A Cooperative Demand Response Scheme Using Punishment Mechanism and Application to Industrial Refrigerated Warehouses

***Abstract*—This paper proposes a cooperative demand response scheme for load management in smart grid. The cooperative demand response scheme is formulated as a constrained optimization problem that generates a Pareto-optimal response strategy profile for consumers. Comparing with the noncooperative response strategy (i.e., Nash equilibrium) obtained from the one-shot demand management game, the Pareto-optimal response strategy reduces the electricity costs to the consumers. We further develop an incentive-compatible trigger-and-punishment mechanism to avoid the noncooperative behaviors of the selfish consumers. Furthermore, the cooperative demand response scheme is applied to load management of industrial refrigerated warehouses. To implement the cooperative demand response scheme in large-scale system, we divide the refrigerated warehouses into different clusters and implement the cooperative demand response scheme inside each cluster. Numerical results demonstrate that the cooperative demand response scheme can reduce the electricity costs, drop the electricity prices, and curtail the total energy consumption comparing with the noncooperative demand response scheme.**

Keywords*—*Smart grid, Demand response, Pareto optimality, Cooperation, Mechanism design, Industrial refrigerated warehouses.

NOMECLATURE

$\mathcal{N}, N, i$	Set, number, and index of consumers.
$\mathcal{M}, M, m$	Set, number, and index of clusters.
$\mathcal{N}^d$	Set of noncooperative consumers.
$\mathcal{N}^c$	Set of cooperative consumers.
$\mathcal{N}_m$	Set of consumers in cluster m.
k	Index of time slots.
$\boldsymbol{l}$	Strategy profile of consumers.
$\boldsymbol{l}^d$	Strategy profile with noncooperative behaviors.
$\boldsymbol{l}^c$	Social-optimal strategy profile of consumers.
S_i	Set of possible strategies of consumer i.
l_i	Actual energy consumption of consumer i (kWh).
$\hat{l}_i$	Normal energy consumption of consumer i (kWh).
l_i^d	Energy consumption of noncooperative consumer i (kWh).
l_i^c	Social-optimal energy consumption of consumer i (kWh).
$p(\boldsymbol{l})$	Electricity price (cents/kWh).
$p^d(\boldsymbol{l}^d)$	Electricity price with noncooperative behaviors (cents/kWh).
V_i	Total costs to consumer i (cents).
V_i^q	Discomfort costs to consumer i (cents).
V_i^p	Electricity payments to consumer i (cents).
$\bar{V}_i$	Average costs to consumer i over multiple time slots (cents).
U_i	Payoff of consumer i (cents).
U_i^{NE}	Payoff of consumer i obtained from one-shot demand management game (cents).
U_i^c	Payoff of consumer i obtained from cooperative demand response scheme (cents).
$\bar{U}_i$	Average payoff of consumer i over multiple time slots (cents).
δ	Discount factor.
δ^{min}	Lower bound of discount factor.
L	Forecast demand (kWh).
L_m	Forecast demand of cluster m (kWh).
ΔL	Change of total energy consumption (kWh).
$\Delta \hat{L}$	Average change of total energy consumption with noncooperative behaviors (kWh).
η	Detection threshold (kWh).
$\eta^{\text{max}}, \eta^{\text{min}}$	Maximal and minimal detection thresholds (kWh).
α^c	Critical probability of noncooperative behaviors.
$\hat{q}$	Indicator of detection results.
q	Indicator of the existence of noncooperative behaviors.
T	Number of time slots with punishment.
T^{min}	Minimal number of time slots with punishment.
T_0	Time slot at which the punishment starts.
Q_i^{in}	Actual indoor temperature set point (°F).
$\hat{Q}_i^{\text{in}}$	Desired indoor temperature set point (°F).
Q_i^{in}	Outdoor temperature (°F).
θ_i	Cost coefficient.
β_i, γ_i	Thermal parameters.
λ, p_0	Pricing parameter and base price (cents/kWh).

I. Introduction

DEMAND response is defined as the changes in electricity usage by end-use consumers in response to the power grid needs from electricity markets [1]. In general, there are two categories of demand response schemes: incentive-based scheme and price-based scheme [2]. For the direct load control in the incentive-based demand response scheme, the energy provider manages the loads of the participating consumers directly [3]–[5]. For the price-based demand response scheme, the energy provider adjusts the loads by flexible pricing, such as critical peak pricing [6], real-time pricing [7], regulation pricing [8]. To support the demand response, an advanced metering infrastructure (AMI) is given to collect the energy consumption and announce the electricity price [9], [10].

Typically, there are two types of consumers for price-based demand response: price-taking consumers [11]–[13] and price-anticipating consumers [14]–[20]. The price-taking consumers assume that their energy consumption cannot affect the electricity price, whereas the price-anticipating consumers believe that their energy consumption can change the electricity price. In fact, price-anticipating consumers usually refer to large energy consumers such as industrial facilities and commercial buildings. It was proven that both the industrial facilities and the commercial buildings have large potential in demand response [21]–[23].

Recently, game theory has been used for studying the demand response of price-anticipating consumers. For example, noncooperative games were utilized to study the cost minimization of interactive consumers [14]–[16] and the charging control of plug-in electric vehicles [17], [18]. Stackelberg games were employed to model the interactions between the consumers and the utility companies [19], [20], [24]. However, neither the Nash equilibrium nor the Stackelberg equilibrium are Pareto optimal in the two game models. Generally, Pareto optimality is an important criterion for evaluating economic systems and public policies. If economic allocation in any system is not Pareto efficient, there is potential for a Pareto improvement–an increase in Pareto efficiency. Nevertheless, few papers are devoted to the Pareto improvement for the demand response of price-anticipating consumers. In this study, we develop a cooperative demand response scheme and obtain a Pareto-optimal response strategy such that all the consumers have lower electricity costs than that obtained from the noncooperative strategy (i.e., Nash equilibrium).

The novelty of this work is twofold. First, we formulate the cooperative demand response as a social optimization problem and develop an incentive-compatible trigger-and-punishment mechanism to avoid the noncooperative behaviors of the consumers. Second, we apply the cooperative demand response scheme to achieve load management of industrial refrigerated warehouses. To the best of our knowledge, this is the first work using punishment mechanism to construct cooperative demand response scheme for industrial refrigerated warehouses.

The rest of the paper is organized as follows. Some preliminaries are given in Section II. In Section III, the cooperative demand response is formulated as a social optimization problem, and the social-optimal response strategy is obtained. In Section IV, an incentive-compatible trigger-and-punishment mechanism is developed to avoid the noncooperative behaviors of the selfish consumers. In Section V, the cooperative demand response scheme is applied to load management of industrial refrigerated warehouses with heating ventilation air conditioning (HVAC) systems, and a heuristic method is developed to obtain the sub-optimal response strategy by dividing the refrigerated warehouses into different clusters. Numerical results are given in Section VI, and conclusions are summarized in Section VII.

II. Preliminaries

A. Noncooperative Game and Nash Equilibrium

Definition 1. *[25] A noncooperative game is defined as a triple* $G = \{\mathcal{N}, (S_i)_{i\in\mathcal{N}}, (U_i(\boldsymbol{l}))_{i\in\mathcal{N}}\}$*, where* $\mathcal{N} = \{1, 2, \cdots, N\}$ *is the set of active players participating in the game,*

$$S_i = \left\{ l_i \,\middle|\, l_i \in \left[l_i^{min}, l_i^{max}\right] \right\} \tag{1}$$

is the set of possible strategies that player i *can take, and* $U_i(\boldsymbol{l})$ *is the payoff function.*

Definition 2. *[25] For a noncooperative game* $G = \{\mathcal{N}, (S_i)_{i\in\mathcal{N}}, (U_i(\boldsymbol{l}))_{i\in\mathcal{N}}\}$*, a vector of strategies* $\boldsymbol{l}^* = (l_1^*, l_2^*, \cdots, l_N^*)$ *is a Nash equilibrium if and only if* $U_i(l_i^*, \boldsymbol{l}_{-i}^*) \geq U_i(l_i', \boldsymbol{l}_{-i}^*)$ *for all* $i \in \mathcal{N}$ *and any other* $l_i' \in S_i$*, where* $\boldsymbol{l}_{-i} = (l_1, l_2, \cdots, l_{i-1}, l_{i+1}, \cdots, l_N)$ *denotes the set of strategies selected by all the players except for player* i*,* $(l_i, \boldsymbol{l}_{-i}) = (l_1, l_2, \cdots, l_{i-1}, l_i, l_{i+1}, \cdots, l_N)$ *denotes the strategy profile, and* $U_i(l_i, \boldsymbol{l}_{-i})$ *is the resulting payoff for the player* i *given the strategies of the other players.*

B. Taguchi Loss Function

Definition 3. *[26] The Taguchi loss function is a statistical method that captures the cost to society due to the manufacture of imperfect products. The loss function is given as*

$$V = \tau(y - \hat{y})^2, \tag{2}$$

where y *is the value of quality characteristic,* $\hat{y}$ *is the desired value of* y*,* V *is the loss in dollars, and* τ *is a constant coefficient. The quadratic representation of the loss function is minimum at* $y = \hat{y}$*, increases as* y *deviates from* $\hat{y}$*. The Taguchi loss function defines the relationship between the economic loss and the deviation of the quality characteristic from the desired value. For a product with desired value* $\hat{y}$*,* $\hat{y} \pm \Delta_0$ *represents the deviation at which functional failure of the product occurs. When a product is manufactured with the quality characteristic at the extremes,* $\hat{y} + \Delta_0$ *or* $\hat{y} - \Delta_0$*, some countermeasure must be undertaken by the customers. Assuming the cost of countermeasure is* A_0 *at* $\hat{y}+\Delta_0$ *or* $\hat{y}-\Delta_0$*, we define the constant* τ *as*

$$\tau = \frac{A_0}{\Delta_0^2}. \tag{3}$$

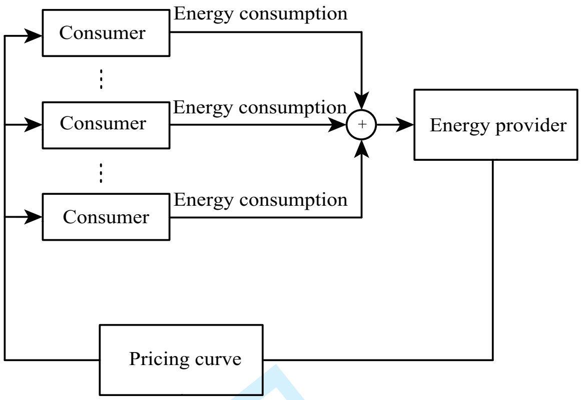

Fig. 1. Demand management system with price-anticipating consumers.

III. Problem Formulation

We consider a demand management system composed of an energy provider and several consumers, as shown in Fig. 1. The energy provider can adjust the loads by periodically announcing the pricing curve to the consumers. We assume that the consumers are price-anticipating consumers and know that the price is affected by their energy consumption. According to the updated electricity price, the consumers can adjust their energy consumption to reduce the electricity costs. The electricity costs are composed of two parts: the discomfort costs and the payments. Generally, the discomfort costs are increased with the change from normal energy consumption and can be denoted as a continuous, increasing, and convex function[1], such as the quadratic function [11], [13], [16], the logarithmic function [27], [28], and the weighted linear function [29], [30]. The discomfort cost function is defined as $V_i^q(l_i,\hat{l}_i)$, and the electricity payments of consumer i are denoted as

$$V_i^p = p(\boldsymbol{l})l_i,\ i \in \mathcal{N}, \tag{4}$$

where $\mathcal{N} = \{1, 2, \ldots, N\}$ denotes the set of consumers, i denotes the index of consumer, $\hat{l}_i$ is the normal energy consumption, l_i is the actual energy consumption, $\boldsymbol{l} = \{l_1, l_2, \ldots, l_N\}$ is the strategy profile, and $p(\boldsymbol{l})$ is the announced electricity price, which is assumed to be an increasing function of the total energy consumption. Then, the electricity costs to consumer i can be defined as

$$V_i \quad = \quad V_i^q(l_i,\hat{l}_i) + p(\boldsymbol{l})l_i. \tag{5}$$

The discomfort costs and the electricity payments usually conflict with each other, and the consumers need to make a tradeoff between them. From the cost formulation (5), the energy consumption of one consumer will change the electricity price and further affect the electricity costs to the other consumers. Thus, the demand response can be formulated as the following noncooperative game:

Definition 4. *(One-shot demand management game) A demand management game is defined as a triple* $G = \{\mathcal{N}, (S_i)_{i\in\mathcal{N}}, (U_i)_{i\in\mathcal{N}}\}$, *where* $\mathcal{N} = \{1, 2, \cdots, N\}$ *is the set of active consumers participating in the game,* S_i *is the set of possible strategies that consumer* i *can take, and* $U_i = -V_i = -V_i^q(l_i,\hat{l}_i) - p(\boldsymbol{l})l_i$ *is the payoff function.*

The stable solution of the one-shot demand management game is the Nash equilibrium, which can be obtained from $\partial U_i/\partial l_i = 0, i \in \mathcal{N}$, i.e.,

$$-\partial V_i^q(l_i,\hat{l}_i)/\partial l_i - \partial p(\boldsymbol{l})/\partial l_i \cdot l_i - p(\boldsymbol{l}) = 0,\ i \in \mathcal{N}. \tag{6}$$

Generally, the Nash equilibrium is not a Pareto-optimal solution, and thus it is possible to improve the payoffs of all the consumers simultaneously[2]. Next, we develop a cooperative demand response scheme to improve the Pareto efficiency of Nash equilibrium and formulate the cooperative demand response as the following social optimization problem:

$$\text{(P1)} \qquad \text{maximize} \quad \sum_{i\in\mathcal{N}} U_i$$
$$\text{subject to} \quad U_i \geq U_i^{\text{NE}},\ i \in \mathcal{N},$$

where U_i^{NE} denotes the payoff of consumer i obtained from the one-shot demand management game. Let $\boldsymbol{l}^c = \{l_1^c, \ldots, l_N^c\}$ denote the social-optimal energy consumption obtained from (P1) and U_i^c denote the corresponding payoff of consumer i. It is easy to see that $\boldsymbol{l}^c$ is a Pareto-optimal solution and U_i^c is not smaller than U_i^{NE} for all $i \in \mathcal{N}$. Since (P1) is in general a nonconvex optimization problem, the optimal solution $\boldsymbol{l}^c$ is hard to obtain. In section V, we will develop a heuristic method to obtain a sub-optimal solution that meets the constraints in (P1).

In the cooperative demand response scheme, some of the consumers are possible to improve their payoffs by taking the noncooperative strategies when the other consumers keep cooperative. We assume that some of the consumers ($i \in \mathcal{N}^d$) take the noncooperative strategies while the other consumers ($j \in \mathcal{N}^c$) keep cooperative, where $\mathcal{N}^d$ is the set of noncooperative consumers and $\mathcal{N}^c$ is the set of cooperative consumers. Then, the energy consumption of the noncooperative consumers can be obtained from

$$-\partial V_i^q(l_i,\hat{l}_i)/\partial l_i - \partial p^d(\boldsymbol{l}^d)/\partial l_i \cdot l_i - p^d(\boldsymbol{l}^d) = 0,\ i \in \mathcal{N}^d, \tag{7}$$

where $p^d(\boldsymbol{l}^d)$ is the price when some of the consumers take the noncooperative strategies and $\boldsymbol{l}^d = \{l_1^d, \ldots, l_{N^d}^d, l_1^c, \ldots, l_{N^c}^c\}$, where l_i^d ($i \in \mathcal{N}^d$) denotes the energy consumption of the noncooperative consumers and l_j^c ($j \in \mathcal{N}^c$) denotes the energy consumption of the cooperative consumers. The corresponding payoffs of the noncooperative consumers are denoted as

$$U_i^d = -V_i^q(l_i^d,\hat{l}_i) - p^d(\boldsymbol{l}^d)l_i^d,\ i \in \mathcal{N}^d, \tag{8}$$

and the payoffs of the cooperative consumers are denoted as

$$U_j^d = -V_j^q(l_j^c,\hat{l}_j) - p^d(\boldsymbol{l}^d)l_j^c,\ j \in \mathcal{N}^c. \tag{9}$$

For example, the noncooperative consumer can increase its payoff (8) by taking the noncooperative strategy when all of

[1]The price-anticipating consumers generally refer to industrial or commercial consumers that have continuous aggregate loads.

[2]Improving the payoff is equivalent to reducing the electricity costs.

the other consumers keep cooperative, i.e., each consumer has the motivation to take the noncooperative strategy. Therefore, the social-optimal energy consumption is not a stable solution in one-shot demand response.

IV. Trigger-and-Punishment Mechanism

To make the social-optimal energy consumption stable, we consider giving punishments to the consumers if they adopt the noncooperative strategies. In that case, the consumers will care more about the long-term electricity costs. The average electricity costs to consumer i over multiple time slots are defined as

$$\bar{V}_i = \sum_{k=1}^{\infty} \delta^{k-1} V_i(k), \quad (10)$$

where k is the index of the time slot and $\delta \in (0,1)$ is the discount factor, which represents how the consumers discount their future costs. In that case, the consumers not only value the current electricity costs but also the future electricity costs. Therefore, each consumer needs to keep a good reputation to avoid the increased costs in the future. Similarly, we define the average payoff function of consumer i as $\bar{U}_i = -\bar{V}_i = -\sum_{k=1}^{\infty} \delta^{k-1} V_i(k)$.

Next, we will develop a trigger-and-punishment mechanism to avoid the noncooperative behaviors. All of the consumers are assumed to adopt the cooperative strategies in the first time slot. In the subsequent time slots (i.e., $k \geq 2$), the cooperation will be maintained if all of the consumers adopt the cooperative strategies in the previous time slot. If the energy provider observes noncooperative behaviors in the previous time slot, it will keep the consumers noncooperative during the subsequent T time slots and restart the cooperation at the $(T+1)$th time slot. There are two questions to be answered in designing the trigger-and-punishment mechanism: *How the energy provider detects the noncooperative behaviors and what is the punishment strength that can stop the noncooperative behaviors?* In the subsequent sections, we will answer these two questions and omit the time slot index k without causing confusions.

A. Noncooperative behaviors detection

The noncooperative behaviors of the consumers will change the electricity price and the total energy consumption. In this section, we utilize the change of the total energy consumption[3] as the indicator for the noncooperative behaviors that exist in the demand management system. The change of the total energy consumption is defined as

$$\Delta L = \sum_{i \in \mathcal{N}} l_i - \sum_{i \in \mathcal{N}} l_i^c. \quad (11)$$

In practice, the total energy consumption is measured by the energy provider based on the AMI. It is shown that communication loss causes errors to the total energy consumption and thus variations to the change of the total energy consumption

[3]In practice, the change in the total energy consumption is affected by the scale of the demand management system (e.g., the number of consumers). In the simulations, we will discuss it in detail.

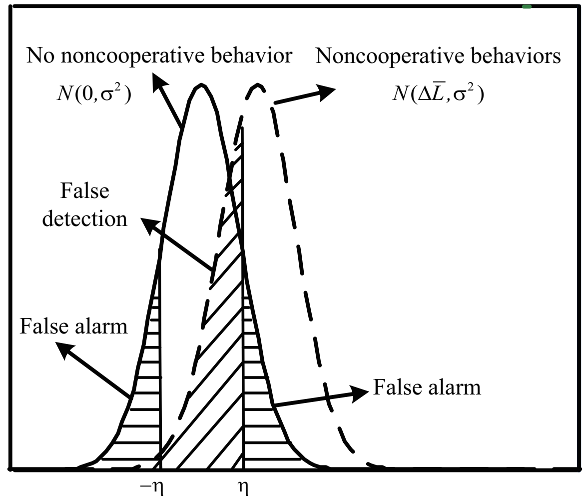

Fig. 2. Distribution of the change of total energy consumption (i.e., ΔL) with and without noncooperative behaviors.

[31], [32]. The change of the total energy consumption is assumed to follow a normal distribution $N(\mu, \sigma^2)$, where σ is the standard variance, $\mu = 0$ if there does not exist any noncooperative behavior, and $\mu = \Delta\bar{L}$ if there exist noncooperative behaviors.

To detect the noncooperative behaviors of the consumers, we define the detection rule as

$$\hat{q} = \begin{cases} 1, & \text{if } |\Delta L| \geq \eta, \\ 0, & \text{if } |\Delta L| < \eta, \end{cases} \quad (12)$$

where η is the detection threshold and $\hat{q}$ is the detection result. Specifically, $\hat{q} = 1$ denotes that the energy provider detects the noncooperative behaviors and $\hat{q} = 0$ denotes that the energy provider does not detect any noncooperative behavior. As shown in Fig. 2, the detection rule (12) causes false alarm and false detection. The false alarm occurs when the noncooperative behaviors are detected in the demand management system that does not have any noncooperative behavior, and the false detection occurs when the noncooperative behaviors are not detected in the demand management system that has noncooperative behaviors. Both the false alarm and false detection have large influences on the accuracy of the noncooperative behaviors detection and thus the social optimality of the cooperative demand response scheme. Next, we will give the optimal detection threshold to minimize the loss of social optimality.

Proposition 1. *Assuming that the probability of performing noncooperative behavior of one consumer is α at time slot T_0, the average loss of social optimality due to the false alarm and false detection is minimal if*

$$\eta = \begin{cases} \eta^{max}, & \alpha > \alpha^c, \\ \eta^{min}, & \alpha \leq \alpha^c, \end{cases} \quad (13)$$

where η^{max} and η^{min} are the maximal and minimal detection *thresholds, and α^c is denoted as*

$$\alpha^c = 1 - \left(\frac{\Delta U^{cn}}{\Delta U^{cn} + \Delta U^{cd}}\right)^{\frac{1}{N}}, \tag{14}$$

with $\Delta U^{cn} = \sum_{k=T_0+1}^{T_0+T}(\sum_{i\in\mathcal{N}} U_i^c(k) - \sum_{i\in\mathcal{N}} U_i^{NE}(k))$ *and* $\Delta U^{cd} = \sum_{i\in\mathcal{N}} U_i^c(T_0+1) - \sum_{i\in\mathcal{N}} U_i^d(T_0+1)$.

Proof: Given that the probability of performing non-cooperative behavior of one consumer is α, the probability of the noncooperative behaviors that occur in the demand management system can be denoted as $1-(1-\alpha)^N$. We set the indicator $q=1$ when there exist noncooperative behaviors and $q=0$ when there does not exist any noncooperative behavior. Then, the false alarm probability can be defined as

$$\begin{aligned}&\Pr[\hat{q}=1|q=0]\\&= \Pr[|\Delta L| \geq \eta, \Delta L \sim N(0,\sigma^2)] = \Phi(\eta),\end{aligned} \tag{15}$$

and the false detection probability can be defined as

$$\begin{aligned}&\Pr[\hat{q}=0|q=1]\\&= \Pr[|\Delta L| < \eta, \Delta L \sim N(\Delta\bar{L},\sigma^2)] = \Psi(\eta),\end{aligned} \tag{16}$$

where $\Phi(\eta)$ is a decreasing function of η and $\Psi(\eta)$ is an increasing function of η.

Under the detection rule (12), the loss of social optimality due to the false alarm (i.e., $\hat{q}=1, q=0$) or the false detection (i.e., $\hat{q}=0, q=1$) is denoted as

$$\begin{aligned}\Delta U^e =& \hat{q}(1-q)\sum_{k=T_0+1}^{T_0+T}(\sum_{i\in\mathcal{N}} U_i^c(k) - \sum_{i\in\mathcal{N}} U_i^{\text{NE}}(k))\\ &+(1-\hat{q})q(\sum_{i\in\mathcal{N}} U_i^c(T_0+1) - \sum_{i\in\mathcal{N}} U_i^d(T_0+1)).\end{aligned} \tag{17}$$

In (17), the first part is the loss of social optimality due to false alarm and is defined as the sum of the loss of social optimality in each time slot with punishment, because the punishment strategy is to make all the consumers adopt the noncooperative strategies (i.e., Nash equilibrium) in the subsequent T time slots. The second part is the loss of social optimality in the next time slot due to the false detection of noncooperative behaviors in the current time slot. Given the false alarm probability and the false detection probability, the average loss of social optimality is denoted as

$$\begin{aligned}&\Delta\bar{U}^e = E[\Delta U^e]\\&= \beta(1-(1-\alpha)^N)\sum_{k=T_0+1}^{T_0+T}(\sum_{i\in\mathcal{N}} U_i^c(k) - \sum_{i\in\mathcal{N}} U_i^{\text{NE}}(k))\\&+(1-\beta)(1-\alpha)^N(\sum_{i\in\mathcal{N}} U_i^c(T_0+1) - \sum_{i\in\mathcal{N}} U_i^d(T_0+1)).\end{aligned} \tag{18}$$

In (18), $\beta = E[\hat{q}]$ represents the probability, estimated by the energy provider, that there exist noncooperative behaviors in the demand management system and it can be calculated by

$$\begin{aligned}\beta &= \Pr[\hat{q}=1|q=0]\Pr[q=0] + \Pr[\hat{q}=1|q=1]\Pr[q=1]\\ &= (1-\alpha)^N \Pr[\hat{q}=1|q=0]\\ &\quad +(1-(1-\alpha)^N)(1-\Pr[\hat{q}=0|q=1])\\ &= (1-\alpha)^N\Phi(\eta) + (1-(1-\alpha)^N)(1-\Psi(\eta))\\ &= f(\eta).\end{aligned} \tag{19}$$

Since $\Phi(\eta)$ is decreasing and $\Psi(\eta)$ is increasing with η, we concludes that β is decreasing with η. Assuming $\eta^{\min} \leq \eta \leq \eta^{\max}$, we have $\beta^{\min} = f(\eta^{\max})$ and $\beta^{\max} = f(\eta^{\min})$. To minimize the average loss of social optimality (18), we obtain the optimal detection threshold:

$$\eta = \begin{cases}\eta^{\max}, & (1-(1-\alpha)^N)\Delta U^{\text{cn}} > (1-\alpha)^N \Delta U^{\text{cd}},\\ \eta^{\min}, & (1-(1-\alpha)^N)\Delta U^{\text{cn}} \leq (1-\alpha)^N \Delta U^{\text{cd}}.\end{cases} \tag{20}$$

The critical condition (20) indicates that there exists a critical probability of the noncooperative behaviors (i.e., α^c) such that $\eta = \eta^{\max}$ if $\alpha > \alpha^c$ and $\eta = \eta^{\min}$ if $\alpha \leq \alpha^c$. The critical probability α^c is obtained from $(1-(1-\alpha)^N)\Delta U^{\text{cn}} = (1-\alpha)^N \Delta U^{\text{cd}}$. ■

It is shown in (14) that α^c is decreased with the number of consumers. In practical demand management system, the number of consumers is very large such that α_c is extremely small. Therefore, $\eta = \eta^{\max}$ is always the optimal threshold.

B. Punishment Strength

Suppose all of the consumers adopt the cooperative strategies, the average payoff of one consumer is denoted as

$$\bar{U}_i^c = \sum_{k=1}^{\infty} \delta^{k-1} U_i^c(k), \tag{21}$$

and the average payoff of the consumer when adopting the noncooperative strategy at time slot T_0 is denoted as

$$\begin{aligned}\bar{U}_i^d =& (\sum_{k=1}^{T_0-1}\delta^{k-1}U_i^c(k) + \delta^{T_0-1}U_i^d(T_0)\\ &+\sum_{k=T_0+1}^{T_0+T}\delta^{k-1}U_i^{\text{NE}}(k) + \sum_{k=T_0+T+1}^{\infty}\delta^{k-1}U_i^c(k)).\end{aligned} \tag{22}$$

To make the social-optimal energy consumption stable and achieve the incentive compatibility of the trigger-and-punishment mechanism, there should be $\bar{U}_i^c > \bar{U}_i^d$ for all $i \in \mathcal{N}$, i.e.,

$$\sum_{k=T_0}^{T_0+T}\delta^{k-1}U_i^c(k) > \delta^{T_0-1}U_i^d(k) + \sum_{k=T_0+1}^{T_0+T}\delta^{k-1}U_i^{\text{NE}}(k), \tag{23}$$

from which, we can obtain the lower bound of the discount factor $\delta^{\min}$ and the minimal duration of punishment $T^{\min}$.

V. Application to Load Management of Industrial Refrigerated Warehouses

In this section, we consider the application to load management of industrial refrigerated warehouses with HVAC systems. Changing the cold storage temperature set points of the refrigerated warehouses will cause the reduction of product quality and further increase economic costs to the industrial consumers. Taguchi loss function is a method that captures economic costs due to the manufacture of imperfect products [26]. According to the Definition 3, the economic costs can be defined as

$$V_i^q(Q_i^{\text{in}}(k)) = \theta_i(Q_i^{\text{in}}(k) - \hat{Q}_i^{\text{in}}(k))^2,\ i \in \mathcal{N}, \tag{24}$$

where θ_i is the cost coefficient, $Q_i^{\text{in}}(k)$ and $\hat{Q}_i^{\text{in}}(k)$ denote the actual temperature set point and the desired temperature set point in time slot k, respectively. The indoor temperature of refrigerated warehouse i evolves according to the following linear dynamics [13]:

$$Q_i^{\text{in}}(k) = Q_i^{\text{in}}(k-1) + \beta_i(Q_i^{\text{out}}(k) - Q_i^{\text{in}}(k-1)) + \gamma_i l_i(k), \tag{25}$$

where β_i and γ_i specify the thermal characteristics of the operating environment and the HVAC system, $Q_i^{\text{out}}(k)$ denotes the outdoor temperature, $\beta_i(Q_i^{\text{out}}(k) - Q_i^{\text{in}}(k-1))$ models the heat transfer, $\gamma_i l_i(k)$ ($\gamma_i < 0$) models the energy-heat transformation of the HVAC system. Assuming that the refrigerated warehouse i requires $\hat{l}_i(k)$ kWh energy to maintain the desired indoor temperature, we have

$$\hat{Q}_i^{\text{in}}(k) = Q_i^{\text{in}}(k-1) + \beta_i(Q_i^{\text{out}}(k) - Q_i^{\text{in}}(k-1)) + \gamma_i \hat{l}_i(k), \tag{26}$$

where $\hat{l}_i(k)$ is different for the refrigerated warehouses with different desired temperature set points. For example, the recommended storage and transit temperatures for food products are from 32°F to 64°F for vegetables and fruits, from 32°F to 39°F for milk and meat, and from -22°F to 0°F for seafood and ice cream [33]. Substituting (25) and (26) into (24) and omitting the time slot index k, we transform the cost function to

$$V_i^q = \theta_i \gamma_i^2 (l_i - \hat{l}_i)^2,\ i \in \mathcal{N}. \tag{27}$$

According to the law of demand [34], the electricity price is defined as

$$p(\boldsymbol{l}) = \lambda(\sum_{i\in\mathcal{N}} l_i - L) + p_0, \tag{28}$$

where λ is a pricing parameter to implement elastic pricing, p_0 is the base price, and L is the forecast demand. Then, the costs to refrigerated warehouse i can be denoted as

$$V_i^r = \theta_i \gamma_i^2 (l_i - \hat{l}_i)^2 + (\lambda(\sum_{i\in\mathcal{N}} l_i - L) + p_0) l_i, \tag{29}$$

with which, (P1) is a nonconvex optimization problem, and the global optimal solution is hard to obtain. Next, we propose a heuristic method to search for the sub-optimal solution of (P1) and divide the refrigerated warehouses into M clusters. The number of refrigerated warehouses in cluster m ($m \in \mathcal{M} = \{1, 2, \ldots, M\}$) is N_m, and the set of refrigerated warehouses in cluster m is denoted as $\mathcal{N}_m = \{1, 2, \ldots, N_m\}$. The details of the cluster-based cooperative demand response scheme are given as follows.

The refrigerated warehouses are first divided into M clusters according to their normal energy consumption $\hat{l}_i$. Specifically, assuming that the highest and lowest energy consumption are $l^{\max}$ and $l^{\min}$, respectively, the refrigerated warehouses are grouped into one cluster if their normal energy consumption lie within $[l^{\min} + (m-1)(l^{\max} - l^{\min})/M, l^{\min} + m(l^{\max} - l^{\min})/M], m \in \{1, 2, \ldots, M\}$. The forecast demand is allocated to each cluster according to the ratio of the total normal energy consumption in one cluster to the total normal energy consumption in the demand management system, i.e.,

$$L_m = \frac{\sum_{i\in\mathcal{N}_m} \hat{l}_i}{\sum_{i\in\mathcal{N}} \hat{l}_i} L,\ m \in \mathcal{M}, \tag{30}$$

where L_m is the forecast demand of cluster m. Similarly, the cooperative demand response scheme in cluster m can be formulated as

$$\begin{aligned} \text{(P2)} \qquad & \text{maximize} \quad \sum_{i\in\mathcal{N}_m} U_i^m \\ & \text{subject to} \quad U_i^m \geq U_i^{\text{NE}},\ i \in \mathcal{N}_m, \end{aligned}$$

where U_i^m is the payoff function of refrigerated warehouse i in cluster m,

$$U_i^m = -V_i^m = -\theta_i \gamma_i^2 (l_i - \hat{l}_i)^2 - (\lambda(\sum_{i\in\mathcal{N}_m} l_i - L_m) + p_0) l_i. \tag{31}$$

To solve (P2), we first consider the following unconstrained optimization problem:

$$\text{(P3)} \qquad \text{maximize} \quad \sum_{i\in\mathcal{N}_m} U_i^m.$$

Next, we give the condition to guarantee a unique global optimal solution in (P3).

Proposition 2. *Given the payoff function U_i^m defined by (31), the optimization problem (P3) has a unique global optimal solution if*

$$\lambda \leq \frac{\theta_i \gamma_i^2}{N_m - 2},\ i \in \mathcal{N}_m. \tag{32}$$

Proof: Given U_i^m defined by (31), the Hessian matrix of (P3) is denoted as

$$H = \begin{bmatrix} -2\theta_1\gamma_1^2 - 2\lambda & -2\lambda & \ldots & -2\lambda \\ -2\lambda & -2\theta_2\gamma_2^2 - 2\lambda & \ldots & -2\lambda \\ \vdots & \vdots & \ddots & \vdots \\ -2\lambda & -2\lambda & \ldots & -2\theta_{N_m}\gamma_{N_m}^2 - 2\lambda \end{bmatrix}. \tag{33}$$

From (32), it is sufficient to show that H is strictly diagonally dominant, i.e.,

$$|H_{i,i}| \geq \sum_{j\neq i, j\in\mathcal{N}_m} |H_{i,j}|, \quad |H_{i,i}| \geq \sum_{j\neq i, j\in\mathcal{N}_m} |H_{j,i}|,\ \forall i \in \mathcal{N}_m. \tag{34}$$

Following Gershgorin's theorem [35], all the eigenvalues are negative, and H is a negative definite matrix. Therefore, the

Algorithm 1 Clustering algorithm

Input: Refrigerated warehouses set: $\mathcal{N} = \{1, 2, \ldots, N\}$; Parameters: γ_i, θ_i, λ; Normal energy consumption: $\hat{l}_i$; Forecast demand: L; Number of clusters: $M = 1$.
Output: Number of clusters: M; Clusters set: $\mathcal{M} = \{1, 2, \ldots, M\}$; Refrigerated warehouses set in cluster m: $\mathcal{N}_m$.

$g = 0$;
for all $i \in \mathcal{N}$ **do**
  Calculate the energy consumption $\boldsymbol{l}^c$ according to (35);
  if $U_i \le U_i^{\text{NE}}$ **then**
    $g = 1$;
  end if
end for
while $g = 1$ **do**
  $M \leftarrow M + 1$;
  for $m \in \mathcal{M}$ **do**
    for $i \in \mathcal{N}_m$ **do**
      if $\hat{l}_i \in [l^{\min} + (m-1)(l^{\max} - l^{\min})/M, l^{\min} + m(l^{\max} - l^{\min})/M]$ **then**
        Add refrigerated warehouse i to cluster m;
      end if
    end for
    Allocate the forecast demand L to cluster m according to (30);
    Calculate the energy consumption $\boldsymbol{l}^c$ for the refrigerated warehouses in cluster m according to (35);
  end for
  $g = 0$;
  for $i \in \mathcal{N}$ **do**
    if $U_i^m \le U_i^{\text{NE}}$ **then**
      $g = 1$;
    end if
  end for
end while

optimization problem (P3) is convex and has a unique global optimal solution. ■

Supposing the condition (32) is satisfied, we can obtain the optimal solution of (P3), i.e.,

$$\boldsymbol{l}^c = \boldsymbol{H}^{-1}\boldsymbol{C}, \tag{35}$$

where $\boldsymbol{C}$ is defined by

$$\boldsymbol{C} = \begin{bmatrix} p_0 - \lambda L_m - 2\theta_1\gamma_1^2\hat{l}_1 \\ p_0 - \lambda L_m - 2\theta_2\gamma_2^2\hat{l}_2 \\ \vdots \\ p_0 - \lambda L_m - 2\theta_{N_m}\gamma_{N_m}^2\hat{l}_{N_m} \end{bmatrix}. \tag{36}$$

Next, we will check the feasibility of the constraints of (P2). If any constraint of (P2) is not satisfied, the energy provider will increase the number of clusters from M to $M+1$ and reallocate the energy consumption to the refrigerated warehouses according to (35) until all the constraints of (P2) are satisfied. The clustering algorithm is shown in Algorithm 1. The number of clusters obtained by Algorithm 1 is a minimal value to guarantee that the constraints of (P2) are satisfied. In practice, the number of clusters can be larger than this minimal value. The impact of the number of clusters on the performance of the cooperative demand response scheme will be studied in the simulations.

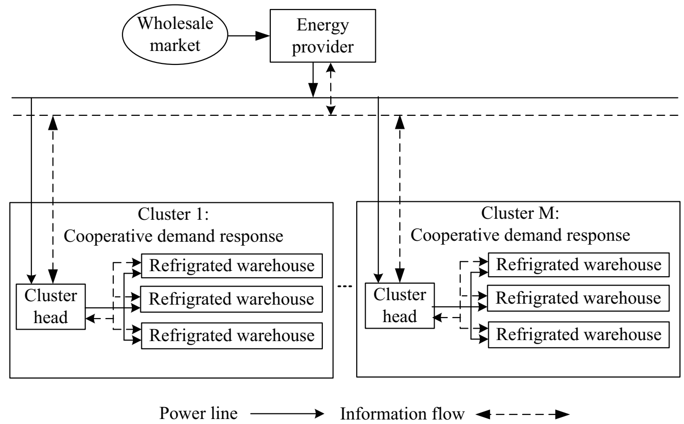

Fig. 3. Cluster-based demand response scheme with industrial refrigerated warehouses.

In each cluster, we introduce a cluster head that is responsible for setting the electricity price inside the cluster and allocating the energy consumption to the refrigerated warehouses using the cooperative demand response scheme, as shown in Fig. 3. When the cluster head observes the change of the total energy consumption from the normal value, it will investigate the reasons for the change, such as the noncooperative behaviors or the detection errors. If the change is caused by the noncooperative behaviors of the refrigerated warehouses, the cluster head will announce the start of the punishment to all the refrigerated warehouses in the next time slot and restart the cooperation after at least $T^{\min}$ time slots. In practice, to obtain the social-optimal energy consumption, the energy provider needs to periodically measure the energy consumption and collect the cost coefficients (e.g., θ_i) from the refrigerated warehouses. However, the information update is not frequent because of large communication overhead. The infrequent communications will further make the energy provider hard to distinguish the noncooperative behaviors from the errors in the total energy consumption. In the simulations, it is shown that the clustering method can benefit the detection of the noncooperative behaviors and reduce the motivations of the refrigerated warehouses to adopt the noncooperative strategies.

VI. Numerical Results

In this section, the performance of the cooperative demand response scheme is evaluated by the Monte Carlo method. We assume that the normal energy consumption of the refrigerated warehouses are uniformly distributed in [100kWh, 150kWh], the cost coefficients $\gamma_i\theta_i^2$ are uniformly distributed in [2, 4] or [3, 5], the base price p_0 is 5 cents/kWh, the forecast demand is estimated by $L = \mu\sum_{i\in\mathcal{N}}\hat{l}_i$, and the pricing parameter λ is calculated by $\lambda = 2/N$ or $\lambda = 1/N$. In the simulations, we consider the case that only one refrigerated warehouse has the

TABLE I. COMPARISONS BETWEEN COOPERATIVE AND NONCOOPERATIVE DEMAND RESPONSE SCHEMES.

	Electricity price (cents/kWh)	Total costs ($)	Average costs ($)	Total energy consumption (kWh)
Cooperation	18.95	5.16×10^3	51.64	0.90×10^4
Noncooperation	64.90	7.74×10^3	77.39	1.13×10^4

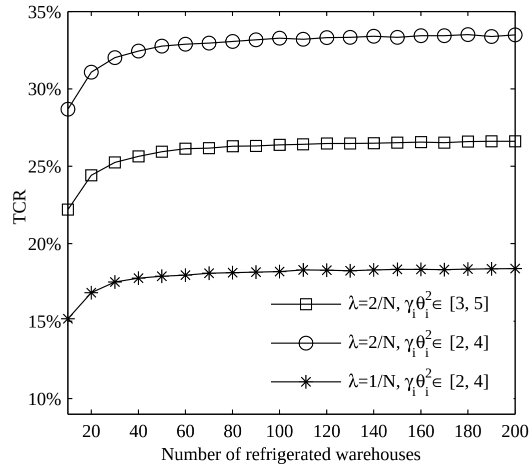

Fig. 4. Total cost reduction of the refrigerated warehouses obtained from the cooperative demand response scheme v.s. Number of refrigerated warehouses.

noncooperative behavior in the demand management system. Before giving the numerical results, we define the performance indexes as follows.

To evaluate the total cost reduction of the refrigerated warehouses obtained from the cooperative demand response scheme, we define the total cost reduction (TCR) as

$$\text{TCR} = \frac{\sum_{i\in\mathcal{N}}(U_i^c - U_i^{\text{NE}})}{\sum_{i\in\mathcal{N}} U_i^{\text{NE}}} \times 100\%. \tag{37}$$

To evaluate the cost reduction of the refrigerated warehouse when adopting the noncooperative strategy, we define the cost reduction due to the noncooperative behavior (CRN) as

$$\text{CRN} = \frac{U_i^d - U_i^c}{U_i^c} \times 100\%,\ \ i \in \mathcal{N}^d. \tag{38}$$

To evaluate the increase of total energy consumption when a refrigerated warehouse adopts the noncooperative strategy, we define the total energy consumption increase due to the noncooperative behavior (EIN) as

$$\text{EIN} = \frac{\sum_{i\in\mathcal{N}^d}(l_i^d - l_i^c)}{\sum_{i\in\mathcal{N}} l_i^c} \times 100\%. \tag{39}$$

A. *Cooperative Demand Response with and without Noncooperative Behavior*

Assuming that the number of refrigerated warehouses is 100, we compare the cooperative and noncooperative demand response schemes in Table I. It is shown that cooperation reduces

TABLE II. COOPERATIVE DEMAND RESPONSE SCHEME WITH AND WITHOUT NONCOOPERATIVE BEHAVIORS (WNB AND WTNB).

	Electricity price (cents/kWh)	Average costs ($)	Total energy consumption (kWh)
WNB	19.58	52.21	0.91×10^4
WTNB	18.95	51.64	0.90×10^4

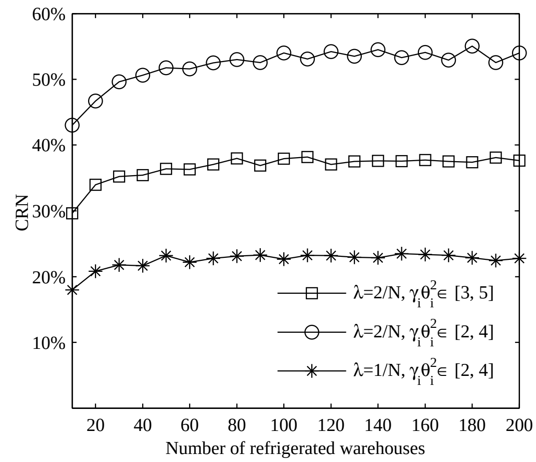

Fig. 5. Cost reduction of the refrigerated warehouse that has the noncooperative behavior v.s. Number of refrigerated warehouses.

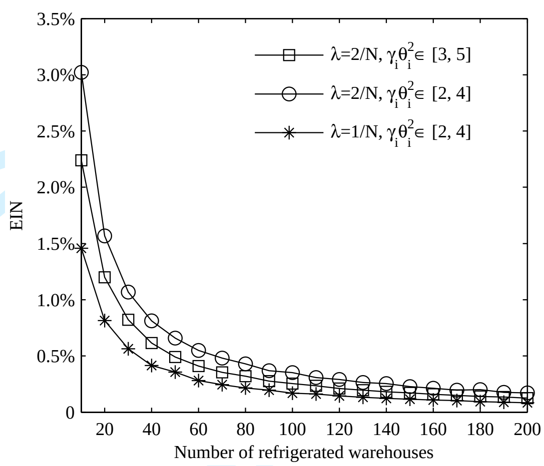

Fig. 6. Increase of the total energy consumption when a refrigerated warehouse has the noncooperative behavior v.s. Number of refrigerated warehouses.

the electricity price, the total costs[4], the average costs, and the total energy consumption effectively. Furthermore, we study the impact of the number of refrigerated warehouses on the performance of the cooperative demand response scheme. As shown in Fig. 4, the total cost reduction obtained from cooperation increases with the number of refrigerated warehouses and

[4]The total costs are composed of the discomfort costs and the payments, and the payments are equal to the product of the electricity price and the total energy consumption.

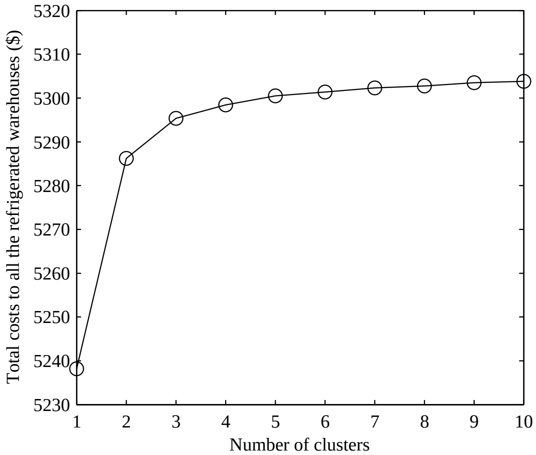

Fig. 7. Total costs to all the refrigerated warehouses in the cooperative demand response scheme v.s. Number of clusters.

starts to saturate when the number of refrigerated warehouses is larger than 60. Assuming that one refrigerated warehouse has the noncooperative behavior and the other refrigerated warehouses keep cooperative, the electricity price, the average costs, and the total energy consumption are all increased, as shown in Table II. The cost reduction of the refrigerated warehouse that has the noncooperative behavior increases with the number of refrigerated warehouses, as shown in Fig. 5, and the increase of the total energy consumption decreases with the number of refrigerated warehouses, as shown in Fig. 6. Both of them saturates when the number of refrigerated warehouses becomes large. From Figs. 4–6, we can also see that a larger pricing parameter (i.e., λ) gives higher TCR, CRN, and EIN, while a larger cost weight (i.e., $\gamma_i\theta_i^2$) gives lower TCR, CRN, and EIN. Furthermore, it is also shown that the noncooperative refrigerated warehouse has relatively large cost reduction and thus strong motivation to adopt the noncooperative strategy, and the increase of the total energy consumption in the demand management system is relatively small when the number of refrigerated warehouses is large. Thus, it is hard to distinguish the noncooperative behavior from the errors in the total energy consumption. To solve this problem, we divide the refrigerated warehouses into different clusters.

B. Cluster-Based Cooperative Demand Response

Assuming that the number of refrigerated warehouses is 100, we study the impact of the number of clusters on the performance of the cooperative demand response scheme. The total costs to all the refrigerated warehouses with clustering are given in Fig. 7. It is shown that the total costs increase with the number of clusters, which indicates that the clustering reduces the social optimality (i.e., the negative total costs) of the cooperative demand response scheme. As shown in Table III, the total cost reduction obtained from cooperation also decreases with the number of the clusters. Assuming that a refrigerated warehouse has the noncooperative behavior and the other refrigerated warehouses keep cooperative, the cost reduction of the noncooperative refrigerated warehouse decreases with the number of clusters, and the increase of the total energy consumption increases with the number of clusters. It is shown that clustering can be helpful for detecting the noncooperative behavior and reducing the motivation of the refrigerated warehouses to adopt noncooperative strategies.

TABLE III. PERFORMANCE OF COOPERATIVE DEMAND RESPONSE SCHEME WITH DIFFERENT NUMBERS OF CLUSTERS.

Number of clusters	TCR	CRN	EIN
1	33.51%	53.42%	0.17%
2	33.25%	53.26%	0.34%
3	32.97%	52.76%	0.51%
4	32.69%	52.23%	0.67%
5	32.41%	51.32%	0.82%
6	32.13%	50.76%	0.98%
7	31.85%	49.80%	1.13%
8	31.57%	49.07%	1.28%
9	31.29%	48.40%	1.43%
10	31.07%	47.53%	1.57%

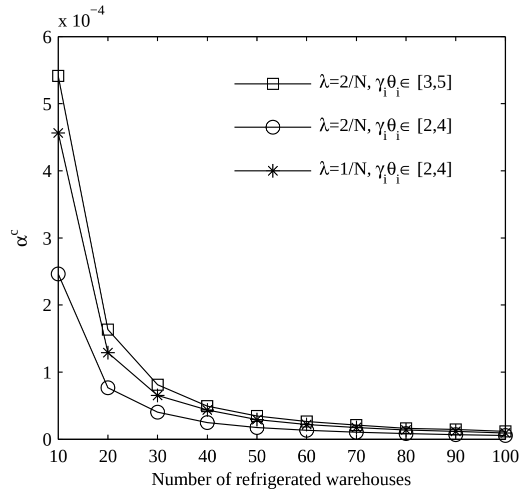

Fig. 8. Critical probability of the noncooperative behavior (α^c) v.s. Number of refrigerated warehouses.

C. Noncooperative Behavior Detection and Punishment

As shown in Fig. 8, the critical probability decreases with the number of refrigerated warehouses. Specifically, even when the number of refrigerated warehouses is 10, the critical probability is smaller than 0.06%, which indicates that $\eta^{\max}$ is always the optimal detection threshold[5], because the number of refrigerated warehouses in the demand management system is larger than 10 and thus $\alpha > \alpha^c$ is satisfied almost everywhere. Furthermore, it is also shown in Fig. 8 that a larger λ gives a lower critical probability and a larger $\gamma_i\theta_i^2$ gives a higher critical probability. Assuming that one refrigerated warehouse

[5]The optimal threshold $\eta^{\max}$ indicates that the false alarm can cause more loss of social optimality than the false detection. Thus, the punishment mechanism should not be triggered more often.

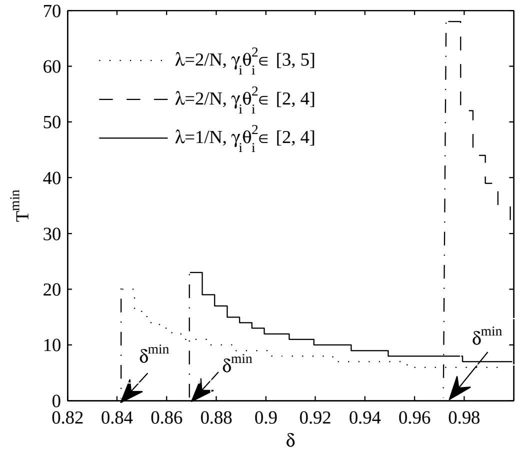

Fig. 9. Minimal duration of punishment v.s. Discount factor.

TABLE IV. MINIMAL DURATION OF PUNISHMENT AND LOWER BOUND OF DISCOUNT FACTOR.

	$\lambda = 2/N, \gamma_i\theta_i^2 \in [3,5]$	$\lambda = 1/N, \gamma_i\theta_i^2 \in [2,4]$	$\lambda = 2/N, \gamma_i\theta_i^2 \in [2,4]$
$T_{\min}$	6	7	32
$\delta_{\min}$	0.84	0.86	0.97

has the noncooperative behavior, we study the minimal duration of punishment (i.e., $T^{\min}$) and the lower bound of the discount factor (i.e., $\delta^{\min}$) under different parameter settings. As shown in Fig. 9, the minimal duration of punishment decreases with the discount factor because the future costs play a more significant role in the average costs and thus less duration of punishment is needed to stop the noncooperative behavior. It is shown in Table IV that a larger λ gives a higher $T^{\min}$ and $\delta^{\min}$, and a larger $\gamma_i\theta_i^2$ gives a lower $T^{\min}$ and $\delta^{\min}$.

VII. Conclusion

In this study, we formulate cooperative demand response as a constrained social optimization problem. It is shown that the cooperative demand response scheme reduces the electricity price, the total costs, the average costs, and the total energy consumption comparing with the noncooperative demand response scheme. We develop the trigger-and-punishment mechanism to keep cooperation and avoid the noncooperative behaviors of the price-anticipating consumers. We establish the condition on the duration of punishment to guarantee the incentive compatibility. The cooperative demand response scheme is further applied to load management of industrial refrigerated warehouses with HVAC systems, and the refrigerated warehouses are divided into different clusters that are managed by cluster heads. The cooperative demand response scheme is executed within each cluster. It is shown that the clustering method can help with the detection of noncooperative behaviors and reduce the motivation of the consumers to adopt noncooperative strategies.

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