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A New Two-Stage Game Framework for Power Demand Response Management in Smart Grids

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A NEW TWO-STAGE GAME FRAMEWORK FOR POWER DEMAND RESPONSE MANAGEMENT IN SMART GRIDS

By

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LIST OF SYMBOLS

n, t, g	index of customers, time slots and power generators respectively
a_n	consumption for customer n
c_n	cost for customer n
c_n^d	punishment for customer n
δ_d	discount factor
p	electricity price
p_0	base price
d_n	dissatisfaction function for customer n
S	power demand
c_g	cost for generator g
P_g	generation for generator g
P_l	transmission loss
U_1	benefit for the utility company
u_g	benefit for the generator g
U_2, U_3	benefits summation for the generators and customers, respectively
L_1,L_2,L_3	lagrangian equation for the utility company, generators and customers, respectively
μ_1,$\mu_{2,g}$,$\mu_{3,n}$	inequality Lagrange multiplier for the utility company, generators and customers, respectively
λ_2,λ_3	equality Lagrange multiplier for the generators and customers, respectively
$\mathbf{S}$	strategy set for leading player
$\mathbf{P}$	strategy set for following players
$\mathbf{U}_L$	utility set for leading player
$\mathbf{U}_f$	utility set for following players
$\mathbf{a}$	strategy set for repeated game player
$\mathbf{U}_R$	utility set for repeated game player
κ	type coefficient for the dissatisfaction function
α	linear coefficient for the dissatisfaction function
β	exponential coefficient for the dissatisfaction function
ω	price coefficient
$c_{2,g}, c_{1,g}, c_{0,g}$	second-order, first-order and constant cost coefficient for generator g, respectively
θ	ratio of actual to estimated total power usage for the utility company
τ	ratio of actual to estimated total power usage for the customer
l_g	length for the binary code
r	random variable greater than 0 while less than 1
P_r	probability for the roulette-wheel-selection operation
P_c	probability for the cross-over operation
P_m	probability for the mutation operation
ϕ	threshold for error detection
Υ	result for error detection
υ	actual result for error detection
ϱ	probability for customer's non-cooperate behavior

LIST OF ABBREVIATIONS

DRM	Demand Response Management
PAR	Peak to Average Ratio
RTP	Real Time Price
NE	Nash Equilibrium
EDP	Economic Dispatch Problem
GP	Optimization for Power Generation
CP	Optimization for Power Consumption
TFT	Tit-for-Tat pricing strategy
TP	Trigger pricing strategy
RTP	Real Time Pricing
TOU	Time of Use
KKT	Karush-Kuhn-Tucker conditions
DF	Discount Factor
PIR	Profit increase ratio
CER	Cost efficient ratio
$\overline{DCR}$	Average-demand-change-ratio

ABSTRACT

Recently, the smart grid technologies have been developed rapidly recently, which an important component is the so called demand response management (DRM). With the help of a DRM program, a utility company can adjust the power demand and electricity price to reduce the cost of power generation and consumption. However, there are many problems in DRM need to be solved. For example, to solve the problem of optimizing a generator's power (GP), the conventional methods such as economic dispatch (EDP) may reduce the profit of the utility company. To solve the problem of optimizing a consumer's power (CP), the existing smart pricing strategies may reduce the long-term benefits of the customers. This dissertation aims to develop a two-stage game model to increase the profit of the utility company and while increase the long-term benefit of the customers.

For solving the GP. It is critical for the power generator and utility company to allocate the power demand properly, but the profit for the utility company may be reduced. To solve the CP, it is difficult for the customers to achieve a long-term beneficial power-usage-pattern with myopic pricing strategies. The stability of the smart grid and the benefit of the customers may also be reduced due to the myopic pricing strategies.

It is difficult for the utility company to use the existing methods (e.g., EDP) to order an optimal power demand from the power generators to earn the maximum profit. There are two issues in the GP. First, the weight function for the utility company and power generators in the GP is not established properly in the existing methods. For example, the value of the weight function for the utility company and power generators are usually the same in an EDP method. However, in a smart grid, the utility company has the privilege to demand the power while the power generators must follow the demand. Hence the value of weight function for the utility company should be greater than the one for the power generators in a GP. Second, the optimal demand for the utility company is most likely not the optimal generation for the generators. The imbalanced power will increase the generation cost significantly.

It is also difficult for a utility company to maintain an efficient DRM for a long-time period by using the existing smart pricing strategies. Applying incentive is the major solution for the utility company to influence the power demand of a customer. However, the traditional pricing strategies are shortsightedly designed, by which the long-time efficiency for the DRM is reduced.

For example, the trigger punishment strategy applies a punishing price to a customer for a long period when a non-cooperation behavior is detected. During the punishment period, the customer chooses its power consumption freely since the punishment will be applied anyway. Such selfish behaviors reduce the long-term efficiency for the DRM and the stability of the smart grid.

In this dissertation, we propose a two-stage game model to solve the GP and CP to increase the long-term efficiency for the DRM, maintain the stability of the smart grid, and also increase the profit of the utility company.

In the first stage, a Stackelberg game model is applied to solve the GP, in which the utility company is the leading player while the generators are the following players. We prove that the GP for the following players is a convex problem mathematically. The following players achieve the Nash equilibrium (NE) state by choosing the unique optimal generation. The leading player reacts with this unique generation to achieve the optimal profit. Both the leading and following players reach an agreement in the NE state, in which they have no motivation to deviate the optimal actions. A genetic algorithm is developed to obtain the optimal demand for the leading and following players. In addition, we introduce a power balance constraint to the leading and following players to avoid the cost from the imbalanced power. By applying the constraint, the generated power is equal to the demand all the time. The smart grid will not need to store the excessive power in the energy storage unit or send the power back to the power generators to keep them idling. The cost is avoided and the efficiency of the DRM is increased.

In the second stage, a repeated game model is applied to solve the CP, in which the customers are the players. The strategy for the players is to minimize the individual power consumption of each customer. The utility function for the players is the cost of the customers. The objective for the players is to minimize the cost. In this work, we prove that the NE state exists for the repeated game. However, it has been shown that in the NE state, the players' myopic behaviors may reduce the benefits for the entire group of players. To avoid the loss, we use a genetic algorithm to find the Pareto-efficient solution for the players, in which no player can increase its benefit by reducing other players' benefit. We apply a Tit-for-Tat (TFT) smart pricing strategy to increase the punishment strength from the utility company. Once an irrational behavior from a player is detected, a punishment will be applied to the player for a short period of time. The player can choose to cooperate or not during the punishment period. Compared to the existing smart pricing strategies, the long-term benefit for the smart grid is increased by applying the TFT strategy to the customers.

The numerical simulations in different scenarios are conducted to evaluate the performance of the proposed two-stage game framework by using MATLAB. All the parameters and constraints of the components are from the Department of Energy's report and the Oasisui online database. Five power generators, one utility company, and one hundred customers have been used in the simulations. Compared with the existing solutions (e.g., EDP and gaming optimization), the cost in power consumption is reduced by 6% percent while the profit for power generation is increased by 8% percent in our test scenarios. With the help of the proposed model, we enhance the efficiency for the DRM. The peak-to-average ratio (PAR) of the power demand of our work is compared with the EDP method. The effect of the PAR is studied. The numerical results show that the proposed model has a similar PAR to that of the EDP method, which implies that the proposed model has no negative influence on the stability of the smart grid. The punishing effort of the TFT strategy is compared with the trigger strategy (TP) to study the punishment influence on the customers. The numerical results show that the customers who are applied with the TFT strategy are more willing to cooperate with the utility company. The impact of the power loss ratio and different types of customers is also simulated and analyzed. The simulation results show that the players with a greater transmission loss ratio are more willing to cooperate. The customers with a greater linear dissatisfaction coefficient are more concerned about the dissatisfaction cost. The customers with greater price-sensitive coefficients are more concerned about the consumption cost.

In summary, compared to the existing solutions, the proposed two-stage game model improves the performance of the DRM while maintain the stability of the smart grid. We also discuss the future research issues in the related areas.

CHAPTER 1

INTRODUCTION

1.1 Background

With the rapid development of the smart grids technology, a utility company can adjust the electricity price and power demand to reduce the cost of power generation and consumption [53],[8], and [9]. We define such ability as the first-mover's privilege of the utility company. However, in a GP problem, such privilege has not been studied adequately [55], [38] and [14]. Meanwhile, the long-term benefit for the customers is reduced by applying the existing pricing strategies (e.g., TP). This work aims to develop a two-stage game model to increase the benefit for the utility company while reduce the cost for the customers [20], [46], and [30].

There are two variables in a GP: the power demand and electricity purchase price. Generally, the power demand is collected by a utility company from the customers by a day-ahead scheme [51],[48]. The electricity purchase price is related to the real-time demand in a smart grid [2]. The GP for the utility company and the power generators are solved separately [10], [55] and [27]. However, the solutions for the utility company and the generators may not be optimal. The demand produced by the generators must be consumed by the customers at the same time, which is called the power balanced constraint. By solving the GP separately, the optimally generated power is most likely not the optimal power to be consumed. The imbalanced power must be stored or transferred back to the generators, which may cause a huge cost. The generators must follow the demand from the utility company [1]. Naturally, the utility company can utilize such privilege to increase its profit. However, the existing solutions for GP ignore such privilege [35] and [26].

The Stackelberg game is a suitable tool for modeling and analyzing the GP and gains researchers' interest recently [27], [53], [50] and [12]. In a Stackelberg game, the leading player first announces its strategy to the following player. Then the following player chooses its best strategy based on the leader's strategy to maximize its benefit. By analyzing the strategy that the following player would take, the leading player updates the best strategy to maximize its benefit accordingly [26],

[47], [6] and [24]. In a GP, it is natural to model the utility company and generators as the leading and following player, respectively.

The primary variables are the amount of power consumption and electricity retail price in a CP [41], [54], [42] and [13]. The customers adjust their consumption according to the real-time electricity price, i.e., they shift the heavy power-consuming appliances to a lower price time to reduce the bills. There are two primary objectives for the utility company to achieve in a CP [43], [53] and [4]: 1) the utility company needs to maintain the stability of the smart grid, a sudden peak/valley demand must be avoided; and 2) the long-term cost reductions for the customers must be fulfilled. Because the customers do not change utility company frequently, both the utility company and customers can increase their benefits and reduce cost by cooperating with each other.

The repeated game model is a suitable tool to solve the CP for the customers [19], [43]. In a repeated game model, customers are the players who participate in an infinitely repeated game. The CP is formulated as a multi-stage repeated game. In each stage, all players choose their best strategies to reduce their cost. Based on the historical behaviors (e.g., the individual consumption) of the players, the utility company decides to give incentives or punishment to the customers. The TP strategy is the most popular pricing strategy of the utility company to punish the customers [43] and [23]. Once a non-cooperative (e.g., customers do not cooperate with the utility company) behavior is detected by the utility company, TP will be triggered and a long time punishment (e.g., a much higher electricity price) will be applied to the customer. By implementing the TP strategy, the customers become willing to cooperate with the utility company and the efficiency of the DRM is therefore increased. However, the TP strategy can lead to the myopic behaviors for the customers and the long-term benefit of the smart grid is reduced. Fig. 1.1 is an illustration of the DRM.

A TFT punishment strategy generally has three states, i.e., the usual, punishment, and recovery state [25]. In the TFT, a usual state means the customer cooperates with the utility company; an incentive will be given to the customer. A punishment state implies that the customer's non-cooperative behavior is detected by the utility company; a punishing price will be applied to the customer. In a recovery state, the customer goes back to the usual state if he cooperates with the utility company during the punishment state; otherwise, it stays. Compared to the TP strategy, the customers are more willing to cooperate with the utility company in the TFT strategy. The reason is that the customers can reduce the punishment cost greatly. While in a TP, no matter

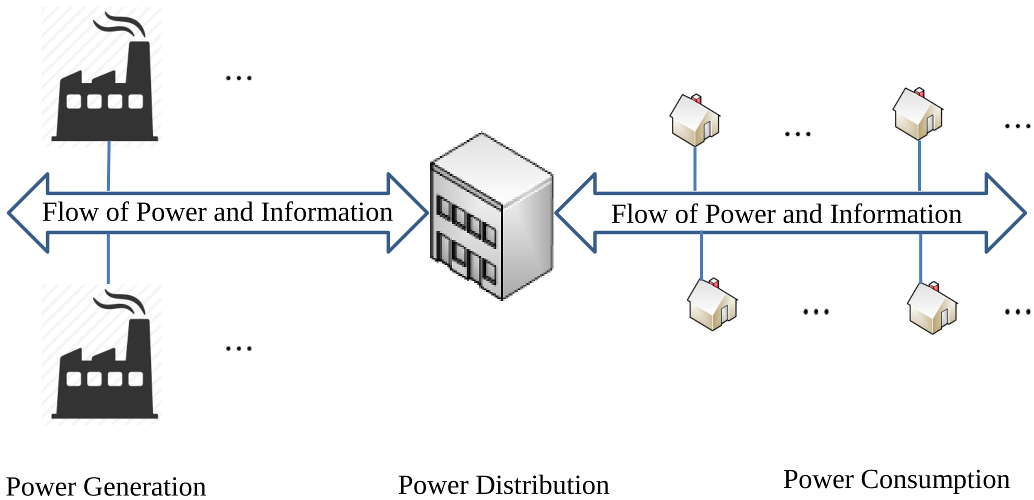

Figure 1.1: An illustration of the DRM

what the customer does, the punishing price is applied to the customer until the punishment is finished, such a strategy reduces the flexibility of the DRM.

1.2 State-of-the-Art

In this section, we present the existing optimization methods to the DRM of the power generators, utility companies, and customers. The optimization methods to solve the DRM can be categorized into three groups. The methods in the first group are mainly applied to optimize the cost for power generation, where the power is the optimization variable. Generally, the optimization objective for the methods is to minimize the cost [15], [40], [56], [21], [36], [32], [49] and [51]. The methods in the second group are applied to maximize the profit for the utility company, where the major optimization variable is the demand [39], [3], [33], [27], [11], [52], [45], [37], [42], [28], and [29]. The methods in the third group are applied to minimize the consumption cost, where the customer's power consumption is the optimization variable [16], [27], [43], and [53].

1.2.1 The Optimization of Power Generation Cost

The power dispatch is a traditional problem for the power generators. The main goal of solving a power dispatch problem is to reduce the power generation cost. To solve the problem, conventional methods require the generators in a centralized deployment [15], [40]. A decentralized method is designed in [56] to solve the problem, in which the power outputs at a decentralized network need to reach a consensus to minimize the power dispatch. The authors develop an increment cost consensus algorithm to find a leader that collects all the necessary information, such as the power dispatch and power generation ramp. The leader then reports the information to the control center. The difference of power output between iterations has been chosen as the incremental cost. The simulation results show that the power generation cost decreases significantly by implementing the incremental-cost-consensus algorithm. Furthermore, the convergence of the algorithm is fast enough to meet the constraint of the power generation limit.

When we design a smart grid, we consider the maximum power demand in building the power generators [21], [36]. To meet the maximum power demand, the generators may have to waste some of the generation capacity, because we need the peak load for only a short time. In [32] and [49], a new solution has been proposed to reduce the peak demand. One major objective for the DRM solution is to reduce the waste of generation capacity. Nowadays many low-cost energy storage units have been deployed in smart grids to store the excessive energy [22]. However, the cost of storing a unit of energy is usually ten times higher than that of producing it. If we cannot use the storage units efficiently, the total cost of energy consumption will be very high. In [51], the authors discuss how to utilize the storage units efficiently to reduce the consumption cost. A non-cooperative game framework has been designed. In the framework, the energy storage units are players. The objectives of the work is to reduce the PAR of the smart grid, keep the customers' power usage privacy, and reduce the customers' bills. A distributed algorithm has been introduced to find the unique NE state for the players. In the NE state, all of the players gain maximum benefits, in which no player wants to change its strategy. The simulation results prove that the PAR is reduced by storing energy properly in the NE state while the electricity bills are reduced.

1.2.2 The Optimization of Utility Company Profit

In [4] and [39], the authors focus on the problem of optimizing the profit of the utility company [3]. A long-term pricing strategy may have a significant influence on the customers to encourage them to cooperate with the utility company. Before deciding his power usage pattern, a price-anticipating customer reviews the historical electricity price. He may reduce his electricity bill by not cooperating with the utility company. The DRM efficiency of the smart grid is reduced by such selfish behaviors. A new pricing strategy is applied by the utility company to reduce such

Table 1.1: Comparison with existing GP methods

	Objective	**Balance**	**Leader advantage**
[55]	Optimizing multiple power generators outputs	N	N
[38]	Optimizing multiple power generators output with one utility company	Y	N
[29]	Optimizing multiple power generators outputs	N	N
Our work	Optimizing multiple power generators output with one utility company	Y	Y

myopic behaviors [33]. In [27], a repeated game framework has been established, in which the customers are the players. The existence of an NE state has been proven for the repeated game. The utility company chooses critical-peak-price (CPP) as the pricing strategy. The players concern their long-term benefits rather than the short-term ones. In [11], real-time-price (RTP) is applied instead of CPP. The customers can reduce their electricity bills greatly by cooperating with the utility company.

Different from the work in [52] and [45], in [27], the smart buildings are the players in the repeated game. Each smart building has a manager. The manager's objective is to maximize his profit by adjusting the building's shiftable loads. A TP has been designed in the repeated game framework. The electricity price is low if the building manager follows the utility company. The price will be increased for a long period if the building manager does not cooperate. The building manager needs to find the optimal power usage pattern to reduce his bill. The authors design a heuristic algorithm to find the optimal power usage patterns. The simulation results show that the TP can help the rational building manager reducing his bills by 20%.

The smart-pricing strategy and direct-load-control are the two major methods for a utility company to influence the power usage of customers. In [37], the authors discuss how to combine smart-price and direct-load-control to minimize the customers' electricity bills. The pricing strategy used by the utility company is RTP. The objective of the customers is to maximize their benefits. There are two levels in the framework. In the first level, the customers solve a distributed DRM problem to obtain their minimum electricity bills. In the second level, the utility company solves the power output allocation problem to obtain its maximum profit. Finally, an NE sate has been achieved between the two levels. The simulation results show that customers can reduce their electricity bills by re-scheduling their heavy workload appliances (i.e., plug-in-hybrid-vehicles and heating-ventilation-air conditioning) at the NE state.

Two major objectives of a utility company in the optimization problem are maximizing its profit and reducing the PAR [34], [31] and [42]. The utility company wants to increase the electricity price to earn more profits. However, if the price is too high, the customers may switch to another utility company that has a lower electricity price or reduce their power demands. Losing customers or changing demands will lead to an unstable grid. In [28], the authors introduce a non-cooperative game framework. The main objective of their work is to find an NE state, i.e., a suitable electricity price, for the utility company to gain maximum profit while keep the customers. Furthermore, a fairness problem between the utility companies has been studied. Small utility companies can sell electricity at a lower price that the large ones to encourage the customers to stay. A mechanism with a discriminated pricing strategy has been proposed to solve the fairness problem.

Most DRM programs only contain one utility company. However, in a smart grid, there may have several utility companies. Meanwhile, protecting a customer's privacy (i.e., power consumption habit) is a security issue that needs to be further investigated. In [29], the authors introduce a multi-leaders Stackelberg game framework. They also develop a mechanism to protect the customers' privacy. The unique NE state of the Stackelberg game is achieved by using the proposed heuristic algorithm, both the utility companies and customers get their maximum benefits. Meanwhile, the privacy of the customers is protected. Only the utility company can gather the power consumption information of customers.

1.2.3 The Optimization of Customer Power Consumption

The rational customers can be categorized into two groups: the price-takers and price-anticipating customers. The price-takers are more concerned about the price while the price antiquating customers are more concerned about the incentives. In [16], the authors establish a decentralized aggregated game framework to study the behaviors of the price-anticipating customers. The customers have been divided into different isolated groups, in which the customers talk to neighbors to get the price information. An NE state seeking strategy has been designed to find the optimal power outputs for the customers. The simulation results show that the customers can reduce their electricity bills greatly by exchanging information with their neighbors properly.

The power demand is growing greatly nowadays. The smart grid developers have to fulfill the demand required by the customers. However, the unpredictable demand from the customers may reduce the stability of the smart grid. The authors in [27] introduce a coupled constraint game, in which the appliances of the customers are players. The authors investigate the relationship between the customers' power consumption and the stability of the smart grid. The customers can shift their consumption freely to reduce the bills. The authors apply a dual decomposition method to find the best responses for the utility company. A gradient projection method is developed to reduce the cost for the customers. The simulation results show that the proposed framework can reduce the smart grid's PAR and reduce the electricity bills for the customers.

The power demands from customers have a great influence on the power generation cost. Most of the existing DRM solutions focus on how to shift the heavy loads to normal hours efficiently. However, few solutions have discussed how to adjust the customers' power demand to reduce the cost. The utility company can reduce the customers' demand by applying a smart pricing strategy, by which the generation of power is changed accordingly. In [43], the authors develop a Stackelberg game framework to study the relationship between the customers and the utility company. The utility company is the leading player while the customers are the following players. The leader uses the smart pricing strategy to influence the demand of the followers. At the first stage, the leader announces the electricity price to the customers. At the second stage, the customers adjust their demand to reduce the bills. A heuristic algorithm has been developed to obtain the optimal power demand. The simulation results show that the two-stage framework can help the customers to reduce their electricity bills and increase profit for the utility company.

In a traditional power grid, the electricity price is fixed. With the rapid deployment of smart meters, the utility companies design smart pricing strategies to improve the DRM efficiency. The RTP pricing strategy is a popular one among them. Under the RTP pricing strategy, the customers can reduce the electricity bills by adjusting loads properly. In [53], the authors introduce a game framework, in which the smart pricing strategy is RTP. In this work, the customers are players that participate in a Stackelberg game. The main objective of the player is to reduce the electricity bills. An NE state for the player has been achieved and analyzed. In the NE state, no player wants to change its strategy to gain more benefit. However, there are two issues : 1) the cost function does not have the dissatisfaction, and thus it's not accurate; 2) in the unique NE state, the cost for the whole group may not be the minimal one. Further investigation is needed.

Table 1.2: Comparison with existing CP methods

	Objective	**Dynamic price**	**Punishment**	**Historical info.**
[27]	Minimizing multiple customers cost	N	N	N
[53]	Maximizing one utility company profit	N	N	N
[43]	Maximizing benefit for the customers	Y	N	Y
[23]	Minimizing cost for the customers	Y	Y	N
Our work	Minimizing cost for the customers and maximize profit for the utility company	Y	Y	Y

1.3 Summary of the Existing Work

Based on the above discussion, it can be summarized that the existing DRM optimization methods cannot be applied to solve the following problems: the weight function for the generators and utility company is inaccurate in a GP; the myopic pricing strategies of the utility company may reduce the long-term benefit for the smart grid in a CP; and the imbalance between the optimal power generation and consumption may increase the cost of the smart grid greatly. More specifically, there are three problems.

First, to solve the GP, most existing methods use a linear or weight function to describe the relation for the profit (for a utility company) and cost (for the power generators) in the optimization problem. However, such a model is neither precise nor practical. Compared to the power generators, the utility company has the privilege to decide the demand. With this privilege, the utility company holds more power in the GP. Furthermore, such privilege cannot be described by a linear nor weight factor. We need to find a new model to describe the relationship between the power generators and the utility company in a GP.

Second, the utility company's pricing strategies are designed myopically in existing methods for solving the CP, by which the long-term benefit for the smart grid may be reduced. A myopic pricing strategy may fail to keep the customers to cooperate with the utility company for a long period. Selfish customers naturally choose the best strategies to minimize their electricity bills. The PAR and the electricity cost for the whole group of customers can be increased by such selfish behaviors. We need to design a new pricing strategy for the utility company and customers, so that the long-term benefit for the smart grid can be increased.

Third, the optimal generation and demand are usually different since they are solved separately with different power constraints in the existing solutions. It could be dangerous for a smart grid if the generation and demand are not balanced. For instance, the customers find their optimal consumption and report it to the utility company. Then the utility company requests the optimal demand from the generators. The demand may not be optimal for the generators since the power balance constraint has yet to be considered. The utility company may need to store (i.e., in a storage unit) or transfer the excessive energy (i.e., to keep the generators idling) back to the generators. A huge cost may be caused by the imbalanced power. We need to find a new model with the power balance constraint to raise the profit of the utility company and avoid the imbalanced power.

1.4 Contributions of This Work

The contributions of our work can be categorized into three aspects.

Firstly, we develop a Stackelberg game model to solve the GP. The utility company has the privilege to decide the demand, which is called the first-mover's privilege. Existing solutions ignore such privilege. With the help of the first-mover's privilege, the utility company can optimize the power demand to increase the profit. A Stackelberg game model to optimize the demand and generation is applied to analyze the GP. We find an optimal demand for the utility company. Compared to the existing solutions, the utility company's profit is increased significantly.

Secondly, we propose a new method to obtain the Pareto-efficient power usage guideline for the customers. The Pareto-efficient guideline can increase the long-term benefit for the smart grid. A TFT punishment strategy is designed to encourage the customers to cooperate with the utility company. The utility company influences the customers' consumption by applying a smart pricing strategy to the customers. The existing pricing strategies may reduce the stability of the smart grid. For instance, rational customers naturally move their heavy loads to the lower price time. If they all move the loads to the time, which leads to an unexpected peak demand at the low price time, then the smart grid becomes unstable. To avoid the problem, a new pricing strategy (TFT) is developed to improve the performance of the DRM. Compared with the RTP and TOU, the TFT strategy has two advantages: 1) it helps the utility company and customers to maximize their long-term benefits; 2) with the historical information, the utility company can influence the customers' behaviors more efficiently. For instance, if a customer always cooperates with the utility company, the utility company gives the customer a low electricity price as an incentive; otherwise, the utility company applies a higher electricity price for the customer as a punishment when the non-cooperative behavior is detected. The punishment strength is based on the historical behavior of the customers. The TFT strategy helps the utility company to solve the DRM problem more efficiently.

Thirdly, we combine the GP and CP optimization problem to avoid the imbalanced power. The GP and CP are solved separately in the existing methods. This may cause a huge cost of power production and unexpected peaks for the smart grid. For instance, a power generator may generate a lot of power at the time when its cost is low to increases its profit. Meanwhile, the optimally generated power is highly likely not equal to the utility company's demand. A time of low generation cost usually means a time of low demand too [1]. However, the excessive power must be stored in a storage unit, which is extremely expensive (the unit storage cost may be ten times higher than the cost of power generation) or be transferred to power auxiliary facilities (excessive power is wasted to keep the generators idling) [2]. In a smart grid, we can synchronize the power demand and generation in a relatively short time as compared to the traditional grids. This feature gives us an opportunity to combine the GP and CP to avoid the imbalanced power. In this way, we save a lot of money on the generation cost, reduce the unexpected peak load, and increase the customers' benefits.

Compared to the existing solutions, our numerical results show that by implementing the proposed two-stage game model, the profit for the utility company is increased while the cost for the customers is reduced, while the efficiency of the DRM is maintained. We have conducted extensive numerical simulations to evaluate the effectiveness of the proposed two-stage game model and the performance of the proposed genetic algorithm. Firstly, compared to the existing EDP solution and conventional game optimization method, the proposed two-stage game model has improved the performance of the GP and CP significantly. For example, in our tested scenarios, the profit for the utility company and cost for the customers have been raised about 8% and reduced 6%, receptively. Secondly, compared to the one-stage game model (e.g., solve the GP and CP in a one-stage game), the proposed two-stage game model reduce the total cost for about 10% in our tested scenarios. The stability of the smart grid has no major differences between our work and the comparison groups. Thirdly, the impacts of the power loss ratios, the linear coefficient of the dissatisfaction, and the punishment effort of the TFT on the GP and CP have been simulated and analyzed. In a GP, a greater power loss ratio indicates that the players are more willing to cooperate with the utility company. In a CP, a greater linear coefficient of the dissatisfaction means the customers are more concerned about their cost.

In the next chapters, we will present the details of our work.

CHAPTER 2

THE DEMAND RESPONSE MANAGEMENT PROBLEM

A typical configuration of smart grids contains the smart meters, control units, and price regulators. A smart meter is mounted in the customers' home, by which a utility company can deal with the consumption and electricity price for the customers. The information collected by the smart meters will be delivered to the utility company. The utility company analyzes the information and then announces the demand to the generators. Normally the estimated demand is obtained by a day-ahead scheme [1]. After receiving the demand, the generators generate the power and then transfer it to the customers through the power transmission line. Price regulators installed at the utility company are used to adjust the price to control the consumption.

The power must be consumed at the same time as it is generated. There are three ways to consume the power: 1) the majority parts of the generated power are consumed by the customers; 2) a small percentage of power is lost during the transmission process; 3) the excessive power (i.e., the generated power is more than the demanded one) is stored in a storage unit or transferred back to the power generator to keep it idling [1]. Consuming one unit of the excessive power normally costs ten times greater than generating one unit. Therefore, we introduce a power balance constraint to avoid the cost from the excessive power.

2.1 Power Consumption

The set of customers is denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$. Each customer is equipped with a smart meter, which collects the data for the utility company to calculate the real-time power demand and price. The utility company is equipped with a price regulator that analyzes all the data from the smart meters. The set of time is denoted by $\mathcal{T} = \{1, 2, \cdots, T\}$, each time equals one hour [27]. A customer may have different types of appliances, such as heating, ventilation and air conditioning, washing machine, dryer, and plug-in-hyper-vehicle, which are curtailable loads that can be utilized to reduce the cost. We combine the curtailable and non-curtailable loads. The individual power consumption can be represented by:

$$a_n(t) = b_n(t) + r_n(t), \tag{2.1}$$

where $a_n(t)$ is the actual power consumption of customer n at time t, $b_n(t)$ is the non-curtailable load, $r_n(t)$ is the curtailable load.

A sudden jump or drop in power demand may cause damages to the smart grid. The utility company estimates the power usage of customers in advance to avoid unwanted demand. The cost for a customer can be represented by [23]:

$$c_n = pa_n + d_n, \tag{2.2}$$

where

$$p = p_0 + \omega(\sum_{n=1}^{N} a_n - \hat{a}_n), \tag{2.3}$$

$$d_n = \kappa \hat{a}_n \beta_n \left(\left(\frac{\hat{a}_n}{a_n} \right)^{\alpha_n} - 1 \right), \tag{2.4}$$

where p is the electricity price, and d_n is the cost of dissatisfaction. The first term in the right hand side (RHS) in Eqn. (2.2) is the monetary cost, where p_0 is the base price, ω is the price coefficient; the second term in the RHS in Eqn. (2.3) is total price change from the difference between the actual and estimated demand. From Eqn. (2.3), we learn that the price is increasing when the demand is rising. The second term in the RHS in Eqn. (2.2) is the dissatisfaction cost, where the estimated amount of demand for customer n at time t is denoted by $\hat{a}_n$; κ, β_n and α_n are the type, linear and exponential coefficients for the a_n, where κ is a positive integer that is related to the type of the customer; β_n is a positive integer, and α_n is a positive real number. d_n has three properties: 1) it is positive when the power demand of customer n is not fulfilled, i.e., $a_n \leq \hat{a}_n$, otherwise the value of d_n is negative; 2) the first order derivative of d_n is positive while the second order is negative; 3) the dissatisfaction cost is zero if $a_n = \hat{a}_n$ [53].

The objective for the utility company is to find a set of optimal power usage guidelines for all the customers to achieve the minimum cost $\sum_{n=1}^{N} c_n$. We denote the optimal guideline by $\mathbf{a}^* = \{a_1^*, \cdots, a_N^*\}$, $a_n^*, n \in \mathcal{N}$ is the optimal consumption for customer n at time t. $\mathbf{a}^*$ is determined by the estimated power demand, individual dissatisfaction function, and the real-time electricity price. Punishment will be applied to the non-cooperative behavior of the customers that do not cooperate with the power usage guideline. An optimal guideline can be achieved if all the players are rational.

Remark 1: In practice, the purchase and retail price of the electricity are not the same. Normally the retail one is slightly higher than the purchase one [2]. In this work, to simplify the problem without losing the generality, we assume that the retail and purchase price are the same.

2.2 Power Generation

The set of the power generators is denoted by $\mathcal{G} = \{1, 2, \cdots, G\}$. In our work, there are G power generators and one utility company in the GP. The cost of power generation is represented by a quadratic function [38]:

$$c_g = c_{2,g} \left(P_g\right)^2 + c_{1,g} P_g + c_{0,g}, \tag{2.5}$$

where $c_{2,g}$, $c_{1,g}$ and $c_{0,g}$ are the second-order, first-order, and constant cost coefficients (all of them are positive) for power output P_g at time t, respectively. The benefit function for a power generator can be represented by [38]:

$$u_g = pP_g - c_g, \tag{2.6}$$

where the first term in the RHS of Eqn. (2.6) is the selling profit for the generator and the second item is the cost for power generation.

To avoid the cost from the imbalanced power. We introduce a power balance constraint, which can be represented by:

$$S = \sum_{n=1}^{N} a_n, \quad \sum_{g=1}^{G} P_g - P_l = S, \tag{2.7}$$

$$P_l = \sum_{g=1}^{G} P_g L_g, \tag{2.8}$$

where S is the amount of the demand at time t. P_l is the transmission loss. All produced power is ensured to be consumed at the same time. During the power transmission process, there is a certain amount of power P_l will be consumed, where L_g in Eqn. (2.8) is the loss coefficient for generator $g \in \mathcal{G}$, which is a real number that is related to the distance between the generator and the utility company.

By acknowledging the transmission loss, the benefit function of the utility company can be represented by:

$$U_1 = pS - pP_l, \tag{2.9}$$

where the first in the RHS represents the selling profit for the utility company; the second item is the transmission loss.

The objective of the utility company is to find the optimal power demand $\mathbf{S}^*$ to get the optimal benefit U_1^*. Since the coefficients for transmission loss are fixed, from Eqn. (2.9) we learn that U_1^* is related to the power outputs P_g and the electricity price.

2.3 The Challenges in Solving the GP

One major challenge in solving the GP is to find a precise relationship between the generators and the utility company. For example, in [38], the objective of the GP can be written as:

$$\max \quad \{U_1 - \sum_{g=1}^{G} u_g\}, \tag{2.10}$$

where the benefits of the generators $\sum_{g=1}^{G} u_g$, and the profit of the utility company U_1 are treated equally. However, in a GP, the generators have to follow the utility company. The utility company, therefore, has a first-mover's privilege to make the demand. Obviously, the utility company's objective is more important than that of the power generators in the GP. To improve the benefit for the utility company, some researchers (e.g., the work in [23]) use a weight factor to describe the relationship between the generators and the utility company. For instance, they apply a weight factor that is denoted by w to the profit of the utility company, where w is a positive real number greater than 1/2 but less than 1; the power generator also has a weight factor less than 1/2 but greater than 0, the sum of the two weight factors equals to one. The GP's objective is to maximize the sum of benefits for the utility company and generators, which can be written as:

$$\max \quad \{(1 - w)U_1 - w\sum_{g=1}^{G} u_g\}. \tag{2.11}$$

The optimization result of Eqn. (2.11) is more practical than Eqn. (2.10). However, there are still two issues need to be addressed: 1) it is difficult to find a suitable value for w, because the optimal benefits for the utility company and power generators are not linear; 2) a weight factor cannot represent the utility company's first-mover's privilege; the utility company can adjust its power demand to get a better profit. In Eqn. (2.11), the utility company does not have the privilege to adjust the demand to earn more benefit. To solve the above two issues, we propose to adapt a Stackelberg game framework to analyze the benefits for the utility company and the generators.

In the Stackelberg game framework, the utility company is the leading player, the generators are the following players. The leading player updates the demand through the reaction of the followers to get its maximum profit. The leading player in the Stackelberg game has a first mover's privilege. By finding the unique NE state for the players, both of the utility company and the generators can gain their maximum profit. Neither the leading nor following players have the motivation to change the strategy in the NE state, i.e., a stable state is achieved.

2.4 The TFT Punishment Strategy

To avoid the unwanted peak demand, the existing methods apply punishment to the customers that do not cooperate with the utility company [43], and [23]. The issues for designing a punishment pricing strategy include: 1) fairness issue, how long should the punishment be? The punishment time cannot be too long, because it may reduce the customers' enthusiasm to cooperate with the utility company; 2) how heavy should the punishment be? Different customers have different tolerances for the punishing price. A customer may not care much about the punishment if its demand is relatively small. However, a commercial customer with heavy demand is concerned more about the punishing price. In [23], a TP has been applied. If a customer's non-cooperative behavior is detected by the utility company, it will be given an extremely high electricity price for a long time. In our work, we develop a TFT strategy to improve the performance of punishing effort.

We apply a repeated game framework to reduce the long-term cost for the customers. In our work, all the customers participate in an infinitely repeated game. The utility company records the consumption of the customers'. Punishments are applied to the customers based on the historical

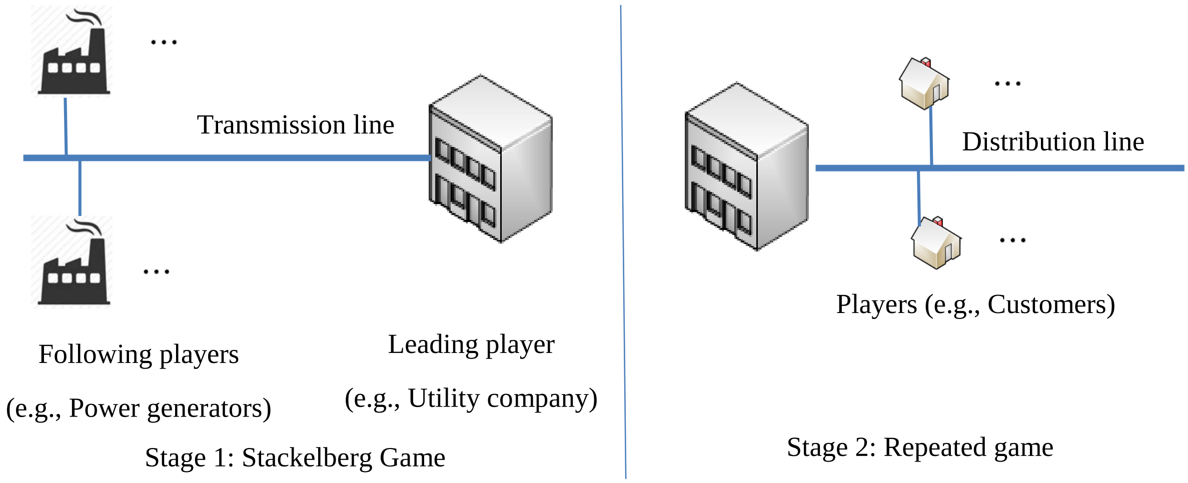

Figure 2.1: An illustration of the two-stage game model

behaviors. A TFT punishment strategy is applied to ensure that the rational customers receive a long-term benefit from the utility company.

TFT punishment strategy is widely used in the game theory applications [19], [25]. Compared to the TP strategy, a TFT strategy gives more flexibility to the utility company when applying the punishment to the customers. This is because in a TP strategy, once the punishment is applied, whether the customers choose to cooperate or not during the punishment time, the punishing price will be applied until the punishment ends. But in a TFT, the customer can stop receiving the punishing price by choosing to cooperate with the utility company during the punishment time. We give the details in Chapter 2.7.

2.5 Solutions of the GP

Fig. 2.1 is an illustration of the two-stage game. In the next chapter, we learn that the GP for the generators is a convex problem. Therefore, it can be solved by the following convex optimization method. The Lagrange's multiplier for the equality constraint is denoted by λ_2, while for the inequality constraints the multipliers are denoted by $\{\mu_{2,1},...,\mu_{2,G}\}$. The benefit summation for the generators is denoted by $U_2 = \sum_{g=1}^{G} u_g$. The Lagrange equation for the generators can be represented by [7]:

$$L_2 = U_2 + \lambda_2(\sum_{g=1}^{G} P_g - P_l - S) + \sum_{g=1}^{G} \mu_{2,g} P_g. \tag{2.12}$$

where the first term in the RHS is the target function of Eqn. (2.12), the second and third terms are the equality constraint and inequality constraints for the optimization problem, respectively. There must exist λ_2^*, $\{\mu_{2,1}^*,...,\mu_{2,G}^*\}$ and $\mathbf{P}^* = \{P_1^*, ..., P_G^*\}$ that satisfy the Karush-Kuhn-Tucker (KKT) conditions, which can be represented by [7]:

$$\left.\begin{aligned} \bigtriangledown U_2 + \bigtriangledown \lambda_2^*(\sum_{g=1}^{G} P_g^* - P_l - S) + \bigtriangledown \sum_{g=1}^{G} \mu_{2,g}^* P_g^* = 0, \\ P_g^* \geq 0, \\ \sum_{g=1}^{G} P_g^* - P_l - S = 0, \\ \mu_{2,g}^* \geq 0, \\ \mu_{2,1}^* P_1^* = 0, \\ \vdots \\ \mu_{2,G}^* P_G^* = 0. \end{aligned}\right\} \tag{2.13}$$

The first equation in Eqn. set (2.13) is the stationarity. The second and third equation are the primal feasibilities. The forth equation is the dual feasibility, and the rest equations are the complementary slacknesses. We analyze the following cases to find the optimal solution for the generators.

Case 1: all the generators are generating power. By submitting Eqns. (2.3), (2.5), (2.6) and (2.7) into Eqn. (2.13), we have:

$$\left.\begin{aligned} P_g^* \geq & \ 0, \\ \mu_{2,g}^* \geq & \ 0, \\ \mu_{2,1}^* P_1^* = & \ 0, \\ \vdots & \\ \mu_{2,G}^* P_G^* = & \ 0. \end{aligned}\right\}$$

In this case, the optimally generated power is greater than zero, i.e., $P_g^* > 0$. We learn that the inequality Lagrange multipliers for the generators are equal to zero, i.e., $\mu_{2,g}^* = 0, g \in \mathcal{G}$. Eqn. (2.13) can be rewritten as:

$$\boldsymbol{AX} = \boldsymbol{b}, \tag{2.14}$$

where $\boldsymbol{A}$ equals to:

$$\begin{bmatrix} 2c_{2,1} & 0 & \cdots & 0 & 1 \\ 0 & 2c_{2,2} & \cdots & 0 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 2c_{2,G} & 1 \\ 1-L_1 & 1-L_2 & \cdots & 1-L_G & 0, \end{bmatrix}$$

and $\boldsymbol{X} = [P_1^*, ..., P_G^*, \lambda_2^*]^{\mathrm{T}}$. $\boldsymbol{b}$ equals to:

$$\begin{bmatrix} c_{1,g} - p_0 - \omega(S - \hat{S}) \\ \vdots \\ c_{1,g} - p_0 - \omega(S - \hat{S}) \\ S. \end{bmatrix}$$

where $c_{2,g}$, $c_{1,g}$, L_g, p_0, ω, S, and $\hat{S}$ are positive real numbers, we have:

$$rank(\boldsymbol{A}) = rank(\boldsymbol{A}, \boldsymbol{b}) = G + 1$$

so there must exist a unique solution set for the generators.

Case 2: some of the generators are not working, i.e., there exist $P_g = 0, g \in \mathcal{G}$. By submitting Eqns. (2.3), (2.5), (2.6) and (2.7) into Eqn. (2.13), we have:

$$\left.\begin{aligned} 2c_{2,1}P_1^* + A_1 + \lambda_2^* + \mu_{2,1}^* = {} & 0, \\ & \vdots \\ 2c_{2,G}P_G^* + A_G + \lambda_2^* + \mu_{2,G}^* = {} & 0, \\ P_g^* \geq {} & 0, \\ \sum_{g=1}^{G} P_g^* - P_l - S = {} & 0, \\ \mu_{2,g}^* \geq {} & 0, \\ \mu_{2,1}^* P_1^* = {} & 0, \\ & \vdots \\ \mu_{2,G}^* P_G^* = {} & 0. \end{aligned}\right\} \tag{2.15}$$

where $A_g = c_{1,g} - p_0 - \omega(S - \hat{S})$, $g \in \mathcal{G}$. Since equation set (2.15) has $2G+1$ equations and $2G+1$ variables, we can find the solution set for Eqn. (2.15) by using the least squares method. The inequalities $P_g^* \geq 0$ and $\mu_{2,g}^* \geq 0$ can be used to verify the solution.

Case 3: $P_g = 0, g \in G$. In this case $\lambda = 0$, $\{\mu_{2,1}, \cdots, \mu_{2,G}\}$ are uncertain and non-negative real values. This is an extreme case. The power grid is cut off and no generators are working.

In the Stackelberg game model, the leading player's objective is to gain a maximum profit. The asset for the leading player depends on two parts, i.e., the monetary profit and transmission loss. The GP for the utility company can be represented by:

$$\left.\begin{aligned} \max \quad & U_1 = pS - pP_l, \\ \text{s.t.} \quad & \frac{S}{\hat{S}} \leq \theta + 1, \end{aligned}\right\} \tag{2.16}$$

where the first term in the RHS of Eqn. (2.16) is the monetary cost, and the second term in the RHS of Eqn. (16) is the transmission loss. θ is the ratio of actual to estimated total power usage of the utility company, which is applied by the utility company to ensure the actual power consumption will not be too far away from the estimation. Usually, the value of θ is around 0.20 [1]. The utility company can earn more profit by selling more electricity. Therefore, the actual power demand S is always greater than $\hat{S}$.

In the next chapter, we learn that the GP for the utility company is a convex problem. The Lagrangian equation for the utility company can be represented by:

$$L_1 = U_1 + \mu_1(S - \hat{S}(1+\theta)), \tag{2.17}$$

where the Lagrangian multiplier for the equality constraint is denoted by μ_1. The optimal demand is denoted by S^*, which must satisfy the KKT conditions:

$$\left.\begin{aligned} \triangledown U_1 + \triangledown \mu_1^*(\theta\hat{S} + \hat{S} - S^*) = 0, \\ \mu_1^*(\theta\hat{S} + \hat{S} - S^*) = 0, \\ \theta\hat{S} + \hat{S} - S^* \geq 0, \\ \mu_1^* \geq 0. \end{aligned}\right\} \tag{2.18}$$

By submitting Eqns.(2.3), (2.7), (2.8), (2.9) and the P_g^*, $g \in \mathcal{G}$ into Eqn. (2.18), we have:

$$\left.\begin{aligned} p + \frac{dp}{dS^*} + \sum_{g=1}^{G} \frac{dP_g^*}{dS^*} + \triangledown \mu_1^*(\theta\hat{S} + \hat{S} - S^*) = 0, \\ \mu_1^*(\theta\hat{S} + \hat{S} - S^*) = 0, \\ \theta\hat{S} + \hat{S} - S^* \geq 0, \\ \mu_1^* \geq 0. \end{aligned}\right\} \tag{2.19}$$

Eqn. set (2.19) has two equations, two variables, and two inequalities. We apply a genetic algorithm to find the S^* [44].

The given variables of the genetic algorithm are $c_{2,g}$, $c_{1,g}$, $c_{0,g}$, p_0, ω, $\hat{S}$, and k; the unknown variables are l_g, P_c, P_m, and P_r; the results are P_1^*,...,P_G^*, S^*.

The first step to design the proposed algorithm is to obtain the length of the binary code for the problem. The individual of the genetic algorithm is denoted by S, the length of the binary code is denoted by l_g, which can be obtained from:

$$2^{l_g-1} \leq (S_{max} - S_{min})/d_g \leq 2^{l_g}, \tag{2.20}$$

where the S_{max} and S_{min} are the maximum and minimum demand, respectively. d_g is the precision requirement. In this work we take the precision of two degrees after zero, i.e., 10^{-2}.

The second step is to initialize the population $\mathscr{N} = (1, ..., N_g)$; binary-coding the S_1,...,S_{N_g} and generating r_1,...,r_{N_g} random numbers, where $1 \geq r_i \geq 0, i \in \mathscr{N}$.

The third step is to calculate the fitness $U_1(S_1)$,...$U_1(S_{\mathscr{N}})$. If there exist an $S_i, i \in \mathscr{N}$ that satisfies Eqns. (2.15) and (2.19), we stop the algorithm. Otherwise, we go to next step.

The fourth step is the roulette-wheel-selection. We denote the probability for the roulette-wheel-selection by $Pr_i, i \in \mathscr{N}$, which can be obtained from:

$$Pr_i = \frac{U_1(S_i)}{\sum_{i=1}^{N_g} U_1(S_i)}, \tag{2.21}$$

the cumulative probability for Pr_i is denoted by $Fr_i = \sum_{j=1}^{i} Pr_i$. If $Fr_{i-1} \leq r_i \leq Fr_i$, S_i is selected to go to next step. Otherwise, S_i is eliminated.

The fifth step is the cross-over. The probability of the cross-over is denoted by P_c, which can be obtained from:

$$P_c = \begin{cases} \dfrac{k_1(U_{1,max} - U_{1,c})}{U_{1,max} - U_{1,avg}}, & U_{1,c} \geq U_{1,avg}, \\ k_2, & otherwise, \end{cases} \tag{2.22}$$

where $U_{1,max}$ is the maximum fitness. $U_{1,c}$ is the fitness to be cross-overed, and $U_{1,avg}$ is the average fitness. k_1, and k_2 are the cross-over constants close to but less than 1. If $P_{c,i} \geq r_i, i \in \mathscr{N}$, we cross-over the individual S_i.

The sixth step is the mutation. The probability of the mutation is denoted by P_m, which can be obtained from:

$$P_m = \begin{cases} \dfrac{k_3(U_{1,max} - U_{1,m})}{U_{1,max} - U_{1,avg}}, & U_{1,m} \geq U_{1,avg}, \\ k_4, & otherwise, \end{cases} \tag{2.23}$$

where k_3, and k_4 are the mutation constants close to but greater than 0. $U_{1,m}$ is the fitness to be mutated. If $P_{m,i} \geq r_i, i \in \mathscr{N}$, we mutate the individual S_i. After the mutation, we go back to step 3.

The genetic algorithm can be summarized as:

Algorithm 1 Algorithm 1

1: Initializing $\mathscr{N} = (1, ..., N_g)$, S_1,...,S_{N_g}, and r_{N_g}; Obtaining l_g
2: Calculating $U_1(S_1)$,...$U_1(S_{\mathscr{N}})$
3: If $S_i, i \in \mathscr{N}$ satisfy Eqns. (2.15) and (2.19)
4: Then the optimal demand is found, end.
5: Otherwise go to next step.
6: Roulette-wheel-selection.
7: Finding Fr_i.
8: If $Fr_{i-1} \leq r_i \leq Fr_i$.
9: Then S_i is selected to go to next step.
10: Cross-over
11: If $P_{c,i} \geq r_i, i \in \mathscr{N}$.
12: Then cross-over S_i.
13: Mutation
14: If $P_{m,i} \geq r_i, i \in \mathscr{N}$.
15: Then mutate S_i.
16: Return the S_1,...,S_{N_g} to step 3

2.6 Solutions of the CP

In the next chapter, we learn that the CP for the customers is a convex problem. The Lagrange's multiplier for the equality constraint is denoted by λ_3, while for the inequality constraints the multipliers are denoted by $\{\mu_{3,1},...,\mu_{3,N}\}$. The benefit summation of the generators is denoted by $U_3 = \sum_{n=1}^{N} c_n$. The Lagrange equation for the generators can be represented by [7]:

$$L_3 = U_3 + \lambda_3(\sum_{n=1}^{N} a_n - S) + \sum_{n=1}^{N} \mu_3(a_n - \hat{a}_n(1 + \tau)). \tag{2.24}$$

where τ is the ratio of actual to estimated total power usage of the customer. The utility company applies τ to the customers to ensure the actual power consumption is not too far from the estimation. Usually, the value of τ is around 0.30 [1]. In our work, the actual power consumption a_n is always greater than $\hat{a_n}$. Because the customer always wants to consume more power.

Since the CP for the customers is a convex problem, there must exist λ_3^*, $\{\mu_{3,1}^*,...,\mu_{3,N}^*\}$, and $\mathbf{a}^* = \{a_1^*, ..., a_N^*\}$ that satisfy the KKT conditions, which can be represented by [7]:

$$\left.\begin{aligned} \triangledown U_3 + \triangledown \lambda_3^* (\sum_{n=1}^{N} a_n^* - S) + \triangledown \sum_{n=1}^{N} \mu_3^* (a_n^* - \hat{a}_n(1+\tau)) = 0, \\ (\hat{a}_n(1+\tau) - a_n^*) \geq 0, \\ \sum_{n=1}^{N} a_n^* - S = 0, \\ \mu_{3,n}^* \geq 0, \\ \mu_{3,1}^*(a_1^* - \hat{a}_1(1+\tau)) = 0, \\ \vdots \\ \mu_{3,N}^*(a_N^* - \hat{a}_N(1+\tau)) = 0. \end{aligned}\right\} \tag{2.25}$$

The first equation in Eqn. set (2.25) is the stationarity. The second and third equations are the primal feasibilities. The forth equation is the dual feasibility, and the rest equations are the complementary slacknesses.

By submitting Eqns. (2.1), (2.2), (2.3), (2.4), and (2.7) into Eqn. (2.25), we have:

$$\left.\begin{aligned} B_1 a_1^* + \lambda_3 + \mu_{3,1}^* &= 0, \\ &\vdots \\ B_N a_N^* + \lambda_3 + \mu_{3,N}^* &= 0, \\ (\hat{a}_n(1+\tau) - a_n^*) &\geq 0, \\ \sum_{n=1}^{N} a_n^* - S &= 0, \\ \mu_{3,n}^* &\geq 0, \\ \mu_{3,1}^*(a_1^* - \hat{a}_1(1+\tau)) &= 0, \\ &\vdots \\ \mu_{3,N}^*(a_N^* - \hat{a}_N(1+\tau)) &= 0, \end{aligned}\right\} \tag{2.26}$$

where $B_n = \alpha_n^2 \kappa \hat{a}_n \beta_i \left(\frac{\hat{a}_n}{a_n}\right)^{\alpha_n}$. Eqn. set (2.26) has $2N+1$ equations, and $2N+1$ variables. We can use the least squares method to find the solution set for the customers. The KKT conditions can be applied to verify the solution set. If we cannot find the real roots of Eqn. set (2.26) by using the least squares method, we use algorithm 2 to obtain the optimal power consumption of the customers, it is summarized as [44]:

The given variables are κ, β_n, α_n, p_0, ω, $\hat{a_n}$, and k. The unknown variables are $l_{g,c}$, Pc_c, Pc_m, and $P_{2,i}$. The solutions are a_1^*,...,a_N^*.

The first step to design the algorithm is to find the length of the binary code. The individual of the proposed genetic algorithm is denoted by $a_i, i \in \mathcal{N}$. The length of the binary code is denoted by $l_{g,c}$, which can be obtained from:

$$2^{l_{g,c-1}} \leq (a_{i,max} - a_{i,min})/d_g \leq 2^{l_{g,c-1}}, \tag{2.27}$$

where the $a_{i,max}$ and $a_{i,min}$ are the maximum and minimum consumption, respectively. d_g is the precision requirement. In this work we take the precision of two degrees after zero, i.e., 10^{-2}.

The second step is to initialize the population $\mathscr{N}_c = (1, ..., N_c)$; binary-coding the a_1,...,a_{N_c} and generating r_1,...,r_{N_g} random numbers, where $1 \geq r_i \geq 0$, and $i \in \mathscr{N}$.

The third step is to calculate the fitness $U_3(\mathbf{a}_1)$,...,$U_3(\mathbf{a}_{\mathscr{N}_c})$. If there exist a set of $\mathbf{a}_1, i \in \mathscr{N}_c$ satisfies Eqn. set (2.26), we stop the algorithm. Otherwise, we go to next step.

The forth step is the roulette-wheel-selection. We denote the probability of the roulette-wheel-selection by $P_{2,i}, i \in \mathscr{N}$, which can be obtained from:

$$P_{2,i} = \frac{U_3(\mathbf{a}_i)}{\sum_{i=1}^{N_c} U_3(\mathbf{a}_i)}, \tag{2.28}$$

the cumulative probability for $P_{2,i}$ is denoted by $F_{2,i} = \sum_{j=1}^{i} P_{2,i}$. If $F_{2,i-1} \leq r_i \leq F_{2,i}$, $\mathbf{a}_i$ is selected to go to next step. Otherwise, $\mathbf{a}_i$ is eliminated.

The fifth step is the cross-over. The probability of the cross-over is denoted by Pc_c, which can be obtained from:

$$Pc_c = \begin{cases} \dfrac{k_5(U_{3,max} - U_{3,c})}{U_{3,max} - U_{3,avg}}, & U_{3,c} \geq U_{3,avg}, \\ k_6, & otherwise, \end{cases} \tag{2.29}$$

where $U_{3,max}$ is the maximum fitness. $U_{3,c}$ is the fitness to be cross-overed, and $U_{3,avg}$ is the average fitness. k_5, and k_6 are the cross-over constants close to but less than 1. If $Pc_{c,i} \geq r_i, i \in \mathscr{N}_c$, we cross-over the individual $\mathbf{a}_i$.

The sixth step is the mutation. The probability of the mutation is denoted by Pc_m, which can be obtained from:

$$Pc_m = \begin{cases} \dfrac{k_7(U_{3,max} - U_{3,m})}{U_{3,max} - U_{3,avg}}, & U_{3,m} \geq U_{1,avg}, \\ k_8, & otherwise, \end{cases} \tag{2.30}$$

where k_7, and k_8 are the mutation constants close to but greater than 0. $U_{3,m}$ is the fitness to be mutated. If $Pc_{m,i} \geq r_i, i \in \mathscr{N}_c$, then we mutate the individual $\mathbf{a}_i$. After mutating $\mathbf{a}_i$, we go back to step 3.

The algorithm 2 can be summarized as:

Algorithm 2 Algorithm 2

1: Initializing $\mathscr{N}_c = (1, ..., N_c)$, finding l_g, $\mathbf{a}_1$,...,$\mathbf{a}_{N_c}$, and r_{N_c}
2: Calculating $U_3(\mathbf{a}_1)$,...$U_1(\mathbf{a}_{N_c})$
3: If $\mathbf{a}_i, i \in \mathscr{N}_c$ satisfy Eqns. (2.26) and (3.9).
4: Then the optimal consumption is found, end.
5: Otherwise, go to next step.
6: Roulette-wheel-selection.
7: Finding $F_{2,i}$
8: If $F_{2,i-1} \leq r_i \leq F_{2,i}$.
9: Then $\mathbf{a}_i$ is selected to go to next step.
10: Cross-over.
11: If $Pc_{c,i} \geq r_i, i \in \mathscr{N}$.
12: Then cross-over $\mathbf{a}_i$.
13: Mutation.
14: If $Pc_{m,i} \geq r_i, i \in \mathscr{N}$.
15: Then mutate $\mathbf{a}_i$.
16: Return the $\mathbf{a}_1$,...,$\mathbf{a}_{N_c c}$ to step 3.

Summary for the proposed Algorithm 1 and 2. By applying the adaptive genetic algorithm, we try to find the optimal demand for the utility company and consumption for the individual customers. Compared with the conventional genetic algorithm, the adaptive genetic algorithm improves the method to build the cross-over and mutation. It can find the solutions faster, and the probability of being trapped in a local optimum is reduced.

Eqns. (2.22) and (2.29) are applied to find the cross-over probability for the individuals (i.e., the demand and the consumption). Eqns. (2.23) and (2.30) are applied to find the mutation probability for the individuals. For the more suitable fitnesses (i.e., greater profit for the utility company), we reduce the probability of the cross-over and mutation operation. For the less suitable fitnesses, we increase the probability of the cross-over and mutation operation. By doing so, the suitable probabilities of the cross-over and mutation are found.

The cross-over and mutation are important for the genetic algorithm to find the solutions quickly and precisely. The value of the cross-over probability should be suitable. If it is too close to 1, although the speed for generating new individual is faster, the genetic algorithm may fail to find the solution. If it is too close to 0, it may spend much longer time to find the solution. The value of the mutation probability should be suitable, too. If it is too close to 0, it is hard to produce a new individual. If it is too close to 1, the genetic algorithm is similar to the random-searching algorithm, by which it may take a relatively long time to find the solution.

From the simulation results in Chapter 4, we see that the proposed adaptive genetic algorithm finds the solutions in a relatively short time. All the solutions meet the KKT conditions and have not been trapped in the local optimum.

2.7 The Punishment Strategy

The consumption of customers is difficult to be predicted in a smart grid. It is important for the utility company to find an effective pricing strategy to encourage the customers to cooperate. The effective strategy can help the utility company with controlling the demand, reducing the PAR and increasing the profit. We analyze the myopic behaviors of the customers. The objective of a myopic customer can be represented by [14], [56], and [31]:

$$\min c_n(t). \tag{2.31}$$

From Eqn. (2.31), we learn that the historical behavior (e.g., $c_n(t-1)$) of the customer has no influence on the customer's objective. Therefore, the CP is solved myopically. The long-term benefits of the customers are ignored. Such myopic behaviors are harmful to the smart grid. From Eqn. (2.3), we learn that the price is higher when the demand is greater. Therefore, the customers may shift their consumption to reduce the cost. By doing so, the smart grid may face such situations: 1) during the peak hour, the excessive power needs to be consumed by the storage units of the smart grid (usually, the cost of storing electricity is ten times greater than the generation); 2) during the lower price period, the utility company receives an unwanted peak demand, which may be extremely dangerous to the smart grid [1].

If customer n chooses to cooperate with the utility company all the time, his average cost can be represented by [43]:

$$\bar{c}_n = (1 - \delta_d) \sum_{t=0}^{\inf} \delta_d^h c_n(t), \tag{2.32}$$

where δ_d, $0 < \delta_d < 1$ is the discount factor (DF) that represents the current value of the future cost for customer n [17]. A greater discount factor implies the customer is more concerned with the long-term benefit than that of the short-term one [25]. The utility company needs to design a suitable pricing strategy to encourage the customer to cooperate. It is well known that if the electricity price is low, the price-sensitive customers increase their consumption. By doing so, the utility company receives an unwanted peak demand. We apply a TFT strategy to the utility company to avoid the unwanted peak demand. The TFT has such features[17]: 1) fairness, the TFT is fair to all customers, i.e., the punishment is applied to any customer who is not cooperating; and 2) strength, the punishment is substantial enough to encourage the customers to cooperate.

A TFT punish strategy has three states, i.e., the normal, punishment, and recovery states [25]. A customer stays in the normal state implies he is cooperating with the utility company. A customer stays in the punishment state implies his irrational behavior is detected by the utility company, a punishing price will be applied to him. In the recovery state, the punished customer returns to the normal state if he cooperates with the utility company during the punishing period; otherwise, he stays. The punishment of the customers must satisfy the following inequality:

$$\tilde{c}_n(t) + c_n^d(t + t') \geq \bar{c}_n(t) + \bar{c}_n(t + t'), \tag{2.33}$$

where t' is the length of punishment. $\tilde{c}_n$ is the minimal cost of customer n at time t, and c_n^d is the punishment. The procedure of the TFT strategy can be summarized as:

1: The utility company announces the power consumption to the customers.

2: The customers choose to cooperate with the consumption or not.

3: The utility company detects the actual consumption of the customers.

3: Once a non-cooperative behavior from customer n is detected. c_n^d is applied to the customer n for t' time.

4: After time t'. If customer n does not cooperate with the utility company during the punishing period, the punishment will be applied to n in the following time $t' + 1$.

5: After time t'. If customer n cooperates with the utility company during the punishing period, the punishment will be removed. Customer n returns to the normal state.

6: Repeat steps 1 to 5.

CHAPTER 3

ANALYSIS OF THE DEMAND RESPONSE MANAGEMENT PROBLEM

In this chapter, we present the analysis of the solution of the proposed two-stage game. The first and second section will be the convex analysis of the GP and CP, respectively. Section three and four will be the analysis of the Stackelberg and repeated game, respectively. Section five will be the analysis of the error detection.

3.1 Analysis of the GP

In this work, there are G power generators, and one utility company in the GP. The utility company first receives the estimated demand $\hat{S}$ from the customers. Then, it announces $\hat{S}$ to the generators. Finally, the generators find the optimal power outputs to maximize their benefits. The Stackelberg game model provides us with a suitable tool to analyze such scenario [17].

Definition 3.1: The GP Stackelberg game can be defined as: $G_S = \{\{\mathcal{G}\}, \{P_g\}, \{S\}, \{U_2\}, \{U_1\}\}$, where $\{\mathcal{G}\}$ is the set of the players, i.e., the utility company and generators. $\{P_g\}$ is the set of strategies of the following players. $\{S\}$ is the set of strategies of the leading player. $\{U_1\}$ is the benefit set of the leading player, and $\{U_2\}$ is the benefit set of the following players.

The followers' benefit function can be represented by [38]:

$$U_2 = \sum_{g=1}^{G} u_g. \tag{3.1}$$

The followers' objective is to maximize their total benefits, which can be formulated as:

$$\begin{aligned} \max \quad & U_2, \\ \text{s.t.} \quad & \sum_{g=1}^{G} P_g - P_l = S, \\ & P_g \geq 0, \end{aligned} \tag{3.2}$$

where the first equality is the constraint of power balance, and $P_g \geq 0$ is applied to ensure the generators are generating power.

By submitting Eqns. (2.5), (2.6), and (2.7) into Eqn. (3.2), the Hessian matrix of Eqn. (3.2) can be represented by:

$$\frac{\partial^2 \sum_{g=1}^{G} U_g}{\partial P_i \partial P_j} = \begin{cases} -2c_{2,g}, & i = j, i, j \in \mathcal{G}. \\ 0, & i \neq j, i, j \in \mathcal{G}. \end{cases} \tag{3.3}$$

where the diagonal elements of Eqn. (3.3) are negative due to properties of $c_{2,g}$, $g \in \mathcal{G}$. All of the off-diagonal elements are zero. Therefore, the Hessian matrix is strictly negative definite [7].

Theorem 3.1: The GP is a convex problem with both equality and inequality constraints.

Proof: The Hessian matrix at the feasible region for U_2 is strictly negative definite, and U_2 has continuous second-order-partial-derivatives in the feasible region. We assume there exists $\mathbf{P}^{(1)} = \{P_1^{(1)}, ..., P_G^{(1)}\}$, and $\mathbf{P}^{(2)} = \{P_1^{(2)}, ..., P_G^{(2)}\}$ belong to the feasible region for the GP. The Taylor expansion of U_2 can be written as:

$$\begin{aligned} U_2(\mathbf{P}^{(1)}) =& U_2(\mathbf{P}^{(2)}) + \nabla U_2(\mathbf{P}^{(2)})^T(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}) + \frac{1}{2}(\mathbf{P}^{(1)} - \mathbf{P}^{(2)})^T \cdot \\ & \nabla^2 U_2(\mathbf{P}^{(2)} + \lambda_g(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}))(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}), \end{aligned} \tag{3.4}$$

where $\lambda_g \in (0, 1)$, since :

$$\mathbf{P}^{(2)} + \lambda_g(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}) = \lambda_g \mathbf{P}^{(1)} + (1 - \lambda_g)\mathbf{P}^{(2)}, \tag{3.5}$$

we have that $\mathbf{P}^{(2)}$, and $\mathbf{P}^{(1)}$ belong to the feasible region of the GP. Therefore, $\mathbf{P}^{(2)} + \lambda_g(\mathbf{P}^{(1)} - \mathbf{P}^{(2)})$ belongs to the feasible region of the GP. We take Eqn. (3.5) into Eqn. (3.4), Eqn. (3.4) can be rewritten as:

$$(\mathbf{P}^{(1)} - \mathbf{P}^{(2)})^T \nabla^2 U_2(\mathbf{P}^{(2)} + \lambda_g(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}))(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}) \geq 0, \tag{3.6}$$

which can be rewritten as:

$$U_2(\mathbf{P}^{(1)}) \geq U_2(\mathbf{P}^{(2)}) + \nabla^2 U_2(\mathbf{P}^{(1)})^T(\mathbf{P}^{(1)} - \mathbf{P}^{(2)}), \tag{3.7}$$

from Eqns. (3.2), (3.6), and Eqn. (3.7), we learn that the GP for the following players is a convex problem with both equality and inequality constraints.

3.2 Analysis of the CP

In the proposed CP repeated game, the customers are the players. The objectives of the players are to find the optimal consumption to minimize their cost. Meanwhile, there are such objectives for the utility company to achieve in a CP: 1) maintaining the stability of the smart grid; and 2) earning as much profit as possible. To achieve the objectives for the utility company and customers, we develop a Pareto-efficient guideline of power usage, by which no player can reduce its cost by increasing other players' cost. The utility company encourages the customers to cooperate with the power usage guideline by applying the TFT punishing strategy to the customers.

Definition 3.2: The repeated game at time t is defined as a triple: $G = \{\{\mathcal{N}\}, \{a_n\}, \{c_n\}\}$, where $\{\mathcal{N}\}$ is the set of the players, i.e., the customers. $\{a_n\}$ is the strategy set of player's, and$\{c_n\}$ is the cost set of the players. The Nash equilibrium of the customers' repeated game can be defined as: players choose the best strategies to minimize their cost, which can be formulated as [17]:

$$\{\mathbf{c}_{-n}\} \geq \tilde{c}_n, \tag{3.8}$$

where $\mathbf{c}_{-n}$ is the cost of customer n by not choosing the best strategies. $\tilde{c}_n$ is the minimal cost that customer n can get. c_n is a continuous function, the solution of Eqn. (3.9) must satisfies $\frac{\partial c_n}{\partial a_n} = 0$. Usually, the best strategy for the individual player is not the best solution for the entire group. This is called the tragedy of the commons [17]. To avoid the common tragedy, we apply a Pareto-efficient solution that can be accepted by all the players, which is written as:

$$\min \sum_{n=1}^{N} c_n. \tag{3.9}$$

To simplify the problem, we have:

$$\sum_{n=1}^{N} c_n = C(a_n). \tag{3.10}$$

By submitting Eqns. (2.3), (2.4), (2.5) and (2.7) into Eqn. (3.10), we see that the elements of the Hessian matrix for Eqn. (3.10) are:

$$\frac{\partial^2 \sum_{n=1}^{N} c_n}{\partial a_i \partial a_j} = \begin{cases} \alpha_i^2 \kappa \hat{a}_i \beta_i \left(\dfrac{\hat{a}_i}{a_i}\right)^{\alpha_i}, i = j; \\ 0, i \neq j. i, j \in \mathcal{N}, \end{cases} \tag{3.11}$$

where the diagonal elements of the Hessian matrix are negative due to the properties of the coefficients of c_n, and all the other elements are zero. Therefore, the Hessian matrix for Eqn. (3.10) is strictly negative definite.

Theorem 3.2: The CP for the customers is a convex problem with both equality and inequality constraints.

Proof: The Hessian matrix at the feasible region of $C(a_n)$ is strictly negative definite. $C(a_n)$ has continuous second-order-partial-derivatives in the feasible region. We assume there exists $\mathbf{a}^{(1)} = \{a_1^{(1)}, ..., a_N^{(1)}\}$, and $\mathbf{a}^{(2)} = \{a_1^{(2)}, ..., a_N^{(2)}\}$ belong to the feasible region of $C(a_n)$. The Taylor expansion of $C(a_n)$ can be written as:

$$\begin{aligned} C(\mathbf{a}^{(1)}) =& C(\mathbf{a}^{(2)}) + \nabla C(\mathbf{a}^{(2)})^T(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}) + \frac{1}{2}(\mathbf{a}^{(1)} - \mathbf{a}^{(2)})^T \cdot \\ & \nabla^2 C(\mathbf{a}^{(2)} + \lambda_c(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}))(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}), \end{aligned} \tag{3.12}$$

where $\lambda_c \in (0, 1)$, since:

$$\mathbf{a}^{(2)} + \lambda_c(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}) = \lambda_c \mathbf{a}^{(1)} + (1 - \lambda_c)\mathbf{a}^{(2)}, \tag{3.13}$$

where $\mathbf{a}^{(2)}$, and $\mathbf{a}^{(1)}$ belong to the feasible region of the CP. Therefore, $\mathbf{a}^{(2)} + \lambda_c(\mathbf{a}^{(1)} - \mathbf{a}^{(2)})$ belongs to the feasible region of the GP. We apply Eqn. (3.13) into (3.12), we have:

$$(\mathbf{a}^{(1)} - \mathbf{a}^{(2)})^T \nabla^2 C(\mathbf{a}^{(2)} + \lambda_g(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}))(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}) \geq 0, \tag{3.14}$$

which can be rewritten as:

$$C(\mathbf{a}^{(1)}) \geq C(\mathbf{a}^{(2)}) + \nabla^2 C(\mathbf{a}^{(1)})^T(\mathbf{a}^{(1)} - \mathbf{a}^{(2)}). \tag{3.15}$$

Eqn. (3.15) is a standard format for a convex problem. From Eqns. (3.9), (3.10), and (3.15), we learn that the CP for the customers is a convex problem with both equality and inequality constraints.

3.3 Analysis of the Stackelberg Game

In this section, we present the analysis of the Stackelberg game. We see that there are one leading player and G following players in the game. The leading player's strategy set is represented by:

$$\mathbf{S} := \{S(1) \times S(2) \times ...S(T)\}, \tag{3.16}$$

the following players' strategy set is represented by:

$$\mathbf{P} := \{\mathbf{P}(1) \times \mathbf{P}(2) \times ...\mathbf{P}(T)\}, \tag{3.17}$$

where

$$\mathbf{P}(t) := \{P_1(t), ..., P_G(t)\}, \tag{3.18}$$

the benefit set of the leading player is represented by:

$$\begin{aligned} \mathbf{U}_L : &= \{U(1) \times U(2) \times ...U(T)\} \\ &= \{p(1)S(1) - p(1)P_l(1)\} \times \{p(2)S(2) - p(2)P_l(2)\} \times ...\{p(T)S(T) - p(T)P_l(T)\} \end{aligned} \tag{3.19}$$

the benefit set of the following player is represented by:

$$\begin{aligned} \mathbf{U}_f : &= \{U_1(1) \times U_1(2) \times ...U_1(T)\} \\ &= \{p(1)P_g(1) - c_g(1)\} \times \{p(2)P_g(2) - c_g(2)\} \times ...\{p(T)P_g(T) - c_g(T)\} \end{aligned} \tag{3.20}$$

From Eqn. (3.19) and Eqn. (3.20), we see that the value of the benefit set of the players is related to the amount of power (e.g., $P_{1,,,}P_G$). In the proposed Stackelberg game, the objective of the players is to maximize their benefits.

Based on the backward induction theory, the following players select the best reactions, which are related to the leading player's strategy to maximize their benefits [17]. The leading player can obtain this best reaction one step earlier, which is called the first-mover's privilege. The best strategy for the leading player can be obtained from:

$$\mathbf{S}^* = arg \quad max \quad \mathbf{U}_L, \tag{3.21}$$

and the followers' best strategies can be obtained from:

$$\mathbf{P}^* = arg \quad max \quad \mathbf{U}_f. \tag{3.22}$$

Lemma 3.1: In a Stackelberg game, if the strategy sets of the leading and following players are compact, and the benefit sets of the leading and following players are real-valued continuous function. There must exist a unique best strategy set for the players [17].

Based on Lemma 3.1, we introduce the following theorem:

Theorem 3.3: In the Stackelberg game, if no player can gain more benefits by changing its strategy, we define it as an NE state. A unique Stackelberg NE state exists for the leading and following players only if: 1) the strategy sets of the leading and following players are nonempty, convex and compact; 2) the following players have a set of unique optimal strategies; and 3) the leading player has a unique optimal strategy, which is related to the following players' reactions.

Proof 1): The leading and following players' strategy sets are linear equality (e.g., Eqn. (3.16) and (3.17)) with convex constraints (e.g., Eqn. (2.6) and (2.7)). Therefore, condition 1 is satisfied.

Proof 2): Based on Eqn. (2.12), the following players' best strategy can be obtained from:

$$\begin{aligned} &\mathbf{P}^* = arg \quad max \quad \mathbf{U}_f, \\ \text{s.t.} \quad &\sum_{g=1}^{G} P_g^* - P_l = S, \\ &P_g^* \geq 0, \end{aligned} \tag{3.23}$$

In section 3.1, we learn that the GP for the generators is a convex problem. Therefore, the solution of Eqn. (3.23) is unique. Condition 2 is satisfied.

Proof 3): The best strategies for the following players are $\mathbf{P}^*$, which can be obtained from algorithm 1. The leading player's best strategy can be represented by:

$$\begin{aligned} &\mathbf{S}^* = arg \quad max \quad \mathbf{U}_L, \\ \text{s.t.} \quad &p = \lambda\left(S - \hat{S}\right) + p_0, \\ &P_l = \sum_{g=1}^{G} L_g P_g, \\ &\frac{S}{\hat{S}} \leq \theta + 1. \end{aligned} \tag{3.24}$$

In section 3.1, we learn that the GP for the utility company is a convex problem, the solution of Eqn. (3.24) is the unique optimal strategy for the leading player. Condition 3 is proved.

The procedure of the Stackelberg game can be summarized as: 1) the leading player announces the power demand S to the following players; 2) the following players receive the S, they choose the optimal outputs $\mathbf{P}^*$; 3) the leader updates its optimal strategy $\mathbf{S}^*$.

In the existing GP methods, the utility company and the generators take actions at the same time. While in our Stackelberg game, the generators react to the utility company's action. Therefore, the actions are not taken at the same time. The numerical results in chapter 4 show that the utility company can always gain more benefits compare to the EDP method. If the utility company and generators choose to take actions at the same time, the benefit of the utility company is reduced while the generators' benefit is increased. The biggest difference between the existing GP methods and our work can be summarized as: in the existing methods, the utility company and generators take actions in the same time. But in our work, the utility company has a first-mover's privilege, by which it can take action one step earlier than the generators. Based on the game theory, taking actions earlier than the competitor always means the leading player (e.g., the utility company) can earn more benefit [17].

In the proposed Stackelberg game, the following players know the leading player choose strategy S^*. More importantly, the leading player knows the following players know the S^*. To analyze the problem, we assume that the leading player chooses S^*, the following players choose P_g without knowing S^*. If the following players believe the leading player's strategy is S^*, they choose the best reactions $\mathbf{P}^*$. However, if the leading player knows the following players best reactions, it will react to $\mathbf{P}^*$ to obtain a new best strategy rather than S^*. The leading player changes its strategy. Therefore, the following players change their reactions, too. Based on the backward theory, the outcomes of the players are the same with the one when the leading and following player take actions in the same time [17].

3.4 Analysis of the Repeated Game

Definition 3.3: The one-stage game for the customers' is defined as $G_R = \{\{n\}, \{a_n\}_{n \in N}, \{c_n\}\}$. The benefit set of the one-stage game is c_n. The action set is a_n. In the repeated game, the players play the one-stage game repeatedly. For each time slot, the constraints, coefficients, and configurations of the players stay the same. The price and consumption are changed with the time. The game is a repeated game with perfect information, by which one players' actions are known to all the others.

We assume the players stay in the same smart grid for a relatively long time, which indicates the repeated game is played infinitely. The players' action set can be represented by:

$$\mathbf{a} : a_1 \times a_2 \times , , , a_n \tag{3.25}$$

where

$$a_n = b_n + r_n,$$

the historical action set is represented by:

$$\mathbf{a}^H = \{\mathbf{a}(1), \mathbf{a}(2), ..., \mathbf{a}(t-1)\}. \tag{3.26}$$

We assume the historical actions can be observed by all the players. The benefit set of the players can be represented by:

$$\mathbf{U}_R := \{\mathbf{c} \times \mathbf{c} \times ...\mathbf{c}\} \tag{3.27}$$

where $\mathbf{c} = \{c_1, c_2, ..., c_N\}$. The average benefit of the players in an infinitely repeated game can be represented by:

$$\begin{aligned} \overline{\mathbf{U}}_R &= \sum_{t=1}^{T} \mathbf{U}_R(\mathbf{a}(t)) \\ &= (1-\delta_d) \sum_{t=0}^{\inf} \delta_d^h \mathbf{c}, \end{aligned} \tag{3.28}$$

where $\delta_d^h \in (0,1)$ is the discount factor, which is a decimal number multiplied by the benefit value to discount it back to the present value [17].

The objective of the players in an infinitely repeated game is to minimize their cost, which can be represented by:

$$\min \overline{\mathbf{U}}_R. \tag{3.29}$$

Before we analyze the infinitely repeated game, we present the analysis of the one-stage repeated game. In an NE state of the one-stage game, the player's cost must satisfy:

$$c_n \leq c_n^- \tag{3.30}$$

where c_n^- represents all the other cost that the player can obtain from the one-stage game. At the NE state, all of the players reach their own optimal cost. However, a Nash equilibrium for a repeated game may not exist, or there can be more than one NE states. The players have to find the best one among them.

Proposition 3.1: The players in the repeated game are rational, which implies the NE cost of the players must greater than the minimal one. By doing so, the players have no motivation to change their strategies to disturb the NE state. The cost of the player is obtained from Eqns. (2.2), (2.3), (2.4), and (2.7).

Lemma 3.2: Folk theorem: in an infinitely repeated game. With the Proposition above, there exists some $\underline{\delta_d} < 1$, by which for all the $\delta_d \geq \underline{\delta_d}$, the players can reach an NE state eventually [17].

Lemma 3.2 implies that if the players are patient enough, they can get the optimal cost in the NE state eventually. However, the cost of optimal individual may not be the optimal cost of the entire group. Conversely, in the NE state, the total cost can go even higher.

Theorem 3.4: In the infinitely repeated game, the players can reach a unique NE state. However, the cost from the NE state of the player is not the global optimal solution of the entire group, which is known as the common tragedy.

Proof: The cost of player n can be represented by:

$$\begin{aligned} c_n =& p a_n + d_n \\ =& (\omega(\sum_{n=1}^{N} a_n - \hat{a}_n) + p_0) a_n + \kappa \hat{a}_n \beta_n \left(\left(\frac{\hat{a}_n}{a_n} \right)^{\alpha_n} - 1 \right) \end{aligned} \tag{3.31}$$

the optimal cost of a_n is represented by:

$$\underline{c}_n \leq c_n^-. \tag{3.32}$$

where $\underline{c}_n$ is the minimum cost that player n can achieve. c_n^- represents all the other possible cost that player n can get. The optimal strategy for the player n is represented by:

$$\underline{a}_n : \frac{\partial c_n(\underline{a}_n)}{\partial \underline{a}_n} = 0, \tag{3.33}$$

by solving Eqn. (3.33), we find the optimal strategy $\underline{a}_n$ of player n. We take $\underline{a}_n$ into Eqn. (3.31), we have:

$$\underline{c}_n(\underline{a}_n) \leq c_n^-, \tag{3.34}$$

we know that the cost function c_n is a strictly monotone increasing function, which implies the infinitely repeated game reaches a unique NE state. Therefore, we have:

$$\underline{a}_n < a_n^-, \tag{3.35}$$

where a_n^- represents all the other strategies that player n can choose. Since c_n is a strictly monotone increasing function, we have:

$$\sum_{n=1}^{N} \underline{a}_n < S, \tag{3.36}$$

from Eqn. (3.36) we learn that in the unique NE state, the total power demand $\sum_{n=1}^{N} \underline{a}_n$ is less than S^*, by which it may cause an unstable problem to the smart grid. All the player can observe the cost of other players, a rational player naturally reduces its consumption to reduce cost. Such selfish behaviors may encourage other players to take the non-cooperative actions. An unwanted peak or low demand is harmful to the smart grid. Theorem 3.4 is proofed.

To avoid the negative effect to the smart grid from the common tragedy, we propose a Pareto-efficient solution to the CP, which can be represented by:

$$\sum_{n=1}^{N} a_n^* \leq \sum_{n=1}^{N} a_n^-, \tag{3.37}$$

where a_n^- represents all the other strategies of the players during the infinitely repeated game. a_n^* is the Pareto-efficient strategy of player n. The solution of Eqn. (3.37) is obtained in section 2.6. The players may not be cooperative because the individual optimal strategy $\underline{a}_n$ is not the same as a_n^*. Therefore, we apply a TFT punishment strategy to incentive the rational customers to cooperate with the utility company.

3.5 Error Detection

In this section, we change the method in [23] to analyze the profit reduction of a utility company from errors. The errors can reduce the performance of the two-stage game. For example, a customer cooperates with the utility company all the time. But a malfunctioning smart meter sends a wrong-reading to the utility company. A wrong punishment will be applied to the innocent customer.

The detection result of a smart meter is related to the customer's consumption. The difference between the optimal and actual power consumption can be represented by:

$$\Delta a_n = a_n^* - a_n. \tag{3.38}$$

The probability of the difference is assumed to follow a normal distribution, i.e., $\Delta a_n \sim N(\mu, \delta^2)$ [23], where μ and δ^2 are the expectation and variance of the normal distribution, respectively. The detection result of the smart meters is represented by:

$$\Upsilon = \begin{cases} 1, |\Delta a_n| > \phi; \\ 0, |\Delta a_n| \leq \phi, \end{cases} \tag{3.39}$$

where Υ is the detection result. ϕ is the detection threshold. If $|\Delta a_n| > \phi$, it indicates that the utility company detects a non-cooperative behavior of customer n, a punishing price will be applied to the customer. In some cases, the smart meter may send a wrong reading to the utility company, by which it is called an error of smart meter. To analyze the error's influence on the proposed two-stage game, we denote the actual error result by a binary variable υ. Therefore, the detection results can be represented by:

Table 3.1: Detection results

	Υ	υ
Detection error	1	0
Detection failure	0	1
No detection error	1	1
No detection failure	0	0

When $\Upsilon = 1, \upsilon = 0$, there is no non-cooperative behavior. But the smart meter shows the customer is not cooperating; we call it a detection error. When $\Upsilon = 0, \upsilon = 1$, the smart meter fails to detect the non-cooperative behavior; we call it a detection failure. Both detection error and failure cause unnecessary benefit loss. To minimize the loss, we find the best detection thresholds for the smart meters.

The cumulative distribution function of the detection error can be represented by [18]:

$$\begin{aligned} Pr\{\Upsilon = 1|\upsilon = 0\} &= Pr\{|\Delta a_n| \geq \phi\}, \\ &= 1 - Pr\{|\Delta a_n| \leq \phi\}, \Delta a_n \sim N(0, \delta^2), \end{aligned} \tag{3.40}$$

and the cumulative distribution function of the detection failure can be represented by:

$$\begin{aligned} Pr\{\Upsilon = 0|\upsilon = 1\} = Pr\{|\Delta a_n| \leq \phi\}, \\ \Delta a_n \sim N(\Delta a_n, \delta^2), \end{aligned} \tag{3.41}$$

$Pr\{\Upsilon = 1|\upsilon = 0\}$ is decreasing when the value of ϕ is decreasing, while $Pr\{\Upsilon = 0|\upsilon = 1\}$ is increasing when ϕ is increasing.

In this work, we have changed the assumption regarding the probability of the customers' non-cooperative behaviors by applying the type coefficients in the formula for error detection. So that the analysis of the error detection is more practical. We define the probability of the non-cooperative behavior by $\kappa\varrho$, where ϱ is a constant that is related to the demand [23]. κ is the type coefficient of the dissatisfaction function that is related to the price-sensitivity of the customers. To simplify the problem, we assume all the customers have the same ϱ. The estimated probability of the non-cooperation of N customers can be represented by [18]:

$$\begin{aligned} \hat{\varrho} =& P\{\Upsilon = 1|\upsilon = 0\}P\{\upsilon = 0\} + P\{\Upsilon = 1|\upsilon = 1\}P\{\upsilon = 1\} \\ =& (1 - (1 - \kappa\varrho)^N)Pr\{|\Delta a_n| \geq \phi\} \\ &+ (1 - \kappa\varrho)^N(1 - Pr\{|\Delta a_n| \geq \phi\}). \end{aligned} \tag{3.42}$$

From Eqn. (3.42), we learn that $\hat{\varrho}$ is decreasing when ϕ is decreasing.

The total benefit loss of the detection error and failure can be represented by:

$$U_l = \sum_{n=1}^{N} \hat{\varrho}(1 - \kappa\varrho)^N(c_n^d - \bar{c}_n) + (1 - \hat{\varrho})(1 - (1 - \kappa\varrho)^N)(\bar{c}_n - \tilde{c}_n). \tag{3.43}$$

where c_n^d is the punishment to the customer. $\bar{c}_n$ and $\tilde{c}_n$ are the average and minimal cost for customer n, respectively. In real world, the punishing cost is much greater than the optimal cost, which can be represented by:

$$(1 - \kappa\varrho)^N(c_n^d - \bar{c}_n) >> (1 - (1 - \kappa\varrho)^N)(\bar{c}_n - \tilde{c}_n). \tag{3.44}$$

From Eqn. (3.44), we learn that the benefit loss U_l is more related to the first term in the RHS of Eqn. (3.43). Therefore, a greater ϕ can help us to reduce the benefit loss U_l.

By changing the assumption regarding the probability of the non-cooperation of the customers. We mathematically prove that a greater threshold for the error detection leads to a smaller benefit loss. Compared with the work in reference [23], the probability of the non-cooperative behavior becomes directly related to the type and demand of the customers, which is more practical.

CHAPTER 4

VALIDATION AND SIMULATIONS

4.1 Simulation Design

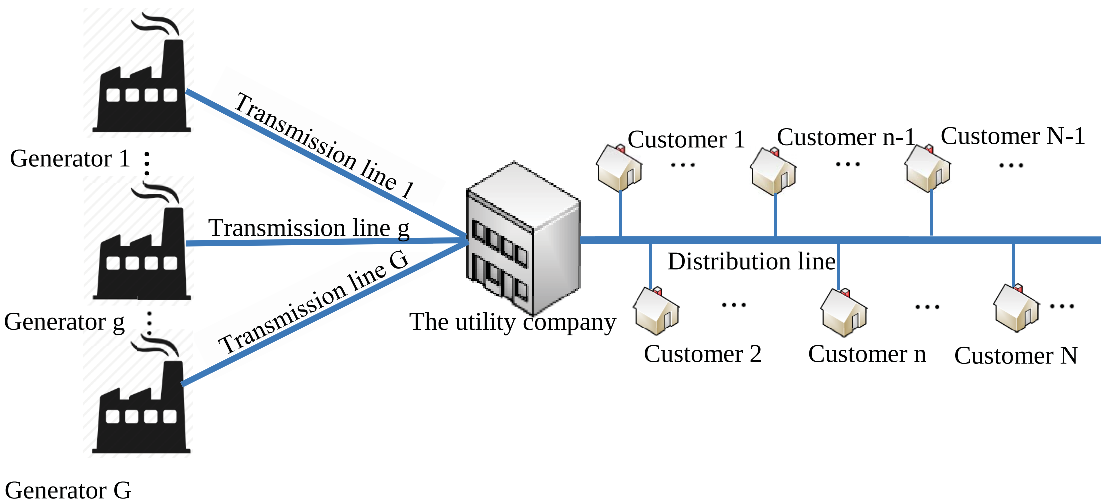

Figure 4.1: A typical configuration of a smart grid [1]

In this section, we validate the performance of the proposed two-stage game model. We first compare the performance of our work to the EDP and gaming optimization methods. Then, we compare the outputs from our work to the one from the one-stage game with the same configuration. After that, we evaluate the stability of the smart grid. Finally, we study the impacts of different dissatisfactions on a CP; different generating limitations on a GP and different discount factors on a CP.

Fig. 4.1 is a typical configuration of a smart grid [1]. We use five power generators, one utility company, and one hundred customers to demonstrate the performance of the two-stage game. All of the parameters are from the Department of Energy annual report and OASIS-smart-pricing system [1], and [2]. The coefficients of the five generators' cost function are presented in table 4.1 [5].

The parameters of the transmission loss are from the OASIS-smart-pricing system[2]:

Table 4.1: Parameters of the power generators

unit	$c_{2,g}$	$c_{1,g}$	$c_{0,g}$
1	561	7.92	0.001562
2	310	7.85	0.00194
3	78	7.8	0.00482
4	561	7.92	0.001562
5	78	7.8	0.00482

$$L_{1,g} = [0.05, 0.055, 0.06, 0.065, 0.07]$$

$$L_{2,g} = [0.08, 0.085, 0.09, 0.095, 0.1]$$

The real-time electricity price can be represented by:

$$p = \omega(\sum_{n=1}^{N} a_n - \hat{a}_n) + p_0,$$

where the price coefficient ω is a number that is related to the number of customers, which is 0.01. p_0 is 50 dollars/MWh [2]. Each time slot equals to one hour. We assume $T = 24$. The one hundred customers are divided into three groups. Thirty customers' dissatisfaction parameters $< \beta_n, \alpha_n >$ are $< 5, 2 >$. Forty customers' parameters are $< 20, 0.5 >$. The rest customers' parameters are $< 40, 1.7 >$. The type coefficient κ is 1, 3 and 5, respectively [53]. The ratio of actual to estimated total power usage of the utility company is 20%, which implies the optimal demand cannot be 20% different from the estimation [38]. The demand of the customers is from the Department of Energy's annual report [1]. In each time slot, the demand of the 100 customers is a set of random number. For instance, from 23:00 to 0:00, a customer's demand is a random number between 1.6 MWh and 1.8 MWh. Figure 4.2 shows the demand boundaries of the customers [1], [2].

4.2 DRM Performance Evaluation Metrics

The performance evaluation metrics of the proposed two-stage game can be divided into four categories. The first category is the benefits of the DRM components (e.g., the utility company, power generators and customers). The benefit of a power generator is equal to the profit minus the cost, where the profit is the product of the price and power, and the cost is a quadratic equation

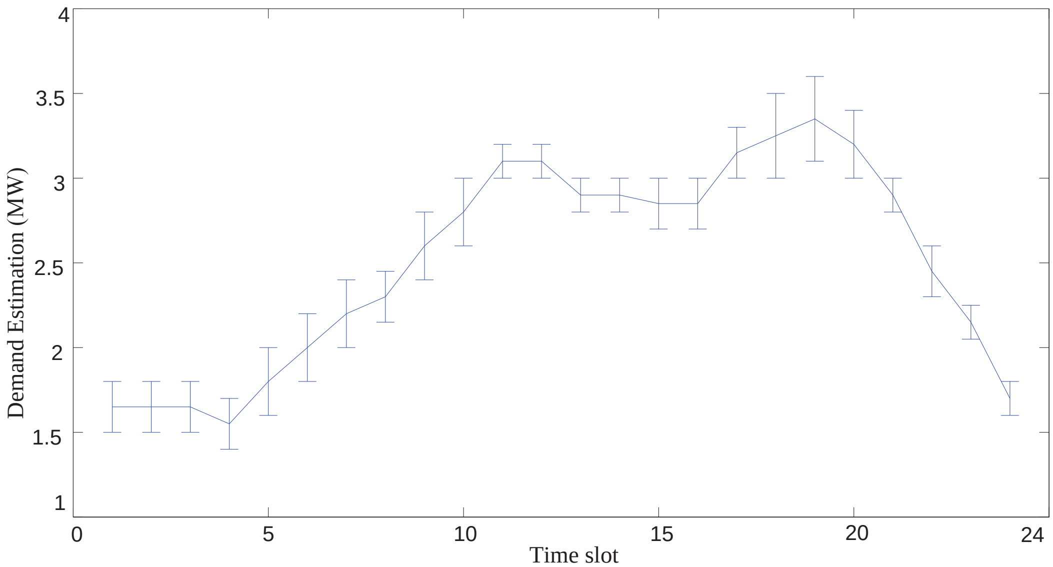

Figure 4.2: The demand boundaries of the customers during each time slot

that is represented by Eqn. (2.5). In a GP, the objective of a generator is to maximize its benefit. The benefit of a utility company equals to the profit minus transmission loss, where the profit is the product of the demand and price, and the transmission loss is the product of the delivered power and power loss coefficient. In a GP, the objective of a utility company is to maximize its benefit. The cost of customers is represented by the sum of consumption and dissatisfaction, where the consumption is equal to the product of the consumed power and electricity price, and the dissatisfaction $d_n(t)$ is an exponential function that is represented by Eqn (2.4). The objective of customers is to minimize its cost.

The second category is the stability of the smart grid. Generally, we use the PAR of the demand to evaluate the stability of a smart grid [27]. A smaller PAR indicates the smart grid is more stable. In our work, we compare the PAR of our two-stage game to the one from the EDP method.

The third category is the impact of different coefficients on a DRM. For example, we study the impacts on the optimal power outputs in a GP by applying different power loss ratios to the utility company. The impacts on the optimal demand in a CP by applying different type and dissatisfaction to the customers. The impacts on the punishment effort to the customers in a CP by using different punishing strategies, etc.

The fourth category is the impact of different constraints on a DRM. We study the impacts on power generators in a GP by applying different amount of curtailable-power. We study the impacts on a utility company by applying different amount of curtailable-demand in a CP. We study the impacts on customers in a CP by applying different amount of curtailable-consumption.

Table 4.2 shows the evaluation metrics of DRM performance. The major objectives of a DRM can be summarized as: maintaining the stability of a smart grid, and optimizing the benefit of its components. In this work, we mainly focus on optimizing the benefit of the DRM components, i.e, increasing the profit for a utility company, and reducing the cost for customers.

Table 4.2: The evaluation metrics of DRM performance

	Objective	**Category of Metrics**
[55]	Minimizing cost for generation	1,2
[38]	Minimizing cost for generation and consumption	2,3
[29]	Minimizing cost for generators	3,4
[27]	Minimizing consumption cost	2,4
[53]	Minimizing consumption cost	2,3
[43]	Minimizing consumption cost	1,4
[23]	Minimizing consumption cost	1,2,4
Our work	Optimizing power consumption and generation	1,2,3 and 4

4.3 Numerical Results

In this section, we present the numerical results from the simulations.

4.3.1 Comparison with the Existing GP Method

In this section, we compare our GP results of the utility company to the EDP method [55], [38]. The GP is solved by a consensus algorithm in the EDP method. The objective of a GP can be represented by: $max\{U_1\}$. Given the same parameters and configuration, the comparison of the profit is shown in Fig. 4.3:

From Fig. 4.3, we see that the profit of the utility company is always greater in the Stackelberg game method. Especially, when the demand is higher, i.e., around the 20:00 hours. The profit of the utility company in the Stackelberg method is 8% higher than the one from the EDP method. During the lower power demand hours, the profits of the two methods have no major differences.

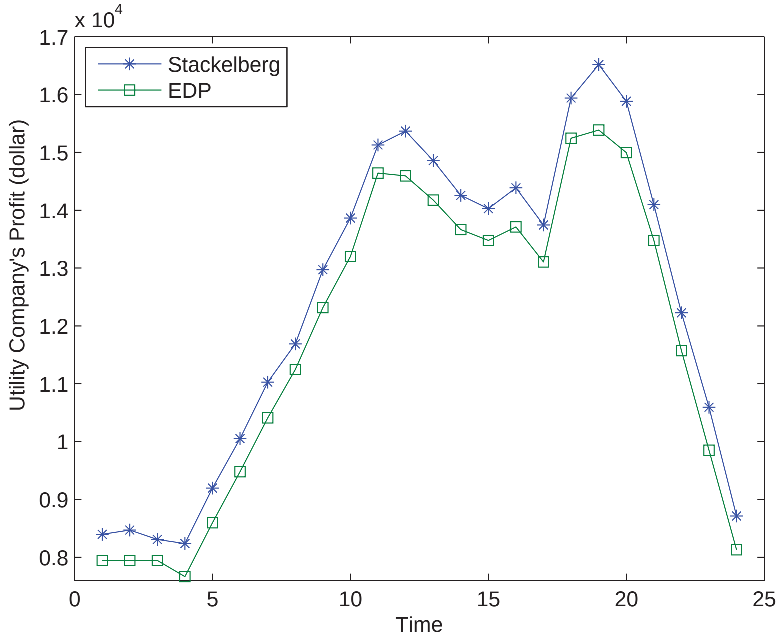

Figure 4.3: The profit of the utility company in different GP

This is reasonable because the utility company is more willing to adjust its demand to earn a greater benefit during the peak period.

4.3.2 Comparison with the Existing CP Method

In this section, we compare the CP consumption to the one from the gaming optimization [27]. The CP is solved by minimizing the total cost of customers in the gaming optimization [27], which can be represented by:

$$min \quad \{\sum_{n=1}^{N} c_n\}. \tag{4.1}$$

Given the same parameters and configuration, the comparison of the cost of customers is shown in Fig. 4.4. The total cost of customers is always greater in the gaming optimization method. The imbalanced power increases the cost of customers from the comparison method. By applying the power balance constraint, the cost of customers in the repeated game method is reduced significantly.

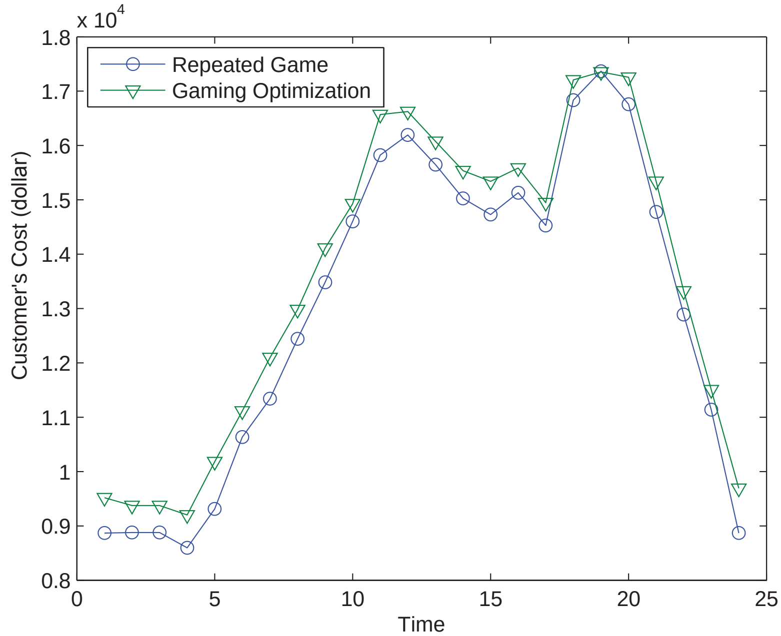

Figure 4.4: The cost of customers in different CP

4.3.3 Comparison with the One-Stage Game

In this section, the cost of the one-stage and two-stage game is presented and studied. In the two-stage game model, we maximize the profit for the utility company in the first stage, and minimize the cost for the customers in the second stage. The objective of the one-stage game model is to minimize the sum of power generation and consumption, which can be formulated as [38]:

$$min \quad \{\sum_{n=1}^{N} c_n - U_1\}, \tag{4.2}$$

In our two-stage game, the cost can be represented by:

$$\sum_{n=1}^{N} c_n^* - U_1^*, \tag{4.3}$$

where c_n^* is the Pareto-efficient cost of the customers, and U_1^* is the utility company's optimal profit for the Stackelberg game model.

We develop two methods to compare the performance of the two-stage game to the one-stage game. In the first one, the balance constraint is not applied to the one-stage game, we compare

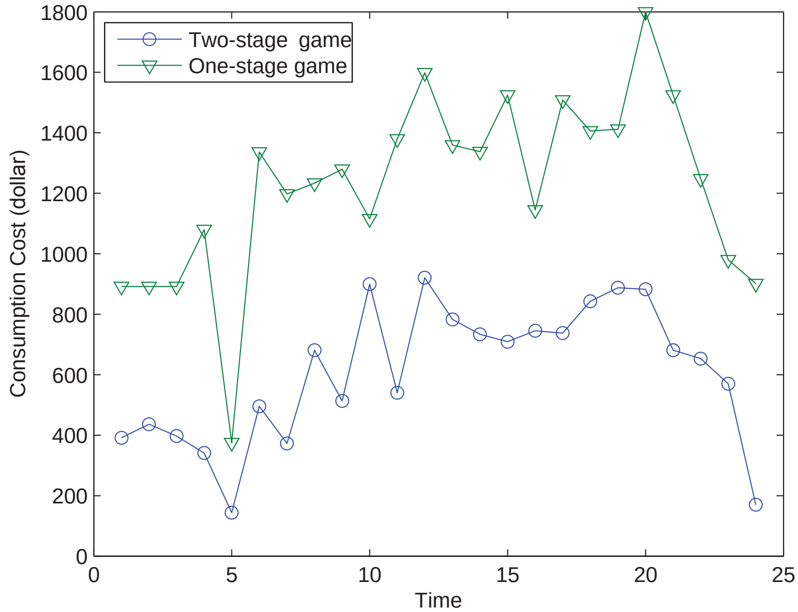

Figure 4.5: The cost of customers in the one-stage game and two-stage game

the cost. In the second one, the balance constraint is applied to the one-stage game, we compare the utility company's profit. From Fig. 4.5, we see that the cost of the two-stage game is much smaller than the one from the one-stage game. The imbalanced-power significantly increases the cost of the one-stage game.

From Fig. 4.6, we see that, for the utility company, the profit of the two-stage game is always greater than the one from the one-stage game. This is because the utility company has a first-mover's privilege to increase its profit. In real world, the utility company naturally chooses the two-stage game to earn more profit.

4.3.4 Comparison with the Peak-to-Average Ratio

There are two major objectives for a DRM to achieve: 1) reducing the cost; and 2) maintaining the stability of a smart grid. In this section, we discuss the smart grid's stability with different optimal methods, i.e., two-stage game model, and EDP. We use the PAR to evaluate the stability

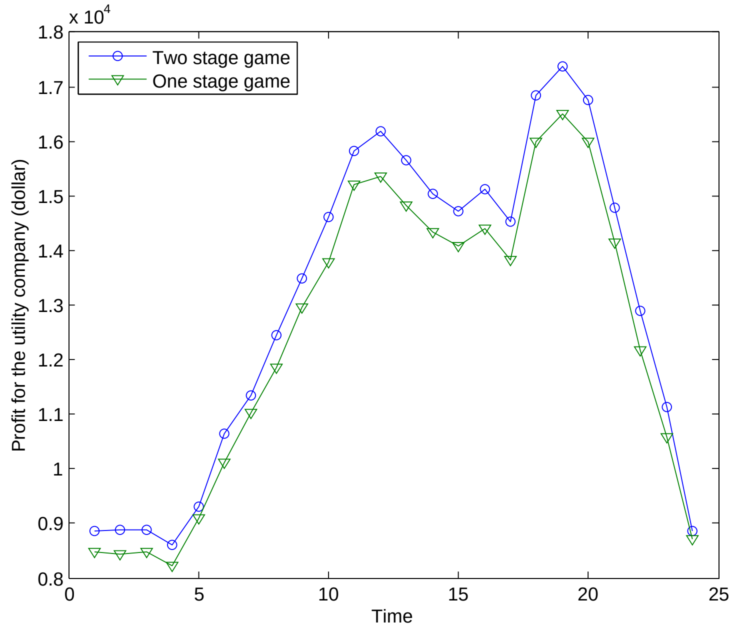

Figure 4.6: The profit for the utility company in the one-stage game and two-stage game

of a smart grid. The PAR can be formulated as [27] :

$$PAR = S/\sum_{t=1}^{24} S, \tag{4.4}$$

We compare the PAR of our method to the work in [55]. The results are presented in Fig. 4.7. There are no major differences between the two PARs. The main objective of our work is to reduce the consumption cost of the smart grid. From Fig. 4.7, we see that the two-stage model doesn't reduce the stability of a smart grid.

4.3.5 The Impacts of Power Loss Ratio

In this section, we discuss the impacts of different power loss ratios on the optimal results in a GP. There are two comparison groups in this section. In the first group, the transmission line has an average of 6% power loss, while in the second group the transmission line has an average of 9% power loss [38]. We use the profit-increase-ratio (PIR) to evaluate the impacts, which is represented by:

$$PIR = (U_1^* - U_1)/U_1, \tag{4.5}$$

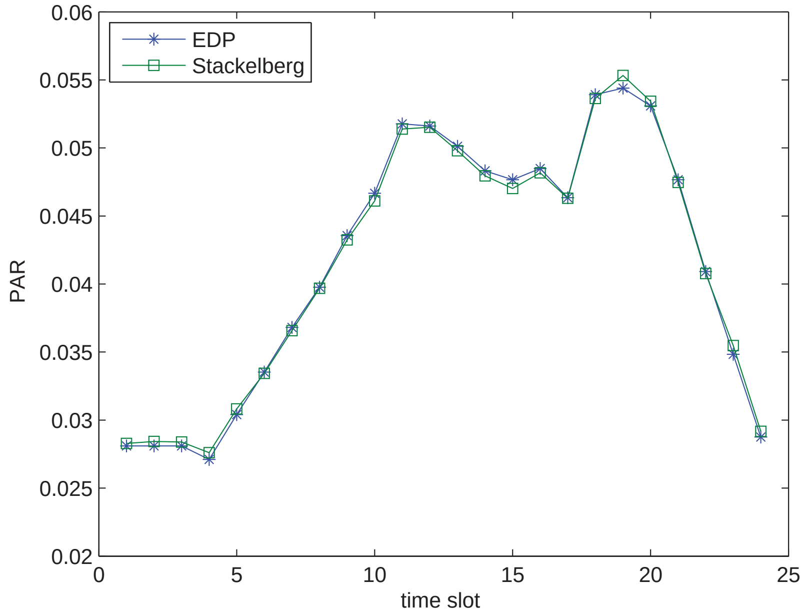

Figure 4.7: The PAR in the EDP and two-stage game model

where the U_1^* is the optimal benefit of the utility company. U_1 is the original profit of the utility company. From Fig. 4.8, we can see that the PIR is greater in the first group. During the peak hours, the PIR in the first group is greater than the one from the lower hours. The generators are more willing to cooperate with the utility company when the price is high. By doing so, the utility company in the Stackelberg game can earn more profit.

4.3.6 The Impacts of the Linear Coefficient on a CP

The impacts of linear coefficients on a CP is evaluated by applying different type coefficients to the customers. Two linear coefficients (e.g., κ) of the dissatisfaction function are selected from reference [53]. We use the cost-efficient-ratio (CER) to evaluate the impacts, which can be represented by:

$$\sum_{n=1}^{N} \{c_n^* - c_n\}/c_n, \tag{4.6}$$

From Fig 4.9, we see that the customers with a greater sensitivity (e.g., $\kappa = 5$) have a greater CER. The high price-sensitive customers are more willing to cooperate with the utility company to reduce their cost. The CER of the customers who have lower κ (e.g., $\kappa = 1$) is small, which implies

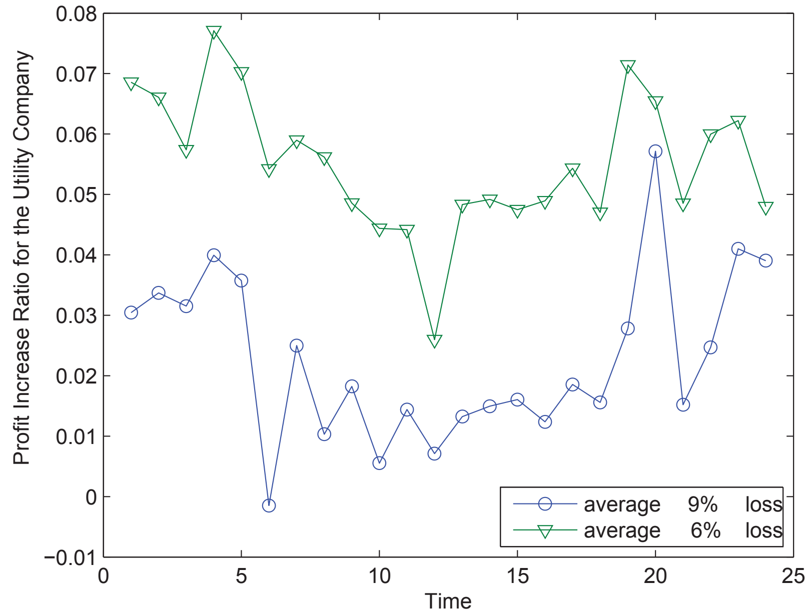

Figure 4.8: The PIR with a ave. transmission loss of 6% and 9%

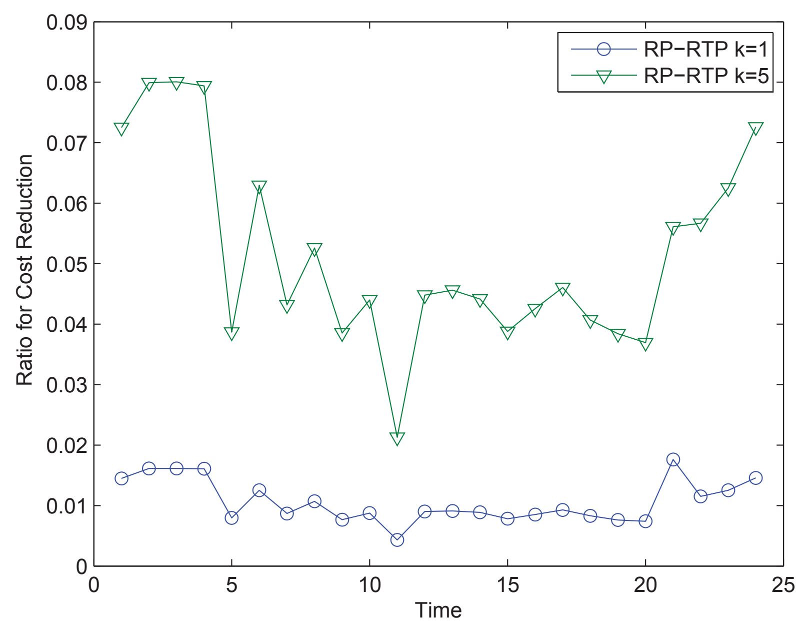

Figure 4.9: The CER of customers with different sensitive types

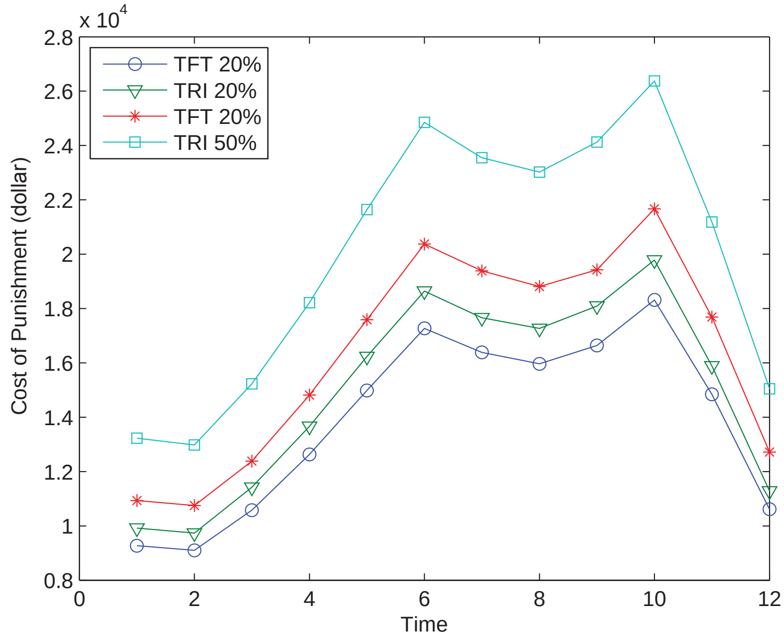

Figure 4.10: The cost of customers in the TFT and trigger strategies

the low price-sensitive customers have little motivation to cooperate with the utility company to reduce their cost.

4.3.7 The Punishing Efforts of the TFT and Trigger Strategies

The punishing efforts of the TFT and trigger strategies are studied in this section. We use the TFT punishment strategy to the customers in the first group, while in the comparison group we use the trigger strategy. We add 20% and 50% to the normal price as the punishing price, respectively [43].

Fig. 4.10 shows the cost of customers with different punishment strategies. In the same period, the customers in the trigger group receive the highest punishing cost. Therefore, the customers' motivation to cooperate with the utility company is reduced. The punishing cost is fixed in the trigger group, the customers naturally choose the selfish actions to reduce their cost during the punishing period. In the TFT group, the customers have smaller punishing cost. Therefore, they are more willing to cooperate with the utility company. The punishment will be removed if they cooperate with the utility company during the punishing period.

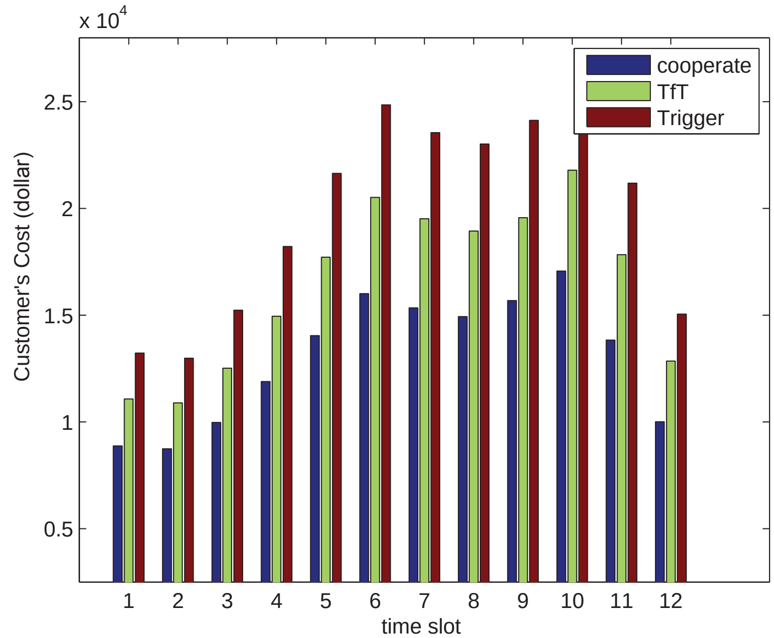

Figure 4.11: The cost of customers in the TFT and trigger strategies(a)

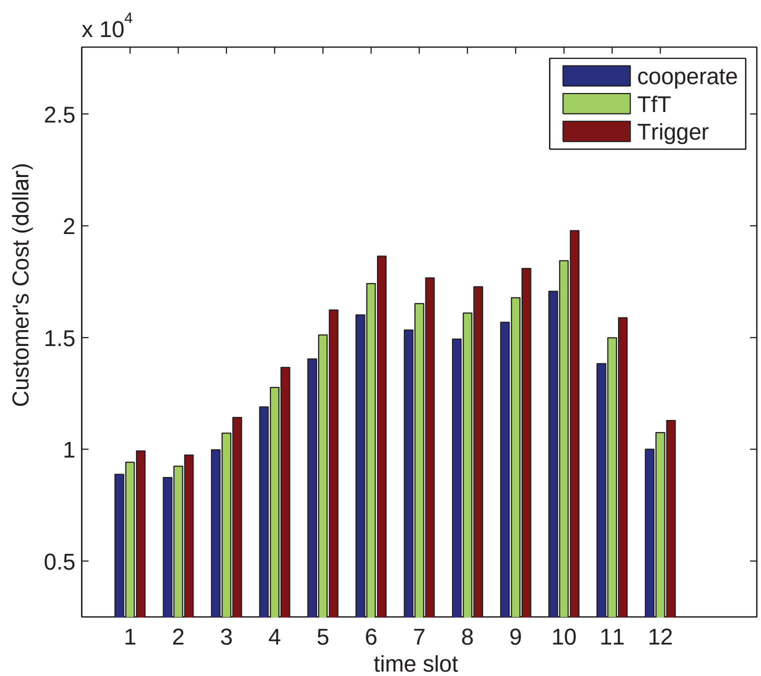

Figure 4.12: The cost of customers in the TFT and trigger strategies(b)

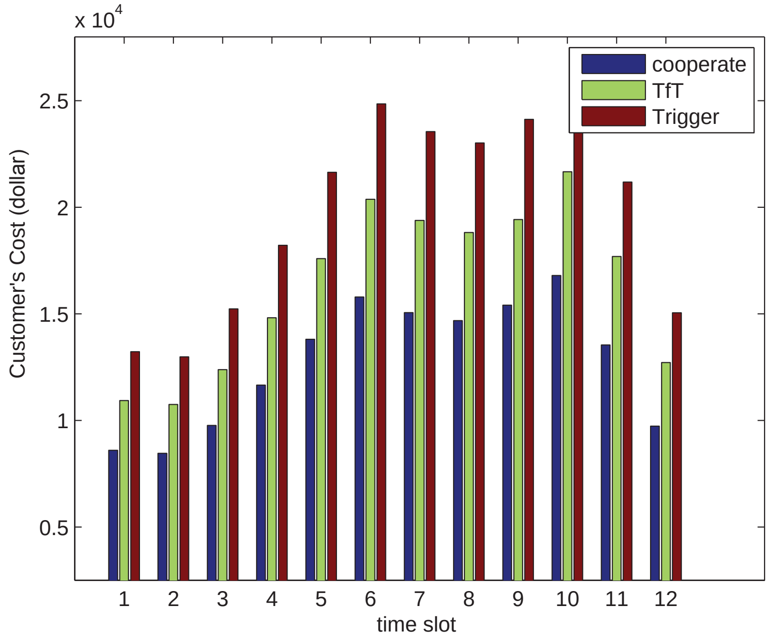

Figure 4.13: The cost of customers in the TFT and trigger strategies(c)

Figure 4.11, 4.12, and 4.13 show the cost of the customers. The type coefficients (e.g., κ) of the customers equal to 1, 3 and 5, respectively. The cost of customers is highest when $\kappa = 5$. This is because the customers are more sensitive with the cost when the value of κ is higher. The cost difference for the customers between the trigger and TFT group is higher when κ is higher, which implies the price-sensitive customers are more willing to change their consumption to reduce the cost.

4.3.8 The Impacts of Different Types of Customers on a CP

In this section, we discuss the impacts on a CP by applying different type-coefficients for the customers. There are three types of customers. The dissatisfaction parameters (e.g., $< \beta_n, \alpha_n >$) are set to be $< 5, 2 >$, $< 20, 0.5 >$, and $< 40, 1.7 >$, respectively. These parameters are similar to the work in [53]. We use the average-demand-change-ratio (e.g., $\overline{DCR}$) to evaluated the impacts of d_n on a CP, which can be represented by:

$$(\sum_{n=1}^{N} |a^*(n) - a^{est}(n)|/a^{est}(n))/N, \tag{4.7}$$

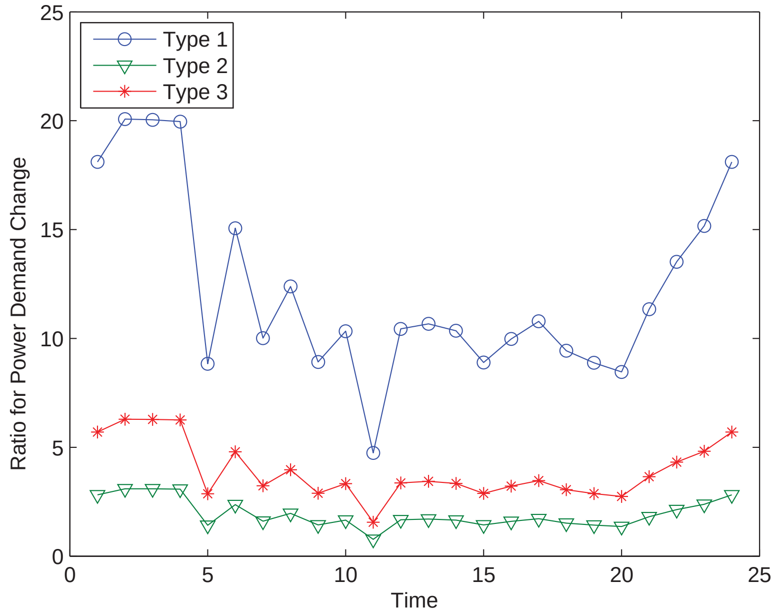

Figure 4.14: The $\overline{DCR}$ for different types of customers in each time slot

From Fig. 4.14, we see that the customers with a greater β_n are more willing to change their consumption. Therefore, a greater β_n implies the cost of the dissatisfaction is higher. The customers have to change the consumption to reduce their cost.

4.3.9 The Impacts of Power Loss Ratio on a GP

In this section, we compare the profit of a utility company from the RTP method to our work. The pricing strategy is RTP in the comparison group [1]. The profit from the two-stage game is shown with the SB-RTP (e.g., SB is short for the Stackelberg game)label, while the profit from the comparison group is shown with the RTP label.

In Fig. 4.15, the average-power-loss-ratio for the utility company is 6% and 9%, respectively. In the 6% average-power-loss-ratio group, the profits of the utility company are similar. In the 9% average-power-loss-ratio group, the profit in the SB-RTP group is higher. This is because the utility company is more willing to adjust the demand to get a greater profit when the transmission-loss is higher.

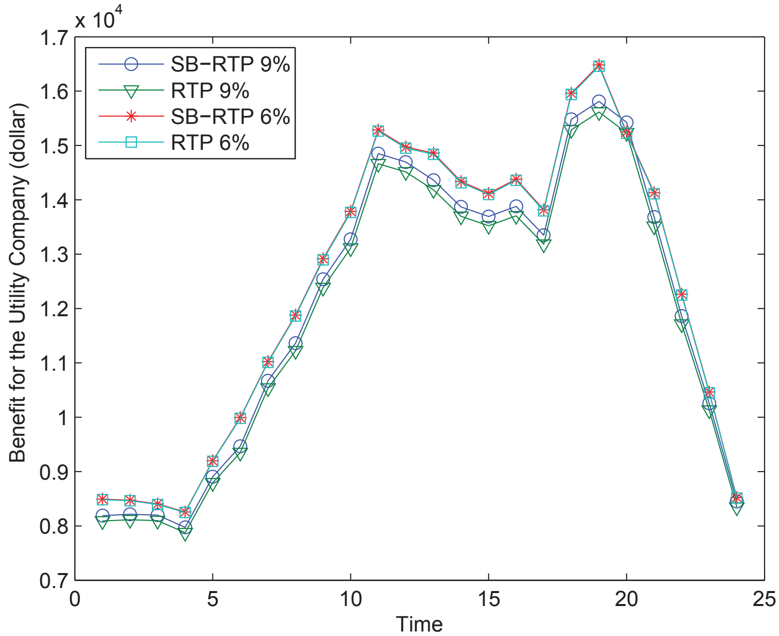

Figure 4.15: The profit of the utility company with different power loss ratios

4.3.10 The Impacts of Price Coefficient λ on a GP

In this section, we study the impacts on the profit from the two-stage game model by applying different price coefficients in a GP. We assume the price coefficients ω are set to be 0.01, 0.02, and 0.005, respectively [53]. Fig 4.16 shows the profits of a utility company with different ωs. The profits have no significant differences, which implies the optimal result for the GP is not related to the price coefficient. From Eqn. (2.2), we see that the price does not change much with different ωs. Therefore, the impact of *omega* on a GP can be ignored.

4.3.11 The Impacts of Curtailable-Loads on a CP

We assume the curtailable-loads of the customers are set to be 0%, 10%, and 20%, respectively, which are similar to the work in [55]. Fig. 4.17 shows the cost of customers with different curtailable-loads in a CP. The customers' cost has no significant differences when the percentage of the curtailable-loads is small. The cost of the customers with 20% curtailable-loads is smaller than the other two. Generally, the customers with a higher percentage of curtailable-loads can reduce more cost.

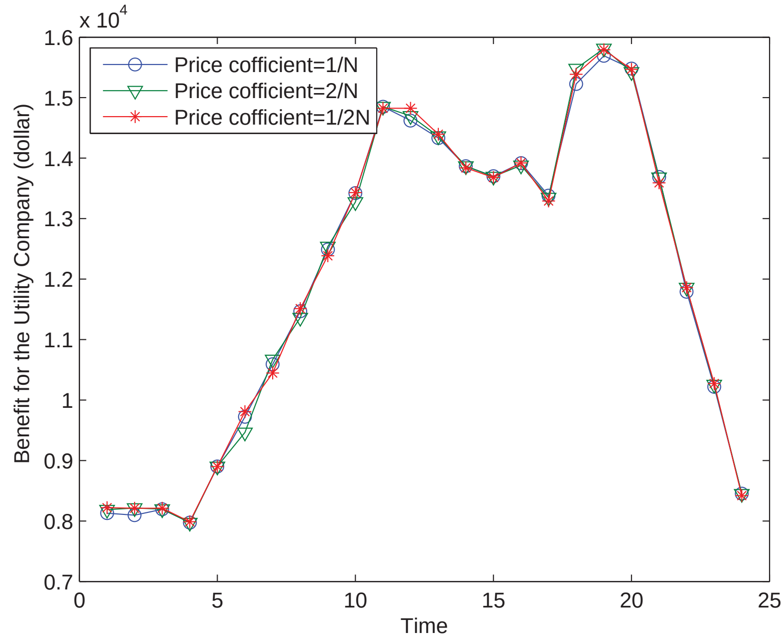

Figure 4.16: The profits of a utility company with different price coefficients

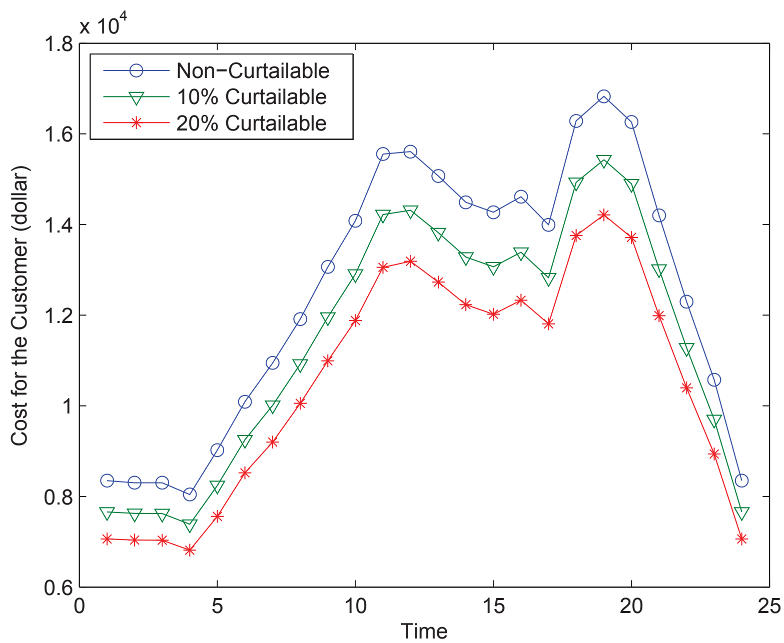

Figure 4.17: The cost of customers with different amount of curtailable-loads

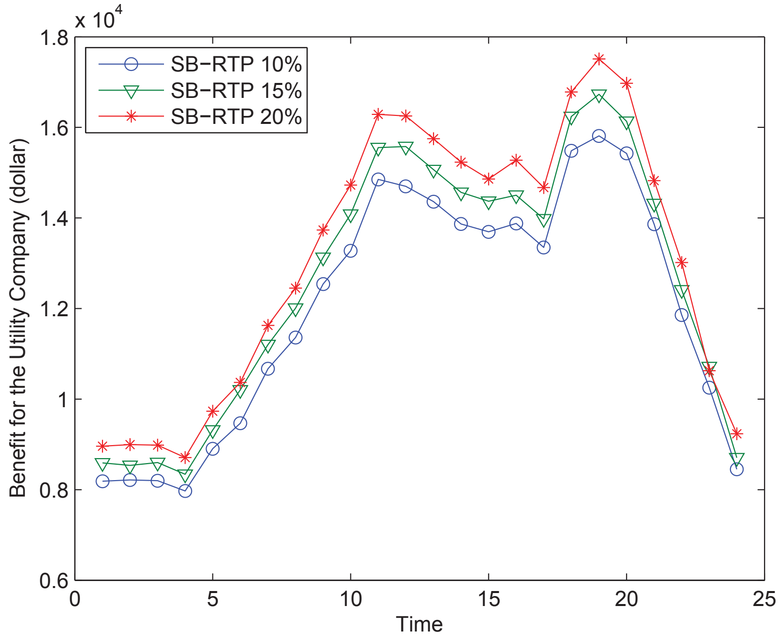

Figure 4.18: The profit of the utility company with different θ

4.3.12 The impacts of Curtailable-Generations on a GP

We assume the curtailable-generations for the generators are set to be 10%, 15% and 20%, respectively [55]. Fig. 4.18 shows the profit of a utility company with different curtailable-generations. The utility company can earn more profit by increasing its curtailable-generations. During the peak period (e.g., 18:00 to 20:00), the utility company earns more than the one from the low hours (e.g., 23:00 to 24:00). With a greater curtailable-generation, the utility company can earn more profit.

4.3.13 The Impacts of Discount Factors on a CP

In this section, we investigate the punishment effort to the customers by applying different DFs. The DFs of customers are set to be 0.9 and 0.6, respectively. The linear coefficients of dissatisfaction function are set to be 1 and 5, respectively [43]. From Fig. 4.19, we see that the punishment is higher when κ and DF is higher. Generally, a higher DF implies the future cost is more valuable in the current stage [25]. Therefore, the customers are more willing to cooperate with the utility company to reduce their cost.

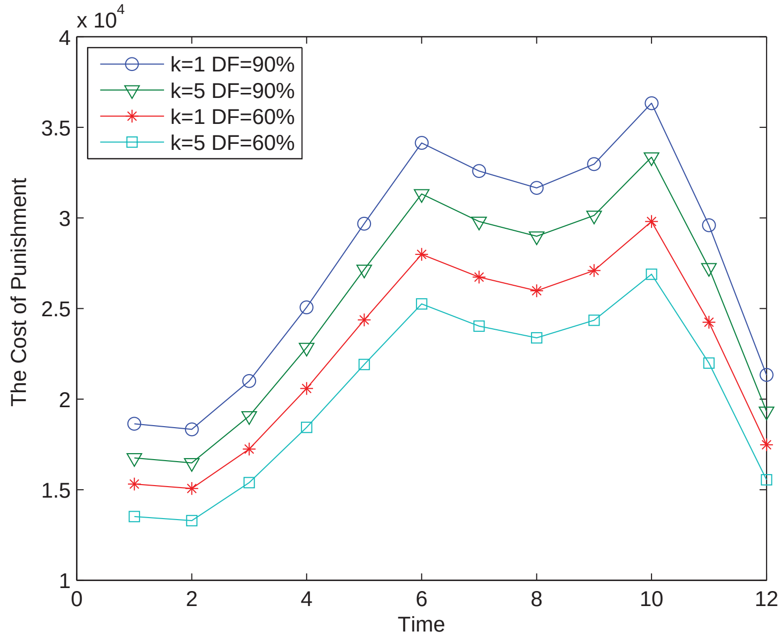

Figure 4.19: The punishment of customers with different discount factors

4.4 Summary of the Numerical Results

To demonstrate the effectiveness of the proposed two-stage game model in solving the CP and GP, we simulate our model with a typical smart grid configuration by using MATLAB. From the numerical results in the previous sections, we see that the proposed two-stage game model improves the performance of DRM significantly.

To evaluate the performance of the two-stage game model to solve a GP, a smart gird with one utility company and five power generators is demonstrated in the simulations, where the real-time electricity price, power generators' cost coefficients, and transmission loss ratios are from the Department-of-Energy's annual report, and Oasisui online system [1], [2]. The profit of the utility company increases by 10% compare to the one from the conventional GP method (e.g., EDP). Mathematical analysis shows that the proposed Stackelberg game can always increase the profit for the leading player (e.g., the utility company), while the follower's profit may be reduced (e.g., the power generators). The impact on the stability of the smart grid has also been demonstrated.

The simulation results show that the profit of the utility company is increased while the stability of the smart gird has no major changes.

To evaluate the performance of the two-stage game model to solve a CP, a smart grid with one hundred customers is demonstrated in the simulations, by which the customers' power demand and other parameters are from the OASIS system [2], [53], [43], and [23]. Compared with the traditional CP method (e.g., gaming optimization), the cost of the customers is reduced by 8% by applying our method to a CP in the test scenarios. The mathematical analysis also proves that the proposed repeated game can reduce the total cost for the customers.

The impacts of the power generation and consumption constraints, power transmission loss ratios, customers' dissatisfaction and punishment efforts on the performance of the two-stage game model are presented and studied. From the simulation results, we learn that: 1) the performance of the two-stage game is better with more flexible constraints; 2) the utility company can earn more profit in the Stackelberg game when the power transmission loss ratio is higher; and 3) the customers are more willing to cooperate with the utility company in a repeated game with the TFT punishing strategy.

In summary, the numerical results show that the proposed two-stage game improves the performance of the DRM, and maintains the stability of the smart grid.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

In the proposed two-stage game, we first develop a Stackelberg game model to solve the GP in the first stage, by which the utility company utilizes its first-mover's privilege to earn more profit. Secondly, we develop a repeated game model to obtain the Pareto-efficient consumption for the customers in the second stage. The customers are more willing to cooperate with the utility company to reduce their long-term cost. A TFT punishment strategy is applied to enhance the effectiveness of the punishment strategy. Thirdly, we combine the GP and CP with the power balance constraint. The profit is increased while the cost is reduced. The excessive cost caused by the imbalance power is eliminated. We evaluate the performance of the proposed two-stage game in several typical smart gird scenarios. Compared with the existing solutions, the numerical results have shown that by applying the proposed two-stage game model to solve the GP and CP, the utility company increases its profit while the cost for the customers are reduced and the stability of the smart grid can be maintained.

5.1 Conclusions and Remarks

In the first stage, a Stackelberg game model is applied to solve the GP. The first-mover's privilege has been introduced to the utility company. The GP for the utility company and generators has been discussed and analyzed. A genetic algorithm is applied to obtain the optimal profit for the utility company. Different from the conventional methods, the utility company can earn more profit by utilizing its first-mover's privilege in the proposed Stackelberg game. Meanwhile, the imbalanced power is eliminated between the power generation and consumption, by which the cost is reduced greatly. The performance for the proposed Stackelberg game model is evaluated. A smart grid with five power generators and one utility company is demonstrated in the simulation. The impacts of power loss ratios, power generator constraints, and cost coefficients on the GP are presented and studied in the simulation.

In the second stage, a repeated game model is applied to solve the CP. The historical information for the customers is stored and utilized by the utility company. With the historical information, the utility company can apply a Pareto-efficient consumption to the customers. The long-term benefit of the DRM is increased. A genetic algorithm is applied to find the consumption. We evaluate the performance of the proposed game by comparing the cost for the customer with the one from the conventional methods for game optimization. One utility company and one hundred customers are used to demonstrated in the repeated game. It is shown that the cost is reduced about 6% in the two-stage game group as compared to the game optimization method. Different from the traditional game optimization methods, the customers are more concerned with the long-term benefit rather than the short-term ones in the repeated game. Meanwhile, the punishment strength is enhanced by applying the TFT pricing strategy to the customers. The impacts of the coefficients of the dissatisfaction function, the sensitive types of the customers, and the discount factors on the CP are presented and studied.

5.2 Future Work

We assume that the customers are rational in the proposed two-stage game model. Reducing the cost for the customer is the major objective for the CP. However, in practice, there are many reasons for the customers not to cooperate with the utility company. Reducing the cost is not the only objective for the customers in a CP. The various customers raise difficulties for the utility company to predicate their consumption. An incomplete-information game model may be suitable to model the customer's different power consumption.

In the proposed two-stage game, we prove that the optimization problems are convex problems with equality and inequality constraints. The smart grid's configuration in our work is fixed. However, the components (e.g., power generators and customers) are removable in a smart grid. Adding or removing a component to or from the smart grid changes the formulation for the optimization problem accordingly. So that the GP and CP may not be convex. In such a case, the stop criterion for the proposed genetic algorithm needs to be revised. In the future work, a new genetic algorithm is needed to solve the GP and CP with portable components.

In our work, there is only one leading player (e.g., the utility company) in the Stackelberg game model for solving the GP. However, there may exist two or three utility companies in a smart grid.

The Stackelberg game, therefore, has more leading players accordingly. The Bertrand competition and Cournot competition model may be applied to solve the multi-leading-multi-following-players Stackelberg game.

The wind turbos and solar generators have been largely deployed recently. However, it is still a big problem to merge the renewable energy into the smart grid efficiently. For example, in the proposed two-stage game, we assume the power is always available. But this may not be the case when there exists a renewable energy source in the smart grid. The wind turbo and solar generator's generation largely depends on the weather condition. In the future work, the unreliable energy source should be considered in the GP.

In summary, we propose a two-stage game model to find the optimal solution for the GP and CP. However, there may be many issues to be further studied in the future.

APPENDIX A

LIST OF PUBLICATION DURING PHD STUDY

[1] Huipu Fan and Ming Yu. A New Two-Stage Game Framework for Power Demand/Response Management in Smart grids. (submitted to the Journal of Electric Power Systems Research, manuscript NO.: EPSR-D-18-01199)

[2] Huipu Fan and Ming Yu. A New Two-Stage Game Framework for Power Demand/Response Management in Smart grids. 2017 IEEE 14th International Conference on Networking, Sensing and Control, Calabria, Southern Italy, May 16-18, 2017.

[3] Huipu Fan, Yizhou Dong, Leonerd Tung and Ming Yu. Security Threats against the Communication Networks for Traffic Control Systems. 2013 IEEE International Conference on Systems, Man, and Cybernetics, Manchester, United Kingdom, October 13-16, 2013.

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BIOGRAPHICAL SKETCH

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