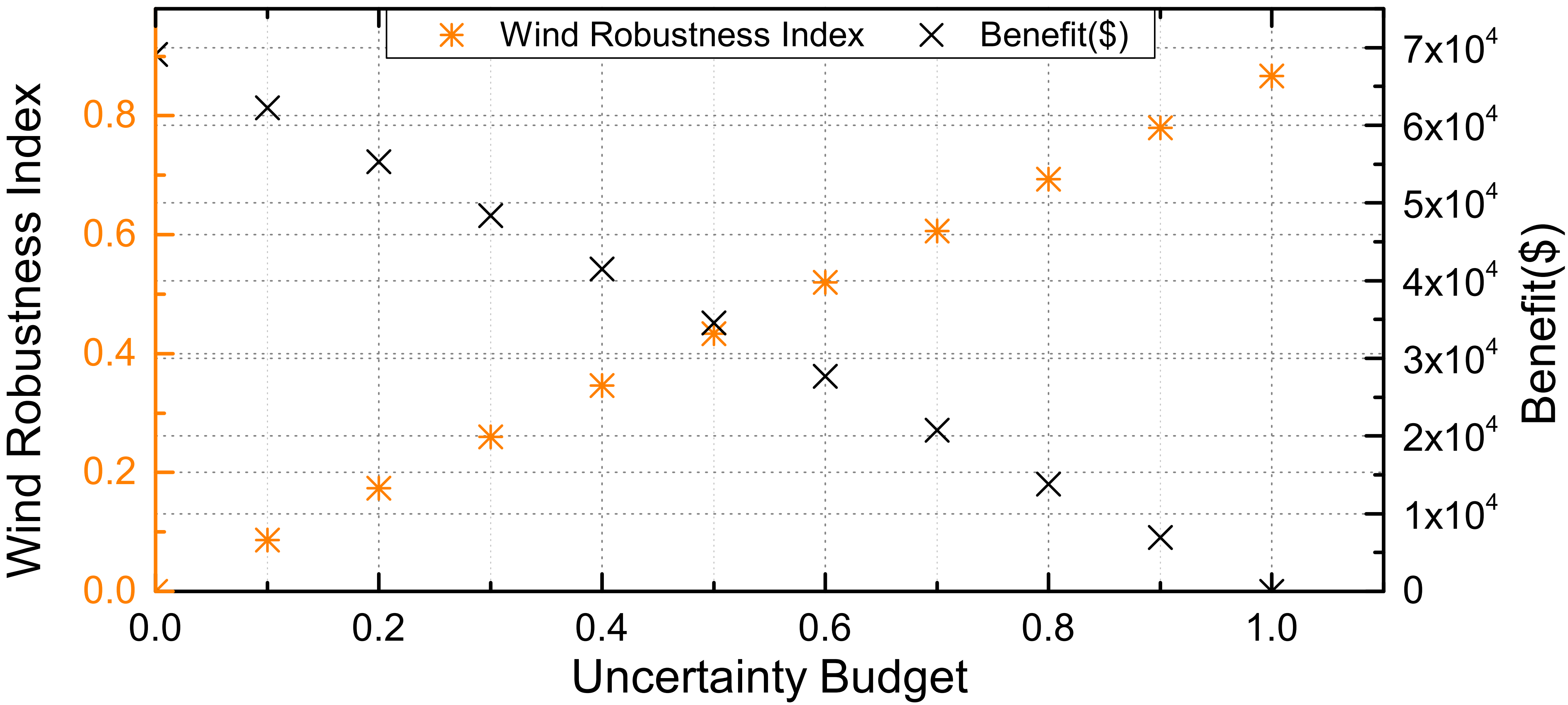
Wind Robustness Index
Benefit($)
1.0
0.8
0.6
0.4
0.2
0.0
8.0x10^4
6.0x10^4
4.0x10^4
2.0x10^4
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Uncertainty Budget
Wind Robustness Index
Benefit($)

Figure 14 b



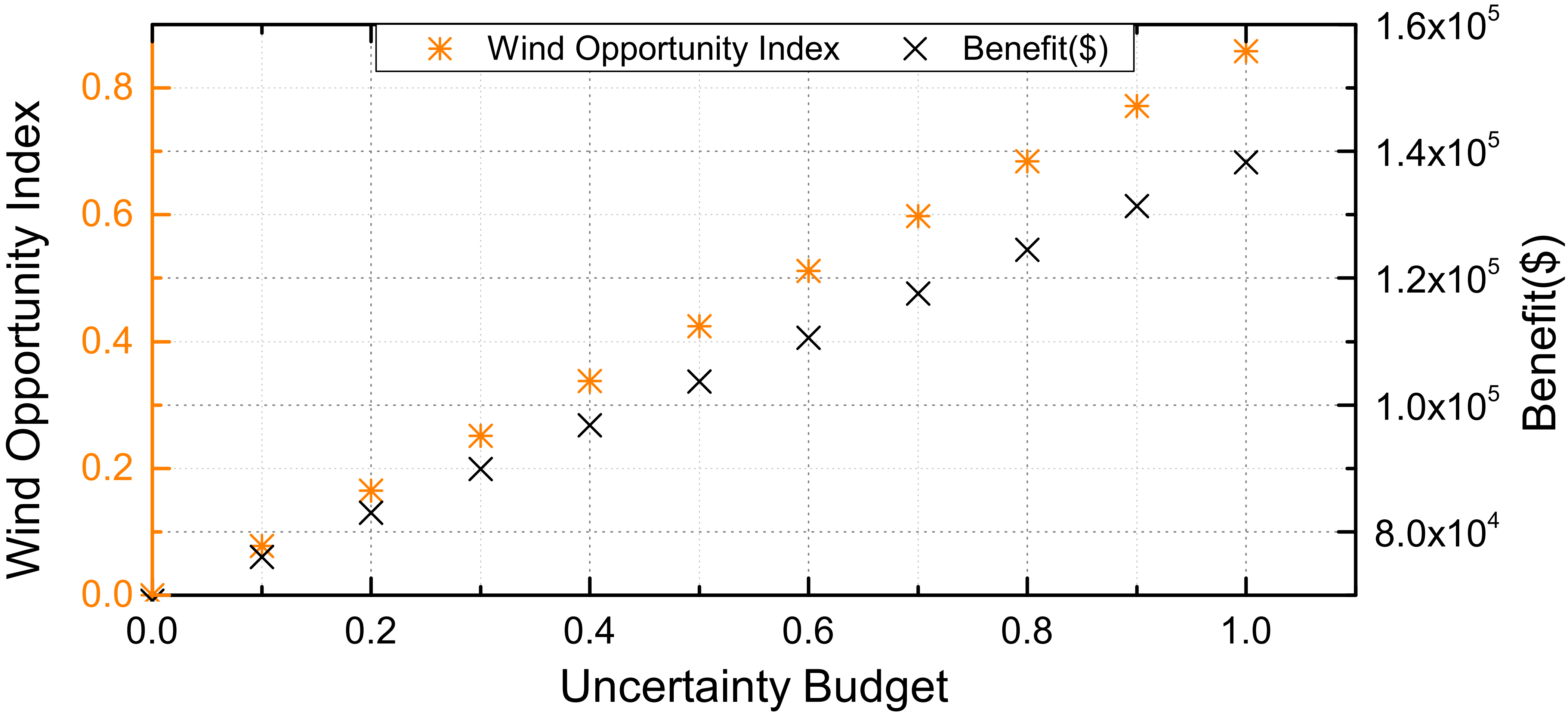
Wind Opportunity Index
Benefit($)
0.8
0.6
0.4
0.2
0.0
1.6x10^5
1.4x10^5
1.2x10^5
1.0x10^5
8.0x10^4
0.0
0.2
0.4
0.6
0.8
1.0
Uncertainty Budget
Wind Opportunity Index
Benefit($)

figure 15 a



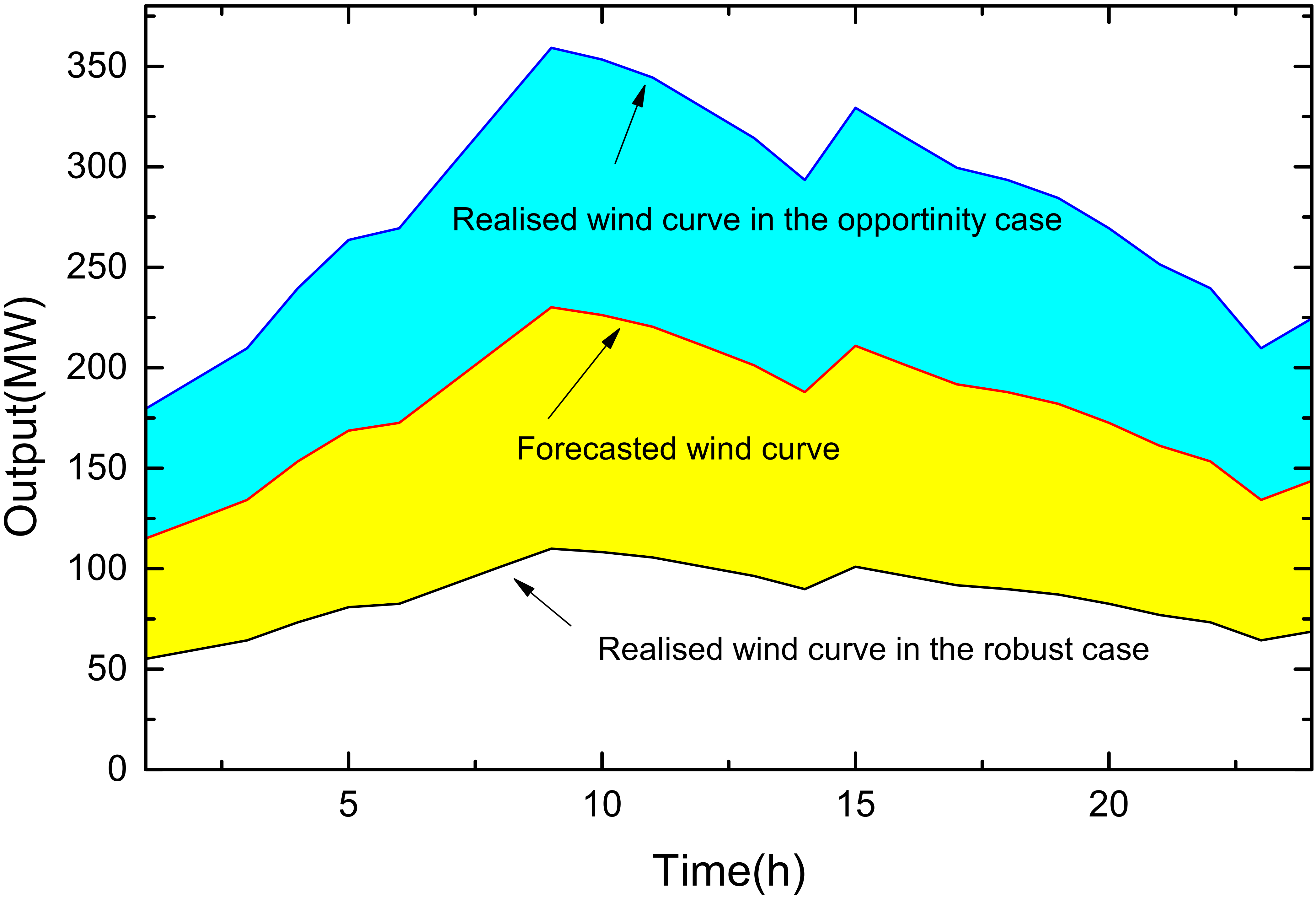
Wind Robustness Index
Benefit($)
0.0
0.2
0.4
0.6
0.8
0
1x10^4
2x10^4
3x10^4
4x10^4
5x10^4
6x10^4
7x10^4
0.0
0.2
0.4
0.6
0.8
1.0
Uncertainty Budget
Wind Robustness Index
Benefit($)

figure 15 b



Wind Opportunity Index
Benefit($)
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
Wind Opportunity Index
Uncertainty Budget
8.0x10^4
1.0x10^5
1.2x10^5
1.4x10^5
1.6x10^5
Benefit($)

figure 16



Output(MW)
Time(h)
0
50
100
150
200
250
300
350
5
10
15
20
Realised wind curve in the opportinity case
Forecasted wind curve
Realised wind curve in the robust case

figure 17 a

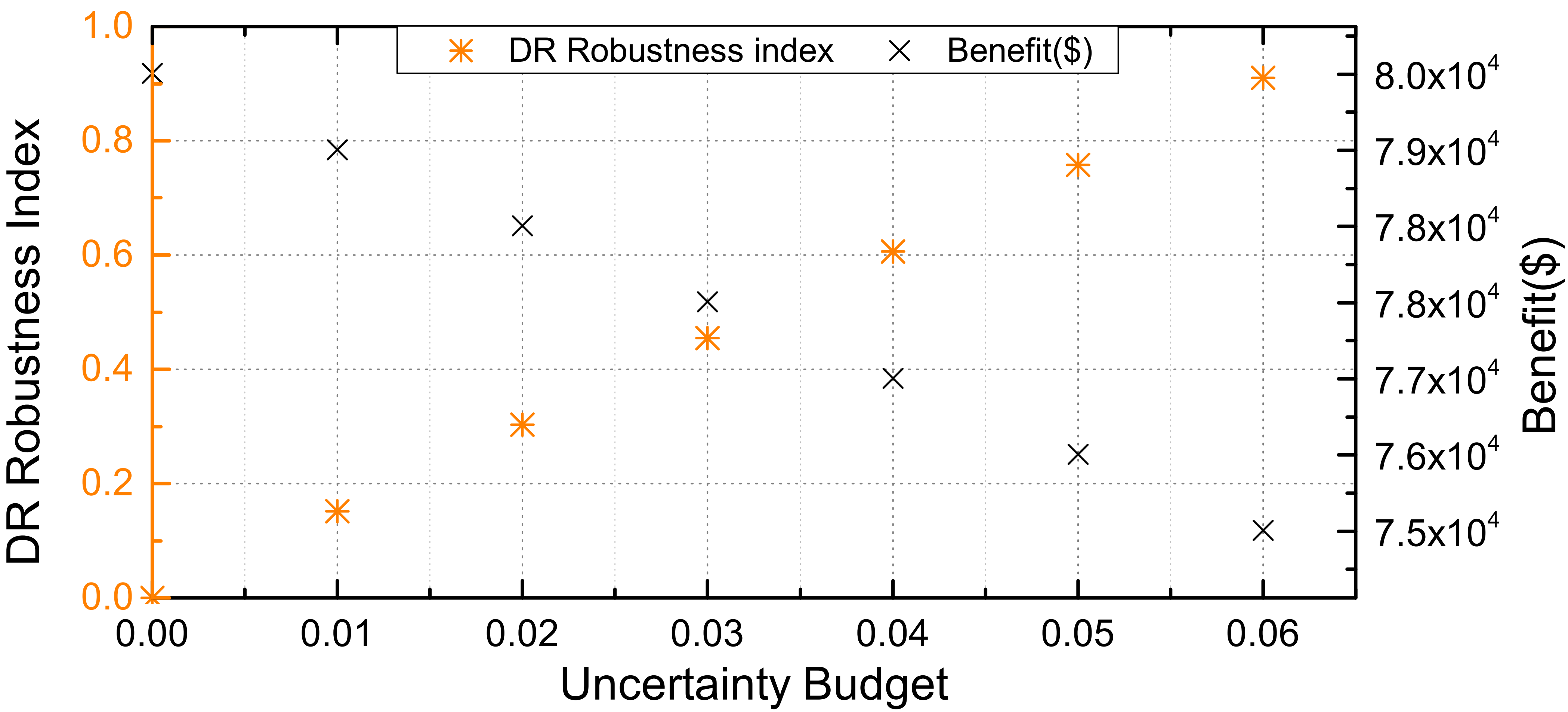
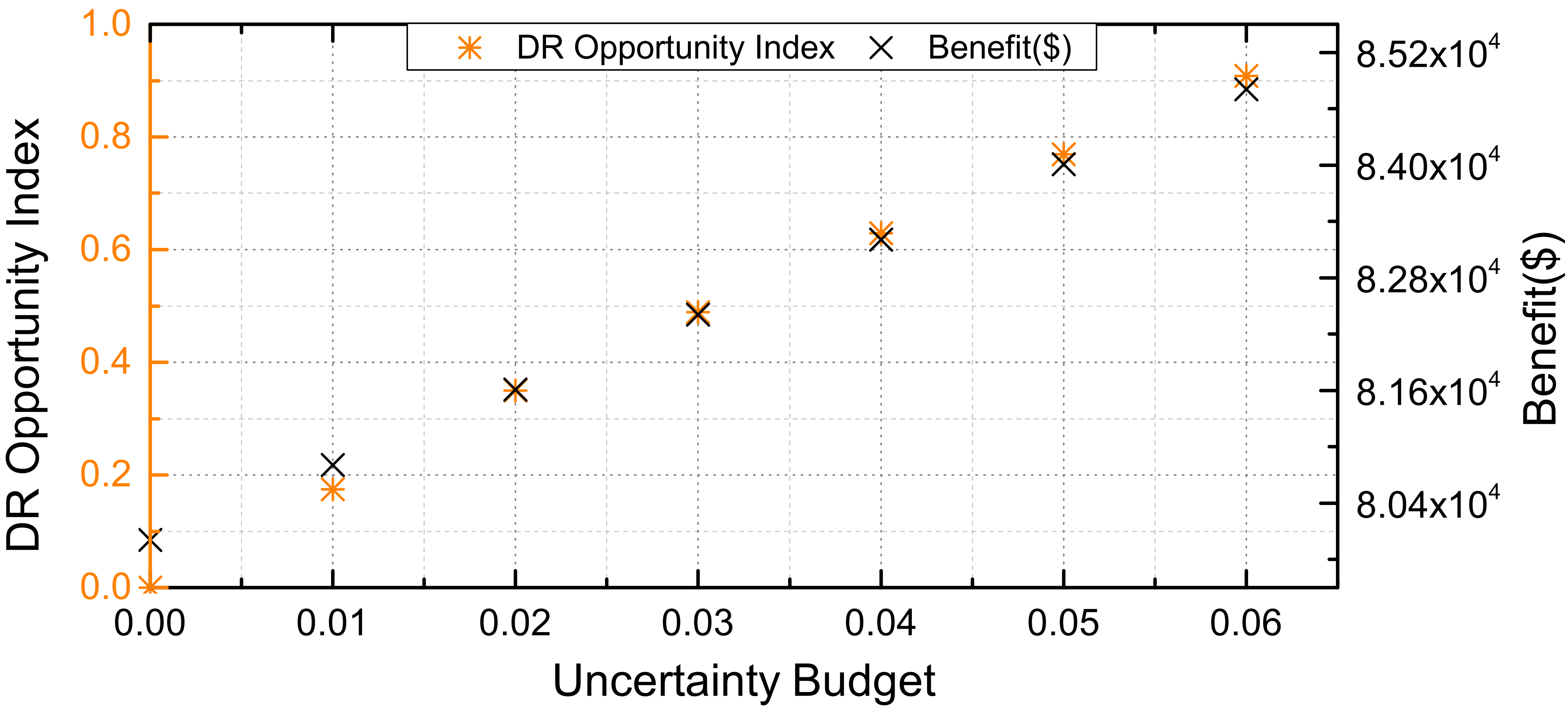
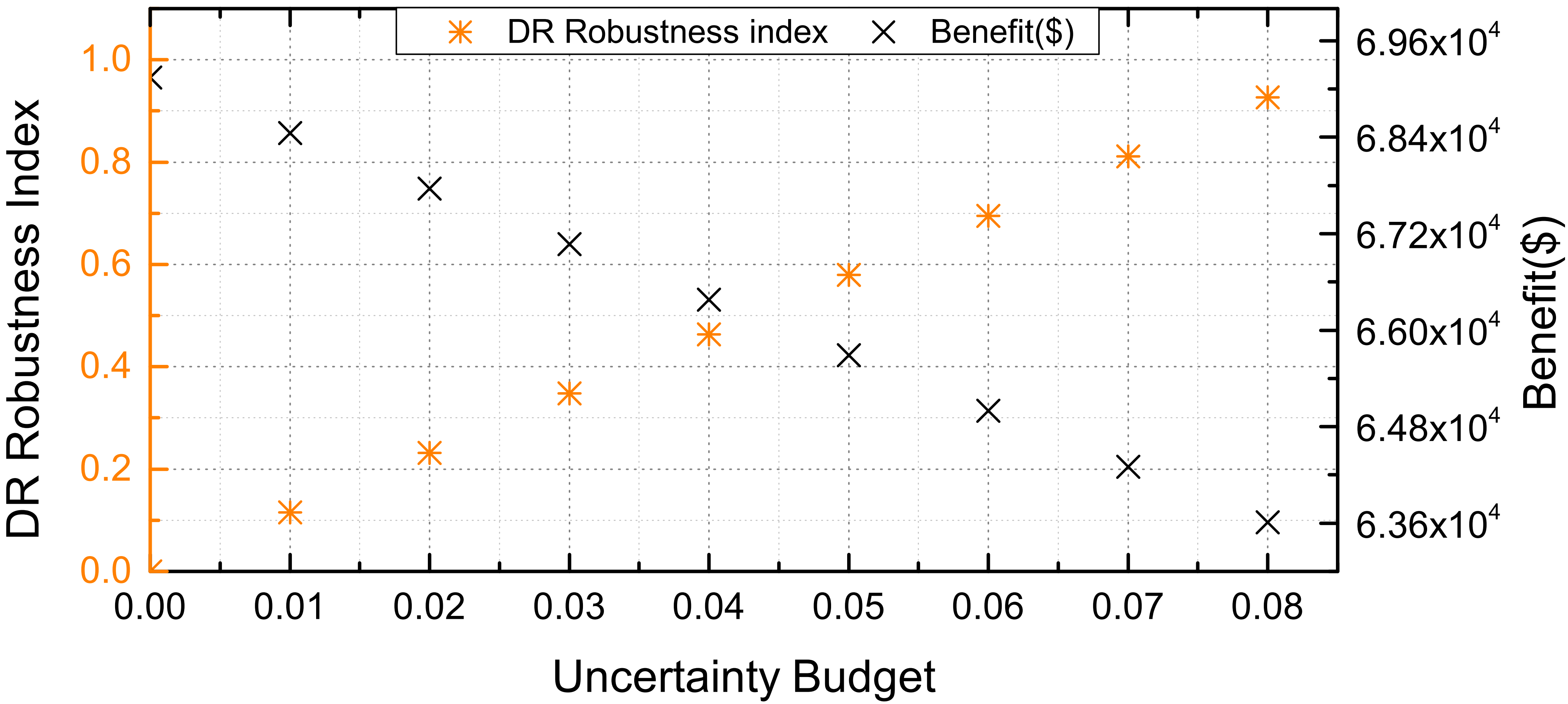

DR Robustness index
Benefit($)
1.0
0.8
0.6
0.4
0.2
0.0
DR Robustness Index
8.0x10^4
7.9x10^4
7.8x10^4
7.8x10^4
7.7x10^4
7.6x10^4
7.5x10^4
Benefit($)
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Uncertainty Budget

figure 17 b



DR Opportunity Index
Benefit($)
1.0
0.8
0.6
0.4
0.2
0.0
8.52x10^4
8.40x10^4
8.28x10^4
8.16x10^4
8.04x10^4
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Uncertainty Budget
DR Opportunity Index
Benefit($)

figure 18 a



DR Robustness index
Benefit($)
1.0
0.8
0.6
0.4
0.2
0.0
DR Robustness Index
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
Uncertainty Budget
6.96x10^4
6.84x10^4
6.72x10^4
6.60x10^4
6.48x10^4
6.36x10^4
Benefit($)

figure 18 b

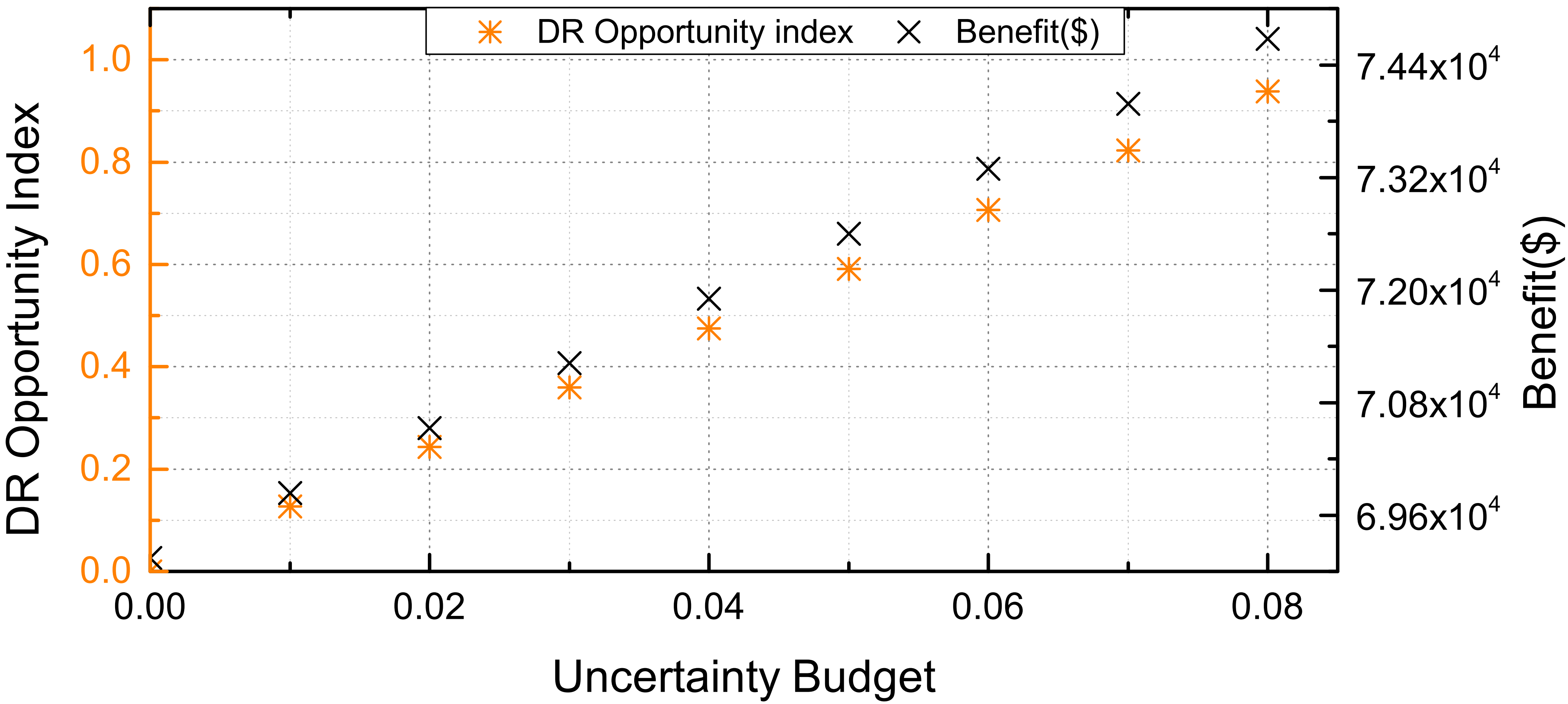

DR Opportunity index
Benefit($)
1.0
0.8
0.6
0.4
0.2
0.0
DR Opportunity Index
7.44x10^4
7.32x10^4
7.20x10^4
7.08x10^4
6.96x10^4
Benefit($)
0.00
0.02
0.04
0.06
0.08
Uncertainty Budget

figure 19 a

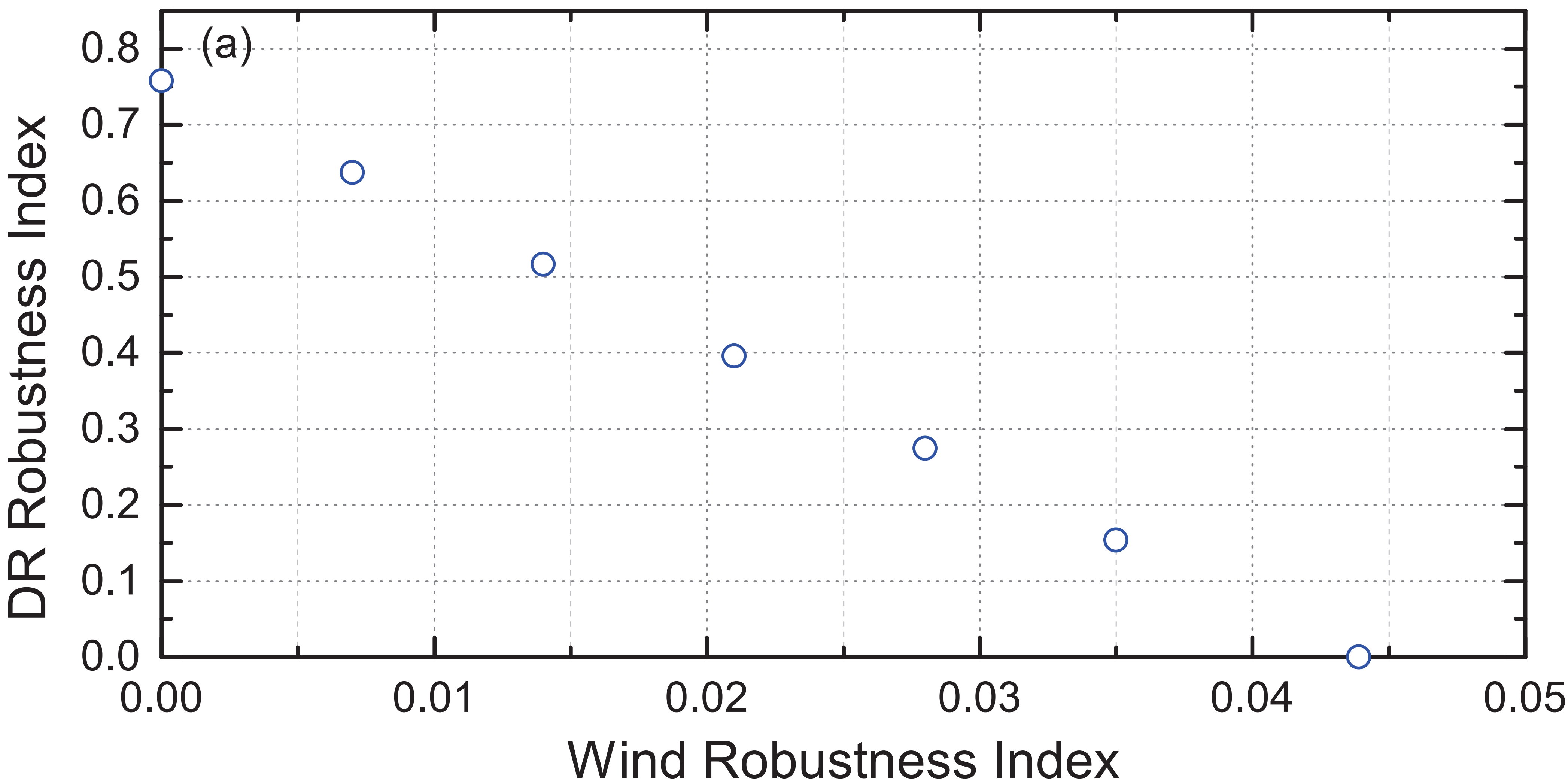

(a)
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
DR Robustness Index
0.00
0.01
0.02
0.03
0.04
0.05
Wind Robustness Index

figure 19 b

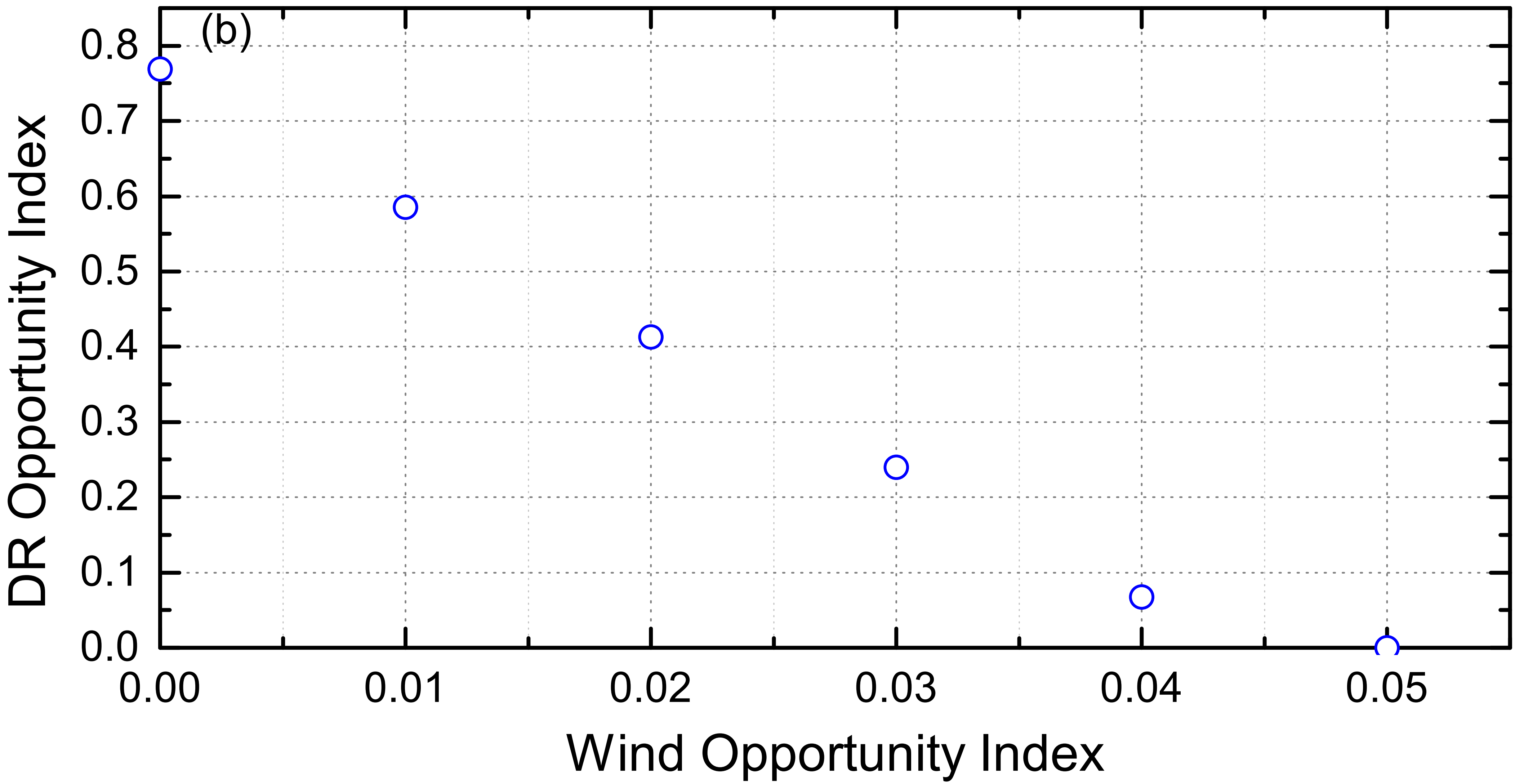

(b)
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
DR Opportunity Index
0.00
0.01
0.02
0.03
0.04
0.05
Wind Opportunity Index

figure 20 a

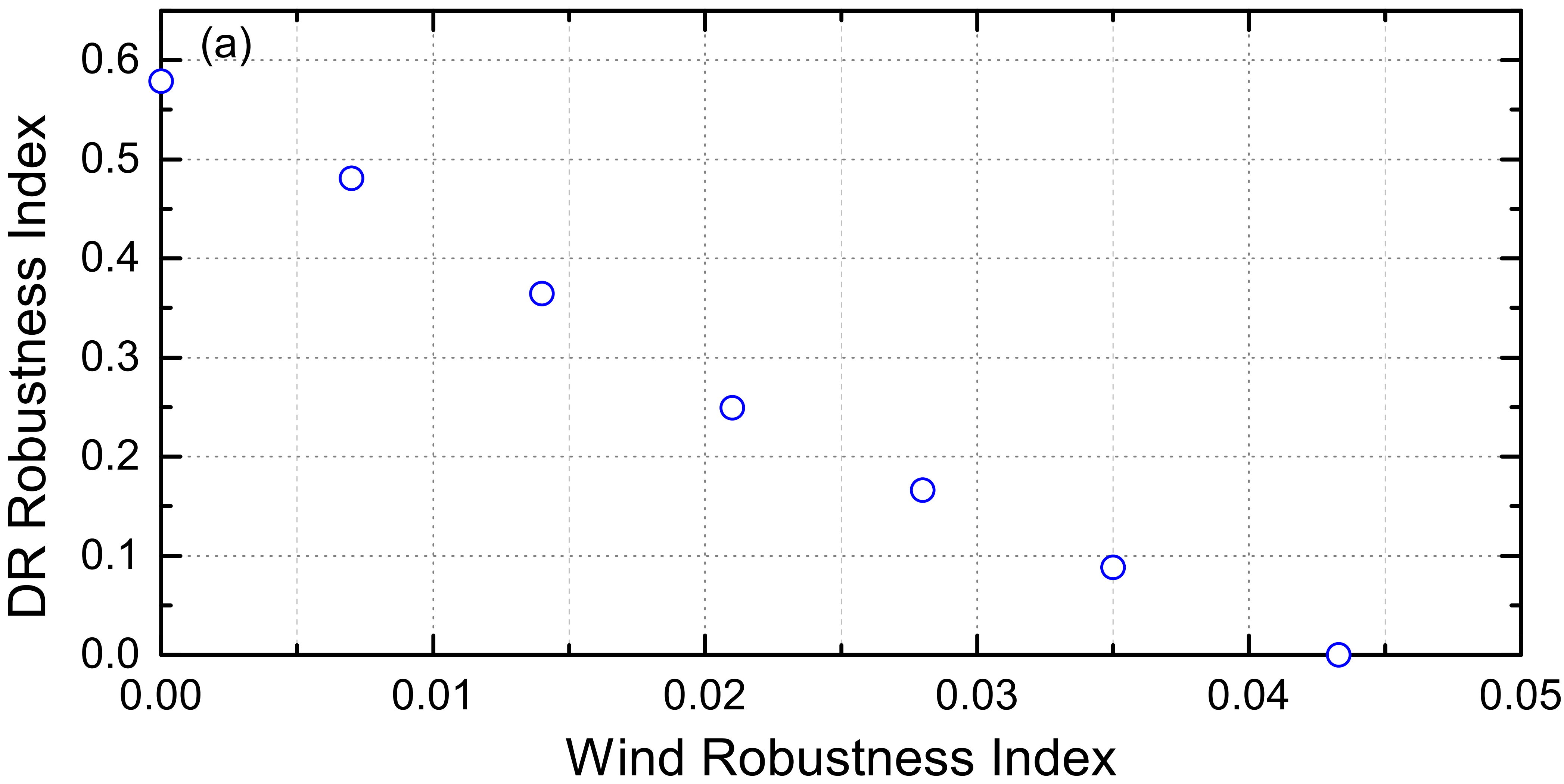

(a)
DR Robustness Index
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Wind Robustness Index
0.00
0.01
0.02
0.03
0.04
0.05

figure 20 b

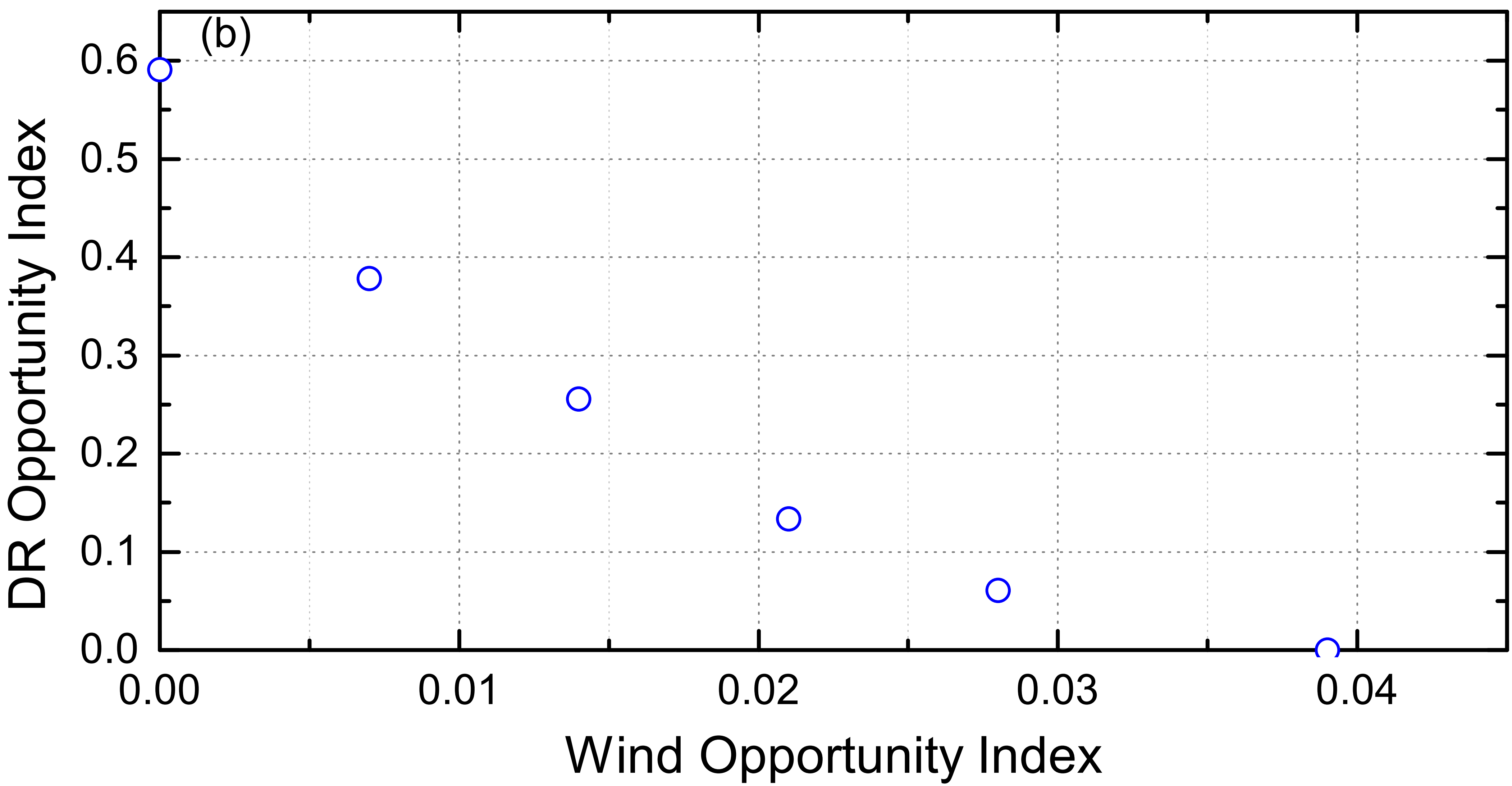

(b)
0.6
0.5
0.4
0.3
0.2
0.1
0.0
DR Opportunity Index
0.00
0.01
0.02
0.03
0.04
Wind Opportunity Index

figure 21 a

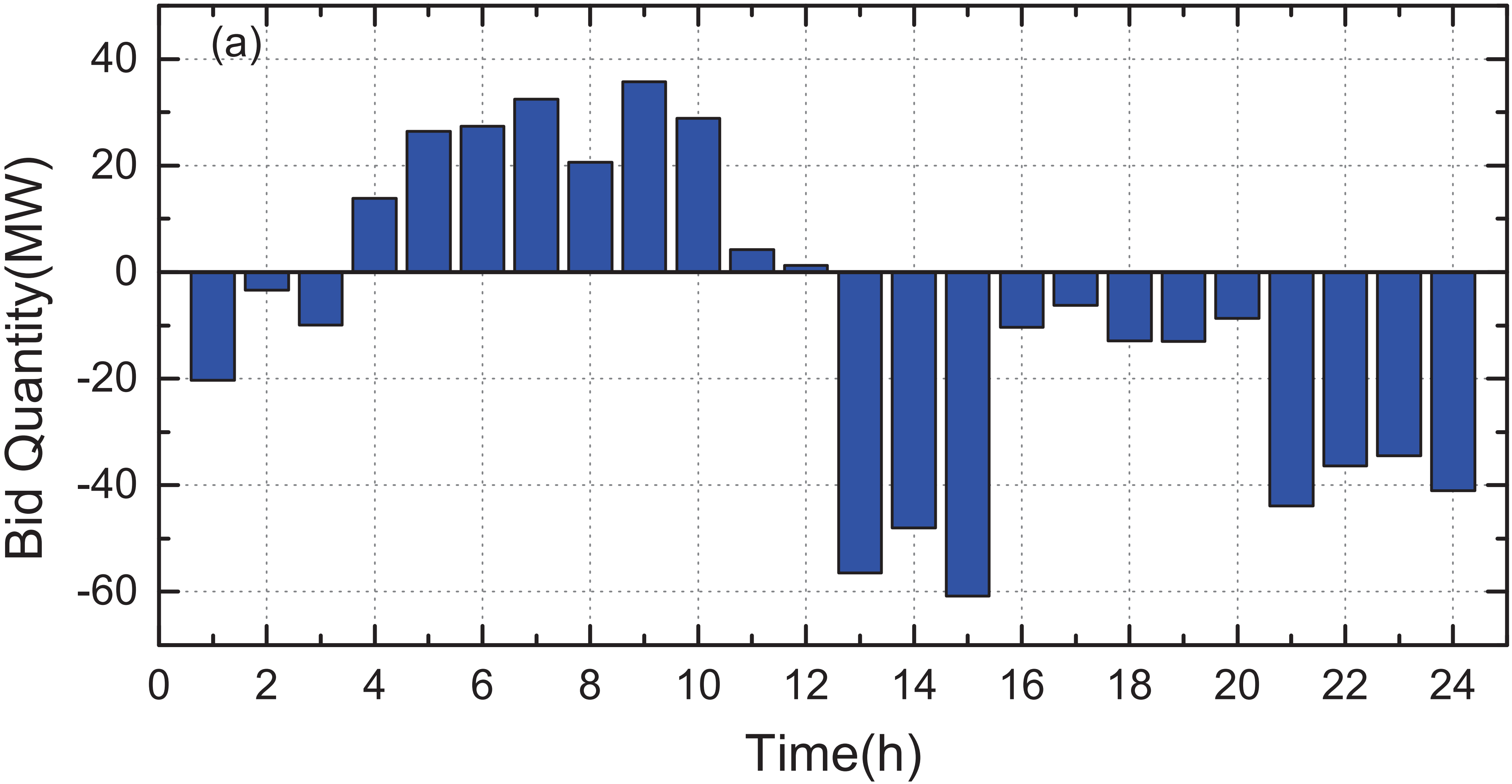
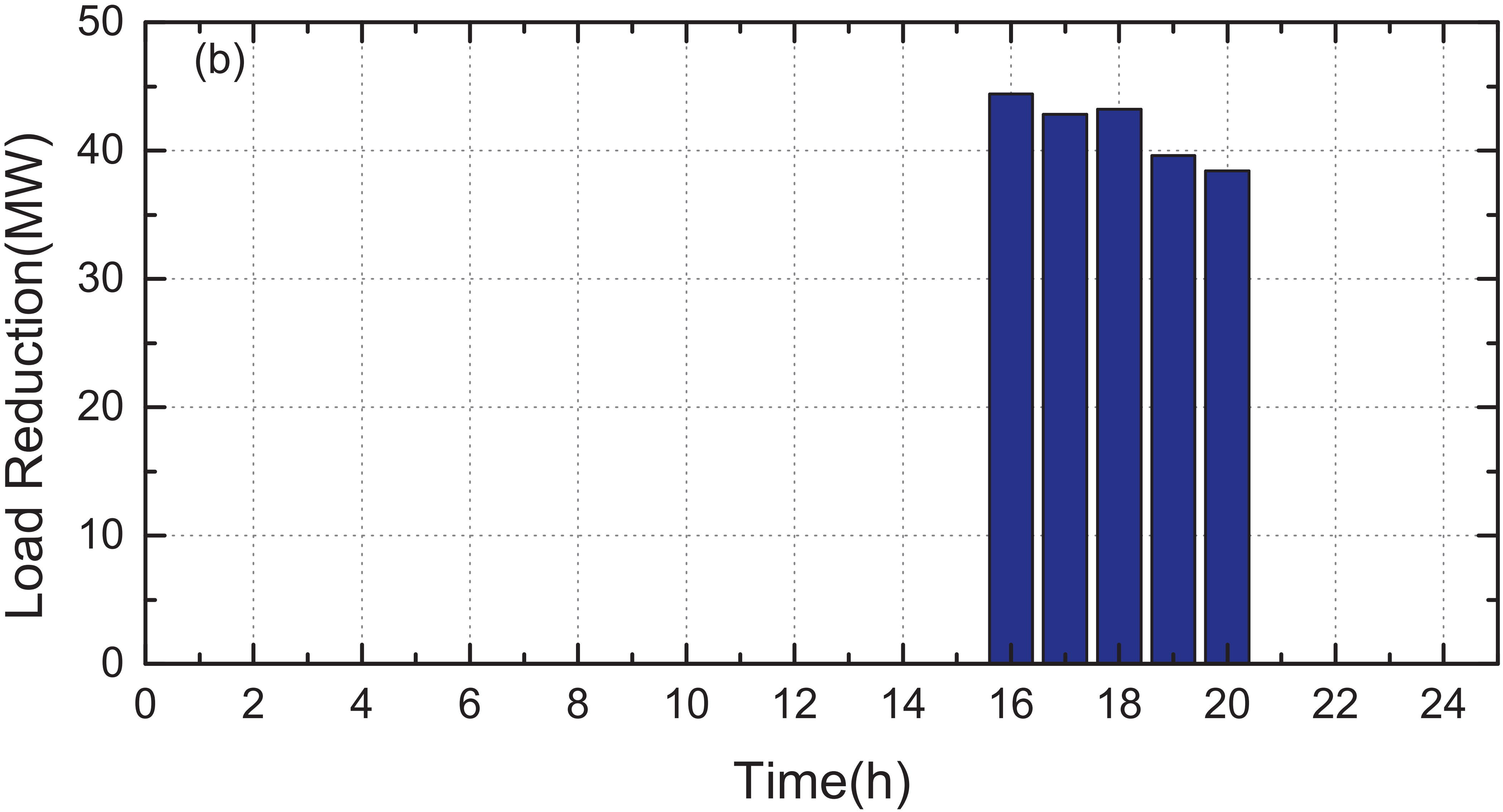
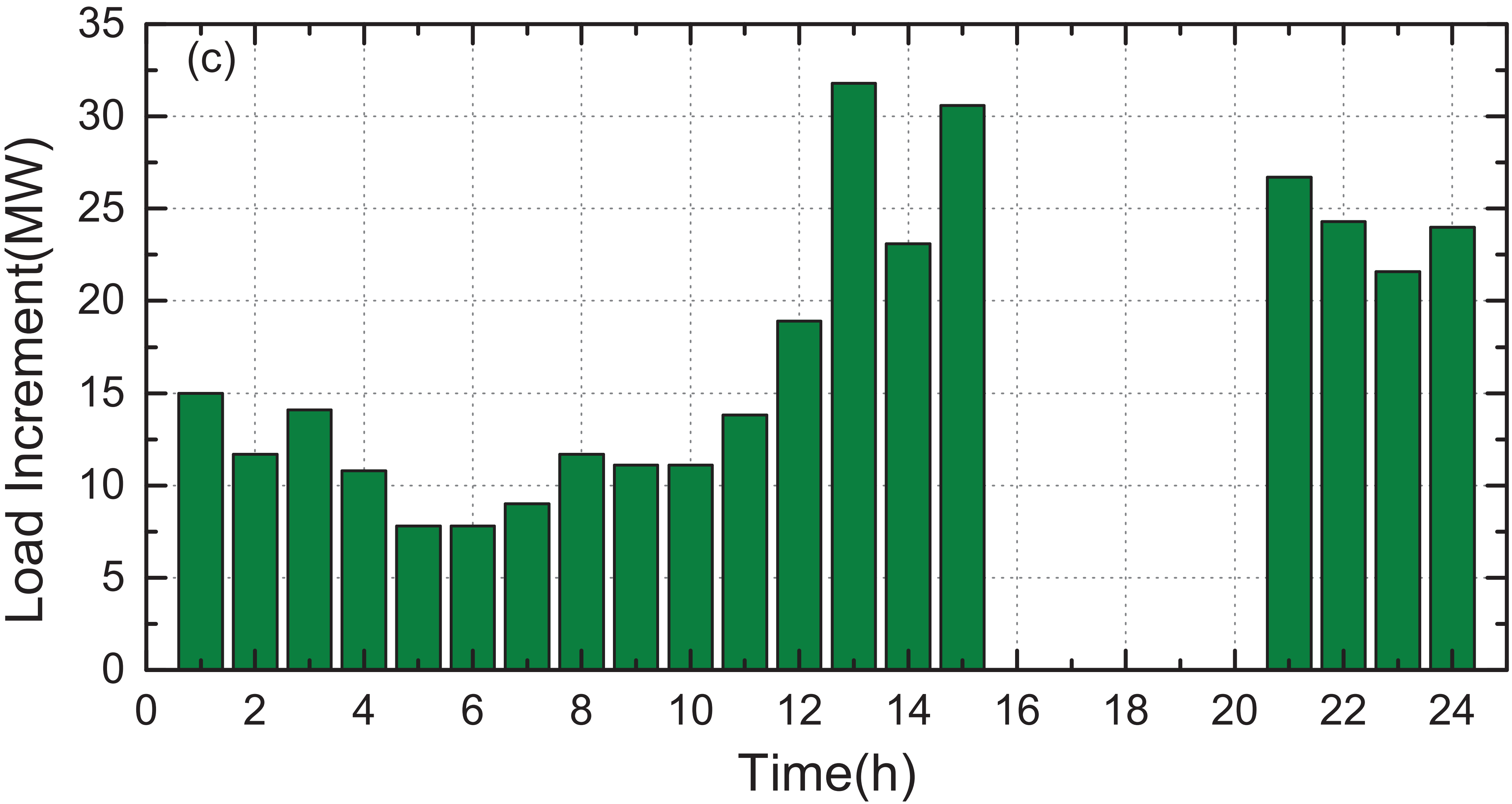

(a)
40
20
0
-20
-40
-60
Bid Quantity(MW)
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 21 b



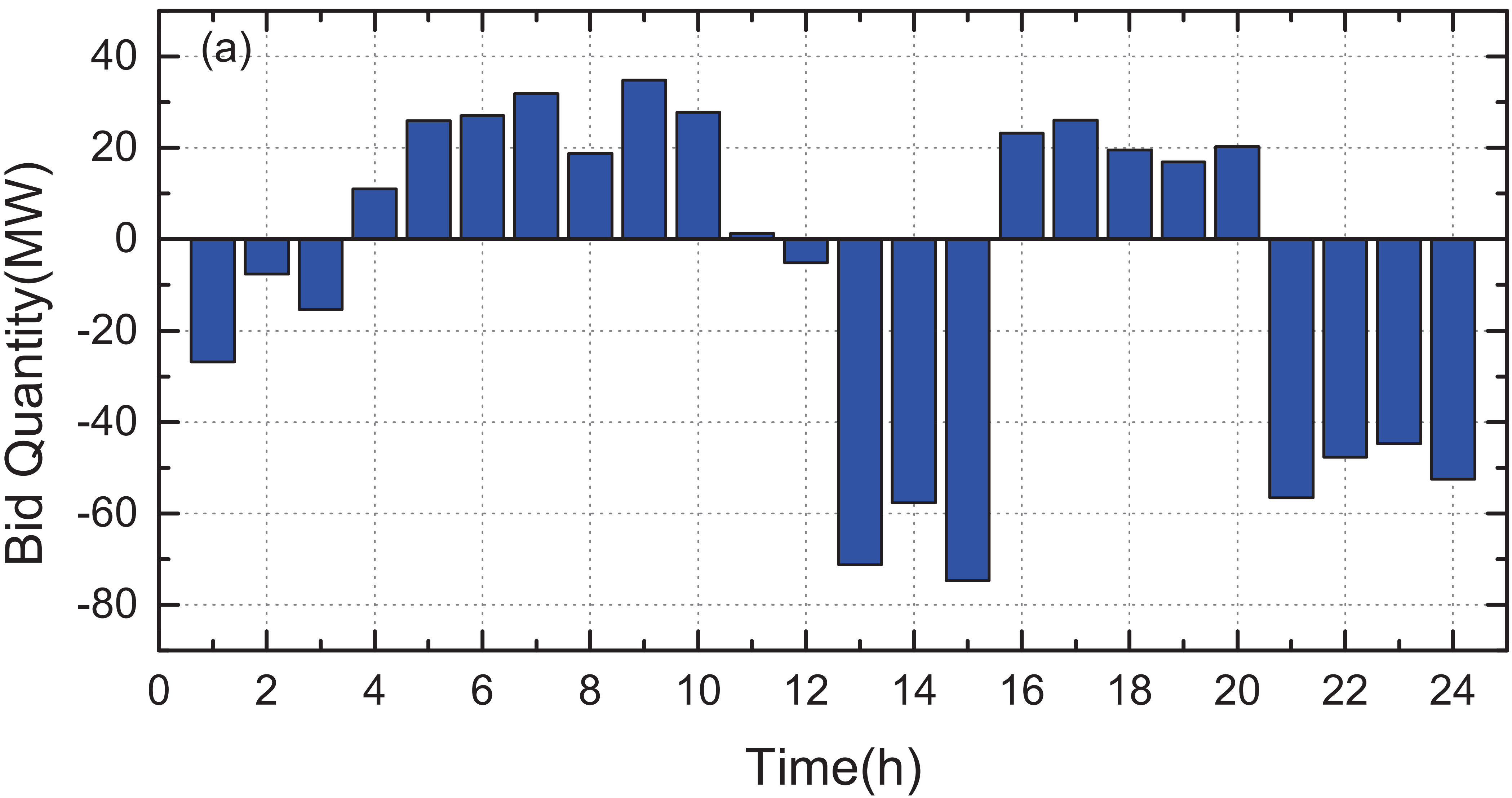
(b)
Load Reduction(MW)
50
40
30
20
10
0
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 21 c



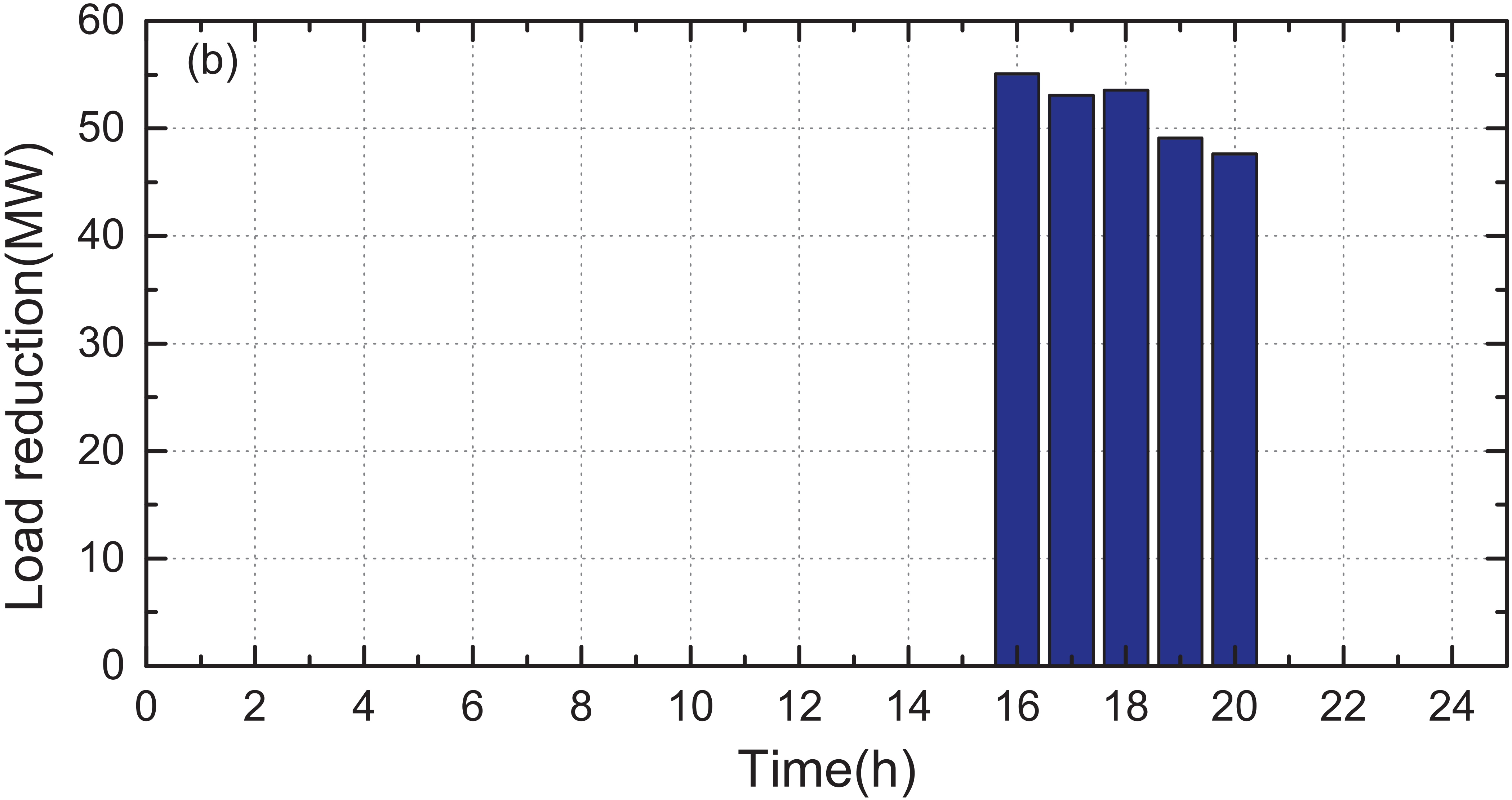
(c)
Load Increment(MW)
Time(h)
0
5
10
15
20
25
30
35
0
2
4
6
8
10
12
14
16
18
20
22
24

figure 22 a



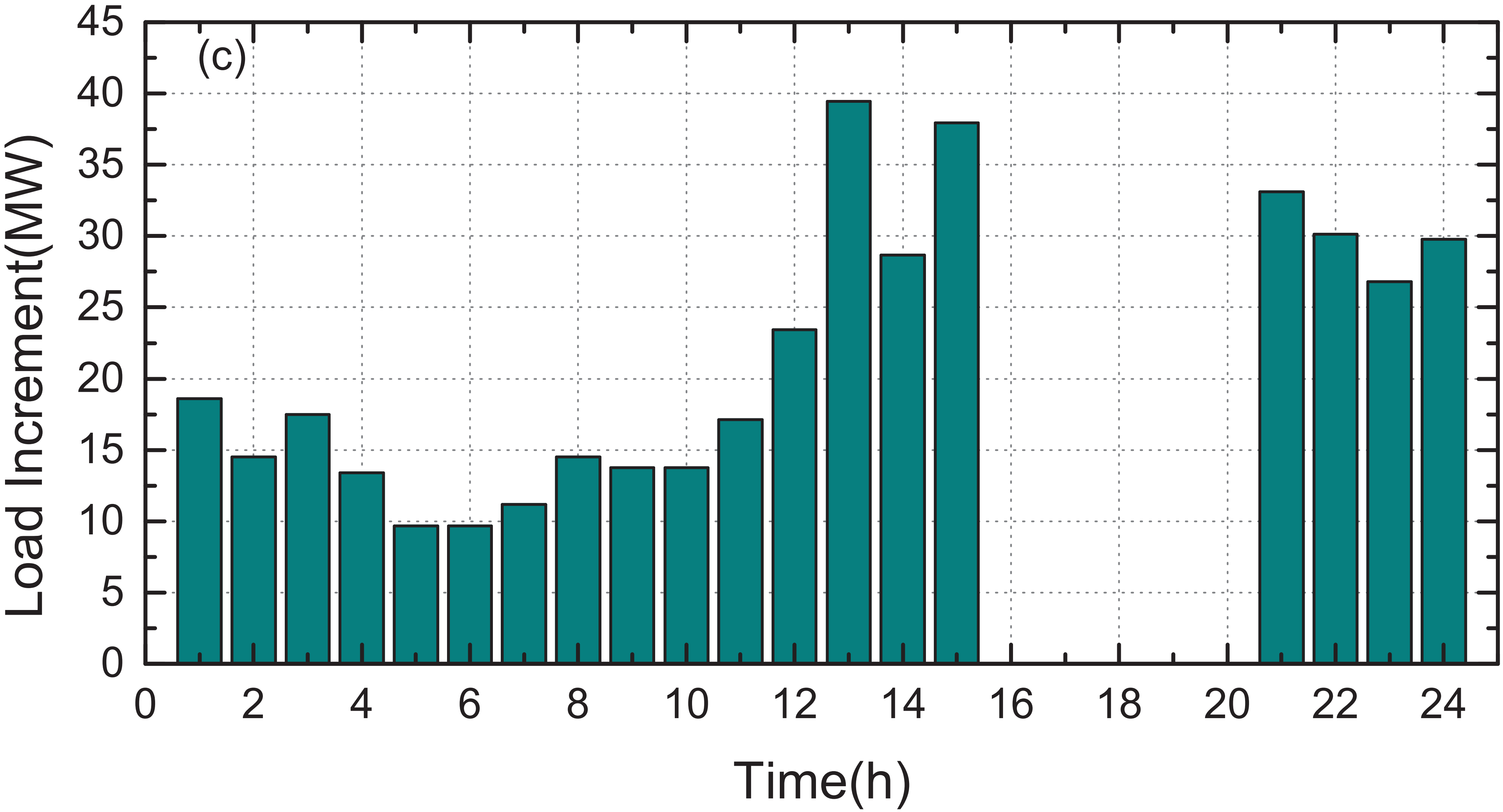
(a)
Bid Quantity(MW)
40
20
0
-20
-40
-60
-80
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 22 b



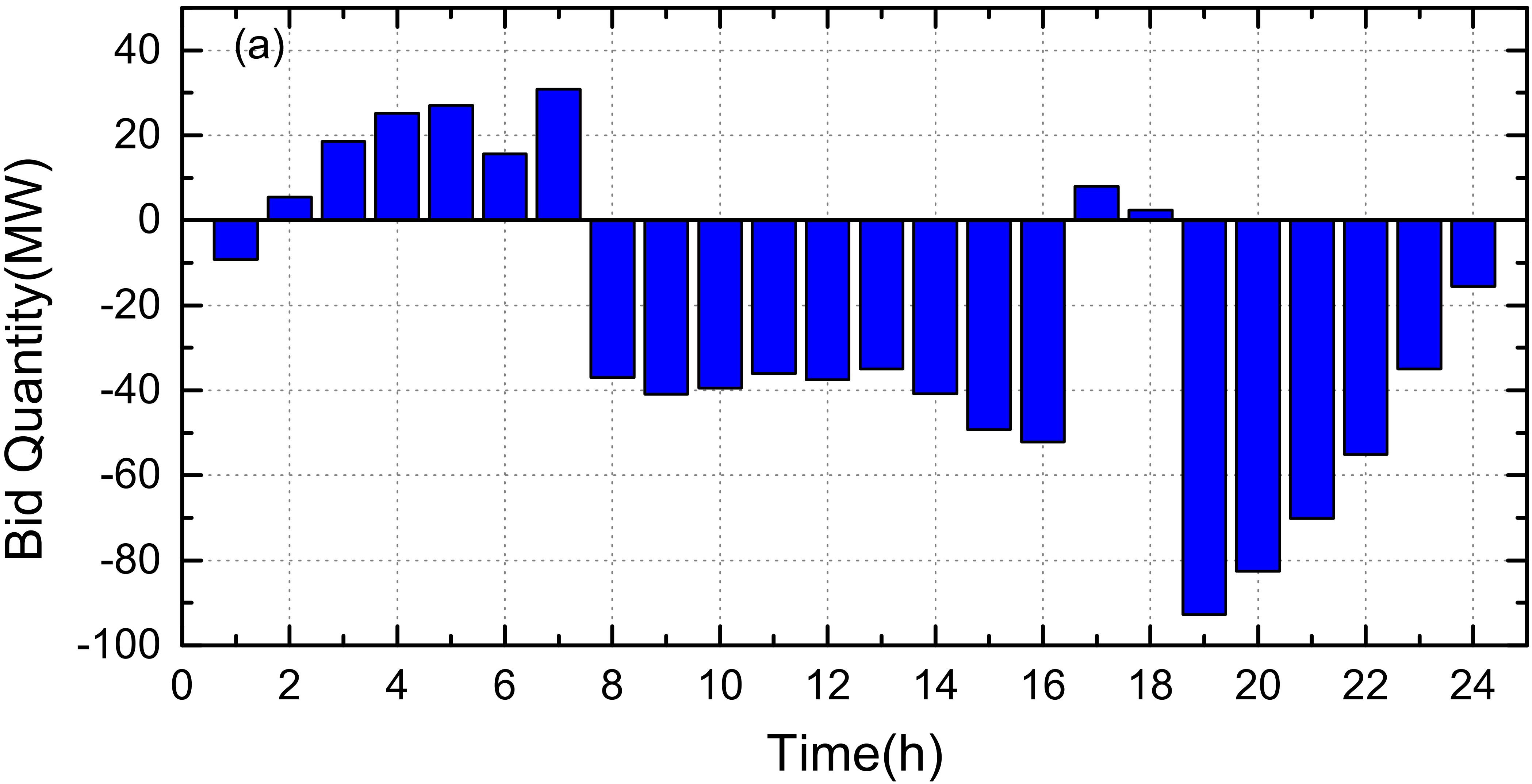
(b)
Load reduction(MW)
0
10
20
30
40
50
60
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 22 c



(c)
Load Increment(MW)
Time(h)
0
5
10
15
20
25
30
35
40
45
0
2
4
6
8
10
12
14
16
18
20
22
24

figure 23 a



(a)
40
20
0
-20
-40
-60
-80
-100
Bid Quantity(MW)
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 23 b

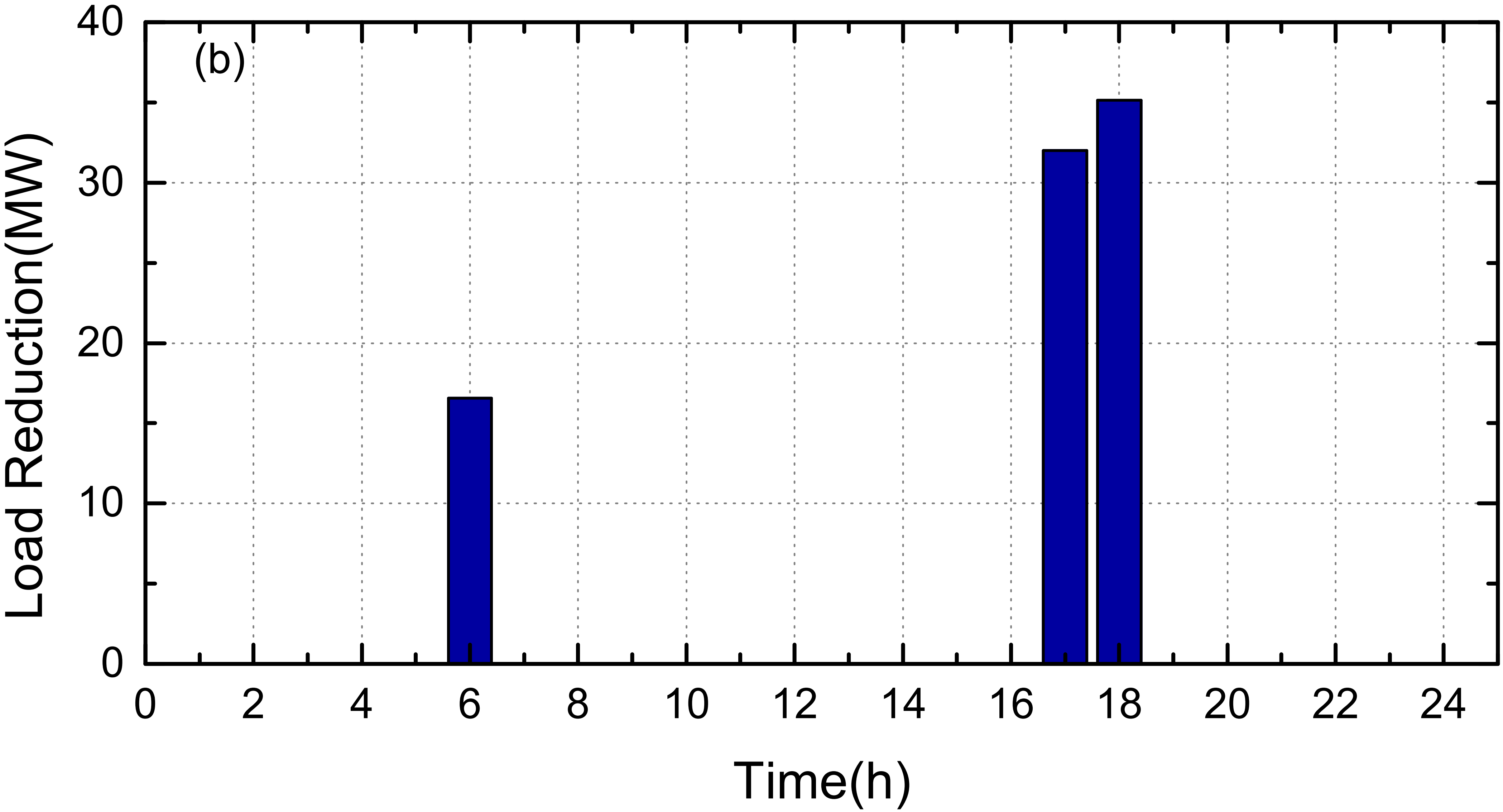

(b)
Load Reduction(MW)
0
10
20
30
40
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 23 c

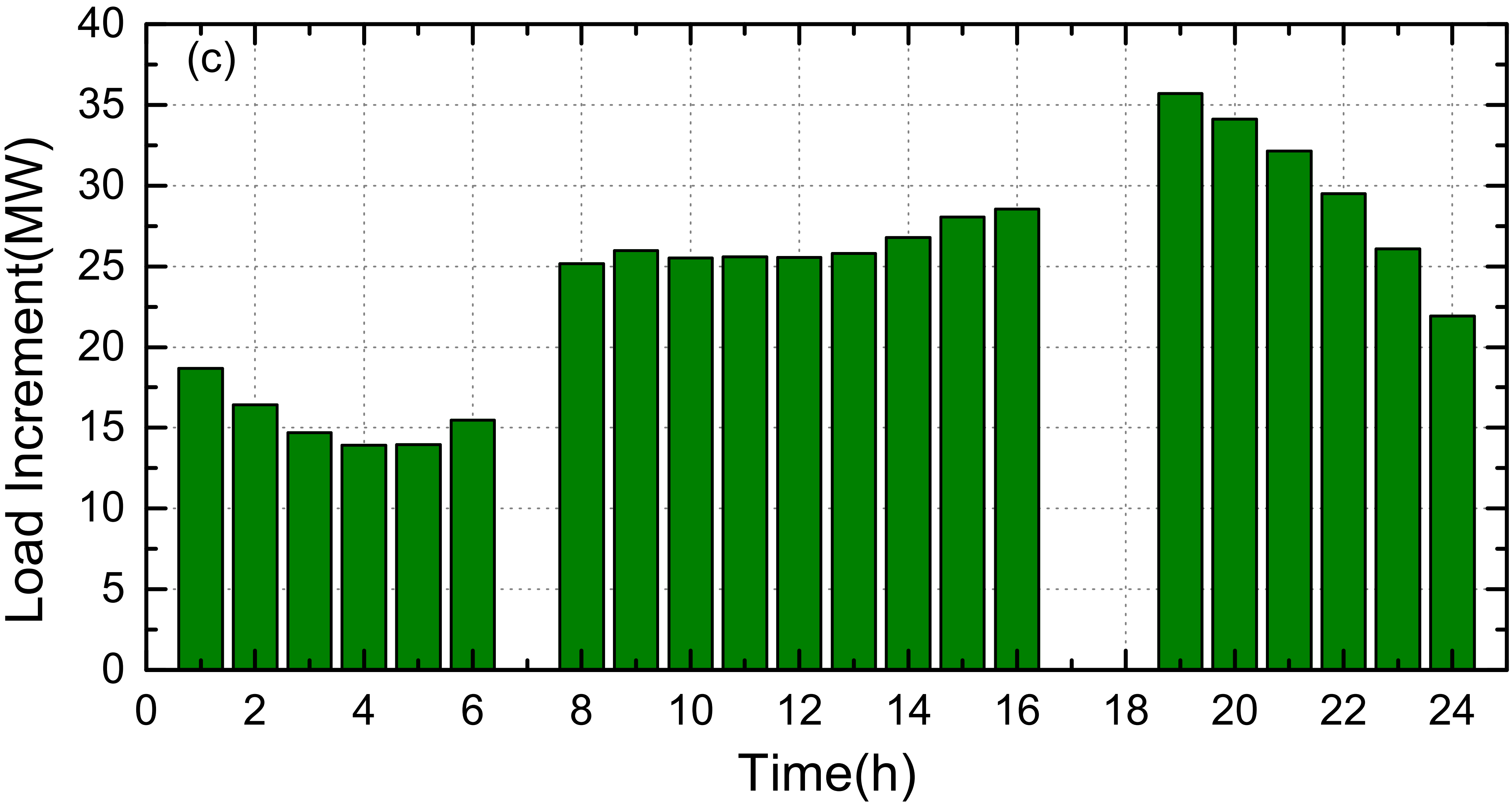
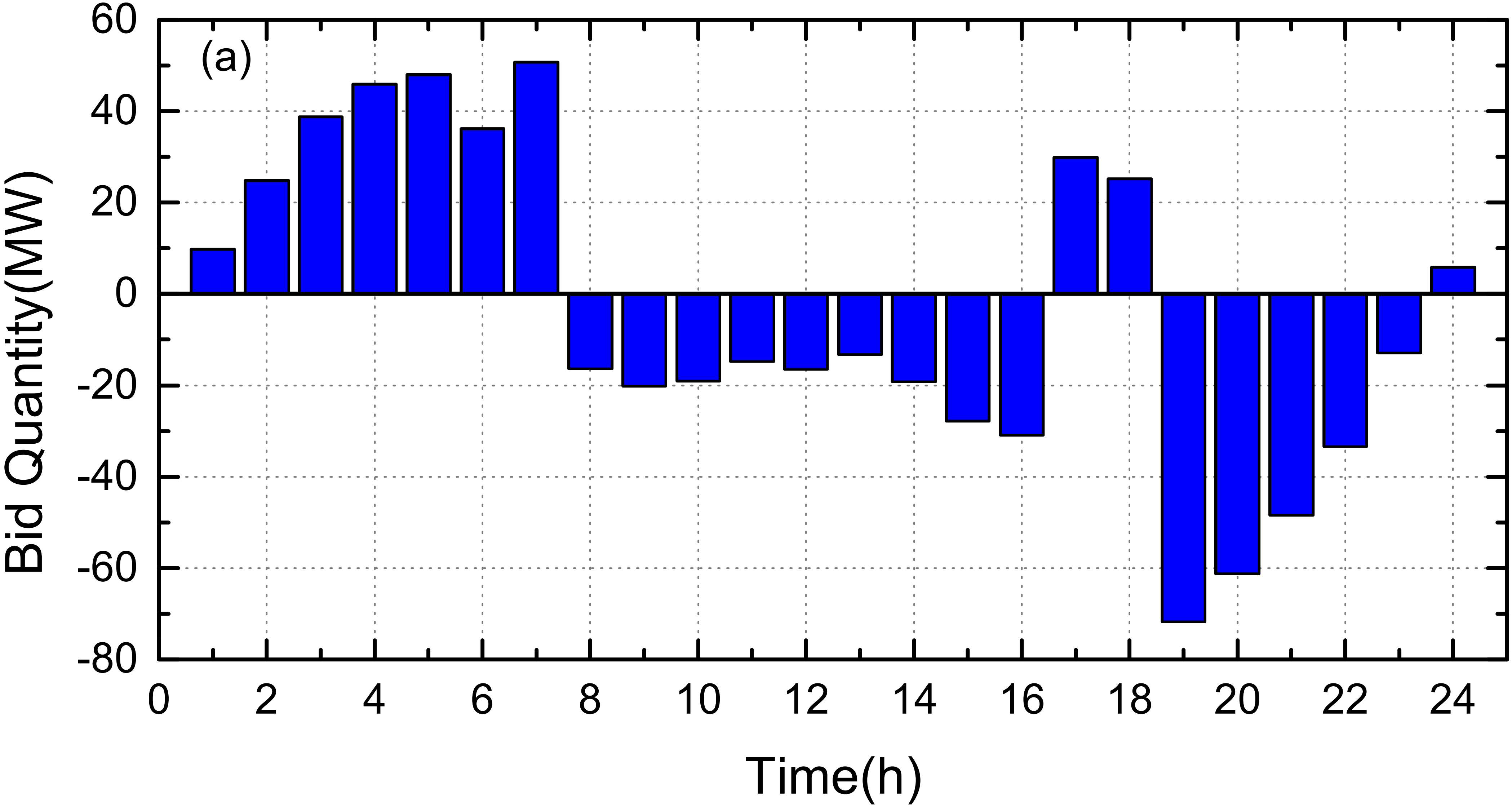
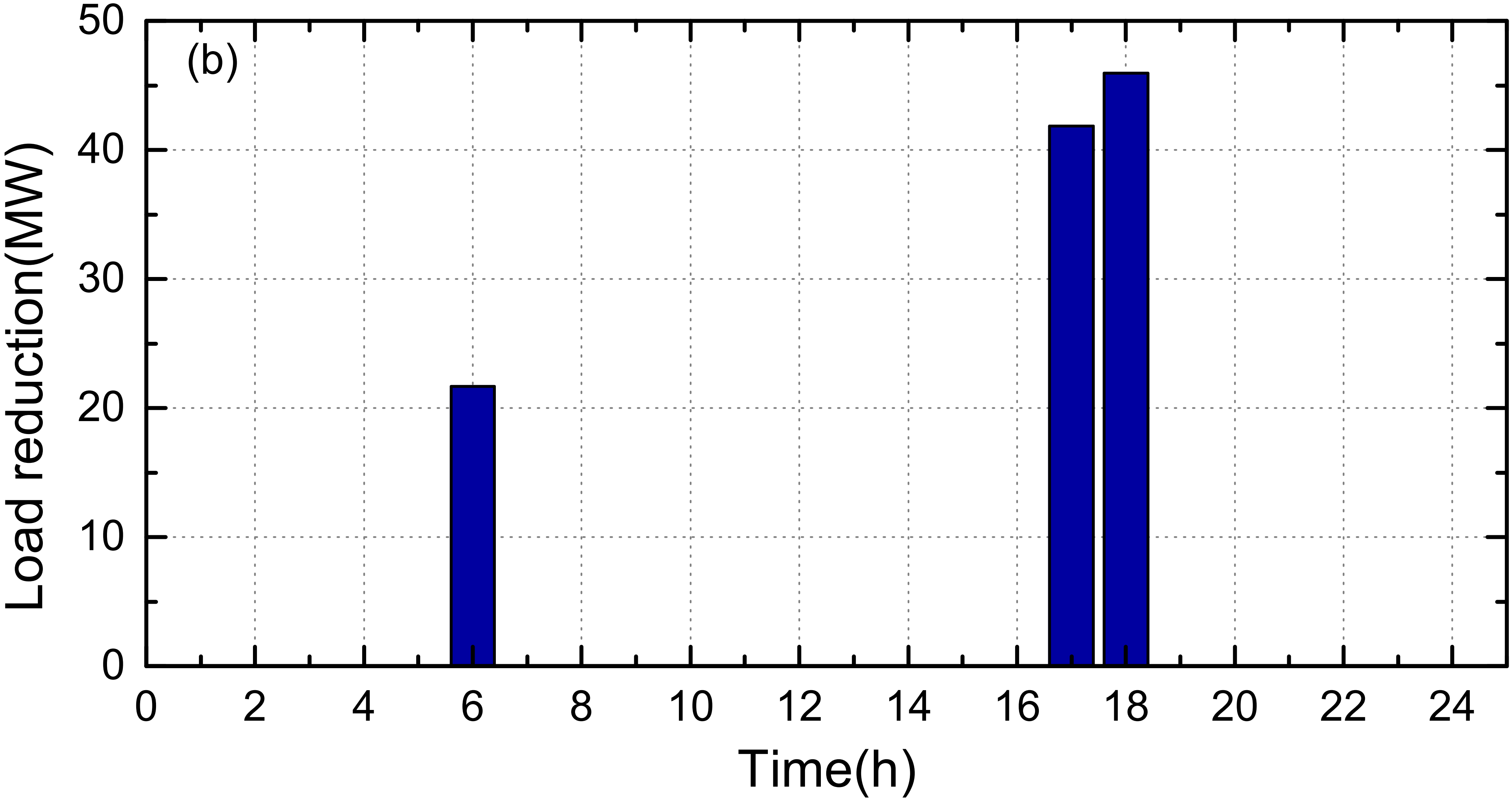

(c)
Load Increment(MW)
0
5
10
15
20
25
30
35
40
Time(h)
0
2
4
6
8
10
12
14
16
18
20
22
24

figure 24 a



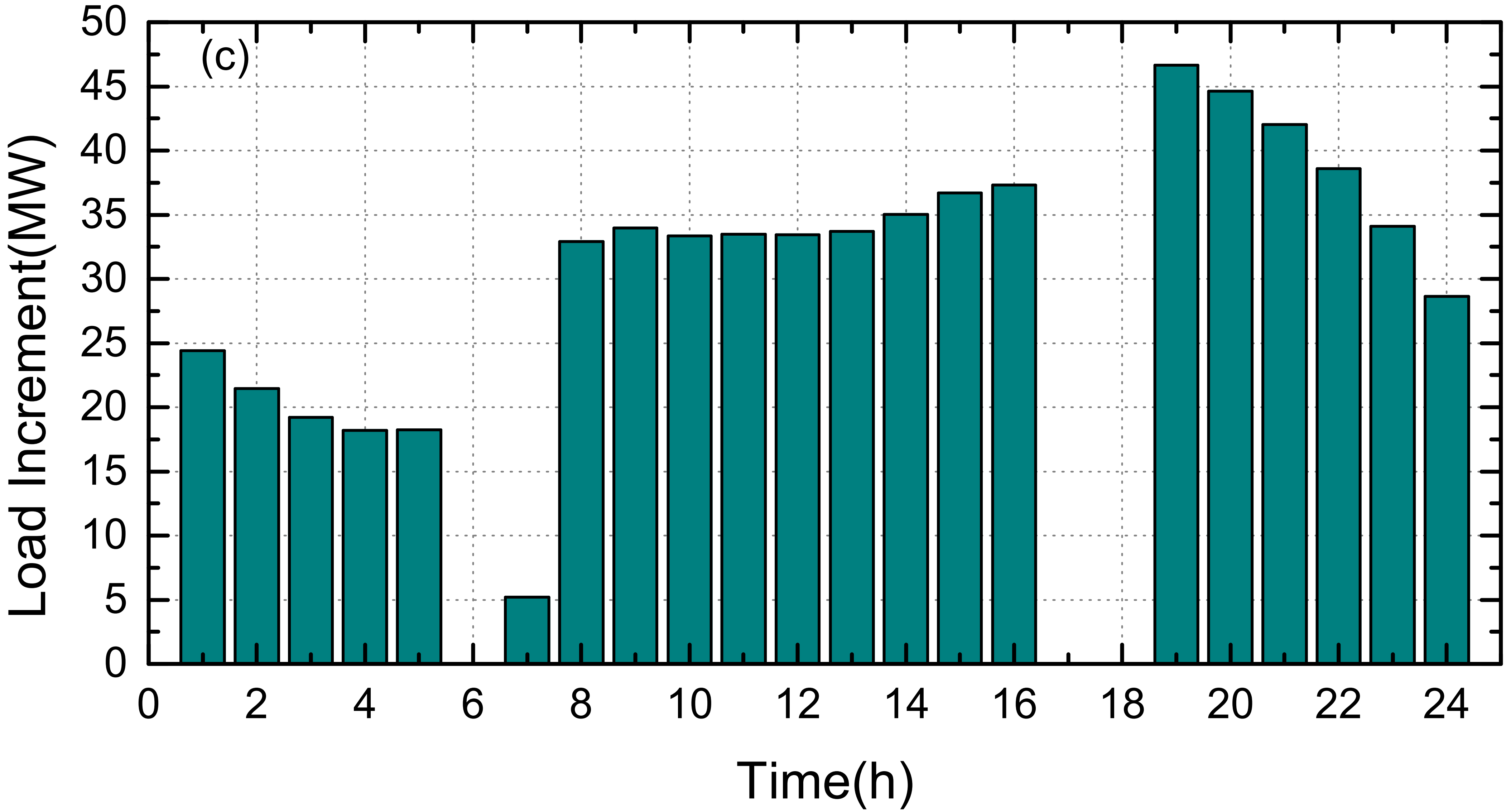
(a)
60
40
20
0
-20
-40
-60
-80
Bid Quantity(MW)
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 24 b



(b)
Load reduction(MW)
0
10
20
30
40
50
0
2
4
6
8
10
12
14
16
18
20
22
24
Time(h)

figure 24 c



(c)
Load Increment(MW)
Time(h)
0
5
10
15
20
25
30
35
40
45
50
0
2
4
6
8
10
12
14
16
18
20
22
24

Figure 25

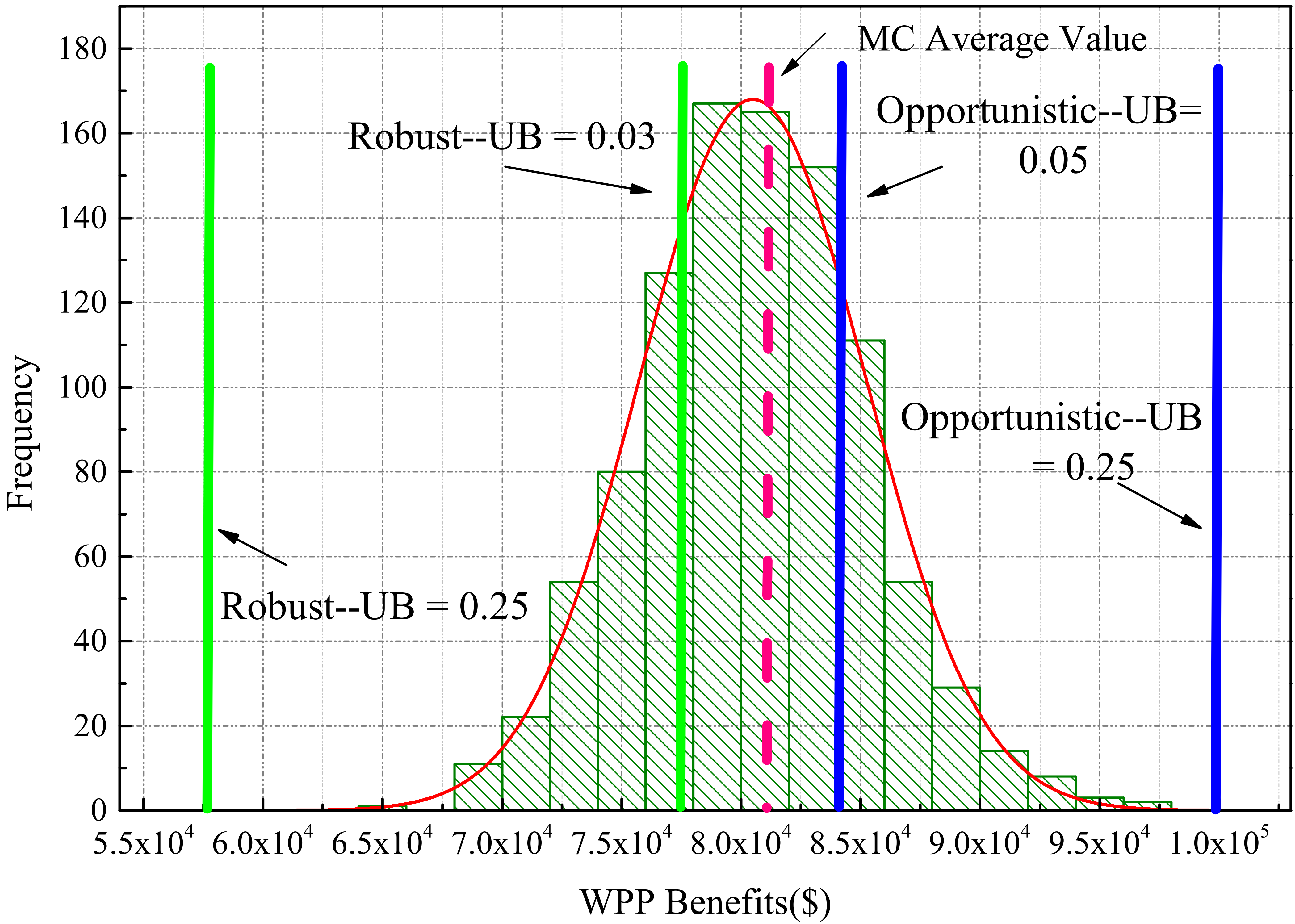
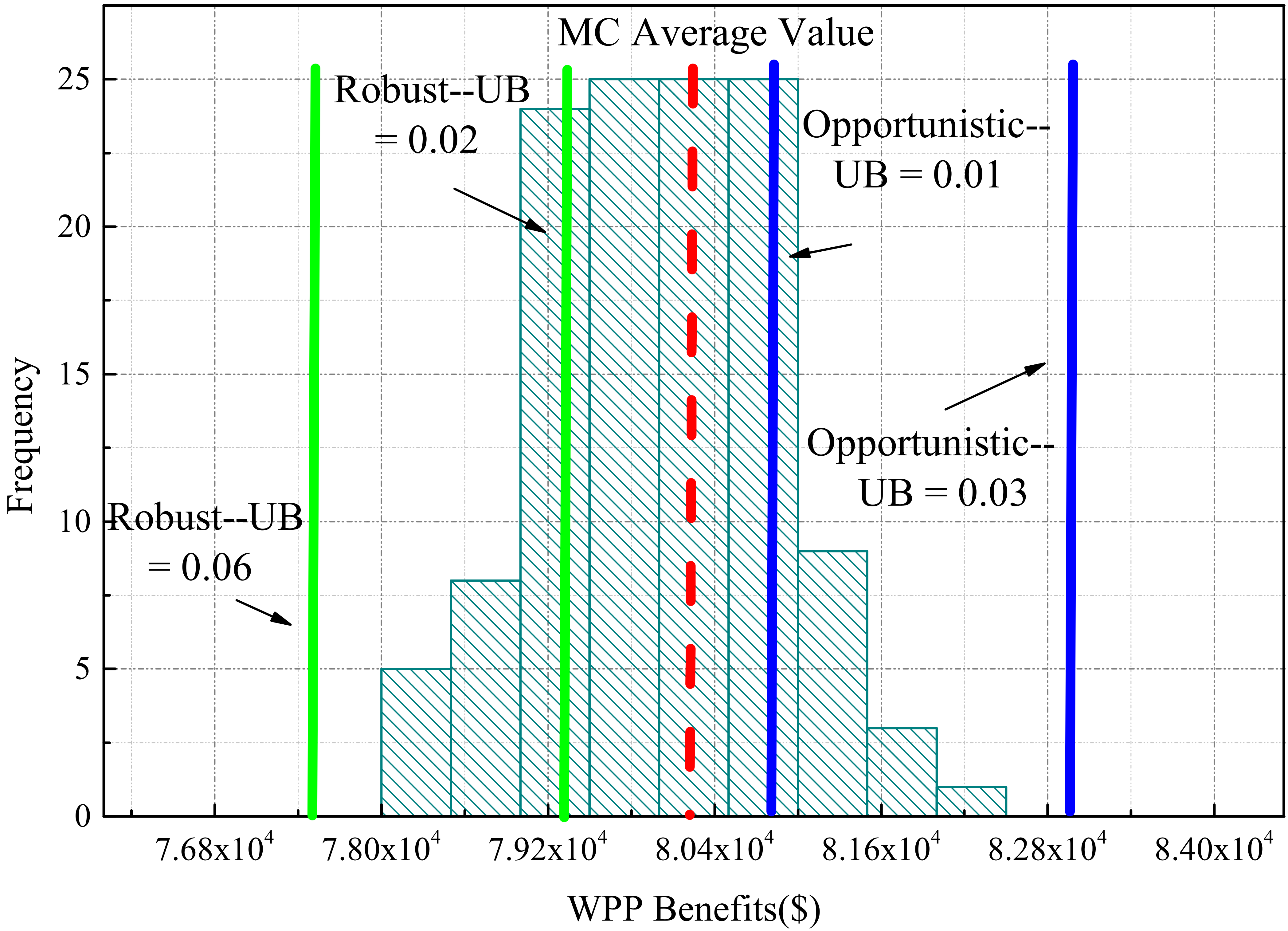

MC Average Value
Robust--UB = 0.03
Opportunistic--UB=
0.05
Opportunistic--UB
= 0.25
Robust--UB = 0.25
Frequency
0
20
40
60
80
100
120
140
160
180
5.5x10^4
6.0x10^4
6.5x10^4
7.0x10^4
7.5x10^4
8.0x10^4
8.5x10^4
9.0x10^4
9.5x10^4
1.0x10^5
WPP Benefits($)

Figure 26



MC Average Value
Robust--UB
= 0.02
Opportunistic--
UB = 0.01
Opportunistic--
UB = 0.03
Robust--UB
= 0.06
Frequency
25
20
15
10
5
0
7.68x10^4
7.80x10^4
7.92x10^4
8.04x10^4
8.16x10^4
8.28x10^4
8.40x10^4
WPP Benefits($)