A New Deregulated Demand Response Scheme for Load Over-Shifting City in Regulated Power Market

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Abstract*-- Time-based demand response (DR) is an effective way to improve the reliability of power grid and reduce energy costs. Time-Of-Use tariff (TOU) has been adopted by many countries and achieved good performance. However, in cities with a large proportion of industrial consumers, load over-shifting phenomenon leads to new peak electricity consumption and reduces the effect of TOU. This paper proposes a new deregulated demand response scheme (DDR) to solve the load over-shifting problem. The scheme selects industrial consumers with large shiftable load in the city as load adjustment component and provides independent tariff to each consumer. Different to other methods with the requirement of entire scheme replacement, the proposed DDR only influences a small group of consumers with much lower implementation risk. Also, the cost of consumers and profit of agent can be improved at the same time as shown in the numerical study. In the proposed scheme, the interests of consumers and the agent need to be considered in the formulation of independent tariff, which forms a nested optimization problem that is difficult to solve quickly. In this paper, a novel and efficient approximate algorithm is proposed to solve the optimization problem. The proposed algorithm can produce optimal solutions similar to Genetic Algorithm with higher computational efficiency.

Keywords: Load Over-Shifting, Deregulated demand response, Independent tariff, Nested optimization

Nomenclature

Variables

Pr_n	Dynamic price offered to the nth OSC
L_opt_n	Total load of the nth OSC after optimization
$Bill\_opt_n$	Electric bill of the nth OSC after optimization
AL	All loads in the city, including OSCs' and other users'
$Bill_n$	Electric bill of the nth OSC
$l_{n,t}$	Total load of the nth OSC at time slot t
G	Output power of units
$g_{m,t}$	Output power of the mth unit at time slot t
$L_{Tra,t}$	Total load in the city at time slot t from all consumers except OSCs
$st_{n,m,t}$	The operational status of the mth device in the nth OSC at time slot t
$st\_opt_{n,m,t}$	The operational status of the mth device in the nth OSC at time slot t after optimization

Other Function

$Pf()$	Output the cost of agent according to Γ and L_opt
$Bf_n()$	Represents how a OSC changes behaviors and load with newly offered dynamic price
$\underset{x}{\overset{obj}{argmin}}\,(\Upsilon)$	Output the optimal solution x of the optimization problem whose objective function is 'obj' and the boundary condition set is Υ

Parameters

A,B,C	Parameters of generation cost
Φ_n	Operational parameters set in the nth OSC
Γ	Parameters set except changed load from OSCs
$Bill_{n\_max}$	The max electricity bill that the nth OSC can accept
KD	Load correlation matrix
KP	Unit correlation matrix
SF	Shifting factor matrix
R_{max}	The max climbing power of power units
PL_{max}	Upper boundary for power transmission in the transmission line
$g_{m,max}$	Maximum output power of the mth unit
$g_{m,min}$	Minimum output power of the mth unit
$DPcons_{n,t}$	The total unshiftable load of nth OSC at time slot t
$DP_{n,m}$	The power of the mth device in the nth OSC
$STC_{n,m}$	The total working time of the mth device in nth OSC in one day

Abbreviations

OSC	Over-Shifting contributors
DR	Demand Response
DDR	Deregulated Demand Response
TOU	Time-of-Use
RTP	Real-Time-Price
PDRC	Provincial Development and Reform Commission

I. Introduction

A. Background And Problem Definition

Demand Response (DR) consists of various methodologies to achieve supply-demand balancing in modern power system. DR aims to modify power consumption to adapt power system's operation by economic encouragement adjustment [1~6]. US National Institute of Standards, and Technology (NIST) and US Federal Energy Regulatory Commission (FERC) had classified DR into two categories, which is time-based DR and event-based DR [7,8]. Time-Of-Use tariff (TOU) is a typical time-based DR which is popular in many districts. For example, Tucson in USA [9] adopts TOU tariffs for both residential and industrial consumers. The peak periods and the tariffs are not the same between residential, industrial and commercial consumers. The tariffs for industrial consumers with different power consumption scales are also different [9]. In Jiangsu Province of China [10], TOU is adopted for large industrial users and cooling and heating loads. In France [11], EDF offers off-peak electricity tariff for residential users. TOU's higher/lower price period is usually set to the period whose load is relatively higher/lower so that consumers are expected to shift their power consumption from higher price period to lower price period. With this behaviour change, difference between peak load and valley of a districts are expected to be moderately reduced and the generation cost of power system will be decreased [12~18]. However, the expected effect may not always occur. Fig. 1 shows an example from a typical city in China.

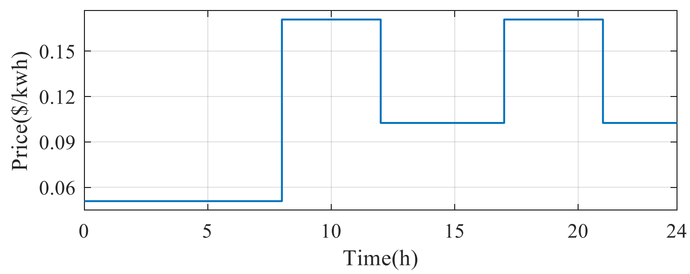


Fig.1 (a): The TOU Tariff in A Typical City with Large Industrial Consumers

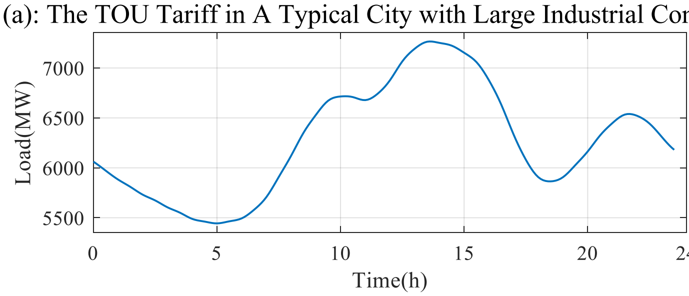


Fig.1 (b): The Total Electric Load of a Typical City

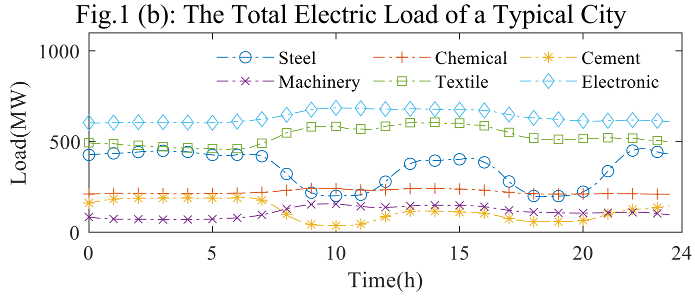


Fig.1 (c): Electric Load of Typical Industries in the City

In Fig. 1(a) and (c), TOU actually promotes consumers to shift their electricity consumption (i.e., load) from high price period (9:00 – 13:00 and 18:00-22:00) to lower price period (e.g., 13:00 – 18:00). But the amount of shifted load is too large so that new peaks occur in 13:00 – 18:00. This means that the TOU in the case of Fig.1 creates a new load peak instead of reducing original peak moderately. As the power system cost reduction comes from the difference reduction between load peak and load valley, this new peak creation may reduce the positive effect of TOU and even contributes larger cost.

The reason for TOU's effect loss in Fig. 1 comes from the power load over-shifting (i.e., too much load is shifted into a same time period). It means that this city contains too much price responsible load, which usually comes from the following two factors.

Factor 1: Too many consumers are offered the same TOU. The price in Fig.1 (a) of a typical city is deployed to all industrial consumers whose capacity is larger than 100 kVA. It may lead to a similar load shifting direction for many consumers group.

Factor 2: A TOU covering area contains consumers with extremely large shiftable load. For example, the typical city in

Fig. 1 contains cement manufacturing and steel manufacturing industries, whose shiftable load is up to 30 MW in total.

Electricity consumers in China are heavily influenced by factor 1. Nearly all official TOU tariff is offered to all large industrial consumers with a same shape in each province, which is normally generated by Provincial Development and Reform Commission (PDRC) [10, 19, 20]. TOUs with a same shape mean that the relatively high/low relationship of price level between each two hours are the same. Factor 2 generally occurs in areas with large heavy industries. In this case, electricity consumers in China are affected by Factor 2 because nearly 68% electricity is consumed by industrial consumers. Cities with multiple large shiftable loads are common. In summary, load over-shifting of TOU is a possible unexpected phenomenon for areas with Factor 1 & 2, which China is a typical example. This phenomenon decreases the effect of TOU and increase the operation and construction cost of power system.

Gap of DR Scheme on Over-Shifting Phenomenon: In summary, cities with Factor 1 and 2 require new scheme to not only inherit the load improvement capability of TOU but also reduce the effect of over-shifting phenomenon. Also, the new scheme is expected to contain less implementation cost and risk by changing tariff of too many consumers.

B. Literature Review

Target areas of this paper is with load over-shifting phenomenon, which indicates two practical situations. Situation 1 is that many consumers are already offered a same-shape TOU tariff. Situation 2 is that load over-shifting phenomenon occurs. To prevent large social cost and risk from changing electric tariff for an extremely large consumer group, this paper tries to improve traditional TOU with influencing only a small section of consumers, which means that this small section of consumers may receive independent prices.

A literature review is deployed for the consideration above. There are tremendous number of materials on demand response and TOU tariff. Houman Jamshidi Monfared et al [21] proposed a mixed price demand response scheme for residential consumers. This scheme combines the advantages of TOU and real-time price (RTP), reduces the peak valley difference and improves the social benefits. This scheme is for all residential consumers and needs a large number of residential consumers to participate in the response to achieve better results. Ziyang Wang et al [22] proposed a new interactive real-time pricing scheme based on a comfort evaluation model. Through the interaction between the behavior of residential consumers and the RTP, the scheme can reduce the difference between peak and valley of load, stabilize the load fluctuation and reduce the electricity cost of consumers. This scheme requires the participation of all residential consumers, and the consumers should pay attention to the change of RTP frequently. Mohsen Khorasany et al [23] proposed a new two-stage trading scheme in day-ahead and real-time market. This scheme can reduce the cost of each consumer and the whole community, through bidding and coordination between agents and community coordinator in day ahead and real-time market. This scheme needs the interaction of consumers, agents and community coordinator in the whole community to achieve the best economic effect, which is easy to cause fatigue. Rui Tang et al [24] proposed a dynamic tariff demand response scheme based on game theory. The scheme can reduce the fluctuation of load demand, improve the profit of power grid and reduce the cost of consumers. This scheme requires all buildings to participate in the bidding in day-ahead market to formulate the dynamic tariff until Nash equilibrium is reached. The frequent game process will make consumers feel inconvenient.

C. In summary, majority of research works on DR attempt to analyse or initiate a scheme for a large consumer group other than a scheme compensation to an implemented DR. Generally, changing tariff of too many consumers may lead to large implementation difficulties and social risk. Moreover, there are rare materials are target to the scheme improvement of traditional TOU with consideration on over-shifting phenomenon in this literature review. Original Contribution

Facing the issue above, this paper initiates a Deregulated Demand Response scheme (DDR) to reduce the effect of over-shifting phenomenon. It can be recognized as a scheme compensation to traditional TOU. Details of contributions includes the following 3 points.

- A novel structure of DDR scheme is proposed for areas with over-shifting phenomenon. To prevent changing tariff for too many consumers, DDR only adjusts the tariff of a small group of consumers. By selecting consumers with large shiftable load to that small group, the scheme offers independent tariff to each consumer for a Two-Win solution between power grid and the load-adjustable consumer. This selected small group is recognized as an adjustable load compensation to the city so that the main contributors of over-shifting phenomenon can shift their load into other time periods.
- Considering the controlling variable affiliation, a special optimization structure i.e., nested optimization modelling is selected for DDR so that price maker, consumers and power system operator can only control their variables. The independent price making is set to be the chief optimization and optimization of consumers. Power system operators are nested as sub-optimization into the objective function of chief optimization. This modelling logic ensures a together optimization minimum of price maker, selected large consumers and power grid, which provides much more feasibility of scheme implementation.
- Facing the gradient computation difficulties in nested optimization, a new efficient approximating algorithm is proposed to increase the computational efficiency instead of using stochastic algorithm. The numerical shows that the proposed algorithm can achieve similar optimum to Genetic Algorithm with more than 300 times faster.

II. Structure of Deregulated Demand Response Scheme

A. *Aim of Deregulated Demand Response*

The aim of Deregulated Demand Response (DDR) is to reduce city's peak power load by targeting on a small section of load-flexible-changing consumers without influencing the majority of consumers. From Fig.1, it is obvious that typical industrial load-flexible-changing consumers contribute a lot on city's load over-shifting. A united hourly dynamic electricity price promotes all flexible load into the price valley. To deal with this over-shifting issue in regulated power market (e.g., China), one typical way is to construct a deregulated power market (e.g., Day-ahead Market or Real-time Market in PJM) so that dynamic prices with different shapes in a day are offered to consumers under different buses. But overthrowing the entire regulation in power market immediately is a big revolution and may lead to huge cost and risk to the entire consumers. To prevent the huge cost and risk, a more feasible way is to find out the over-shifting contributors (OSC) and provide independent price with different shapes so that they can shift the load to other time periods. This idea contains the following advantages:

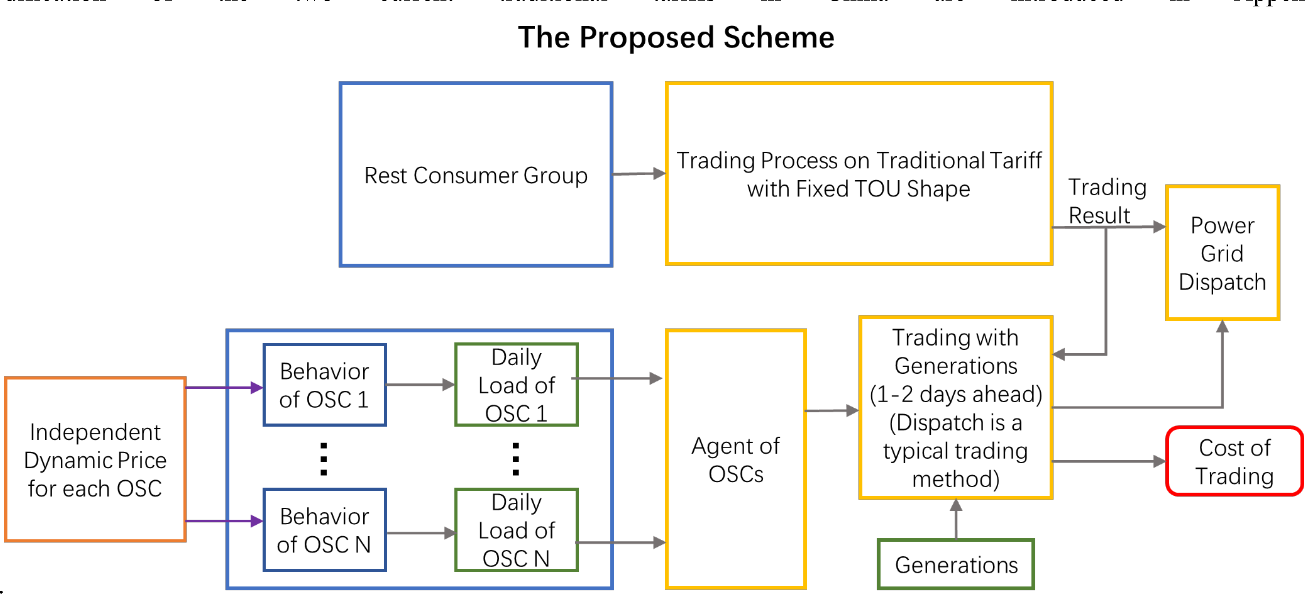
(1) Load of industrial OSCs is usually easier to be shifted by price shape than other consumers. The major contributors of peak over-shifting are sensitive to the shape of daily dynamic price. In other words, it is much easier to shift load from these consumers to other time period by providing a different price shape. In areas with industrial park, these load-flexible-changing consumers are usually large industrial consumers. For example, Fig.1 shows a section of typical daily load of industrial consumers in a typical city in China [25]. In Fig.1, consumers from cement manufacturing and steel manufacturing are this type of consumers.

(2) Targeting on large industrial OSCs can reduce city's peak power without influencing the entire consumer group. Instead of facing the risks and barriers from deregulation on entire power market, focusing on over-shifting contributors are much easier. The number of relevant consumers is much lower and the difficulties on negotiation with consumers are much smaller.

(3) Precedents of providing special price to a part of industrial consumers exist already. Usually, implementation of policies with similar precedents is with less barriers. As an example for China, special electricity price is offered to industrial consumers from high energy-consuming enterprises [10,19]. On the point of providing different electricity price to a small section of industrial consumers, the policy for high-energy-consuming enterprises and the proposed scheme are similar.

B. *Structure of Deregulated Demand Response*

Fig.2 shows the detail structure of DDR. In Fig.2, the entire logic is that the price maker provides independent daily dynamic price to selected OSCs. Each OSC will optimize its behaviours and load under the offered prices and forms a new daily load. Then the agent of OSCs will spend less cost on purchase energy from generations. Neither of selected OSC is forced to join DDR. Each OSC can offer an ensuring power cost reduction level for price maker as their condition on DDR participation. Otherwise, any OSC can choose back to traditional price scheme. In summary, the aim of price maker is to reduce the cost of electricity of energy purchase with ensuring DDR participated OSCs' benefit improvements. So the final objective for price maker is the cost of trading and OSCs benefit improvements are the constraints. The adjustable item for price maker is the independent daily price for OSCs. With this scheme, less load is concentrated in the peak period. The power grid can benefit with less over-loading or instability situation from lower daily consumption peak. Following the proposed scheme, detail modification of the two current traditional tariffs in China are introduced in Appendix.



VI.

Fig.2: Structure of The Proposed DDR

III. Modelling on Deregulated Demand Response Scheme

A. Nested Optimization Modelling Logic

In scheme modelling, behaviors of 3 stakeholders are included. They are the price maker whose behavior is to offer independent prices to selected consumers, the selected consumers whose behaviors are to control their load on the offered prices, and the agent of OSC who represents all OSCs to trade with generation. These behaviors from 3 stakeholders are all with independent degree of freedom. A typical modelling logic is to recognize them all as argument of the entire optimization [26~29]. But it may lead to that the entire optimum sacrifices the benefit of one stakeholder and contributes more to another. This feature may decrease the feasibility of the entire model (practically, each stakeholder only prefers to find out their own optimum without considering others' optimums). In other words, the optimum of entire model and the model of each stakeholder should be achieved synchronously to increase model's feasibility.

So this paper constructs the model respecting the practical influencing chain. The chief modelling is the price making optimization, which corresponds to price maker. As each OSC will optimize its behavior on the offered independent price, the optimization of each OSC is nested into the objective function of chief model, which constructs the influencing chain from price to power load. Moreover, the agent of OSCs will trade with generation with the trading mechanism on the given load. So this process is also nested into the objective function of chief model, which constructs the influencing chain from load to energy benefit.

B. Chief Modelling of DDR

From Fig.2, it is obvious that the problem faced by price maker is an optimization problem. Simply, DDR is to find out the optimal independent daily price to each OSCs for a minimum energy purchasing cost with ensuring each OSC's cost reduction. Equation (1)-(3) can review this logic. Function $Bf_n(\ )$ in Equation (1) represents how a OSC changes behaviors and load with newly offered dynamic price. Pr_n is the dynamic price offered to the nth OSC. Φ_n is other operational parameters in the nth OSC. L_opt_n and $Bill\_opt_n$ are the changed load and electric bill of changed load from the nth OSC. Function $Pf(\ )$ in Equation (2) represents the trading with all changed load from OSCs. Γ is other parameters except changed load from OSCs. Output of function $Pf(\ )$ is the cost of energy trading, which is the final object in the optimization. Equation (3) represents that electric bill of the nth OSC should be lower than an ensuring bill level.

$$[L\_opt_n, Bill\_opt_n] = Bf_n(Pr_n, \Phi_n) \tag{1}$$

$$Min:\ Obj\_1 = Cost = Pf(L\_opt_1, L\_opt_2, \cdots, L\_opt_n, \Gamma) \tag{2}$$

$$Cons\ 1:\ Bill_n \leqslant Bill_{n\_\max} \tag{3}$$

Details of Equation (1) is revealed in part C of section III and details of Equation (2) is revealed in part B of section III.

C. Modelling of Energy Trading

This part introduces detail model on how changed loads from OSCs influence the cost of trading. There are multiple mechanisms for energy trading. In the proposed scheme, the trading mechanism is not only required to capable of generation competition but also consider the impact from OSCs' entire changed load in power grid operation. A typical mechanism capable to these requirements is the economic dispatch model [经济调度可以实现市场化竞争的论文]. In this paper, a typical economic power dispatch model [30~33] is selected and revealed in Equations (4) – (8). Equation (4) is the objective function indicating the cost of economic dispatch. Equation (5) ensures the energy balancing among power generations and loads. Equation (6) ensures transmission lines are used in their secure range. Equation (7) ensures power generation capacity of each power plant is operating within secure range. Equation (8) is the climbing constraint of power units.

$$Min:\ \underset{arg:G}{Obj\_2} = sum(A \cdot G^2 + B \cdot G + C) \tag{4}$$

$$Const\ 2.1: \sum_{m=1}^{M} g_{m,t} = L_{Tra,t} + \sum_{n=1}^{N} l_{n,t} \tag{5}$$

$$Const\ 2.2: -PL_{\max} \leqslant SF \times (KP \times G_t - KD \times AL_t) \leqslant PL_{\max} \tag{6}$$

$$Const\ 2.3: g_{\min} \leqslant g_{m,t} \leqslant g_{\max} \tag{7}$$

$$Const\ 2.4: -R_{\max} \leqslant g_{m,t+1} - g_{m,t} \leqslant R_{\max} \tag{8}$$

This trading model can also reveal the influence from OSCs' changed load to power grid operation, including effect on electricity production, transmission and other relevant constraints.

In Equation (4)-(8), newly changed load values from OSCs are the boundary condition in equality constraint 2.1 and the inequality constraint 2.2. It means that the influencing path from OSCs' changed load to the final cost is constructed by changing the boundary condition of economic dispatch. In other words, function $Pf(\ )$ in Equation (2) is a sub-optimization in the entire optimization problem, as shown in Equation (9).

$$\begin{cases} Min:\ Obj\_1 = Pf(L_1, L_2, \cdots, L_n, \Gamma) = Obj\_2\left(\underset{G}{\overset{Obj\_2}{argmin}}\,(L\_opt_1, L\_opt_2, \cdots, L\_opt_n, \Gamma)\right) \\ \Gamma = \{A, B, C, L_{Tra}, PL_{\max}, SF, KP, KD, g_{\min}, g_{\max}, R_{\min}, R_{\max}\} \end{cases} \tag{9}$$

D. Modelling of Behaviour Optimization in OSC

This part introduces detail model on how offered independent daily dynamic electricity price influence OSCs' load. On the area of relationship between price and consumption, one popular model is price-consumption elasticity [34~39]. This model recognizes the detail relationship between price variation and consumption variation as a simple default model (e.g., a linear model) and use historical data to obtain the unknown parameters. The advantage of elasticity is its simple model structure. But it is usually effective on a large consumer group with enough consumers. It is difficult to predict the consumption variation when the price changes greatly. In the situation of DDR, one independent daily price is only offered to one consumer. Therefore, the power load variation deeply relates to the special industrial operation inside each OSC. The detail behaviour models of industrial OSCs [40~45] should be selected other than price elasticity. One typical general industrial model is referred in this paper to construct the relationship between price and load [25]. Equations (10)-(12) introduce the detail model between price and load. Generally, OSC change their power consumption behaviours is for a lower power cost with the same manufacturing capability and device operation stability. Equation (10) reveals that each OSC's object is to decrease its cost. Variable $DP_{n,m}$ is the power of the *m*th device in the nth OSC. This power is an average power of a device. Actually, the real power load of continuous process and discontinuous process is different. Some discontinuous process from certain industries may fluctuated largely secondly or minutely. But practically, the energy consumption for an industrial device at a certain gear deeply relates to the workload suffered in a longer time period. And the power consumption is deeply relating to the workload suffered by the device. In this case, though power load of discontinuous process may fluctuate secondly or minutely, it can be replaced by an equivalent stable continuous power in its energy computation in a longer period. In this paper, the power load modelling selected from reference [25] is with this consideration. It uses an equivalent stable continuous power load in a longer period, such as hourly power load, to present the energy consumption. And the hourly energy consumption is the focusing point of power bill and some of the power grid operation, such as day-ahead power dispatch. This logic of approximation is similar to the Effective Value of 3-Phase current, which using a stable continuous value to represents the energy aspect of fluctuation. E.g., the process of welding may be discontinuous. So the actual power of welding fluctuates largely at seconds level or minutes level. But when stay at level of one hour or half an hour, the power consumption of weld relates to the workload of welding. Intermittence on higher frequency does not influence the power consumption at certain long period, e.g. hourly. So the average power is used. Variable $st_{n,m,t}$ is the operational status of the *m*th device in the nth OSC at time t. Equation (11) reveals the work load of any device in OSC should be the same. In other words, OSC's behaviour changing should not change the entire manufacturing requirement. Equation (12) ensures that devices' operational status is logical variable.

$$\underset{arg:st_{n,m,t}}{Min:Obj\_3} = \sum_{t=1}^{T}(pr_{n,t} \cdot l_{n,t}) = \sum_{t=1}^{T}\left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M}(st_{n,m,t} \cdot DP_{n,m})\right]\right) \tag{10}$$

$$Const\ 3.1: \sum_{t=1}^{T} st_{n,m,t} = STC_{n,m} \tag{11}$$

$$Const\ 3.2:\ st_{n,m,t} = 0\ or\ 1 \tag{12}$$

Modelling on assembly line processing is compatible in Equation (10)-(12) [25]. If there is no storage, multiple devices of assembly line should be switched at same operational status. In this case, these group of devices can be recognized as one device and one variable on operational status is sufficient. The corresponding device power is the summary of all these devices in the group. Devices with more than two operational statuses are also compatible in the model. For example, if a device is with 3 operational statuses (Off / 1 / 2). It can be modelled as two devices. One device is with status Off / On and the device power is set to power at original 1 status. The other is with Off / On as well and the device power is set to power at original 2 status. Then any operation situation of original device can be modelled with these two devices.

Indeed, not all industrial consumers fit for the model described in Equations (10)-(12). This model is designed for industrial consumers which contains large shiftable load. It means that the relevant industrial consumers should satisfy 2 conditions: One condition is that at least a section of industrial devices are with low start-up cost, whose power load are also not small. High start-up cost usually indicates nonstop operation for devices. The other condition is that the workloads from consumers' orders are not large enough so that those shiftable devices have to keep working without resting time daily. In summary, this model is suitable for consumers who have low shiftable cost and shiftable time space in a day. One method of scope confirmation is to find out the correlation between the price shape and the historical power load. For example, Table R.1 reveals this correlation. It is obvious that consumers with high correlation indicates their high capability and willing in power load shifting.

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In Equation (10)-(12), the offered independent price are the boundary condition in objective function. It means that the influencing path from each independent daily price to OSCs' changed load is constructed by changing the boundary condition

OSC's behaviour optimization. In other words, function $Bf_n(\ )$ in Equation (1) is a sub-optimization in the entire optimization problem, as shown in Equation (13).

$$\begin{cases} [L\_opt_n, Bill\_opt_n] = Bf_n(Pr_n, \Phi_n) \\ \Rightarrow \begin{cases} L\_opt_n = DPcons_{n,t} + \sum_{m=1}^{M} \left(\underset{st_{n,m,t}}{\overset{Obj\_3}{argmin}} (Pr_n, \Phi_n) \cdot DP_{n,m} \right) \\ Bill\_opt_n = L\_opt_n \times Pr_n \end{cases} \\ \Phi_n = \{DP_{n,m}, DPcons_{n,t}, STC_{n,m}\} \end{cases} \tag{13}$$

IV. Efficient Algorithm for Nesting Optimization in The Proposed DDR Scheme

A. Nesting Optimization Structure in DDR

As shown in section III, Equations (1), (2), (3) reveal that the model of DDR is an optimization problem (*Obj*_1), which is finding independent daily prices to each OSC for the lowest cost in power trading. Equations (9) and (13) reveal that computation of objective function in *Obj*_1 with a candidate argument requires to solve two types of sub-optimizations. One is the optimization of economic dispatch (*Obj*_2 and *Const* 2.1-2.4) and the other is optimization of OSC's behaviour optimization (*Obj*_3 and *Const* 3.1-3.2). This mathematical structure is called nesting optimization [30,46], which the objective function of entire problem contains sub-optimizations.

The feature of nesting optimization is that the gradient of optimization object to the argument is usually difficult to be obtained. The reason is that gradient computation usually requires to find out dominant expression from optimal solution to one of the boundary conditions in sub-optimization section. This feature restricts the utilization of gradient based solving algorithms (e.g., Gradient Decent, BFGS, LM and so on), which are popular in high converging efficiency. Excluding gradient based algorithms, stochastic algorithms (e.g., Genetic Algorithm, Partial Swarm Optimization, and Artificial Bee Colony) do not requires gradient computation and are candidates to solve nesting optimization. But the converging time and computational resources of stochastic algorithms are usually much larger. What's more, all sub-optimizations require solving in each individual of stochastic algorithms, which significantly increase the computational work of stochastic algorithm.

B. A New Algorithm for Nesting Optimization in DDR

To prevent the large computational work of stochastic algorithm, this paper proposes a new algorithm for nesting optimization in DDR. The basic logic of the proposed algorithm is that we may try to find out what types of load can decrease the cost of city's energy trading most firstly. Then try to find out the independent daily price that can promote each OSC to achieve that load type. This logic separates the entire optimization problem into two different problems. Each of them is an independent optimization which prevents the nesting optimization structure. The entire algorithm contains 2 modules.

- **Module 1: OSC's Load Modification for Optimal Power Trading Cost**

Following the proposed logic, the first step is to find out what types of loads from OSCs can decrease the cost of energy tradings and the entire cost of city's power mostly. Equations (14)-(19) reveal the model of this step. This model is derived from the sub-optimization of *Obj*_2 (Equation (4)-(8)). The first difference between model in Module 1 and the model in *Obj*_2 is that both G and $st_{n,m,t}$ are the argument in Equation (4) instead of only letting G as argument in *Obj*_2. Leading in $st_{n,m,t}$ represents that the optimal cost of trading relates to different devices' operation status in every OSCs. The second difference is that constraint 3.2 is removed and a penalty term is added in objective function (Equation (14)). This modification change $st_{n,m,t}$ from discrete solution space into continuous solution space. The convex penalty term will still restrict $st_{n,m,t}$ to be close to 0 or 1. Definition of parameters can be referred to Nomenclature in Section I.

$$Min: \underset{arg: G, st_{n,m,t}}{Obj\_4} = sum(A \cdot G^2 + B \cdot G + C) + \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{m=1}^{M} [\alpha_{n,m,t} \cdot st_{n,m,t}^2 \cdot (1 - st_{n,m,t})^2] \tag{14}$$

$$Const\ 2.1: \begin{cases} \sum_{m=1}^{M} g_{m,t} = L_{Tra,t} + \sum_{n=1}^{N} l_{n,t} \\ l_{n,t} = DPcons_{n,t} + \sum_{m=1}^{M} (st_{n,m,t} \cdot DP_{n,m}) \end{cases} \tag{15}$$

$$Const\ 2.2: -PL_{\max} \leq SF \times (KP \times G_t - KD \times AL_t) \leq PL_{\max} \tag{16}$$

$$Const\ 2.3: g_{\min} \leq g_{m,t} \leq g_{\max} \tag{17}$$

$$Const\ 2.4: R_{\min} \leq g_{m,t+1} - g_{m,t} \leq R_{\max} \tag{18}$$

$$Const\ 3.1: \sum_{t=1}^{T} st_{n,m,t} = STC_{n,m} \tag{19}$$

One point should be paid attention that G is always the optimal solution for the minimum of *Obj*_2 corresponding to any $l_{n,t}$

and $st_{n,m,t}$ throughout the optimization process in non-gradient based algorithm (e.g. Genetic Algorithm). It represents that optimal trading cost is always dependent on given loads from OSCs. The economic dispatch considers its own parameters independently to the price maker and OSCs. But in Equation (14)-(19), G and $st_{n,m,t}$ are both argument. So throughout the optimization process of Equation (14)-(19), G cannot be guarantee to be the optimal solution when setting $st_{n,m,t}$ as boundary in *Obj*_2. It means that the power trading platform may not provide a same controls as the G given by optimization on *Obj*_4 when letting the optimized $st_{n,m,t}$ as boundary condition.

To explain the feasibility of Equation (14)-(19) on this point, Lemma 1 is introduced.

Lemma 1: *Let $X=[X_1, X_2]^T$ is the argument of an optimization problem (OP1) with objective function $OBJ=F(\{K\},X)$. X_1 and X_2 are sections of argument elements. $\{K\}$ is the set of boundary conditions of OBJ. $\underline{X}=[\underline{X_1}, \underline{X_2}]^T$ is an extreme point of OP1. Let $X'=[X_2']$ is the argument of an another optimization problem (OP2) with objective function $OBJ= F(\{K, \underline{X_1}\}, X_2')$. Difference between OP1 and OP2 is that argument section of X1 in OP1 and OBJ becomes boundary condition with value $\underline{X_1}$ in OP2 and OBJ'. Then $\underline{X_2}$ is also the extreme point of OP2. (Proof of Lemma 1 is in Appendix I)*

With Lemma 1, at the converging point of optimization in Equations (14)-(19), G and $st_{n,m,t}$ in the solution of *Obj*_4 follow that G is also the extreme point of *Obj*_2 with $st_{n,m,t}$ as boundary condition. The converging point is the final selection through the entire optimization process of *Obj*_4 other than any non-converging solution. In other words, using the converging solution from model in Module 1 withstands the verification on original model of *Obj*_2.

- **Module 2: Price Scheduling for The Modified OSC's Load**

Module 1 outputs the expected behaviours from OSCs for minimum cost of power grid energy dispatch. So the aim of Module 2 is to find out the independent dynamic daily price to promote OSCs to behave with the expected behaviours. Practically, OSC will behave for its minimum electric bill with manufacturing operation satisfaction, as shown in *Obj*_3 in Equation (10)-(12). The optimization problem contains a feature which is shown in Lemma 2.

Lemma 2: *The optimal solution of optimization problem in Equation (10)-(12) contains the following feature: For any t_1 and t_2, when $pr_{n,t_1} > pr_{n,t_2}$, then the optimal solution obeys $st_{n,m,t_1} \leqslant st_{n,m,t_2}$. When $pr_{n,t_1} < pr_{n,t_2}$, then the optimal solution obeys $st_{n,m,t_1} \geqslant st_{n,m,t_2}$. (Proof of Lemma 2 is in Appendix II)*

Lemma 2 indicates that OSC's optimal consumption deeply relates to the daily price shape, which is the comparative relationship between any price at one time period to prices in all other time periods. This feature indicates a price scheduling method. That is setting a negatively correlated price shape to the expected load of an OSC as a constraint. And find out the suitable price level in the shape that satisfying the bill reduction requirement from OSC. Equation (20)-(23) reveals the models on this logic.

$$\begin{cases} \underset{arg:pr_{n,t}}{Max:Obj\_5} = \sum_{t=1}^{T} (pr_{n,t} \cdot l\_opt_{n,t}) = \sum_{t=1}^{T} \left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M} (st\_opt_{n,m,t} \cdot DP_{n,m}) \right] \right) \\ [L\_opt_1 L\_opt_2, \cdots, L\_opt_n] = \underset{st_{n,m,t}}{\overset{Obj\_4}{argmin}} (\Gamma, \Phi_n) \end{cases} \tag{20}$$

$$Const\ 5.1: \forall t_1, t_2 \begin{cases} if\ st\_opt_{n,t_1} \neq st\_opt_{n,t_2} \Rightarrow (st\_opt_{n,t_1} - st\_opt_{n,t_2}) \cdot (pr_{n,t_1} - pr_{n,t_2}) < 0 \\ if\ st\_opt_{n,t_1} = st\_opt_{n,t_2} \Rightarrow pr_{n,t_1} = pr_{n,t_2} \end{cases} \tag{21}$$

$$Const\ 5.2: \sum_{t=1}^{T} (pr_{n,t} \cdot l\_opt_{n,t}) \leqslant Bill\max{}_n \tag{22}$$

$$Const\ 5.3: pr_{\min} \leqslant pr_{n,t} \leqslant pr_{\max} \tag{23}$$

Constraint 5.1 in Equation (21) ensures that the negative correlation between the price shape and the expected load of the OSC. Constraint 5.2 in Equation (22) ensures the electric bill of an OSC is no larger than the required bill reduction. Constraint 5.3 in Equation (23) limits the price level at each time period into a suitable range. With the above 3 constraints, the objective function in Equation (20) maximizes OSC's electric bill. these objective functions indicates that price maker does not have any encouragement to keep reducing OSC's electric bill when the bill reduction requirement is already satisfied.

The price scheduling model in Equations (20)-(23) is a kind of approximation method. This is because Lemma 2 only ensures the negative correlation between the load shape and the price shape. But there are possibly more than one possible load that satisfy a same load shape. So one more verification step should be added to verify the result of price scheduling from Equations (20)-(23) by operating the objective function once in Equation (2). This verification step double checks that if the scheduled price can really achieve similar optimal cost in the economic dispatch.

In summary, using models in Module 1 and Module 2 can achieve the price scheduling result on typical optimization structure instead of nesting optimization.

V. Numerical Study and Analysis

A. Background

A typical Chinese city with multiple large industrial consumers is selected for numerical study. All industrial consumers are suffering a unique TOU tariff as shown in Fig.1, which is formulated by the government [10]. This is a typical city with over-shifting phenomenon. From Fig.1 the unique TOU tariff shifts too much power load into 13:00-17:00 so that a new load peak appears in this time period. It is obvious in Fig.1 that consumers under steel manufacturing and cement manufacturing are typical OSCs for they response strongly to TOU's shape. Consider this feature, 3 factories in cement manufacturing and 8 factories in steel manufacturing in this city are set as OSCs in the numerical study. Data of city's base load and OSCs are introduced in Appendix III [25].

The power grid structure is modified from a typical 9-bus system in Fig.3 [47]. Refer to Table V in Appendix IV for details of loads connected by each OSC. Data of this power grid is introduced in Appendix V.

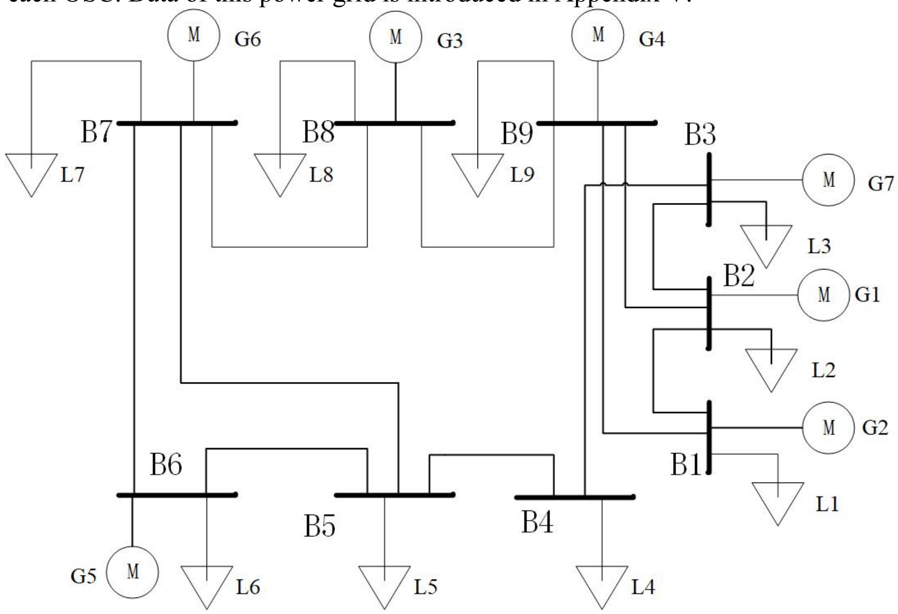

Fig.3: The 9-Bus System Used in Numerical Study

Two typical numerical studies will be introduced in this section. Study 1 is a scheme feasibility study. It compares the proposed scheme and traditional tariff by simulating their models to verify the feasibility. Study 2 is a sensitivity study. This study changes important parameters of model and reveals model's performance variation.

B. Result and Analysis of Study 1

In this study, results from two scenarios are compared. Scenario 1 represents that all industrial consumers are suffering a unite TOU in Fig.1. Scenario 2 represents that all OSCs will join the proposed scheme if their bill can be reduced at least 2% (Constraint 1&5.2). Table I and Fig.4 introduce the result comparison of the two scenarios.

Table I: Result Comparison in Study 1

Item	Traditional United TOU ($/day)	Proposed Scheme ($/day)	Variation
Daily Generation Cost	15734855	15704393.7	Save 0.194 %
Daily Profit of Agent	1077417	1089739.50	Increase 1.144 %
Daily Bill of OSC1	78633.41	77062.42	Save 1.998 %
Daily Bill of OSC2	79835.99	78241.48	Save 1.997 %
Daily Bill of OSC3	79762.15	78167.78	Save 1.999 %
Daily Bill of OSC4	72486.17	71036.44	Save 2.000 %
Daily Bill of OSC5	70214	68809.71	Save 2.000 %
Daily Bill of OSC6	73910.5	72432.6	Save 2.000 %
Daily Bill of OSC7	71176.63	69753.08	Save 2.000 %
Daily Bill of OSC8	103763.6	101688.6	Save 2.000 %

Daily Bill of OSC9	102693.9	100640.4	Save 2.000 %
Daily Bill of OSC10	108161.7	105999.1	Save 1.999 %
Daily Bill of OSC11	66652.95	65320.22	Save 2.000 %
City's Daily Power Consumption	153093 MWH	153093 MWH	0 %

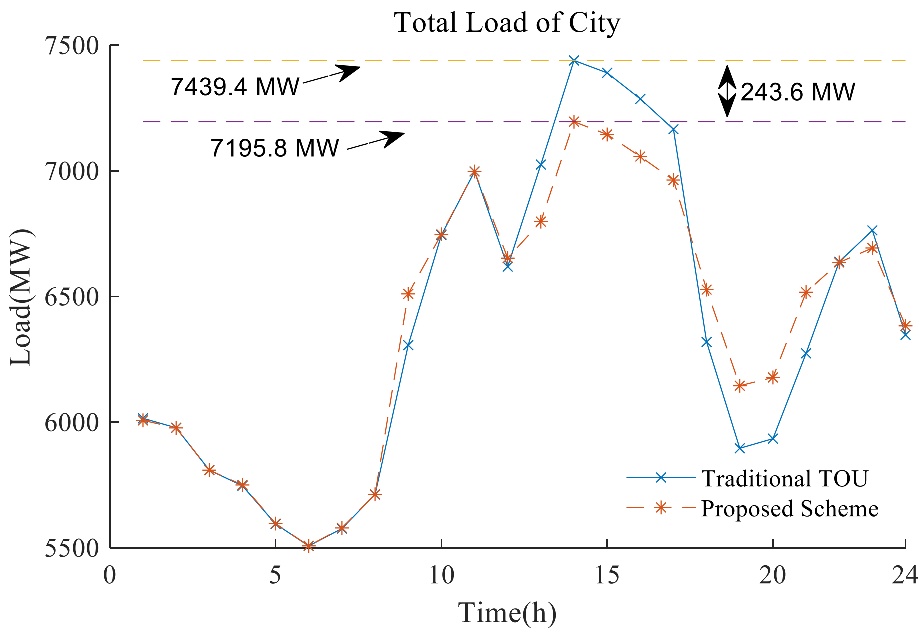

Fig.4: Typical Daily Load Curves of The Target City under Traditional TOU and The Proposed Scheme

In Table I, with a same total daily power consumption, the proposed scheme can reduce the cost of power generation and increase agent's profit. All the benefit comes from the incremental cost reduction in power generation by decreasing city's peak load and shift load in peak period (13:00 – 17:00) to valley period (18:00-21:00). Fig.5 shows the power generation variation of each unit between the two scenarios. The incremental cost reduction is mainly contributed by generation peak reduction in Unit G1, G4, and G6. Total cost of daily power generation is reduced 30462 \$/day in the proposed scheme, which is near 0.2% reduction. This cost reduction is shared by the agent and each participated OSCs. The entire profit of agent has increased 12322 \$/day, which is 1.144% increasing.

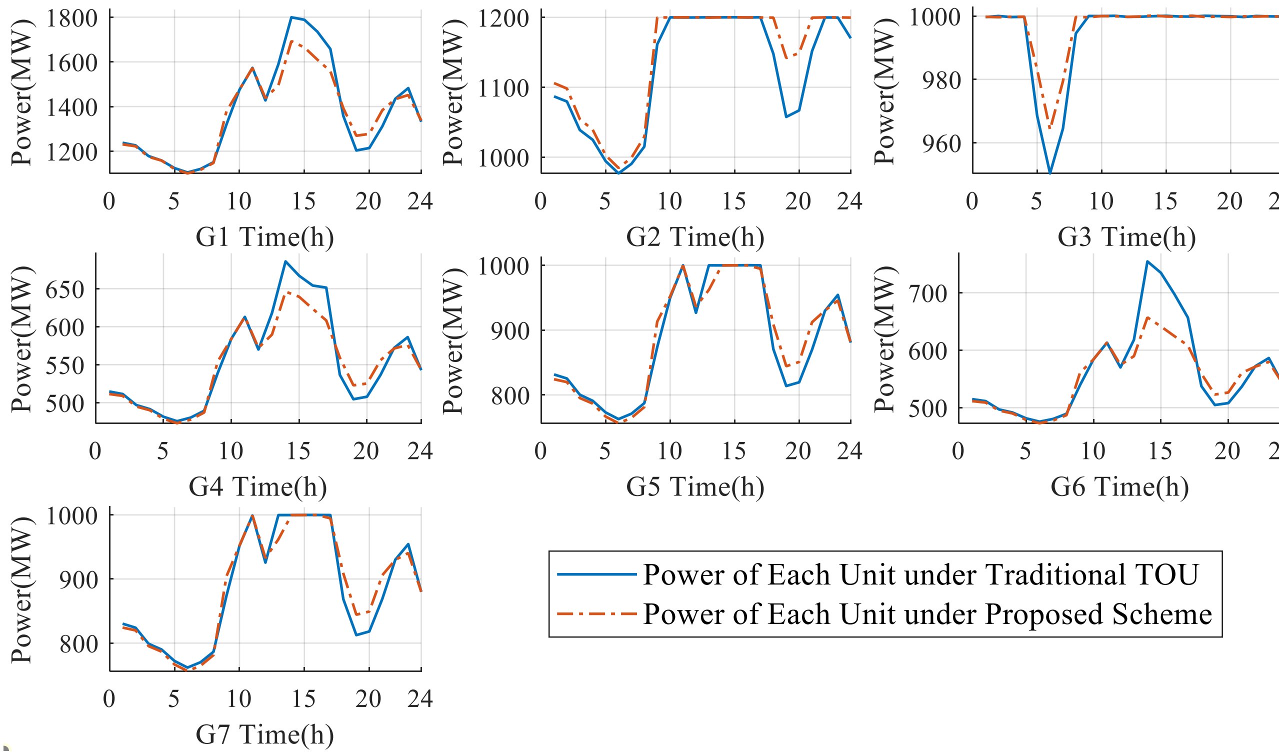

Fig.5: Power Generation of Each Unit under Traditional TOU and The Proposed Scheme

City's peak load reduction comes from decreasing the severity level of over-shifting phenomenon. Under the proposed scheme, each OSC is offered an independent daily price curve, as shown in Fig.6. Though price for each OSC is different, most of the offered prices tend to set lower price between 18:00-21:00 than 13:00-17:00. The model automatically recognizes too much load between 13:00-17:00 and aims to move it to 18:00-21:00 so that the optimization object (total generation cost) can be decrease.

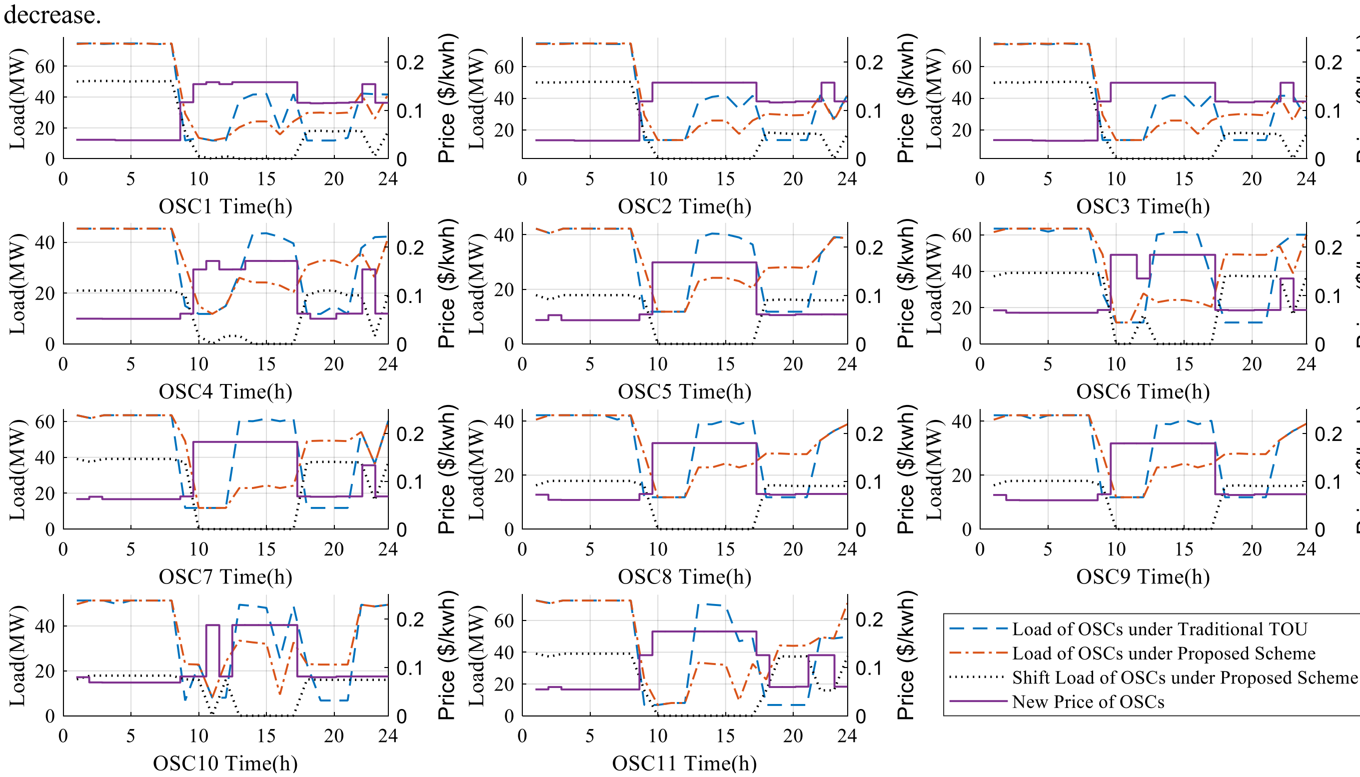

Fig.6: The Operating Situation in Each OSC

In summary, the proposed scheme can effectively decrease the severity of load over-shifting phenomenon in a city. The reason is that model of proposed scheme creates independent price for OSCs with different shape to the united TOU. The independent price encourages OSCs to shift their load from traditional TOU's valley into the independent price's valley so that load of these OSCs will not concentrate into city's load peak. With the proposed scheme, both agent and consumers can earn benefit.

C. Result and Analysis of Study 2

● **Case 1: Sensitivity Analysis of The Minimum Bill Reduction Requirements**

The first case in study 2 is the sensitivity analysis of the minimum electric bill reduction requirement of OSCs ($Bill_{max}$ in Constraint 5.2). In this case, different scenarios of between 1% bill reduction to 4% reduction is simulated and the results are shown in Table II.

Table II: Performance of The Proposed Scheme Under Different OSCs' Minimum Electric Bill Reduction Requirements

Item	Minimum Bill Reduction Requirement of OSCs (%)						
	1.00%	1.50%	2.00%	2.50%	3.00%	3.50%	4.00%
Power Generation Cost Reduction ($/day)	30486	30480	30482	30481	30466	30475	30430
	0.19%	0.19%	0.19%	0.19%	0.19%	0.19%	0.19%
Average OSCs Bill Reduction ($/day)	824	1237	1649	2061	2474	2886	3298
	1.00%	1.50%	2.00%	2.50%	3.00%	3.50%	4.00%
Agent Profit Improvement ($/day)	21418	16876	12343	7805	3255	-1273	-5847
	1.99%	1.57%	1.15%	0.72%	0.30%	-0.12%	-0.54%

From Table II, the power generation cost reduction does not change with the variation of bill reduction requirement. But the profit of OSCs' agent improvement keeps decreasing while the increase of bill reduction requirements. In fact, the benefit of OSCs and the agent is all comes from the power generation cost reduction by decreasing the over-shifting load. When participated OSCs are confirmed, the maximum power generation cost reduction is fixed. This is the reason that power generation cost reduction does not change in all scenarios in Table II. Considering this factor, a higher benefit requirements of OSCs represents lower benefit for the agent. So this is the reason that agent's profit improvement decrease when the bill reduction of OSCs increase. When the minimum bill reduction requirement is higher to 3.5%, the agent's profit improvement becomes negative, which means loss. It indicates that not all scenarios on minimum bill reduction requirement in the proposed scheme will ensure benefit to each stakeholder. The feasibility range in this case is about 0%-3%.

●**Case 2: Algorithm Comparison for Nesting Optimization**

Section IV introduces the structure of nesting optimization. Without a feasible method to construct the gradient computation in nesting optimization, stochastic methods are the few choices. This paper has proposed an equivalent algorithm with 2 modules to avoid the structure of nesting optimization. So this case compares the efficiencies between the proposed equivalent algorithm and a typical stochastic methods on the model in nesting optimization structure without modification. Table III and Fig.7 shows the results. From Table III and Fig.7, the proposed algorithm achieves more than 300 times faster than GA. And the optimum achievement of the proposed algorithm is similar and even a little bit better than GA.

Table III: Performance Comparison Between The Proposed Algorithm and Genetic Algorithm Under Different Number of OSCs

Number of OSCs	Item	Proposed Algorithm		Genetic Algorithm	
5	Algorithm Convergence Time（s）	15.9		7437.8	
	Power Generation Cost Reduction($)	18027	0.11%	17422	0.11%
	Average OSCs Bill Reduction($)	1466	2.00%	1467	2.00%
	Agent Profit Increasing($)	10699	0.99%	10087	0.94%
10	Algorithm Convergence Time（s）	14.3		7658.6	
	Power Generation Cost Reduction($)	30361	0.19%	28505	0.18%
	Average OSCs Bill Reduction($)	1466	2.00%	1473	2.01%
	Agent Profit Increasing($)	15704	1.46%	13775	1.28%
15	Algorithm Convergence Time（s）	37.5		14061.7	
	Power Generation Cost Reduction($)	36786	0.23%	35067	0.22%
	Average OSCs Bill Reduction($)	1470	2.01%	1481	2.02%
	Agent Profit Increasing($)	14732	1.37%	12846	1.19%
20	Algorithm Convergence Time（s）	48.8		16483.2	

	Power Generation Cost Reduction($)	41762	0.27%	38423	0.24%
	Average OSCs Bill Reduction($)	1475	2.01%	1486	2.03%
	Agent Profit Increasing($)	12261	1.14%	8694	0.81%
25	Algorithm Convergence Time（s）	53.8		17832.7	
	Power Generation Cost Reduction($)	44305	0.28%	39535	0.25%
	Average OSCs Bill Reduction($)	1467	2.00%	1485	2.03%
	Agent Profit Increasing($)	7619	0.71%	2409	0.22%
30	Algorithm Convergence Time（s）	60		19560.9	
	Power Generation Cost Reduction($)	45679	0.29%	40924	0.26%
	Average OSCs Bill Reduction($)	1469	2.00%	1492	2.04%
	Agent Profit Increasing($)	1620	0.15%	-3843	-0.36%
35	Algorithm Convergence Time（s）	61.3		19091.4	
	Power Generation Cost Reduction($)	46881	0.30%	40047	0.25%
	Average OSCs Bill Reduction($)	1479	2.02%	1506	2.05%
	Agent Profit Increasing($)	-4884	-0.45%	-12651	-1.17%
40	Algorithm Convergence Time（s）	91.6		23516	
	Power Generation Cost Reduction($)	47601	0.30%	39920	0.25%
	Average OSCs Bill Reduction($)	1479	2.02%	1512	2.06%
	Agent Profit Increasing($)	-11541	-1.07%	-20552	-1.91%

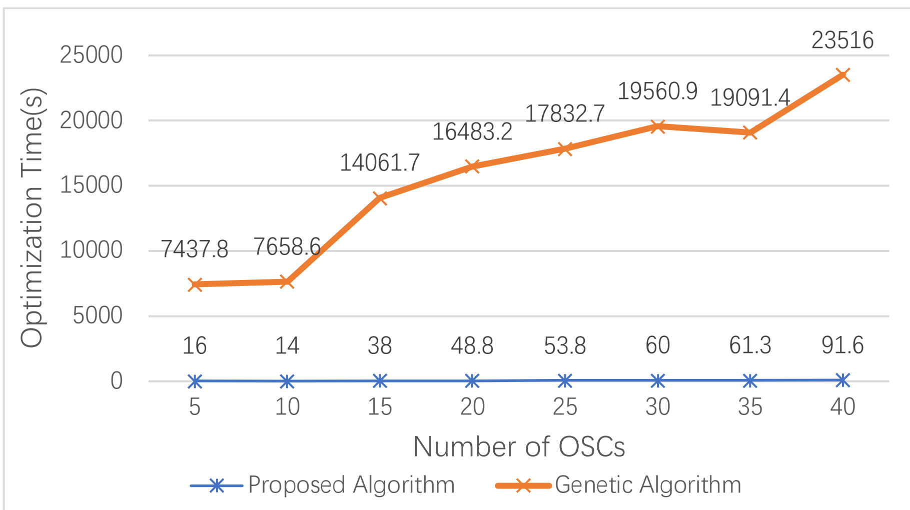

Fig.7: Optimization Time Between The Proposed Algorithm and Genetic Algorithm Under Different Number of OSCs

VI. Conclusion and Future work

Facing the over-shifting phenomenon from typical TOU, this paper proposes a new deregulated demand response scheme to reduce city's peak load. This scheme tries to determine the large load flexible-changing consumers and offers independent dynamic prices to minimize power system's cost. Due to the number scale of large load flexible-changing consumers is small, the proposed scheme prevents risk and cost from influencing extremely large number of consumers. The peak reduction effect is still significant for the load changing capability of the selected consumers.

One issue of the scheme application is that OSCs should be determined before optimization. The predetermination can ensure that consumers with large shiftable load can take part in the scheme. Also, it ensures that information from OSCs can be obtained before optimization.

Another issue is the behaviour uncertainty, which is a practical issue faced by nearly all price based DRs. The uncertainty indicates that consumers may actually behave in a different way from the predefined or pre-estimated behaviours. The reason is that price based DRs use economic signal to promote consumers to change behaviors. But this promotion is not forced. Consumers may change their behavior for other reason, such as shutting down for an unpredictable disaster or keeping all devices fully working for an unexpected order. The proposed scheme has already considered the bill reduction in Equation (3) in the independent price making from traditional tariff. The scheme recognizes OSCs to use ‘following their expected behaviors’ to exchange with ‘an independent price reducing their bill from traditional tariff to an expected level’. Also, the expected behavior is generated on parameters providing by OSCs themselves. So if an OSC does not follows its expected behaviors, it is recognized to violate the promise and should be punished. One typical policy to tackle this issue is to set the load allowance boundary for each OSC. This policy is also implemented in other price based DR [吴皖莉那篇 SCI]. The idea of the allowance boundary is that the agent of OSCs uses the load of expected behaviors as the upper boundary of their actually load. If the load of a certain time exceeds the boundary at this time, the exceeding power will be charged by not only the breach of contract but also a punishing price. The effectiveness of this policy is that it punishes unpredictable increasing power consumption. This punishment ensures that the period with expected lower load can obtain a lower boundary and OSCs may easily receive punishment if their increase load in this period. This punishment does not take effect on decreasing power consumption because decreasing load will not increase degree of load concentration in the peak load period. In this case, OSCs only needs to follow the requirement on breaching of trading contract.

This paper also indicates that the effect differences may occur between the expectation and the deployment of demand response. Large load flexible-changing consumers can be recognized as an adjustable quantity or variable to relief this difference. Let the over-shifting phenomenon as an example. It is probable that load peak of the target city in Fig.1 appears between 9:00-11:00 am and 18:00-22:00 pm before deployment of TOU. The price maker may aim to reduce the peak in these two time periods. But they obviously underestimate the effect of TOU. This is the reason to time occurrence of high price period in TOU. In this case, those large load flexible-changing consumers can be the adjustable variable to reduce the excessive load shifting from TOU. The proposed scheme in this paper is one utilization method for large load-changing consumers.

Actually, the proposed scheme is designed for a specific situation. The suitable scenario contains 2 prerequisites. The first condition is that significant Over-Shifting phenomenon occurs and a unique dynamic price shape is implemented. The second condition is that consumers with extremely large shiftable load exist. With the preconditions, the proposed scheme is capable to be deployed with positive effect in reducing the peak of consumptions. The principle of the proposed method is to offer and independent price shape to consumers with large shiftable load so that they can shift their load with directions other than main-body consumers.

Also, for areas with high degree deregulated power market, the proposed scheme is with less implementing potential. For example, Locational Marginal Price (LMP) can reflect the time period with high system cost by high price level, too. So the proposed scheme is more suitable for initially deregulation of regulated power market. Though there are prerequisites for scheme application, areas satisfying the prerequisites are still many. For example, power markets in 找到统一峰谷曲线的省份 in China, are all contains a unique dynamic price shape. Typical industrial cities in these provinces, such as XX, XX, XX (典型的大工业城市) are all satisfying both conditions.

VII. Declaration

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IX. APPENDIX

Appendix I. Proof of Lemma 1

Lemma 1: *Let $X=[X_1, X_2]^T$ is the argument of an optimization problem (OP1) with objective function OBJ=F({K},X). X_1 and X_2 are sections of argument elements. {K} is the set of boundary conditions of OBJ. $\underline{X}=[\underline{X_1}, \underline{X_2}]^T$ is an extreme point of OP1. Let $X'=[X_2']$ is the argument of an another optimization problem (OP2) with objective function OBJ= F({K, $\underline{X_1}$}, X_2'). Difference between OP1 and OP2 is that argument section of X1 in OP1 and OBJ becomes boundary condition with value $\underline{X_1}$ in OP2 and OBJ'. Then $\underline{X_2}$ is also the extreme point of optimization OBJ'.*

Proof:

(1) $\underline{X}=[\underline{X_1}, \underline{X_2}]^T$ is an extreme point of optimization OBJ.

(2) Due to (1), $\left.\dfrac{\partial OBJ(\{K\},X_1,X_2)}{\partial X}\right|_{X=\underline{X}}=0 \;\Rightarrow\; \left.\dfrac{\partial OBJ}{\partial X}\right|_{\left(K=K,X_1=\underline{X_1},X_2=\underline{X_2}\right)}=0$

(3) At $X_2=\underline{X_2}$, Gradient of OBJ' is $\left.\dfrac{\partial OBJ'\left(\left\{K,\underline{X_1}\right\},X_2\right)}{\partial X}\right|_{X_2=\underline{X_2}}=\left.\dfrac{\partial OBJ'}{\partial X}\right|_{\left(K=K,X_1=\underline{X_1},X_2=\underline{X_2}\right)}$

(4) Consider (2) and (3) together, we have $\left.\dfrac{\partial OBJ'}{\partial X}\right|_{\left(K=K,X_1=\underline{X_1},X_2=\underline{X_2}\right)}=\left.\dfrac{\partial OBJ}{\partial X}\right|_{\left(K=K,X_1=\underline{X_1},X_2=\underline{X_2}\right)}=0$

(5) Due to (4), $\underline{X_2}$ is the extreme point of optimization OP2.

Appendix II. Proof of Lemma 2

Lemma 2: *The optimal solution of optimization problem in Equation (10)-(12) contains the following feature: For any t_1 and t_2, if $pr_{n,t_1} > pr_{n,t_2}$, then the optimal solution obeys $st_{n,m,t_1} \leqslant st_{n,m,t_2}$. (Proof of Lemma 2 is in Appendix II)*

Proof by Contradiction:

(1) Assume $ST\_OPT_n = \underset{st_{n,m,t};\,Cons\ 3.1\&3.2}{\overset{Obj\_3}{argmin}} (Pr_n, \Phi_n) = \begin{bmatrix} \ddots & \cdots & \cdots \\ \vdots & st\_opt_{n,m,t} & \vdots \\ \cdots & \cdots & \ddots \end{bmatrix}^{M \times T}$ is the optimal solution of optimization in Equation (10)-(12). And this optimal solution satisfy condition 1.

$Condition\ 1: \exists\ \overline{m}, t_1, t_2\ \Rightarrow\ (pr_{n,t_1} > pr_{n,t_2}) \& \left(st\_opt_{n,\overline{m},t_1} > st\_opt_{n,\overline{m},t_2}\right)$

(2) Due to ST_OPT$_n$ is the optimal solution, ST_OPT$_n$ satisfies constraint 3.1 and 3.2. That is $\sum_{t=1}^{T} st\_opt_{n,m,t} = STC_{n,m}$.

(3) Set another variable $ST\_2_n = \begin{bmatrix} \ddots & \cdots & \cdots \\ \vdots & st\_2_{n,m,t} & \vdots \\ \cdots & \cdots & \ddots \end{bmatrix}^{M \times T}$.

ST_2$_n$ satisfies $ST\_2_n = \begin{cases} if\ \left(m = \overline{m}\right) \& (t = t_1),\ st\_2_{n,m,t} = st\_2_{n,\overline{m},t_1} = st\_opt_{n,\overline{m},t_2} \\ if\ \left(m = \overline{m}\right) \& (t = t_2),\ st\_2_{n,m,t} = st\_2_{n,\overline{m},t_2} = st\_opt_{n,\overline{m},t_1} \\ \quad other\ m\ and\ t,\ st\_2_{n,m,t} = st\_opt_{n,m,t} \end{cases}$

(4) $\because \begin{cases} \sum_{t=1}^{T} st\_2_{n,m,t} = \sum_{t=1}^{T(t \neq t_1)\&(t \neq t_2)} (st\_2_{n,m,t}) + st\_2_{n,\overline{m},t_1} + st\_2_{n,\overline{m},t_2} \\ \underset{\overline{\overline{\quad}}}{Step\ (3)} \sum_{t=1}^{T(t \neq t_1)\&(t \neq t_2)} (st\_opt_{n,m,t}) + st\_opt_{n,\overline{m},t_2} + st\_opt_{n,\overline{m},t_1} \\ = \sum_{t=1}^{T} st\_opt_{n,m,t} = STC_{n,m} \end{cases}$.

$\therefore$ ST_2$_n$ is a candidate solution optimization problem in Equation (10)-(12).

(5) Value of objective function on ST_OPT$_n$ is:

$$\begin{cases} Obj\_3(ST\_OPT_n) = \sum_{t=1}^{T} \left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M} (st\_opt_{n,m,t} \cdot DP_{n,m}) \right] \right) \\ = \sum_{t=1}^{T(t \neq t_1)\&(t \neq t_2)} \left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M} (st\_opt_{n,m,t} \cdot DP_{n,m}) \right] \right) + pr_{n,t_1} \cdot DPcons_{n,t_1} + pr_{n,t_2} \cdot DPcons_{n,t_2} \\ + pr_{n,t_1} \cdot \sum_{m=1}^{M\left(m \neq \overline{m}\right)} (st\_opt_{n,m,t_1} \cdot DP_{n,m}) + pr_{n,t_2} \cdot \sum_{m=1}^{M\left(m \neq \overline{m}\right)} (st\_opt_{n,m,t_2} \cdot DP_{n,m}) \\ + DP_{n,\overline{m}} \cdot \left(pr_{n,t_1} \cdot st\_opt_{n,\overline{m},t_1} + pr_{n,t_2} \cdot st\_opt_{n,\overline{m},t_2} \right) \end{cases}$$

(6) Value of objective function on ST_2$_n$ is:

$$\begin{cases} Obj\_3(ST\_2_n) = \sum_{t=1}^{T} \left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M} (st\_2_{n,m,t} \cdot DP_{n,m}) \right] \right) \\ = \sum_{t=1}^{T(t \neq t_1)\&(t \neq t_2)} \left(pr_{n,t} \cdot \left[DPcons_{n,t} + \sum_{m=1}^{M} (st\_2_{n,m,t} \cdot DP_{n,m}) \right] \right) + pr_{n,t_1} \cdot DPcons_{n,t_1} + pr_{n,t_2} \cdot DPcons_{n,t_2} \\ + pr_{n,t_1} \cdot \sum_{m=1}^{M\left(m \neq \overline{m}\right)} (st\_2_{n,m,t_1} \cdot DP_{n,m}) + pr_{n,t_2} \cdot \sum_{m=1}^{M\left(m \neq \overline{m}\right)} (st\_2_{n,m,t_2} \cdot DP_{n,m}) \\ + DP_{n,\overline{m}} \cdot \left(pr_{n,t_1} \cdot st\_2_{n,\overline{m},t_1} + pr_{n,t_2} \cdot st\_2_{n,\overline{m},t_2} \right) \end{cases}$$

(7) Consider step (3), (5) and step (6), we have:

$$\begin{cases} Obj\_3(ST\_OPT_n) - Obj\_3(ST\_2_n) \\ \xlongequal{Step\ (3)} \left(pr_{n,t_1} \cdot st\_opt_{n,\bar{m},t_1} + pr_{n,t_2} \cdot st\_opt_{n,\bar{m},t_2}\right) - \left(pr_{n,t_1} \cdot st\_opt_{n,\bar{m},t_2} + pr_{n,t_2} \cdot st\_opt_{n,\bar{m},t_1}\right) \\ = \left(pr_{n,t_1} - pr_{n,t_2}\right) \cdot \left(st\_opt_{n,\bar{m},t_1} - st\_opt_{n,\bar{m},t_2}\right) \end{cases}$$

(8) Consider Step (1) and (7), we have $\Rightarrow \begin{cases} Obj\_3(ST\_OPT_n) - Obj\_3(ST\_2_n) > 0 \\ \Rightarrow Obj\_3(ST\_OPT_n) > Obj\_3(ST\_2_n) \end{cases}$

(9) From step (8), the objective value on ST_2_n is lower than ST_OPT_n. Thus ST_OPT_n is not the optimal solution. It conflicts to the assumption in step (1) that ST_OPT_n is the optimal solution. It means that the optimal solution of optimization in Equation (10)-(12) does not satisfy condition 1.

(10) From step (9), if optimal solution does not satisfy condition 1, then the optimal solution must satisfy the complementary set of condition 1. That is optimal solution satisfy the following condition, which is the statement of Lemma 2.

For any t_1 and t_2, when $pr_{n,t_1} > pr_{n,t_2}$, then the optimal solution obeys $st_{n,m,t_1} \leqslant st_{n,m,t_2}$. When $pr_{n,t_1} < pr_{n,t_2}$, then the optimal solution obeys $st_{n,m,t_1} \geqslant st_{n,m,t_2}$

Appendix III. Data of City's Base Load

Table IV: Data of City's Base Load

	Basic Load(MW)								
	L1	L2	L3	L4	L5	L6	L7	L8	L9
Connected Bus	B1	B2	B3	B4	B5	B6	B7	B8	B9
1h	866	1149	797	531	249	531	549	416	308
2h	842	1141	788	523	245	523	543	409	304
3h	817	1109	763	507	236	507	527	394	294
4h	808	1095	753	500	233	500	520	388	290
5h	785	1065	730	485	225	485	505	376	281
6h	772	1047	717	476	221	476	496	367	276
7h	782	1061	728	483	224	483	503	373	280
8h	803	1088	748	497	231	497	517	385	288
9h	939	1255	929	619	270	617	624	526	349
10h	1005	1342	995	661	308	661	666	564	375
11h	1040	1392	1036	688	322	686	693	585	392
12h	982	1317	978	648	287	648	655	554	369
13h	1000	1356	950	661	302	661	652	550	371
14h	1063	1457	1034	702	321	704	691	577	395
15h	1058	1428	1005	697	320	705	689	586	393
16h	1062	1406	996	687	315	688	677	563	386
17h	1023	1384	972	690	306	676	665	553	379
18h	938	1257	918	620	288	618	625	527	351
19h	878	1171	871	578	267	576	582	489	326
20h	882	1180	875	582	269	580	587	488	328
21h	934	1248	925	616	286	614	621	523	348
22h	944	1278	937	622	279	622	615	506	347
23h	963	1305	931	635	286	636	627	517	355
24h	898	1224	870	601	266	608	605	480	329

Appendix IV. Information of OSCs

Table V: Load Connected by Each OSC

	OSC1	OSC2	OSC3	OSC4	OSC5	OSC6	OSC7	OSC8	OSC9	OSC10	OSC11
Connected with The No. of Basic Load	L4	L6	L8	L1	L2	L3	L7	L8	L9	L5	L3

Table VI: Typical Equipment Information of Steel Factories

Device Name	Power	Working Hours	Transfer or not
	kw	h	
Feeder	48	6	1
Vibration sieve	232	10	1
Coal milling	1600	10	1
Blast furnace	6800	24	0
Converter	3130	19	1
Purification fan	1400	15	0
Gas recovery	2000	15	0
Secondary dust collection	1250	18	0
Continuous caster	770	12	0
Bar line	21230	15	0
Blast furnace fan	16000	15	1

Table VII: Typical Equipment Information of Cement Factories

Device Name	Power	Working Hours	Transfer or not
	kw	h	
Limestone crushing	1710	18	1
Sandstone crushing	385	5	1
Coal pre homogenization stockpile	235	10	1
Coal pre homogenization reclaimer	235	15	1
Raw milling	15000	15	1
Exhaust gas treatment	11020	24	0
Clinkering	7260	15	0
Material cooling	780	24	0
Material cooling	3810	15	0
Gypsum admixture crushing	207	9	1
Cement packaging	120	9	0
Cement bulking	18	12	0
Clinker bulking	20	10	0
Air compressor station	1320	15	0
limestone pre homogenization stockpile	470	13	1
limestone pre homogenization reclaimer	470	15	1
Cement grinding	31700	8	1

Appendix V. Data of Power Grid

Table VIII: Information of Power Grid

Item	Value	Item	Value
Lines_1 B1-B2 impedance(Ω)	0.0576	Lines_1 B1-B2 PL_{max}(MW)	250
Lines_2 B2-B3 impedance(Ω)	0.092	Lines_2 B2-B3 PL_{max}(MW)	450
Lines_3 B3-B4 impedance(Ω)	0.17	Lines_3 B3-B4 PL_{max}(MW)	350
Lines_4 B4-B5 impedance(Ω)	0.0586	Lines_4 B4-B5 PL_{max}(MW)	450
Lines_5 B5-B6 impedance(Ω)	0.1008	Lines_5 B5-B6 PL_{max}(MW)	180
Lines_6 B6-B7 impedance(Ω)	0.072	Lines_6 B6-B7 PL_{max}(MW)	200
Lines_7 B7-B8 impedance(Ω)	0.0626	Lines_7 B7-B8 PL_{max}(MW)	550
Lines_8 B8-B9 impedance(Ω)	0.161	Lines_8 B8-B9 PL_{max}(MW)	250
Lines_9 B9-B1 impedance(Ω)	0.085	Lines_9 B9-B1 PL_{max}(MW)	100
Lines_10 B9-B2 impedance(Ω)	0.084	Lines_10 B9-B2 PL_{max}(MW)	150
Lines_11 B7-B5 impedance(Ω)	0.163	Lines_11 B7-B5 PL_{max}(MW)	100

Table IX: Information of Generator in Power Grid

	G_{max}(MW)	G_{min}(MW)	A($/MW^2)	B($/MW)	C($)	R_{max} (MW/h)
$G1$	1800	0.01	0.0333	24.43	75013.58	300
$G2$	1200	0.01	0.0367	27.12	22567.01	300
$G3$	1000	0.01	0.0350	31.75	26281.83	300
$G4$	1050	0.01	0.1133	-9.11	35006.76	300
$G5$	1000	0.01	0.0650	0.68	28254.66	300
$G6$	1050	0.01	0.1133	-9.11	35006.76	300
$G7$	1000	0.01	0.0650	0.68	28254.66	300

Appendix VI. Structure Deriving From Modification of Current Scheme in China

This scheme is created to solve the over-shifting phenomenon in China. As described in section I, one critical reason to this phenomenon is that a same shape of TOU is offered to too many consumers. In China, two schemes with a same shape of TOU are applied currently.

➢ **Scheme 1:**

Fig.A.1 reveals the first schemes with fixed TOU shape (Scheme 1). This scheme is a typical structure of regulated power market. Most of consumers are offered a fixed electric price. The TOU is fixed by governmental pricing department and is offered to large consumers and sometimes residential consumers. Though prices for consumers under different voltage levels or different industries may be different, the shape of TOU price is the same [江苏地区大工业峰谷电价表]. Under this scheme, power grid utility is operating 3 functions. The first function is the agent of all consumers on electricity purchase under this scheme. The second function is the trading platform with generations. And the third function is the power grid operations. Though the second round reformation of electric power system in China is started in Oct 2015. There are about 20% of energy trading is released into deregulated market. 80% electricity trading are still under scheme 1 in Fig.A.1 [3 个参考文献，说明第二次电力体制改革只有部分开放].

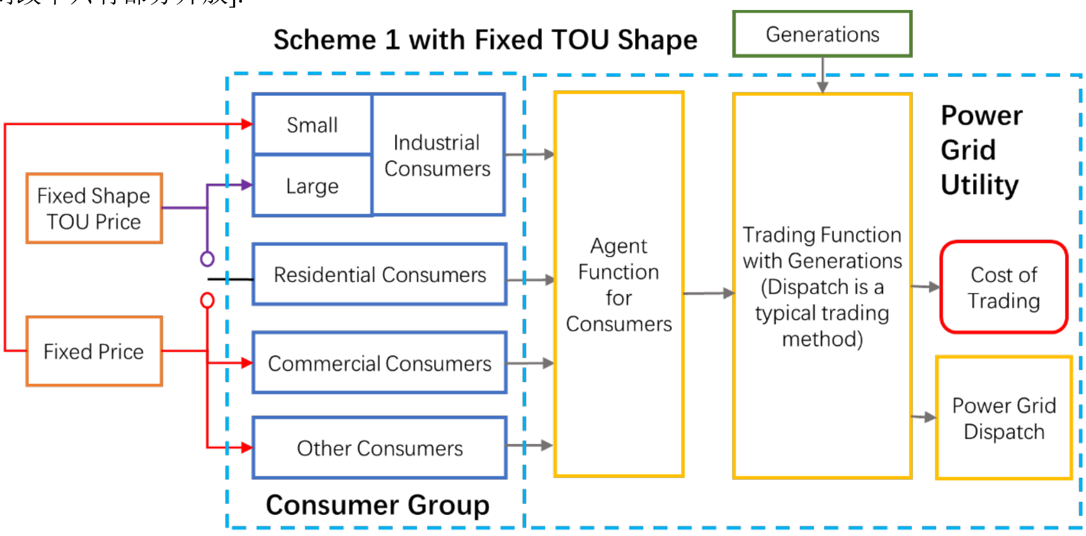

Fig.A.1: Scheme 1 with Fixed TOU Shape in China.

Following the idea in this paper, the scheme 1 in Fig.A.1 can be modified into a new scheme in Fig.A.2. OSCs are selected from the consumers group and forms an OSCs group. Fixed shape TOU price and the fixed price are still offered to rest consumers (non-OSC). The selected OSC may choose to join the new tariff with independent dynamic price. In this case, the power grid utility still performs as the agent of OSCs, trading platform between OSCs and Generations, and the power grid operation. If the independent dynamic price can shift load of OSCs, then load concentration at peak time can be decreased.

At the aspect of benefit, the entire profit comes from the trading cost reduction from generation for incremental cost of generation is reduced by peak reduction. OSCs and power utility will both share this profit. The benefit for OSCs is ensured by constraint 1 in Equation (3). The rest benefit will be left in power grid utility. Due to the suitability of payment on work duty, a more accurate description is that benefit other than OSCs belongs to the agent function of OSCs in power grid utility.

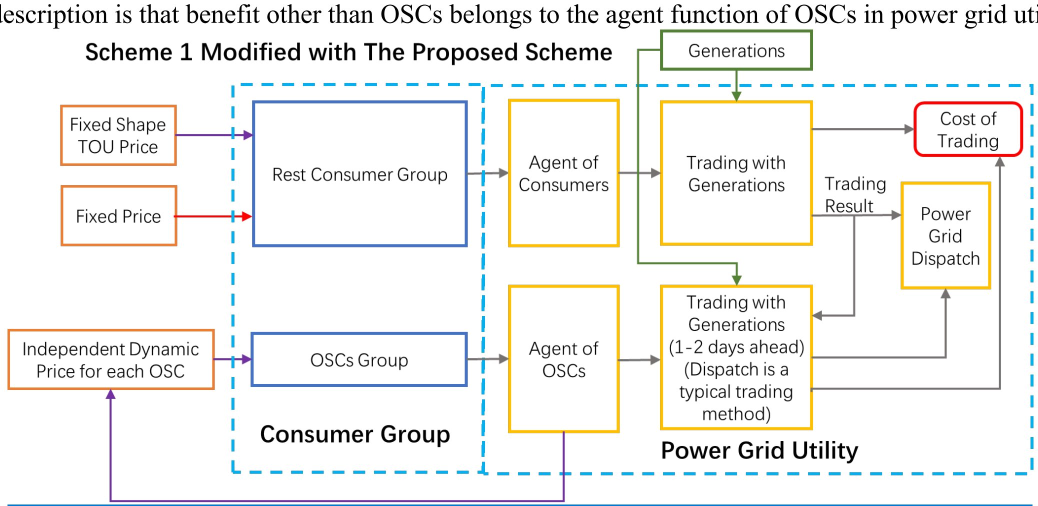

Fig.A.2: Scheme 1 Modified with The Proposed Scheme

➢ **Scheme 2:**

The other scheme with fixed TOU shape in shown in Fig.A.3. It is a kind of deregulated power market. Agents of consumers, power exchange centre and power grid utility are independent to each other. But the deregulated trading corpore is the entire energy quantity within a long time period for consumers. The relatively high/low relation between hourly prices are still fixed by a given TOU shape. In other words, bidding from consumers with higher/lower price in power exchange center means to raise/reduce the entire TOU price to higher/lower level without changing the shape. Scheme 2 is generated in the second round reformation of electric power system in China is started in Oct 2015. In the reformation document released by Chinese central government, policies of daily dynamic pricing can be independently constructed by each power exchange centre with consideration of local situations [9 号文]. Then power exchange centres in many provinces choose to keep the old TOU shape and only release the entire energy trading to the market. Typical areas with deregulated power market and fixed TOU shape includes Guangdong, Jiangsu, XXX [各省份的交易政策文件]. As the load shifting direction under a same shape of TOU are usually similar, scheme 2 may also forms over-shifting phenomenon.

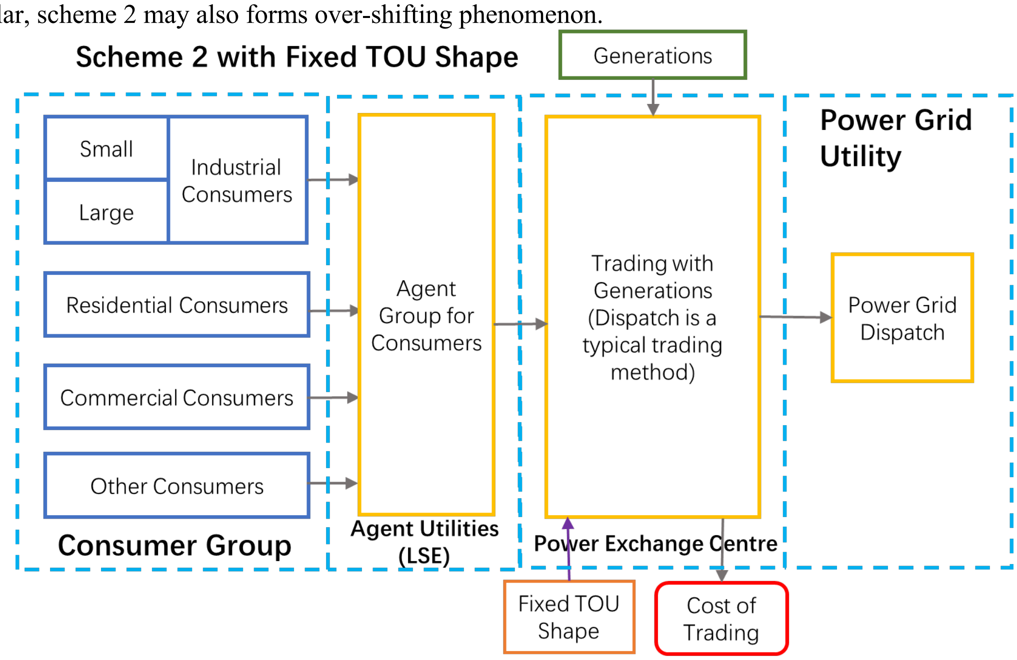

Fig.A.3: Scheme 2 with Fixed TOU Shape in China.

Following the idea in this paper, the scheme 2 in Fig.R.3 can be modified into a new scheme in Fig.A.4. It is quite similar to Fig.A.2. OSCs are separated from consumer group and offered an independent agent. This new tariff is recognized as a small new market to trade with generations. In this case, agent can reduce the trading cost with generation by providing independent dynamic price to OSCs. Same as Fig.A.2, the entire profit comes from the trading cost reduction from generation for incremental cost of generation is reduced by peak reduction. The benefit for OSCs is ensured by constraint 1 in Equation (3). The rest benefit will be left in power grid utility

Different from Fig.A.2, agent function, trading platform and the power grid are independent to each other. Thus, the benefit of the new tariff will be shared by OSCs and their agent. Benefit of OSCs is still ensure by Equation (3) and the rest belongs to agent.

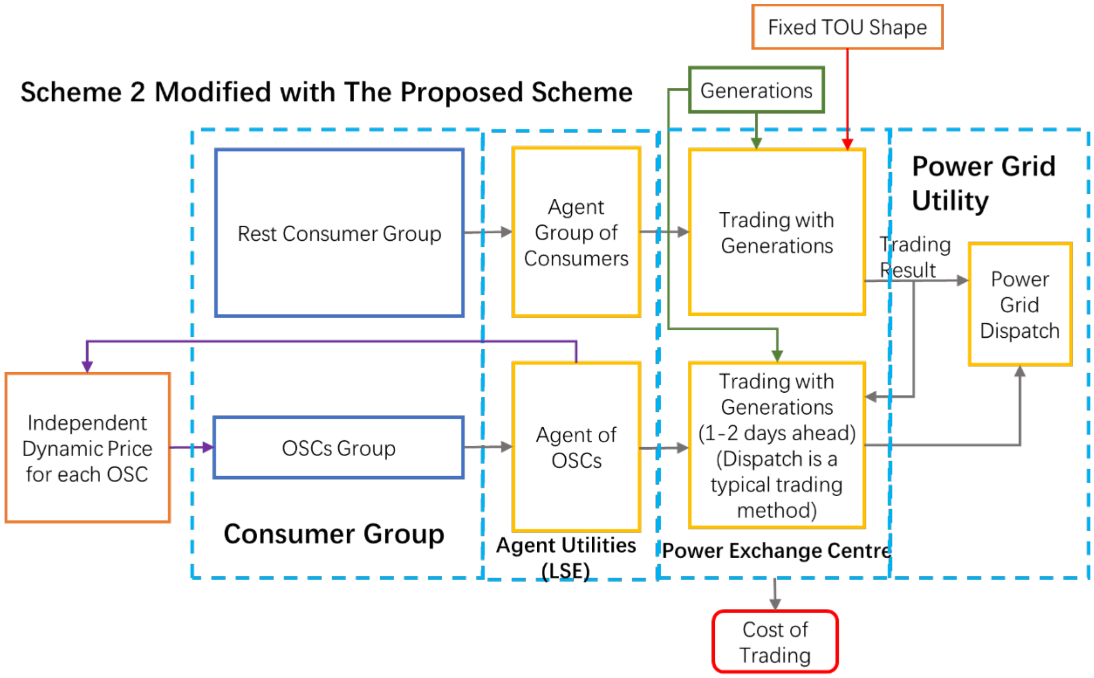

Fig.A.4: Scheme 2 Modified with The Proposed Scheme

➢ **Summary:**

Due to the similarity between Fig.A.2 and Fig.A.4, the proposed idea can be summarized in Fig.A.5. It means that policy maker can promote a DR scheme to compensate the traditional scheme 1 or scheme 2, if facing over-shifting phenomenon. The newly proposed DR scheme is to select a section of consumers with large load shifting potential and willing so that their load can be shifted in non-peak period to reduce the entire peak load. Benefit from the peak load reduction is represents by the trading with generation. No matter facing scheme 1 or scheme 2, the proposed idea can be promoted in similar way. The difference between implementation on scheme 1 and scheme 2 is that the benefit of agent from the proposed scheme belongs to power utility in scheme 1. And the benefit of agent belongs to independent agent in scheme 2.