Fall 11-7-2019

Demand Response Management in Smart Grid Networks: a Two-Stage Game-Theoretic Learning-Based Approach

Pavlos Athanasios Apostolopoulos

Pavlos Athanasios Apostolopoulos

Candidate

Electrical and Computer Engineering

Department

This dissertation is approved, and it is acceptable in quality and form for publication: *Approved by the Thesis Committee:*

Dr. Eirini Eleni Tsiropoulou, Chair

Dr. Marios Pattichis, Member

Dr. Jim Plusquellic, Member

Demand Response Management in Smart Grid Networks a Two-Stage Game-Theoretic Learning-Based Approach

by

Pavlos Athanasios Apostolopoulos

M.S., National Technical University of Athens, 2017

THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

Computer Engineering

The University of New Mexico

Albuquerque, New Mexico

December, 2019

Dedication

To my parents, Theodoros and Eirini, and my brothers for their daily unstopping support, love and encourage that they provide me with.

Acknowledgments

I would like to thank my Ph.D. advisor, Dr. Eirini Eleni Tsiropoulou, who entrusted to me the commission of a really interesting and demanding scientific project, expanding my research interests and providing me the opportunity to be a part of hers research work. I also want to acknowledge Dr. Pattichis and Dr. Plusquellic for being apart of my thesis committee.

I would like also to thank all my team at PROTON lab for their help, encourage, and support. I want to say thank you to each one of you guys and wish you the best luck in your life.

Finally, I would like to express my gratitude to my family, who in this creative period, as in all my life so far, has always been by my side in the good and the difficult times.

Demand Response Management in Smart Grid Networks a Two-Stage Game-Theoretic Learning-Based Approach

by

Pavlos Athanasios Apostolopoulos

M.S., National Technical University of Athens, 2017

M.S., Computer Engineering, University of New Mexico, 2019

Abstract

In this diploma thesis, the combined problem of power company selection and Demand Response Management in a Smart Grid Network consisting of multiple power companies and multiple customers is studied via adopting a distributed learning and game-theoretic technique. Each power company is characterized by its reputation and competitiveness. The customers who act as learning automata select the most appropriate power company to be served, in terms of price and electricity needs' fulfillment, via a distributed learning based mechanism. Given customers' power company selection, the Demand Response Management problem is formulated as a two-stage game theoretic optimization framework, where at the first stage the optimal customers' electricity consumption is determined and at the second stage the optimal power companies' pricing is calculated. The output of the Demand Response

Management problem feeds the learning system in order to build knowledge and conclude to the optimal power company selection. A two-stage Power Company learning selection and Demand Response Management (PC-DRM) iterative algorithm is proposed in order to realize the distributed learning power company selection and the two-stage distributed Demand Response Management framework. The performance of the proposed approach is evaluated via modeling and simulation and its superiority against other state of the art approaches is illustrated.

This work has been published in:

P.A. Apostolopoulos, E.E. Tsiropoulou and S. Papavassiliou: Demand Response Management in Smart Grid Networks: A Two-Stage Game-Theoretic Learning-based Approach in Mobile Networks and Applications, Springer, 2018.

Contents

List of Figures

List of Tables

Glossary

$\mathbb{J}$	Set of Power Companies in the Smart Grid Network.
$\mathbb{I}$	Set of Customers in the Smart Grid Network.
$\mathbb{T}$	Set of timeslots.
A_i	Customer's i set of appliances.
$A_{s,i}$	Customer's i set of appliances with shiftable electricity consumption.
$A_{ns,i}$	Customer's i set of appliances with non-shiftable electricity. consumption.
$d_i^{(t)}$	Customer's i electricity needs for timeslot t.
$e_{i,j}^{(t)}$	Customer's i electricity consumption from power company j.
$X_{a,i}^{(t)}$	Customer's i appliances' electricity needs for timeslot t.
$X_{s,i}^{(t)}$	Customer's i total electricity needs for shiftable consumption.
$X_{ns,i}^{(t)}$	Customer's i total electricity needs for non-shiftable consumption.
$X_{s,i,j}^{(t)}$	Customer's i total shiftable electricity consumption from power company j for timeslot t.

Glossary

$X_{ns,i,j}^{(t)}$	Customer's i total non-shiftable electricity consumption from power company j for timeslot t.
$E_{-i}^{(t)}$	Total electricity consumption of all customers for timeslot t excluding customer i.
$E_{-i}^{(t)}$	Total electricity consumption for timeslot t.
$r_i^{(t)}$	Customer's i relative consumption.
$s_i(r_i^{(t)})$	Customer's i satisfaction function.
$\mathbf{e^{(t)}}$	Vector of all customers electricity consumption for timeslot t.
$\mathbf{e_{-i}^{(t)}}$	Vector of all customers electricity consumption for timeslot t excluding customer i.
$\gamma_i^{(t)}$	Customer's i parameter that indicates its wiliness to spend money
k	Real parameter in customers' satisfaction function.
λ	Real parameter in customers' satisfaction function.
$p_j^{(t)}$	Power company's j for timeslot t.
$\mathbf{p^{(t)}}$	Vector of all power companies prices.
$FPR_i(r_i^{(t)})$	Fair pricing policy for customer i.
$U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}, \mathbf{p^{(t)}})$	Customer's i utility function
$g_j^{(t)}$	Power company's j generated electricity for timeslot t.
$c_j^{(t)}$	Power company's j generation cost per electricity unit.
E_{P_j}	Power company's j peak generated electricity consumption over all timeslots.

Glossary

E_{avg_j}	Power company's j average generated electricity over all timeslots.
PAR_j	Power company's j peak-to-average ratio.
$f_j^{(t)}$	Power company's j announced discount factor.
$Comp_j$	Power company's j competitiveness factor for timeslot t.
RC_j	Power company's j reputation score.
$R_j^{(t)}$	Power company's j revenue for timeslot t.
$C_j^{(t)}$	Power company's j revenue for timeslot t.
$\mathbf{a_i(t)}$	Customer's i action vector for timeslots t.
$\beta(t)$	Tuple of the vectors of all customers' electricity consumption and power companies' prices for timeslot t.
$r_j(t)$	Power company's j reward probability for timeslot t.
$\mathbf{Pr_i(t)}$	Customer's i action probability vector for timeslot t.
b	Learning step parameter.
$e_{i,j}^{(t)*}$	Customer's i optimal electricity consumption for timeslot t.
$p_j^{(t)*}$	Power company's j optimal price for timeslot t.
$\mathbb{G}$	Non-cooperative consumption response game.
$\mathbf{e^{(t)*}}$	Nash Equilibrium consumption vector.
$BR_i(\mathbf{e_{-i}^{(t)}})$	Customer's i best consumption response.

Chapter 1

Introduction

1.1 Smart Grid Networks and Related Work

It is a fact that nowadays there is a revolution in the energy distribution networks. The growing number of users and their demands, as well as the ever-increasing competitive environment in which electricity providers are called upon to coexist, testify that new smart distribution networks need to be studied and developed. The existing network is therefore under great pressure from the various challenges and needs arising from the environment, consumers, market and infrastructure issues. These challenges and needs are more important and urgent than ever, and have led the network to expand and enhance its functions to smarter features with the help of fast-growing technologies. The shift in the development of transmission networks to be smarter has been briefly defined as "Smart Network". Some of the key goals of these new smart energy distribution networks are to optimally serve the needs of consumers as well as the healthy profitability of electricity companies [1].

The term "Smart Network" has been in use since the end of 2003 and the first appearance of the term dates back much earlier. There are several definitions of

the "Smart Network" that focus on either its operation or its technology. The common point of all, is the application of digital processing and communications to the electricity grid, with data flow and management being done by a centralized system called "Smart Grid" [2].

The idea of a smart grid is an electricity grid that can intelligently integrate the actions of all users connected to it, generators or consumers, in order to provide efficient, economical and secure electricity supply. A smart network, uses innovative products and services, combined with intelligent monitoring of the network status [3].

The Smart Network connects supply and demand by enabling both producers and consumers to set their operating needs more flexible and sophisticated. For example, consumers are only able to consume at high prices for extremely important reasons and to shape their consumption according to the information they have about the present consumption price. On the other hand, producers with high flexibility can adjust their sales price to maximize their profits, while at the same time depending on their electricity generation costs, they can offer consumers discount periods, thereby expanding their advertising influence and gaining more users.

Coupled with the smart grid features offered, the liberalization of the electricity market that began last decade, or even earlier, especially in the United States of America, has led to the increasing establishment of smart grids. Consumers now have the option of choosing the company from which they purchase electricity. In Massachusetts, the electricity market was liberalized in 1997 [4], in Maryland in 1999 and in Texas in 2002 [5]. The liberalization of the electricity market forces to create a more effective, flexible and reliable electricity system.

1.2 Utility Theory and Related Work

The utility functions have been widely used in recent literature to model various resource allocation problems and to reflect the consumers' satisfaction. Single variable resource allocation problems have been studied using game theory, where utility maximizers players coexist and compete [6–13], as well as multi variable resource allocation problems requiring a different mathematical approach [14–19]. In addition, utility functions have been used to model complex and multilevel network structures, as in the case of smart networks as discussed in the following chapters [20–25]. Moreover, the resources of a network to be shared with consumers may differ in their nature and properties, for example, continuous and discrete resources. For this reason, appropriate models have been proposed in the literature, so that the utility functions are related to the characteristics of the network resources and to the satisfaction of the consumers [26, 27]. Utility functions have been used to even model consumer behavior and visualize the psychological parameters that characterize them [28].

Based on the above analysis, it is concluded that utility functions are a way of showing the degree of satisfaction of both consumers and electricity companies. From the consumers' point of view, the degree of satisfaction is related to the perceived quality of service that the consumers receive compared to what is required, while in the case of electricity companies, the utility function represents the satisfaction of the companies with respect to the profit that a company perceives by using a specific electricity pricing policy. The utility functions were first introduced from the study of financial systems, but because of their widespread use and effectiveness, they are now widely used as a robust mathematical tool, and they have been applied in many research fields.

In [29] the implementation of utility functions helps meet challenges in business management and development, system and software security, while in [30] utility

functions are used for risk analysis and for describing the rate of investment in financial models based on multiple stochastic processes.

Completely different use of the utility functions is made in [31], where their effectiveness is used for identification purposes, as from a set of classifiers, a selection of the most appropriate one happens according to the value of their utility functions, so that they can be used for dealing with the difficulties of identifying faces in large volumes of data and in low resolution images.

In addition, one of the most important issues in the world of the electricity market is cyber security and how the national electricity infrastructure can be protected by ensuring the privacy of users. The use of utility functions in relevant remarkable research [32], indicates the importance of the role of utility functions in this area. A similar implementation of utility functions is achieved in [33], in which appropriate utility functions are designed for the purposes of secure use of cloud computing resources.

Finally, it is quite important the use of utility functions for designing robust, functional, and secure systems [34]. Utility functions for these purposes are used in [35], where they are combined with economical expressions to design robust systems for Wireless Personal Area Network (WPAN) devices in accordance with IEEE 802.15.4.

1.3 Motivation

The need to develop new smart energy distribution networks to meet all the growing demands has become an urgent need in modern society. The customers' demands are now directly linked to smart electricity distribution networks, where the use of utility functions and the demand response management with new theoretical models,

demonstrate a vital role.

In such smart grids the characteristics of the Demand Response Management (DRM), Network Economics (NE), and electricity company choice, shape the market [36]. The theory of Network Economics aims to determine the price of electricity, in order a successful penetration on the electricity market to be achieved [37]. The process of selecting electricity companies aims to bridge the gap between the electricity companies and the customers, while at the same time enables consumers to make the best choice in terms of saving money, and the companies to meet the electricity demands of the network [38].

In [39], the problem of managing the demand response is dealt with only the customers' point of view, as the authors study the problem of the load control by applying a distributed energy consumption planning to customers and a dynamic pricing strategy to companies. Real-time power planning is calculated by adopting a Stackelberg game model, where the power company is the leader, setting real-time price and customers planning their devices' electricity consumption. A similar approach is discussed in [40]. The problem of load balancing and peaks avoidance is studied in [41], where an incentive-based algorithm for home load management is proposed, reducing overall energy costs and taking into account the satisfaction of the users. Also, aiming at load balancing, the authors in [42] propose an optimal game pricing strategy for smart grid networks, by optimizing the value per day time period, so that the electricity load of the network remains in an equilibrium state rather than in peak values.

The home demand response management problem is studied in [43], taking into account the underlying power distribution network and the associated constraints. The Demand Response Management problem is formulated as a flow power problem, and a distributed algorithm is proposed to determine the optimal demand planning, while allowing communications between the electricity supplier and the households.

The direct interaction between the electricity company and the customer is studied in [44], where the problem of allocating a certain amount of load adjustment by the electricity company to the customers is examined, with the aim of minimizing the total loss of the consumer.

In [45], the authors study the interaction between an energy provider and multiple customers through a Stackelberg game approach, and propose an algorithm that aims to control the loads of the users' devices. A similar approach is being studied in [46] and [47], involving multiple electricity companies and multiple customers, where the aim of the Stackelberg game is to maximize the revenue of each electricity company and minimize the amount of payment that each customer makes.

1.4 Contributions

In this thesis, we jointly study the combined problem of optimal power company selection by the customers based on a reputation and competitiveness distributed learning framework, and the problem of demand response management based on a game theoretic approach. We assume the existence of an open electricity market, and we formulate it as a Smart Grid Network, which consists of multiple power companies and customers. Each power company is associated with a reputation and competitiveness factor per timeslot, while the customers adopt the stochastic learning automata methodology [48–50] in order to select the power company that they will served from. The learning power company selection algorithm runs once at the beginning of each timeslot. To fully capture the interaction between the power companies and the customers in the Smart Grid Network, the demand response management problem is modeled as a two-stage non-cooperative game. At the first stage, the customers by considering the companies' pricing policies, determine their optimal electricity consumption that maximizes their utility, while at the second stage, given

the optimal customers' consumption, the power companies evaluate their optimal pricing policies that maximize their profit. Moreover, in our work the non-shiftable and shiftable customers' demands are treated with different priority. Following the proposed two-stage non-cooperative game theoretic approach, the customers and the power companies can interact and finally reach the Nash Equilibrium point, if proper strategies are selected on both sides. It is noted also, that the demand response management optimization problem consists of multiple iterations at the beginning of each timeslot, thus it is of different time scale compared to the distributed learning power company selection algorithm.

The following specific contributions and innovations of this paper are described in detail, in order to achieve the aforementioned key objective.

1. A distributed learning framework is proposed towards implementing the customers' power company selection at the beginning of each timeslot. The selection probabilities of each customer are updated by considering power companies' reputation and competitiveness factor. The reputation and competitiveness factor of each power company reflects the provided discount, its achievable peak-to-average ratio, and its penetration to the electricity market.

2. Representative power companies' and customers' profit and utility functions, respectively, are introduced to capture their behavior within the electricity market. Specifically, power companies' profit function reflects the tradeoff between company's revenue and its corresponding electricity generation cost. On the other hand, each customer's utility function reflects the tradeoff between the satisfaction of its electricity demands and its corresponding total cost based on a fair pricing policy by considering the electricity consumption of the rest of the customers in the Smart Grid Network.

3. Following the distributed learning based power company selection process by

the customers, the optimization problem of maximizing customers' utility function and power companies' profit function, is formulated as a two-stage game. The Nash Equilibrium point of the two-stage game is achieved based on the selection of appropriate strategies from the customers and power companies, while a distributed algorithm that obtains the aforementioned equilibrium point, is proposed .

The rest of the thesis is organized as follows. In Section 2.1 the Demand Response Management problem and its related work in the literature are provided, while in Section 2.2 the Smart Grid Network is presented. Specifically, in Sections 2.2.1, and 2.2.2 the characteristics of the customers and power companies are presented. Furthermore, in Section 2.3 the Smart Grid Network is formulated as a learning system and the proposed power company selection process based on the stochastic learning automata methodology, is described. In Chapter 3 the Demand Response Management problem is formulated as a two-stage non-cooperative game among the customers and the power companies, and the customers' optimal consumption response and power companies' optimal pricing policy, are determined. In Chapter 4, the Power Company selection and Demand Response Management (PC-DRM) is presented, while detailed numerical and comparative performance evaluation results of the proposed PC-DRM framework are provided in Chapter 5. Finally, Chapter 6 indicates our future work and concludes the thesis.

Chapter 2

Description of the Demand Response Management Problem - DRM

2.1 Demand Response Management and Related Work

With the increasingly demanding challenges of the growing electricity needs, aging infrastructure and the integration of renewable green energy resources, a new way of addressing these demands will need to be developed by electricity distribution networks. As we have already mentioned, new smart electricity distribution networks face these challenges by managing the concept of demand response. Essentially, the demand response management refers to the implementation of techniques to control energy consumption by consumers, improve energy efficiency and reduce the cost of electricity generation from electricity companies [51–54]. One of the key objectives of demand response management is to reduce the differences between electricity

consumption and average consumption in the network so that there is a balance between demand and supply [55].

Modeling the problem of managing the demand response is very important for achieving the goals of the Smart Grid Network. Specifically, there are several different modelings of this problem, but the common point is the aim of balancing consumers' demand for electricity and determining the best plan for electricity supply and pricing from companies' side, in order to increase and reduce companies' profit and generation cost, respectively.

In [56] the authors study the demand response management problem in a centralized manner, by using a finite-horizon Markov decision process (MDP) and a linear programming technique, in order to maximize companies' profit and determine the energy load in a real-time electricity market. On the other hand, a decentralized approach of the demand response management problem is studied in [57], where the authors formulate the problem of managing the demand response as a non-convex optimization problem, where convex relaxation techniques are applied, and the companies' optimal pricing is determined.

A different formulation of the demand response management problem is followed in [58], where the notion of micro-grids is developed in the electricity market in order to fulfill power demand in specific regions. The authors address the problem of demand response management by constructing a Stackelberg game with a unique equilibrium solution. The notion of micro-grids is also studied in [59], where the authors examine the demand response management problem for multiple energy resources (i.e., Fuel cells, PhotoVoltaic modules), and they propose a two-stage stochastic programming approach to minimize the operational cost in energy management.

In [60], a price prediction model with the use of an Artificial Neural Network is introduced by the authors, while the costumers adopt a Reinforcement Learning

mechanism in order to deal with the uncertainty in the feature prices and make optimal decisions regarding their home appliances. A quite similar method, in terms of the construction of a predictive model is followed in [61], where the customers use the prediction control in order to manage in an autonomous manner their ON/OFF periods and determining their optimal decisions for the demand response management problem. A neural network is also used in [62], where the authors introduce a smart grid model that considers the power consumption and the customers' satisfaction, while a projection neural network is used for minimizing the electricity cost for all the users. Furthermore, the demand response management is studied also in [63], as the costumers utilize renewable energy resources, which are controlled by cloud servers, and the use of current security mechanisms (i.e., RSA, AES, ECC) is studied for security purposes.

An incentive-based demand response management optimization framework is introduced in [64], where the customers efficiently determine their optimal households' energy consumption during peak hours, while in [65] the authors address the peak loads in an electricity market by introducing quality of service metrics for the customers, and a data analytical management scheme. The proposed scheme is based on the analysis of consumers' consumption data gathered from smart homes. On the other hand, in [66] the authors implement a heuristic demand response technique for consumption scheduling of appliances, in order to decrease peak to average ratio of power demand. The authors use stochastic programming, and communication requirements, in order to schedule customers' consumption in real time.

The authors in [67] highlight the importance of the use of auto-configured devices, and based on that they design an adaptable energy management system, in order to determine the customers' demand response. The pareto optimal demand response management based on energy costs and load factor is studied in [68], where the authors introduce a multi-objective optimization problem and its pareto optimality

is determined. The demand response management problem has been studied also in the era of multiple datacenters, where in [69] the authors introduce an approach to dynamically adjust the datacenters' load to balance the unstable solar input into the energy grid.

Moreover, in [70] the authors implement a large-scale optimization approach in a distributed manner, in order to control and support the demand response of residential appliances. This scheme is based on a hierarchical control and a coordination system, that enables the exchange of information between the utility and the management system. A hierarchical based system is also used in [71], where the authors introduce a dynamic pricing response algorithm, that considers both the service providers' profit and customers' costs. The hierarchical decision making is made based on a Reinforcement Learning mechanism, where the Q-learning algorithm is adopted to solve the decision making problem.

In [72] the authors examine and consider models from the market place in order to design demand response management to match power supply and meet customers' demands. The authors in [73] propose distributed algorithms for electricity companies and consumers, in order to maximize the social welfare. [74] presents a new algorithm for finding the optimal time of use of electricity.

In addition, it is equally important to apply game theory for modeling the demand response management problem, as game theory is proved to be quite effective in dealing with complex interactions. The authors in [36] formulated the problem as a non-cooperative N-person game, and a distributed demand response management strategy is proposed in order to achieve the minimum energy cost. Network congestion is also studied in [39] and a load management strategy modeled as a "Smart Network" game is proposed. The authors in [75] studied the planning of home energy consumption through a Stackelberg game, in which the electricity companies are the leaders of the network and the consumers adjust their demands.

The key point of all the above research is that in smart electricity distribution networks, there is only one company that supplies electricity to consumers. However, as we have already pointed out, the liberalization of the electricity market now gives consumers the option to choose between many energy providers [46], [76], [77], which brings new challenges to the interaction between companies and consumers. It is therefore imperative to study the problem of managing the demand response in an environment where many electricity companies coexist. A first survey in this multi-company and multi-consumer environment is presented in [74], but the authors do not take into account the power functions of the electricity companies.

In this work we study the problem of managing the demand response when there are multiple electricity companies and multiple consumers in the Smart Grid Network. To fully analyze the interactions between electricity companies and customers, demand response problem management is modeled as a two-stage game, the consumers' stage and the companies' stage. At the customer level, every customer wants to maximize its utility function, which is directly dependent on the electricity price, which is expressed by appropriate fairness criteria with respect to other consumers in the network. It is worth noting that in the proposed framework, the non-changing demand has been treated with a different priority compared to the changing demand. As far as the electricity companies is concerned, by considering the required electricity consumption of the customers, that was set in the first stage, each company determines the price that it will announce to the consumers in order to maximize its welfare function. After the two-stage theoretical optimization framework, customers they can interact with each other and eventually strike a balance if appropriate strategies are selected from both sides.

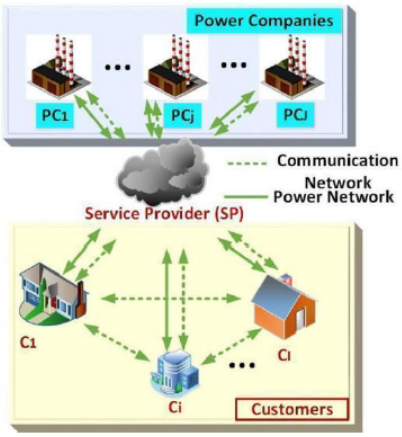

Figure 2.1: Smart Grid Network

2.2 Modeling of the System

Figure 2.1 shows a graphical representation of the considered Smart Grid Network, consisting of multiple users and multiple power companies. There is a two-way communication between companies and consumers that is achieved through a centralized Service Provider (SP) management system. In essence, this centralized management system acts as an intermediary connection between power companies and customers, with which customers and companies are connected through power connection (solid lines), while two-way communication connections (dotted lines), enable the connectivity between companies and customers. The centralized management system allows for the exchange of information, including the power companies' prices and customers' load demand. Each customer is equipped with an Energy Management Controller (EMC), which coordinates the power consumption among customer's smart appliances and is aware of appliances' shiftable and non-shiftable electricity demand and consumption.

A fundamental novelty that differentiates this work from the recent relevant liter-

ature, is that each consumer is informed through the centralized management system about the network's total energy consumption, and as a result each customer's privacy is maintained. The information of the energy consumption, allows us to apply price fairness criteria regarding the consumption price of each customer and so in the Smart Grid Network can coexist harmonious consumers of different economic levels.

We define as $\mathbb{J} = \{1, \cdots, j, \cdots, J\}$ the set of electricity power companies, and with $\mathbb{I} = \{1, \cdots, i, \cdots, I\}$ the set of customers that exist in the Smart Grid Network. The whole operation time is divided in T timeslots, where $\mathbb{T} = \{1, \cdots, t, \cdots, T\}$ denotes the corresponding set. Moreover, $A_{s,i}$, $A_{ns,i}$ denote the set of appliances characterized by shiftable and non-shiftable electricity consumption of customer $i, i \in \mathbb{I}$, respectively, while customer's i overall set of appliances is denoted as $A_i = A_{s,i} \cup A_{ns,i}$.

2.2.1 Utility and Characteristics of Customers

The considered Smart Grid Network consists of multiple customers and power companies. Each customer $i, i \in \mathbb{I}$ is characterized by its demand $d_i^{(t)}[KWh]$ of electricity units per operation timeslot t towards meeting the needs of its appliances $a, a \in A_i$. Based on the availability of the generated electricity by the power companies and its corresponding price, customer i consumes $e_{i,j}^{(t)}[KWh]$ amount of electricity via selecting the power company $j, j \in \mathbb{J}$. At each operation timeslot t, each customer i is served exclusively from one company, while the power company selection of each customer i can vary for different timeslots. In this work, we assume that the power companies are able to cover customers' demands, thus $e_{i,j}^{(t)} \leq d_i^{(t)}$, $\forall i \in \mathbb{I}, \forall j \in \mathbb{J}, \forall t \in \mathbb{T}$.

We denote as $x_{a,i}^{(t)}$ the demand of customer's i appliance $a \in A_i$ for the timeslot t, and $x_{a,i,j}^{(t)}$ the corresponding electricity consumption of customer's i appliance $a, a \in A_i$ from the jth power company. Then, the shiftable and non-shiftable electricity

consumption of customer i in timeslot t from j^{th} power company are determined as $X_{s,i,j}^{(t)} = \sum_{a \in A_{s,i}} x_{a,i,j}^{(t)}$ and $X_{ns,i,j}^{(t)} = \sum_{a \in A_{ns,i}} x_{a,i,j}^{(t)}$. Thus, it is concluded that $e_{i,j}^{(t)} = X_{s,i,j}^{(t)} + X_{ns,i,j}^{(t)} \leq X_{s,i}^{(t)} + X_{ns,i}^{(t)} = d_i^{(t)}$, where $X_{s,i}^{(t)} = \sum_{a \in A_{s,i}} x_{a,i}^{(t)}$ and $X_{ns,i}^{(t)} = \sum_{a \in A_{ns,i}} x_{a,i}^{(t)}$.

At each operation timeslot t, every customer i aims at satisfying its needs for electricity consumption, while giving higher priority to its non-shiftable appliances' electricity needs $X_{ns,i}^{(t)}$. It is noted that in a competitive market, as the one assumed here, though the customer i requests and buys electricity from a power company j, it should also consider the total electricity consumption of the rest of the customers, i.e., $E_{-i}^{(t)} = \sum_{j \in \mathbb{J}} \sum_{i' \in \mathbb{I}, i' \neq i} e_{i',j}^{(t)}$, in the current timeslot t, as the electricity consumption of the rest of the customers in the Smart Grid Network contributes to the configuration of the prices announced by the power companies, as it is presented in the following subsection. This key feature is one of the essentials elements of this work, which differentiate it from similar research work, where each customer's utility function has been formulated considering only its personal electricity consumption. Each customer i is informed about the total electricity consumption $E^{(t)} = \sum_{j \in \mathbb{J}} \sum_{i \in \mathbb{I}} e_{i,j}^{(t)}$ in the Smart Grid Network via the centralized SP and through the communication network. As a result, each customer i is able to deduct its personal consumption $e_{i,j}^{(t)}$, i.e., $E_{-i}^{(t)} = E^{(t)} - e_{i,j}^{(t)}$, and no privacy issues are related to this broadcasted information (i.e., $E^{(t)}$) by the SP, since each customer's consumption $e_{i,j}^{(t)}$ is hidden with the total consumption.

Each customer's i satisfaction function is formulated as an increasing concave function $s_i(r_i^{(t)})$ with respect to the relative customer's consumption, i.e., $r_i^{(t)} = \frac{e_{i,j}^{(t)}}{E_{-i}^{(t)}}$. As Figure 2.2 demonstrates, customer's i satisfaction increases rapidly till its relative non-shiftable consumption, i.e., $\frac{X_{ns,i}^{(t)}}{E_{-i}^{(t)}}$, is satisfied, while after that point its satisfaction increases slowly till it fulfils its relative shiftable electricity needs, i.e., $\frac{X_{s,i}^{(t)}}{E_{-i}^{(t)}}$. Also, for values greater than its overall relative consumption, i.e., $\frac{d_i^{(t)}}{E_{-i}^{(t)}}$, its

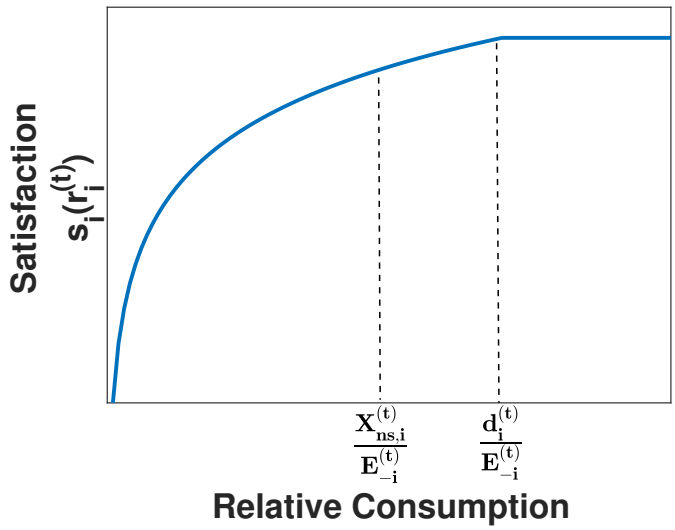

Figure 2.2: Customers' Satisfaction Function

satisfaction is saturated, because there are no other real needs to cover via consuming additional electricity.

In this work, without loss of generality, we adopt a logarithmic customer's satisfaction function with respect to its relative electricity consumption, as:

$$s_i(r_i^{(t)}) = s_i(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) = k \cdot log(1 + \lambda \cdot r_i^{(t)}) \tag{2.1}$$

where $\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}$ denotes the vector of all customers' electricity consumption excluding customer i, and the parameters $k, \lambda \in R^+$ determine the slope of the concave function to reflect its priority to fulfill its relative non-shiftable consumption prerequisities.

Furthermore, another major novelty introduced in this work, is the proposal of a relative fair pricing policy for the customers that is applied by the power companies that exist in the Smart Grid Network. Specifically, the power companies charge each customer i based on its relative electricity consumption, i.e., $r_i^{(t)} = \frac{e_{i,j}^{(t)}}{E_{-i}^{(t)}}$, and not based only on its overall consumption $e_{i,j}^{(t)}$. Based on this pricing policy, the power companies provide the incentive even to the low budget customers to buy affordable

amount of electricity in terms of cost, thus still satisfying, while limiting the high budget customers' greedy behavior who aim to dominate the Smart Grid Network. As a result, the benefits of the proposed fair pricing policy are two-fold:

1. customers are satisfied due to fair charges of electricity consumption

2. the power companies attract more customers, thus increase their profit in a long-term period and improve their penetration in the market.

This fair pricing policy for each customer i based on its relative consumption $r_i^{(t)}$, is formulated as:

$$FPP_i(r_i^{(t)}) = FPP(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}) = \gamma_i^{(t)} \cdot r_i^{(t)} \cdot p_j^{(t)} \tag{2.2}$$

where, $p_j^{(t)}[\frac{\$}{KWh}]$ is the price that is announced by the power company $j, j \in \mathbb{J}$ for the timeslot $t, t \in \mathbb{T}$, and $\gamma_i^{(t)}$ is a time-varying parameter capturing the dynamics of customer's i behavior, i.e., smaller $\gamma_i^{(t)}$ reflects customer's i dynamic behavior to spend money in order to buy more electricity.

Finally, each customer's $i, i \in \mathbb{I}$ utility function is formulated via capturing its satisfaction, i.e., $s_i(r_i^{(t)})$ with respect to its relative electricity consumption, as well as its dissatisfaction due to the associated charges (i.e., pricing), as follows:

$$\begin{aligned} U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}, \mathbf{p^{(t)}}) &= s_i(r_i^{(t)}) - FPP_i(r_i^{(t)}) \\ &= s_i(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}) - FPP_i(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}) \\ &= k \cdot log(1 + \lambda \cdot r_i^{(t)}) - \gamma_i^{(t)} \cdot r_i^{(t)} \cdot p_j^{(t)} \end{aligned} \tag{2.3}$$

where $\mathbf{p^{(t)}} = (p_1^{(t)}, \cdots, p_j^{(t)}, \cdots, p_J^{(t)})$ denotes the vector of the announced prices by the power companies in timeslot $t, t \in \mathbb{T}$.

2.2.2 Welfare and Characteristics of Power Companies

Each power company $j, j \in \mathbb{J}$ generates an amount $g_j^{(t)}[KWh]$ of electricity units per timeslot t, while the generation cost of each electricity unit from the jth power company in timeslot t is $c_j^{(t)}[\frac{\$}{KWh}]$. In this work, we assume that each power company j is able to generate the overall needed amount of electricity, thus $g_j^{(t)} = E_j^{(t)} = \sum_{i \in \mathbb{I}} e_{i,j}^{(t)}$. The peak customers' electricity consumption in the jth power company is $E_{P_j} = \max_{t \in \mathbb{T}} E_j^{(t)} = \max_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} e_{i,j}^{(t)}$, while the corresponding average consumption over T operation timeslots in the jth power company is $E_{avg_j} = \frac{\sum_{t \in \mathbb{T}} E_j^{(t)}}{T} = \frac{\sum_{t \in \mathbb{T}} \sum_{i \in \mathbb{I}} e_{i,j}^{(t)}}{T}$. Moreover, using the peak customers' electricity consumption E_{P_j} and the corresponding average consumption E_{avg_j}, we define the peak-to-average (PAR) ratio in customers' electricity consumption of the jth power company as $PAR_j = \frac{E_{P_j}}{E_{avg_j}}$.

Each power company aiming to achieve a low peak-to-average ratio power consumption, so as to maintain the smooth electricity generation during the day. Also, customers prefer to be served by companies that maintain low peak-to-average rations, as through this way they "feel" more "safe" that they will be satisfied effectively and fulfil their electricity requirements.

A fairly effective way for the power companies to maintain low peak-to-average ratio, is to provide incentives to the customers to shift their consumption from high-peak to off-peak for specific periods of the day. Moreover, the power companies could benefited by the policy of announcing discounts to the customers, regarding their billing prices. Through this way, it is able the electricity needs among the customers to be balanced, and as a result the power companies to maintain low peak-to-average ratio, and at the same time the announcements of discounts to provide incentives to the customers to select the power company, which will result in a long-term improvement of the power company's profit.

Discount strategy is a fairly common technique with which companies manage to win more customers and improve their profit in a long term period. The effectiveness of this technique has already been studied in literature and has been applied in several different fields, as in tourism. The power companies of the Smart Grid Network by studying and analyzing the consumption habits of the customers, are able to determine the most appropriate and effective discounts for their electricity prices.

Each power company is interested to increase its reputation and competitiveness in the electricity market. In a nutshell, each power company's reputation increases as the total price discounts, i.e., $\sum_{t\in\mathbb{T}} f_j^{(t)}$, offered to the customers increases, throughout the day, as well as if the company maintains low peak-to-average ratio. In this work, we formulate the competitiveness of each power company $j, j \in \mathbb{J}$ via its penetration to the electricity market, which is translated to the electricity consumption served by the jth power company over the total electricity consumption in the Smart Grid Network, i.e., $Comp_j = \frac{\sum_{t\in\mathbb{T}} E_j^{(t)}}{E^{(t)}} = \frac{\sum_{t\in\mathbb{T}}\sum_{i\in\mathbb{I}} e_{i,j}^{(t)}}{\sum_{j\in\mathbb{J}}\sum_{t\in\mathbb{T}}\sum_{i\in\mathbb{I}} e_{i,j}^{(t)}}$

Consequently, each power company $j, j \in \mathbb{J}$ is characterized by a reputation and competitiveness score RC_j, which is considered by the customers throughout the power company selection process, and is formulated as follows:

$$RC_j = \sum_{t\in\mathbb{T}} f_j^{(t)} \cdot \frac{1}{PAR_j} \cdot Comp_j \tag{2.4}$$

where, $f_j^{(t)}$ is the discount that is announced by the power company $j, j \in \mathbb{J}$ to the customers during the timeslot $t, t \in \mathbb{T}$.

The profit of each power company is constructed by considering the revenue and the costs of the power company by billing its customers and generating the needed electricity, respectively. Specifically, each power company's $j, j \in \mathbb{J}$ profit function is formulated as follows:

$$P_j^{(t)}(E_j^{(t)}, p_j^{(t)}) = R_j^{(t)}(E_j^{(t)}, p_j^{(t)}) - C_j^{(t)}(E_j^{(t)}) \tag{2.5}$$

where, $R_j^{(t)}$ and $C_j^{(t)}$ express the revenue and the generation cost of the jth power company, respectively. The power company's j revenue $R_j^{(t)}$ per timeslot t depends on the amount of sold electricity to the customers that selected to be served by the specific company, i.e., $E_j^{(t)} = \sum_{i \in \mathbb{I}} e_{i,j}^{(t)}$, the company's price $p_j^{(t)}$ per electricity unit, and the discount $f_j^{(t)}$ that the company announces to the customers on that timeslot. As a result, the power company's j revenue is formulated as:

$$\begin{aligned} R_j^{(t)}(E_j^{(t)}, p_j^{(t)}) &= (1 - f_j^{(t)}) \cdot p_j^{(t)} \cdot \sum_{i \in \mathbb{I}} e_{i,j}^{(t)} \\ &= (1 - f_j^{(t)}) \cdot p_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \sum_{a \in A_i} x_{a,i,j}^{(t)} \end{aligned} \tag{2.6}$$

On the other hand, the power company's j cost for generating the overall amount of electricity that the customers demand, is expressed as:

$$C_j^{(t)}(E_j^{(t)}) = c_j^{(t)} \cdot E_j^{(t)} = c_j^{(t)} \cdot \sum_{i \in \mathbb{I}} e_{i,j}^{(t)} \tag{2.7}$$

where $c_j^{(t)}$ denotes the power company's j electricity production cost per unit of electricity for the timeslot t.

2.3 Modeling of the Smart Grid Network as a Distributed Learning System

Power companies build their reputation and competitiveness for a long time to attract more customers and increase their profits. On the other hand, each company's reputation and competitiveness factor contribute significantly on the customers' choices regarding the power company that they select to be served by. Consequently, the Smart Grid Network can be studied as a learning system, where the customers act as learning automata that interact with the environment to determine which power

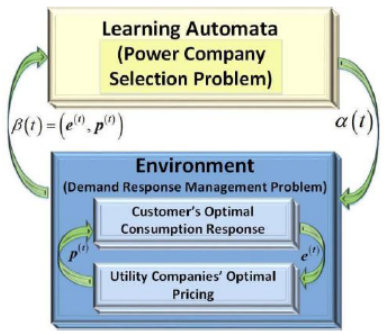

Figure 2.3: Smart Grid Network as a Learning System

company to select to be served from. Figure 2.3 presents the the Smart Grid Network as a learning system and the relationship between the learning automata and the environment. Specifically, each customer/learning automaton at each operation timeslot t has an action vector $\alpha_{\mathbf{i}}(\mathbf{t}) = (\alpha_i^1, \cdots, \alpha_i^j, \cdots, \alpha_i^J)$, where $\sum_{j \in \mathbb{J}} \alpha_i^j = 1$, thus the action vector $\alpha_{\mathbf{i}}(\mathbf{t})$ represents the customer's i power company selection for the timeslot t. Towards making their decision, the learning automata consider the output set $\beta(t) = (\mathbf{e^{(t)}}, \mathbf{p^{(t)}})$, i.e., $\mathbf{e^{(t)}}$ is the vector of all customers' electricity consumption, and $\mathbf{p^{(t)}}$ the pricing vector that contains the power companies' prices, as this is determined by solving the Demand Response Management problem, which is analyzed in Chapter 3. The solution of the Demand Response Management problem refers to customers' and companies' optimal electricity consumption and prices, respectively. Based on the learning automata chosen actions and the corresponding reaction of the environment, the reward probability $r_j(t)$ that is associated with the power company that the customer selected to be served by, is obtained as $r_j(t) = \frac{RC_j}{\sum_{j \in \mathbb{J}} RC_j}$, thus $0 \leq r_j(t) \leq 1$, $\forall j \in \mathbb{J}$. Essentially, the reward probability $r_j(t)$ updates with a higher or a lower probability the customer's selection, regarding the power company j that was selected and with which its reward probability $r_j(t)$ is associated with. The action probability vector of customer i is defined as $\mathbf{Pr_i(t)} = (Pr_{i,1}(t), \cdots, Pr_{i,j}(t), \cdots, Pr_{i,J}(t))$, where $Pr_{i,j}$ represents the

probability of the customer i to select the power company j for the timeslot t. Each customer's i probability vector is updated based on the concept of stochastic learning automata [78], and the update rules are formulated as follows:

$$Pr_{i,j}(t+1) = Pr_{i,j}(t) - b \cdot \frac{RC_j}{\sum_{j \in \mathbb{J}} RC_j} \cdot Pr_{i,j}(t), \text{if } j^{(t+1)} \neq j^{(t)} \tag{2.8}$$

$$Pr_{i,j}(t+1) = Pr_{i,j}(t) + b \cdot \frac{RC_j}{\sum_{j \in \mathbb{J}} RC_j} \cdot (1 - Pr_{i,j}(t)), \text{if } j^{(t+1)} = j^{(t)} \tag{2.9}$$

where $0 < b < 1$ is the learning step parameter that controls the convergence and the complexity of the learning algorithm. Essentially, Eq. 2.8 represents customer's selection probability update rule for the next timeslot for the company that was selected, while Eq. 2.9 represents the update rule that is followed for the rest selection probabilities of the customer, thus for the ones that are associated with the rest power companies. In that way, the customer acting as a learning automaton, increases its probability of selecting the same power company j based on the achievable reward probability $r_j(t)$ of that company, thus the customer explores its environment and converges to the power company that provides a good reward (i.e., reputation score).

It should be noted that initially the overall Smart Grid Network needs no prior knowledge of the reward and action probabilities, and thus the initial power company selection by the users can be simply assumed as $Pr_{i,j}(t) = \frac{1}{J}, \forall j \in \mathbb{J}$. The customers, in a long-term period converge to the most cost-efficient solution of power company selection per operation timeslot t, given also that the overall policies of the power companies (i.e., $c_j^{(t)}, p_j^{(t)}, f_j^{(t)}, \forall j \in \mathbb{J}, \forall t \in \mathbb{T}$) do not change rapidly within a long time period. Finally, it is also highlighted that other learning techniques, such as exponential learning, Q-learning, etc., could be also adopted instead of the learning automata approach that was selected in that work due to the scalable and low-complexity nature.

Chapter 3

Demand Response Management Problem

3.1 Problem Formulation

The Demand Response Management (DRM) porblem is formulated considering the iterations and interactions of both the power companies and the customers. Before the DRM problem, the customers have already selected the power companies that they want to served by, based on their stochastic learning methodology described in Section 2.3. Each power company $j, j \in \mathbb{J}$ aims at maximizing its profit (i.e., Eq. 2.5), by considering the customers' electricity consumption, and it aims to converge to the optimal announced price $p_j^{(t)*}$ per timeslot $t, t \in \mathbb{T}$. On the other hand, each customer's $i, i \in \mathbb{I}$ goal is to maximize its personal utility function (i.e., Eq. 2.3), given the announced electricity prices by the power companies, and determine in a distributed manner its optimal electricity consumption $e_{i,j}^{(t)*}$. The distributed nature in determining both the optimal prices $p_j^{(t)*}, \forall j \in \mathbb{J}$, and each customer's optimal consumption $e_{i,j}^{(t)*}, \forall i \in \mathbb{I}$ is a key component in the formulation and solution of

the DRM problem in order to support the vision of independent and deregulated electricity markets, where no centralized entity is required, as both the customers and the power companies act as distributed decision makers.

Each power company's $j, j \in \mathbb{J}$, and each customer's $i, i \in \mathbb{I}$ DRM optimization problem, is formulated as follows:

$$p_j^{(t)*} = \underset{p_j^{(t)}}{\operatorname{argmax}} \begin{bmatrix} P_j^{(t)}(E_j^{(t)}, p_j^{(t)}) = R_j^{(t)}(E_j^{(t)}, p_j^{(t)}) - C_j^{(t)}(E_j^{(t)}) \\ = (1 - f_j^{(t)}) \cdot p_j^{(t)} \cdot \sum_{i \in \mathbb{I}} e_{i,j}^{(t)} - c_j^{(t)} \cdot \sum_{i \in \mathbb{I}} e_{i,j}^{(t)} \end{bmatrix} \tag{3.1}$$

$$e_{i,j}^{(t)*} = \underset{e_{i,j}^{(t)}}{\operatorname{argmax}} \begin{bmatrix} U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}, \mathbf{p}^{(\mathbf{t})}) = s_i(r_i^{(t)}) - FPP_i(r_i^{(t)}) \\ = s_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) - FPP_i(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) \\ = k \cdot log(1 + \lambda r_i^{(t)}) - \gamma_i^{(t)} \cdot r_i^{(t)} \cdot p_j^{(t)} \end{bmatrix} \tag{3.2}$$

As Eq. 3.1 and Eq. 3.2 depict, the decisions about the optimal prices by the power companies and the optimal electricity consumption by the customers are interconnected problems, as the decision of the one (i.e., power companies) should act as an input to the other (i.e., customers) and vice versa. As a result, the DRM problem is studied as a two-stage game, where at the first stage, the optimal electricity consumption of the customers is determined via formulating the maximization problem of their utilities (i.e., Eq. 3.2) as a non-cooperative game among the customers. At the second stage, each power company, given the optimal electricity consumption of the customers, determines its optimal pricing policy that maximizes its profit (i.e., Eq. 3.1). The interaction and feedback among power companies and customers endure until both conclude to their optimal decisions.

3.2 Customers' Optimal Consumption Response

In the first stage of the DRM problem, each customer $i, i \in \mathbb{I}$ determines its optimal electricity consumption for timeslot $t, t \in \mathbb{T}$, by considering its power company selection and the announced price by the corresponding company. We define as $\mathbb{G} = \left[\mathbb{I}, \{S_i^{(t)}\}, \{U_i^{(t)}\}\right]$ the non-cooperative consumption response game among the customers, which consists of the infinite set of customers $\mathbb{I} = \{1, \cdots, i, \cdot, I\}$, the strategy space $S_i^{(t)} = [0, d_i^{(t)}]$ of each customer $i, \forall i \in \mathbb{I}$ and its utility function $U_i^{(t)}$. The non-cooperative consumption response game $\mathbb{G}$ can be expressed as follows:

$$\begin{aligned} \max_{e_{i,j}^{(t)} \in S_i} \quad & \begin{bmatrix} U_i^{(t)} = s_i(r_i^{(t)}) - FPP_i(r_i^{(t)}) \\ = k \cdot log(1 + \lambda r_i^{(t)}) - \gamma_i^{(t)} \cdot r_i^{(t)} \cdot p_j^{(t)} \end{bmatrix} \\ \text{s.t.} \quad & 0 \leq e_{i,j}^{(t)} \leq d_i^{(t)} \end{aligned} \tag{3.3}$$

The commonly used concept in solving game-theoretic problems is the Nash Equilibrium (NE) at which no customer can improve its utility by unilaterally changing its electricity consumption.

Definition 1 *An electricity consumption vector* $\mathbf{e^{(t)*}} = (e^{(t)*}_{1,ch_1^{(t)}}, \cdots, e^{(t)*}_{I,ch_I^{(t)}})$, *where* $ch_i^{(t)}$ *is the customer's* i *selected power company, is the NE point for the game* $\mathbb{G}$, *if and only if* $U_i^{(t)}(e_{i,j}^{(t)*}, e_{-i}^{(t)*}) \geq U_i^{(t)}(e_{i,j}^{(t)}, e_{-i}^{(t)*})$, $\forall e_{i,j}^{(t)} \leq d_i^{(t)}$.

Towards proving the existence and uniqueness of the NE of the non-cooperative game $\mathbb{G}$, it suffices to show that for every timeslot $t, t \in \mathbb{T}$, each customer's i strategy space $S_i^{(t)}$ is a non-empty, convex and compact subset of the Euclidean space R^I, and the utility function $U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e_{-i}^{(t)}}, p_j^{(t)})$ is continuous in $e_{i,j}^{(t)}$ and quasi-concave in $S_i^{(t)}$ as explained in [14].

Theorem 1 *In the non-cooperative consumption response game* $\mathbb{G}$, *customer's* i *best response strategy to a given electricity consumption vector* $\mathbf{e_{-i}^{(t)}}$ *is* $BR_i(\mathbf{e_{-i}^{(t)}}) = e_{i,j}^{(t)*}$,

as provided in Eq. 3.4, where $s_i^{'-1}$ *is the inverse function of the first derivative of the customer's* i *satisfaction function* s_i*, and* $\tau = \lim_{r_i^{(t)} \to \infty} s_i^{'-1}$

$$BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) = e_{i,j}^{(t)*} = \begin{cases} d_i^{(t)} & \text{if } 0 \leq \gamma_i^{(t)} \cdot p_j^{(t)} \leq \tau \\ min\{d_i^{(t)}, E_{-i}^{(t)} \cdot s_i^{'-1}(0)\} & \text{if } \tau < \gamma_i^{(t)} \cdot p_j^{(t)} \leq s_i^{'-1}(0) \\ 0 & \text{if } \gamma_i^{(t)} \cdot p_j^{(t)} > s_i^{'-1}(0) \end{cases} \quad (3.4)$$

Proof See Appendix A

Based on Theorem 1 that determines each customer's $i, i \in \mathbb{I}$ best responses strategy $BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) = e_{i,j}^{(t)}$ and considering the quasi-concavity property with respect to $r_i^{(t)}$ of customer's utility function $U_i^{(t)}$, the existence and uniqueness of the NE of the non-cooperative game $\mathbb{G}$ is derived as follows.

Theorem 2 *The Nash Equilibrium of the non-cooperative consumption response game* $\mathbb{G}$ *exists and is unique.*

Proof: The NE is by definition the fixed point in the best response function set that satisfies $e_{i,j}^{(t)*} = BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})})$. In the two cases, where $0 \leq \gamma_i^{(t)} \cdot p_j^{(t)} \leq \tau$ and $\gamma_i^{(t)} \cdot p_j^{(t)} > s_i^{'}(0)$, the fixed point of the best response function set is unique, i.e., maximum electricity consumption, i.e., $e_{i,j}^{(t)*} = d_i^{(t)}$ or no consumption, i.e., $e_{i,j}^{(t)*} = 0$, respectively. In the third case, where $\tau < \gamma_i^{(t)} \cdot p_j^{(t)} \leq s_i^{'}(0)$, the uniqueness of the NE point can be proved via adopting the concept of standard function [14], [79]. A function $f(x)$ is characterized as standard if it satisfies the following properties [9]:

1. Positivity: $f(x) > 0$
2. Monotonicity: if $x \geq x'$, then $f(x) > f(x')$
3. Scalability: $\forall a > 1$, $a \cdot f(x) \geq f(a \cdot x)$

If a fixed point exists in a standard function, then it is unique [14], [79]. As it is shown in [9], $e_{i,j}^{(t)*} = BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})})$ for $\tau < \gamma_i^{(t)} p_j^{(t)} \leq s_i^{'}(0)$ (i.e., Eq. 3.4) can easily be shown that it is a standard function. Thus, in the case that $\tau < \gamma_i^{(t)} \cdot p_j^{(t)} \leq s_i^{'}(0)$ the NE exists and is unique.

Finally, as we have already mentioned, the customers' optimal electricity consumption, as this is determined in Eq. 3.4 will act as input to the optimal pricing problem, where each power company determines the optimal price.

3.3 Companies' Optimal Pricing Response

In the first stage of the DRM optimization problem, the optimal electricity of each customer was determined, while in the second stage each power company aims to maximize its profit (i.e., Eq. 2.5) in a distributed manner, via calculating the optimal price to be announced. Combining Eq. 3.1, 3.4, the optimal pricing problem based on customers' optimal consumption response can written as follows [18].

$$p_j^{(t)*} = \underset{p_j^{(t)}}{\operatorname{argmax}} \begin{bmatrix} P_j^{(t)} = R_j^{(t)}(E_j^{(t)}, p_j^{(t)}) - C_j^{(t)}(E_j^{(t)}) \\ = (1 - f_j^{(t)}) \cdot p_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \left[E_{-i}^{(t)} \cdot (\frac{k}{\gamma_i^{(t)} p_j^{(t)}} - \frac{1}{\lambda}) \right] \\ - c_j^{(t)} \sum_{i \in \mathbb{I}} \left[E_{-i}^{(t)} (\frac{k}{\gamma_i^{(t)} p_j^{(t)}} - \frac{1}{\lambda}) \right] \end{bmatrix} \tag{3.5}$$

The optimal pricing problem in response to customers' consumption, as it is rewritten in Eq. 3.5, is a function only of power company's price.

Theorem 3 *Each power company's $j, j \in \mathbb{J}$ optimal price that maximizes its profit,*

given customers' optimal response consumption, is given as:

$$p_j^{(t)*} = \left[\frac{k \cdot \lambda \cdot c_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \frac{E_{-i}^{(t)}}{\gamma_i(t)}}{(1 - f_j^{(t)}) \cdot \sum_{i \in \mathbb{I}} E_{-i}^{(t)}} \right]^{\frac{1}{2}} \tag{3.6}$$

Proof See Appendix B

Chapter 4

Power Company Selection & Demand Response Management Algorithm

4.1 Distributed Learning Algorithm PC-DRM

A two-stage Power Company learning selection and Demand Response Management (PC-DRM) algorithm is proposed in this section that realizes the overall aforementioned framework. In the first part of the algorithm, the stochastic learning automata methodology, is included, where each customer $i, i \in \mathbb{I}$ based on its selection probability vector $\mathbf{Pr_i^{(t)}}$, determines the power company that will be served by. It is noted that the power company selection part runs once at the beginning of each timeslot $t, t \in \mathbb{T}$. After the power company selection of the customers, the second part of the PC-DRM algorithm, implements the DRM optimization problem (i.e., Chapter 3), where each customer's optimal consumption response and each power company's optimal price, are determined. The DRM part of the PC-DRM algorithm, runs at

every timeslot for several iterations until the two-stage game theoretic problem to converge on its NE point, where neither of the customer has the incentive to change its electricity consumption, and as a result the power companies hold their optimal announced prices.

4.1.1 PC-DRM Algorithm

In this section, each step of the PC-DRM algorithm is presented and analyzed, and its pseudo code is presented as well. The steps of the PC-DRM algorithm can be summarized as follows:

1. **Initialization Phase**: At the beginning of the first timeslot, (i.e., $t = 0$), each customer $i, i \in \mathbb{I}$ initializes its probability vector by following a normal distribution, thus $Pr_{i,j}^{(0)} = \frac{1}{J}$, $\forall i \in \mathbb{J}, \forall j \in \mathbb{J}$. Consequently, each customer chooses a power company according to its initial probability vector $\mathbf{Pr_i^{(0)}}$.

2. **Power Company Selection - PC**: At every other timeslot $t, t \in \mathbb{T}$, such that $t > 0$ each customer $i, i \in \mathbb{I}$ chooses a power company to be served from, according to its probability vector $\mathbf{Pr_i^{(t)}}$. If $\forall i \in \mathbb{I}$, $\exists j, j \in \mathbb{J}$ such that $Pr_{i,j}^{(t)} \rightarrow 1$, then stop. Otherwise, $ite = ite + 1$, where ite denotes the iteration of the DRM part of the algorithm.

3. **Customers' Optimal Consumption Response**: Given that all the customers have selected their company that they will be served from, the power companies announce their prices and the total electricity consumption (i.e., $E^{(t)}$) in the Smart Grid Network. Each customer $i, i \in \mathbb{I}$ determines its optimal consumption response based on Eq. 3.4, as $e_{i,j}^{(t)}|_{ite}$

4. **Companies' Optimal Pricing Response**: Given customers' optimal electricity consumption. each power company determines its optimal prices based

on Eq. 3.5, as $p_j^{(t)*}|_{ite}$

5. **Checking for Convergence**: if $|e_{i,j}^{(t)*}|_{ite+1} - e_{i,j}^{(t)*}|_{ite}| \rightarrow 0$ and $|p_{i,j}^{(t)*}|_{ite} - p_{i,j}^{(t)*}|_{ite+1}| \rightarrow 0$, $\forall i \in \mathbb{I}, \forall j \in \mathbb{J}$, then the two-stage non-cooperative game has converged to its NE point. Otherwise go to Step 3.

6. **Stochastic Learning Automata**: Each power company $j, j \in \mathbb{J}$ determines its reward probability $r_j^{(t)}$, and it is broadcasted to the customers. Each customer $i, i \in \mathbb{I}$ updates its probability vector $\mathbf{Pr_i^t}$ based on Eq. 2.8 and 2.9. Return to Step 2.

The PC-DRM learning distributed algorithm can be summarized as follows:

Algorithm 1 PC-DRM Algorithm

Input/Initialization: $\mathbb{I}, \mathbb{J}, d_i^{(t)}, \gamma_i^{(t)}, c_j^{(t)}, Pr_{i,j}^{(0)} = \frac{1}{J} \forall i \in \mathbb{I}, \forall j \in \mathbb{J}, \forall t \in \mathbb{T}$
Output: NE point $\mathbf{e^{(t)*}} = (e_1^{(t)*}, \cdots, e_I^{(t)*}), \mathbf{p^{(t)*}} = (p_1^{(t)*}, \cdots, p_J^{(t)*})\ \forall t \in \mathbb{T}$
for each timeslot $t, t \in \mathbb{T}$ **do**
  $Ite = 0$, $Convergence = 0$
  Each customer $i, i \in \mathbb{I}$ selects a power company based on $\mathbf{Pr_i^{(t)}}$
  while not $Convergence$ **do**
    $Ite = Ite + 1$
    for $i = 1$ to I **do**
      Customer i determines its $e_{i,j}^{(t)*}$ based on Eq. 3.4
    end for
    for $j = 1$ to J **do**
      Power Company j determines its optimal price $p_j^{(t)*}$ based on Eq. 3.5
    end for
    if $(Ite > 0$ && $|e_i^{(t)*}|_{ite} - e^{(t)*}|_{ite-1}| \rightarrow 0$ && $|p_j^{(t)*}|_{ite} - p^{(t)*}|_{ite-1}| \rightarrow 0, \forall i \in \mathbb{I}, \forall j \in \mathbb{J})$ **then**
      $Convergence = 1$
    end if
  end while
end for

The PC-DRM distributed algorithm can be characterized as a low complexity algorithm (as it is also confirmed by the numerical results in Chapter 5), due to the constant in terms of complexity operations that are made both in the customers' and

companies' side. Furthermore, due to its low complexity the PC-DRM algorithm can be installed and realized through the customers' smart meters in a real-time manner, while from the companies' point of view, the proposed algorithm can run at the companies' management and decision-making center. Finally, in Section [Results] it is shown that the action customers' selection probabilities converge fast, something that indicates and confirm the efficiency of the stochastic learning automata methodology, that we propose on this work.

Chapter 5

Experiments and Numerical Evaluation

5.1 Experiment Setup

In this chapter, a detailed numerical performance evaluation and comparative study of the proposed framework is conducted through modeling and simulations. The results illustrate the operation, features and benefits of the proposed demand response management framework. These simulations were generated utilizing the programming suite MATLAB. Initially, in Section 5.2, we focus on the operation performance of our framework, in terms of the obtained optimal customers' consumption responses and companies' prices. Moreover, the distribution of the customers to the available companies in the Smart Grid Network is studied, and the corresponding power companies' profit values are presented. Furthermore, the operation and the convergence of the distributed learning algorithm (i.e., stochastic learning automata) is illustrated, while the Demand and Response Management optimization problem to its stable solution, is presented as well. In addition, in Section 5.3, a detailed

comparative evaluation of our approach against other alternative approaches is provided, and the differences with respect to the achieved customers' and companies' satisfaction, and customers' electricity energy consumption, are discussed.

On our base experimental scenario, we considered a Smart Grid Network consisting of $J = 5$ power companies, and $I = 100$ customers. Also, we considered $k = 1000$, $\lambda = 100$ and as a learning step $b = 0.6$, while the $\gamma_i^{(t)}$ parameter of each customer is randomly generated. Each company has constant characteristics throughout the day (i.e, generation cost $c_j^{(t)}$, and discount policy $f_j^{(t)}$), while the corresponding values that were used are:

1. $\mathbf{f} = \{.0285, .027, .029, 0.3, .028\}$

2. $\mathbf{c} = \{.255, .245, .265, .285, .265\}$

5.2 Operation of the PC-DRM Algorithm

At first, we focus on the power companies' selection process, via adopting the proposed distributed learning framework (i.e., Section 2.3). Each power company $j, j \in \mathbb{J}$ aims to improve its market profile by achieving a low peak to average ratio (i.e., PAR_j) and a high competitiveness (i.e., $Comp_j$). As we mentioned before, the low PAR_j factor indicates that the power company j balances the customers' electricity consumption over the time via avoiding great consumption peaks, which may not be able to support. On the other hand, the high competitiveness factor $Comp_j$ of the power company expresses the company's penetration in the market, in terms of the customers' portion that it serves.

Specifically, Fig. 5.1 and Fig. 5.2 present each power company's $j, j \in \mathbb{J}$ peak to average ratio PAR_j and competitiveness factor $Comp_j$ as a function of the PC-DRM

algorithm's timeslots until the convergence of the distributed learning mechanism. Based on the considered configuration of this experimental setup, it is observed that the power companies 1 and 5 maintain the lowest PAR and competitiveness factor $Comp$. Moreover, it is noted that both the PAR and $Comp$ factors are determined by the solution of the DRM optimization problem, via the customers' optimal consumption to which the two-stage game theoretic part converges at each timeslot.

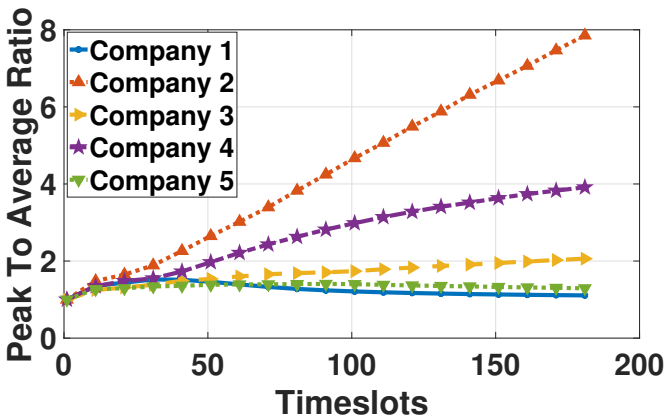

Figure 5.1: Peak to Average Ratio

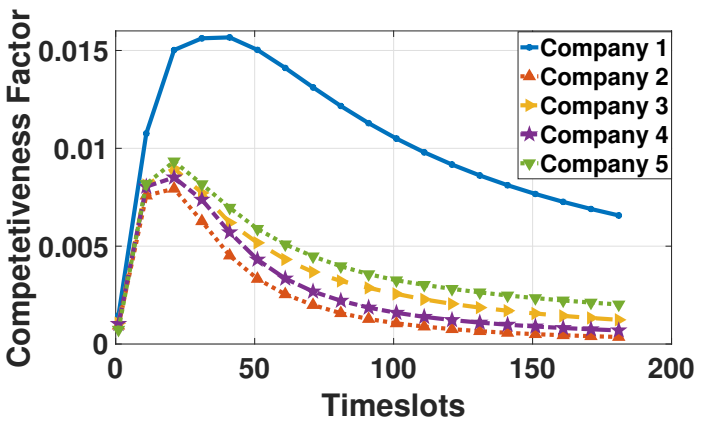

Figure 5.2: Competitiveness Factor

Furthermore, Fig. 5.3 depicts each company's j reputation and competitiveness

factor RC_j, (i.e., Eq. 2.4) as a function of the PC-DRM algorithm's timeslots. The results illustrate that the power companies 1 and 5 build a higher reputation and competitiveness factor RC in the market, compared to the rest, since they both achieve a lower PAR (i.e., Fig. 5.1) and a higher competitiveness factors (i.e., Fig. 5.2). Consequently, these two power companies create a better profile in the market, and the customers by learning and adapting their selection via the stochastic learning automata methodology, they have a higher average selection probability for these two companies (i.e., Fig. 5.4, and these two companies attract a higher portion of customers (i.e., Fig. 5.5 over the timeslots. Specifically, as Fig. 5.5 demonstrates, these two companies serve almost 90% of the market's customers, with company 1 absorbing almost 70%, as it achieves the highest reputation and competitiveness score, (i.e., Fig. 5.3), while company 5 with the second best profile in the market serves approximately 20% of the market's customers.

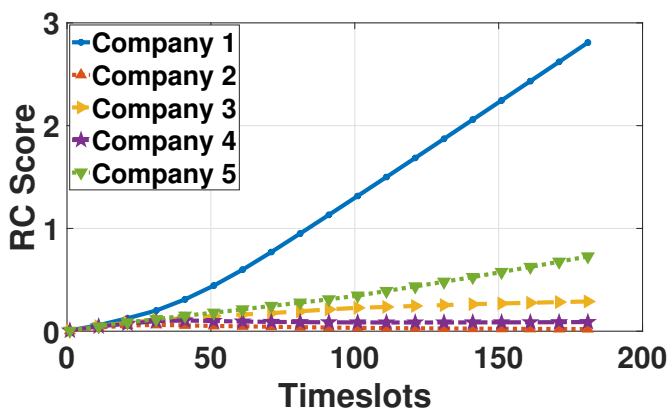

Figure 5.3: Reputation and Competitiveness Factor

Considering the DRM optimization problem, which in this work is studied via adopting a two-stage non-cooperative game theoretic solution (i.e., Section 3), Fig. 5.6 presents two indicative customers' optimal energy consumption as a function PC-DRM algorithm's timeslots until its convergence to the stable customers' association to the power companies. As the customers converge to their stable power

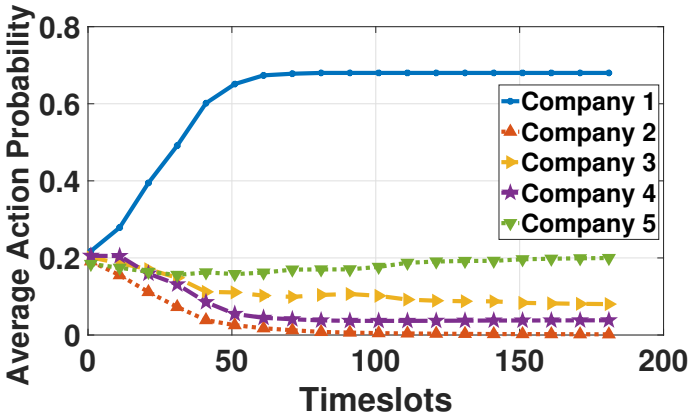

Figure 5.4: Average Selection Probability

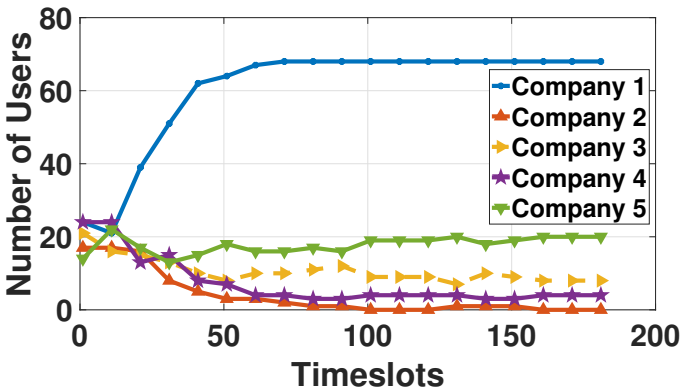

Figure 5.5: Number of Customers per Power Company

company selection, while at the same time they determine their optimal electricity consumption (i.e., $e_{i,j}^{(t)*}$ - Eq. 3.2) for each timeslot by converging to the NE point of the non-cooperative game, their optimal electricity consumption converges to feasible values, while fulfilling their non-shiftable electricity needs (i.e., Min-consumption curves), as a higher priority is given to them, while at the same time the customers do not over-consume electricity, thus $e_{i,j}^{(t)*} \leq d_i^{(t)}, \forall t \in \mathbb{T}$. Moreover, as Fig. 5.6 illustrates, both of the presented customers consume a higher level of electricity than their non-shiftable demands, which confirms that the proposed framework achieves

to satisfy both the non-shiftable and a portion of the shiftable electricity needs of the market's customers.

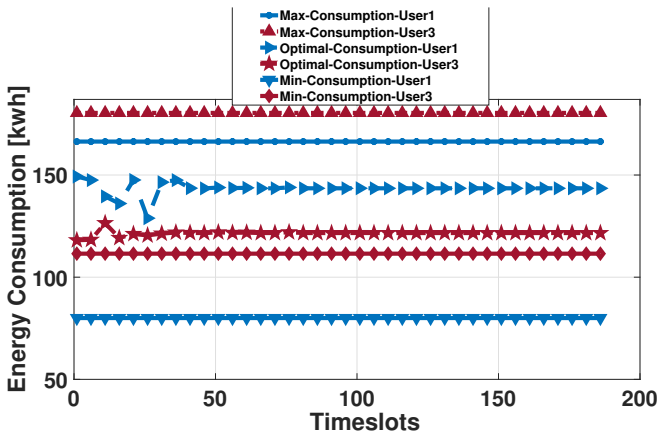

Figure 5.6: Optimal Customers' Electricity Consumption

Additionally, Fig. 5.7 and Fig. 5.8 depict the power companies' prices and profit values' convergence, as a function of PC-DRM algorithms' timeslots, respectively. It is noted that Fig. 5.7 refers to indicative prices units per unit of electricity consumption (e.g., $\frac{\$}{KWh}$). Based on Fig. 5.6, 5.7, and 5.8, it is concluded that the DRM optimization problem converges to its final NE point, as the association between customers and power companies converges to its stable case, where both the customers and the power companies maximize their utilities and profits, leading them to low feasible low energy consumption and pricing policies, respectively. Moreover, it is worth to be noted, that company 5, which absorbs the second highest portion of the markets' customers, is not the company with the second lowest price in the market (i.e., company 3 has a lower prices), which indicates that the announcement of a lower price by a company does not guarantee the absorbing of a higher portion of customers, as the customers select their power companies based on their market's profiles (i.e., reputation and competitiveness score), which depict the overall power companies' behavior in the market through the timeslots. In addition, as Fig. 5.7 illustrates, the companies 1 and 5 due to their higher reputation and competitive-

ness score (i.e., Fig. 5.3) converge to higher profit values compared to the rest power companies, as this concludes to improved customers' preference to be served by these companies as we mentioned in Fig.5.5. Finally, the power company 2 has not been selected by any customer (Fig. 5.5) in the scenario under consideration, and therefore it's announced price is zero and it is not present in Fig. 5.7.

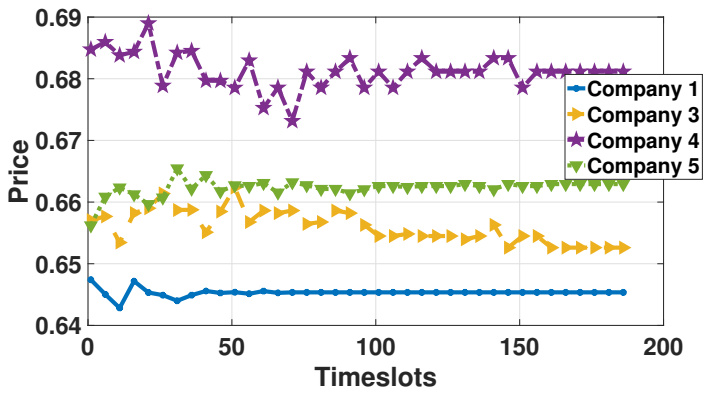

Figure 5.7: Companies' Optimal Announced Prices

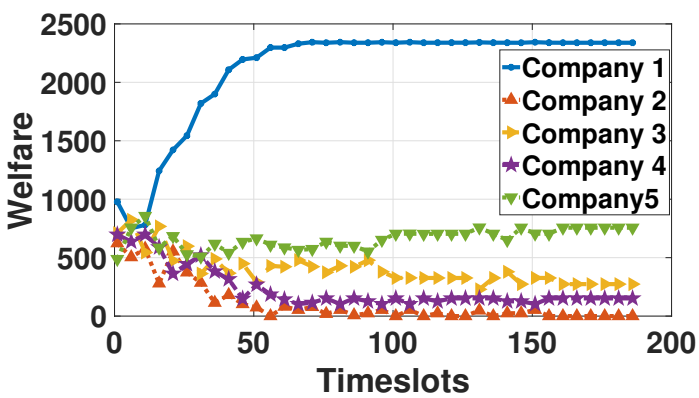

Figure 5.8: Companies' Achievable Profit

5.3 Comparative Analysis

In this section, we provide a detailed comparative evaluation study of the proposed PC-DRM framework against other approaches either from the recent literature or different implementation alternatives, highlighting the benefits of the PC-DRM algorithm in terms of customers' energy consumption and satisfaction. It is noted that for fairness and completeness purposes in the comparison, the power companies' profit values as well as the convergence time of the different frameworks are also evaluated and discussed.

Specifically, we evaluate the proposed PC-DRM framework against to five different approaches:

1. The demand response management algorithm (referred to as Evo) as proposed in [37], where the association of the customers to power companies is modeled as an evolutionary game and the customers form a population which is associated to only one company, as outcome of the evolutionary game.

2. An alternative variation of the proposed PC-DRM algorithm-referred as MLdc, where the customers update their selection probabilities (i.e., Eq. 2.8, 2.9) by using the reward probability $r_j^{(t)} = \frac{f_j^{(t)}}{c_j^{(t)}}$, in order to capture the profile of each power company $j, j \in \mathbb{J}$, in terms of its announced discounts and costs of the electricity generation. As a result, the customers select a power company based only on monetary-related power companies' characteristics (i.e., discount $f_j^{(t)}$, and production cost $c_j^{(t)}$), without considering the electricity-related characteristics of each power company, i.e., peak to average ratio PAR_j and competitiveness factor $Comp_j$. The DRM optimization problem is solved based on the DRM part of the PC-DRM algorithm.

3. A variation of the PC-DRM algorithm - referred as MLlp, by using as a reward

probability the $r_j^{(t)} = \frac{1}{\exp p_j^{(t)*}}$, which is based on the power company's $j, j \in \mathbb{J}$ optimal price $p_j^{(t)*}$. Specifically, the MLlp approach proposes to the customers as the best power company choice, the one with the lowest price.

4. The Random algorithm, where each customer is associated randomly to a power company, as each customer maintains an equal probability $Pr_{i,j}^{(t)} = \frac{1}{J}$ of selecting each power company. The companies' prices and customers' consumed electricity are determined based on the DRM optimization part (i.e., the non-cooperative game) of the PC-DRM framework.

5. The best discount and cost - referred to as Bdc algorithm, which associates all the customers with the power company $j, j \in \mathbb{J}$ that maintains the best $\frac{f_j^{(t)}}{c_j^{(t)}}$ factor and the DRM optimization problem is also solved based on DRM part of the proposed PC-DRM framework.

Figures 5.9, and 5.10 depict customers' perceived average utility and optimal energy consumption, respectively, as a function of the number of timeslots that all the comparative frameworks need in order to converge to stable customers' association to the power companies. As it is shown, the proposed PC-DRM algorithm achieves the highest customers' utilities (i.e., Fig. 5.9), and among the lowest customers' electricity consumption (i.e., Fig. 5.10). This trend stems from the holistic consideration of the power companies' characteristics, i.e., both the monetary and the electricity related characteristics, as these are captured by the reputation and competitiveness factor Eq. 2.4. Moreover, the MLdc variation of the PC-DRM algorithm, which considers only the power companies' monetary-related characteristics in order to perform the customers' association with the power companies, achieves similar customers' utilities and electricity consumption, showing the significance of the monetary factors. This happens mainly because the monetary factors contribute in the optimal power companies' pricing policy (Eq. 3.1) and customers' consumption response (Eq. 3.2), thus they affect the power companies' electricity-related

factors (i.e., PAR, Comp). As a result, our proposed framework consists a more general and holistic approach compared to MLdc, by avoiding possible high peaks of consumption in the case where power companies aim to attract the customers by high discounts in short-term periods, thus the sufficient satisfaction of the customers' is guaranteed by the PC-DRM approach in a long-term period.

On the other hand, the approached that do not provide the opportunity to the customers to learn from their past decisions (i.e., Bdc, Random approaches) achieve the lowest customers' utility and high electricity consumption. Specifically, each customer select its power company on a single time, by not exploring the Smart Grid Network environment for better choices. Furthermore, the Evo [37] algorithm, which is based on the outcome of an evolutionary game theoretic approach, associates all the customers to only one power company, leading in that way into a monopoly scenario where the customers achieve significantly lower average utility, while at the same time their electricity consumption increases. Finally, the MLlp algorithm lead the customers to select the power company with the lowest price, thus they tend to consume more electricity, which creates a domino effect, as the customers' cost increases, and their perceived average utility decreases.

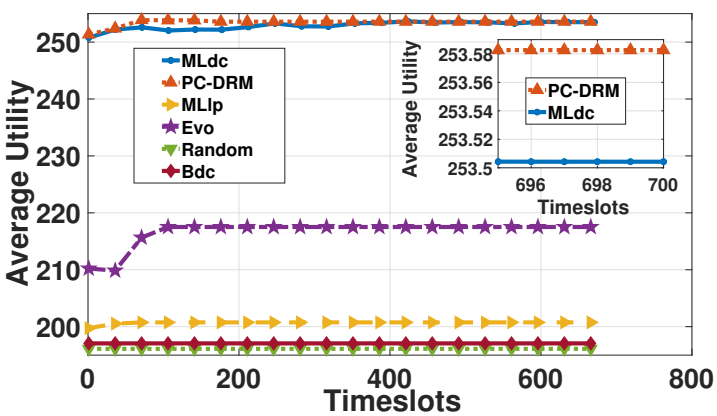

Figure 5.9: Average Customers' Utility

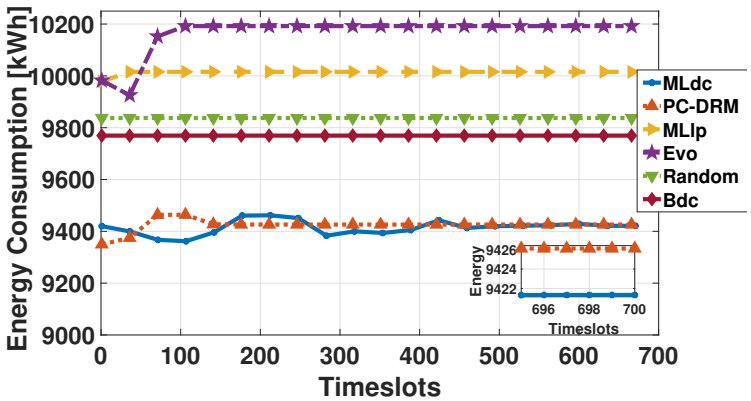

Figure 5.10: Overall Energy Consumption

Scenarios	Profit					Avg. Profit	T(sec)
	C1	C2	C3	C4	C5		
PC-DRM	2338	0	273	151	756	704	1.01
MLdc	951	837	1004	349	374	703	4.86
MLlp	840	1323	784	457	974	876	0.43
Evo	0	4392	0	0	0	878	0.65
Random	479	1380	759	793	848	852	0.04
Bdc	4208	0	0	0	0	842	0.05

Table 5.1: Power companies' welfare and algorithms' convergence time

Table 5.1 includes in a comparative manner, the achieved power companies' profit values, the average profit, and the actual convergence time (in seconds) for all the comparative approaches. As it is shown, the PC-DRM and MLdc algorithms present similar companies' average profit values, while the PC-DRM proposed framework presents significantly lower complexity be achieving almost a five-fold reduction in convergence time. This is observed, since in an open electricity market, where the power companies have similar monetary-related characteristics (i.e., production cost, discounts), the customers may flip among the companies, thus the MLdc approach has a delayed convergence. The more holistic approach of the PC-DRM algorithm, where electricity-related characteristics are also considered, contributes to customers'

faster decision-making in selecting the most appropriate company for receiving service from. The Random and Bdc algorithms, which allow the customers to make a single time power company selection have the lowest convergence time compared to all the other approaches. As we already mentioned, the last two algorithms present quite poor performance in terms of customers' utility and electricity consumption. Finally, both Evo and MLlp approaches achieve similar results in terms of companies' profit values and convergence time.

Chapter 6

Conclusion & Future Work

In this thesis, the joint problem of power company selection and demand response management in a competitive open electricity market of a Smart Grid Network, consisting of multiple power companies and multiple customers is studied. Initially, a low complexity distributed learning approach is proposed, where the customers acting as learning automata explore the environment (i.e., market) and select a power company to be served from in an autonomous manner. Then, the demand response management problem - DRM, is formulated as two-stage non-cooperative, where at the first stage the customers determine their optimal electricity consumption that maximizes their perceived utility and a stable point (i.e., Nash Equilibrium) is achieved, while at the second stage each power company determines its optimal pricing policy that maximizes its profit. Moreover, a distributed iterative and low complexity algorithm is introduced to jointly implement the power company selection and the demand response management processes.

A detailed performance evaluation of the proposed approach was conducted via modeling and simulation, and the presented results confirmed the superiority of the proposed PC-DRM framework, in terms of the achieved customers' and companies'

satisfaction, customers' energy consumption, and implementation complexity. Nevertheless, it is noted that in this work customers' subjectivity and individuality in accordance with their behavioral patterns have not been considered and could be a topic of high research and practical importance. Consequently, based on the proposed framework, it is of high interest to extend this work via studying and proposing customers' Quality of Experience functions, which quantify customers' behavioral patterns based on relative frameworks, including Prospect Theory and the tragedy of the commons [80–83]. Finally, it is among our current and future research goals to study how the dynamic change of customers' behavior can influence the stability of the open market.

Appendices

Appendix A

Proof of Theorem 1

Towards determining customer's best response strategy $BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) = e_{i,j}^{(t)*}$, the first and the second order derivatives of customer's utility function $U_i^{(t)}$ with respect to $e_{i,j}^{(t)}$ are used.

$$\frac{\partial U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}, p_j^{(t)})}{\partial e_{i,j}^{(t)}} = \frac{1}{E_{-i}^{(t)}} \cdot \left[s_i^{'}(r_i^{(t)}) - \gamma_i^{(t)} \cdot p_j^{(t)} \right] \tag{A.1}$$

$$\frac{\partial^2 U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}, p_j^{(t)})}{\partial e_{i,j}^{(t)^2}} = \frac{1}{(E_{-i}^{(t)})^2} \cdot s_i^{''}(r_i^{(t)}) \tag{A.2}$$

As stated in Section 2.2.1, customer's satisfaction function $s_i^{(t)}(r_i^{(t)})$ is an increasing concave function with respect to $r_i^{(t)}$, thus $s_i^{''}(r_i^{(t)}) < 0$ and $\frac{\partial^2 U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}, p_j^{(t)})}{\partial e_{i,j}^{(t)^2}} < 0$. We set $\tau = \lim_{r_i^{(t)} \to \infty} s_i^{'-1}$. Since $s_i^{'}(r_i^{(t)})$ is a strictly decreasing function (due to $s_i^{''}(r_i^{(t)}) < 0$) and as $s_i^{'}(r_i^{(t)}) > 0$, we know that $\tau < s_i^{'}(r_i^{(t)}) \leq s_i^{'}(0)$ and $0 \leq \tau < s_i^{'}(0)$. Hence, for $0 \leq \gamma_i^{(t)} \cdot p_j^{(t)} \leq \tau$, we have $\frac{\partial U_i^{(t)}(e_{i,j}^{(t)}, \mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}, p_j^{(t)})}{\partial e_{i,j}^{(t)}} > 0$ and thus $U_i^{(t)}$ is an increasing function of $e_{i,j}^{(t)}$. In this case, the best response strategy for customer $i, i \in \mathbb{I}$ is to demand its maximum electricity consumption, i.e., $d_i^{(t)}$. So, for $0 \leq \gamma_i^{(t)} \cdot p_j^{(t)} \leq \tau$, we have $BR_i(\mathbf{e}_{-\mathbf{i}}^{(\mathbf{t})}) = d_i^{(t)}$, $\forall i \in \mathbb{I}$. For $\tau < \gamma_i^{(t)} \cdot p_j^{(t)} \leq s_i^{'}(0)$, the equation

Appendix A. Proof of Theorem 1

$\frac{\partial U_i^{(t)}(e_{i,j}^{(t)},\mathbf{e_{-i}^{(t)}},p_j^{(t)})}{\partial e_{i,j}^{(t)}} = 0$ is equivalent to $s_i^{'}(r_i^{(t)}) = \gamma_i^{(t)} \cdot p_j^{(t)} \Leftrightarrow \hat{r}_i^{(t)} = s_i^{'-1}(\gamma_i^{(t)} \cdot p_j^{(t)}), \forall i \in \mathbb{I}$. Note that as $s_i^{'}(r_i^{(t)})$ is a strictly decreasing function, its inverse (i.e., $s_i^{'-1}$) exists, and that $\hat{r}_i^{(t)}$ is a decreasing function of $\gamma_i^{(t)} \cdot p_j^{(t)}$. Since $s_i^{''}(r_i^{(t)}) < 0$ for all $r_i^{(t)}$ and hence $\frac{\partial^2 U_i^{(t)}(e_{i,j}^{(t)},\mathbf{e_{-i}^{(t)}},p_j^{(t)})}{\partial e_{i,j}^{(t)2}} < 0$, the roots of $\frac{\partial U_i^{(t)}(e_{i,j}^{(t)},\mathbf{e_{-i}^{(t)}},p_j^{(t)})}{\partial e_{i,j}^{(t)}} = 0$ maximize $U_i^{(t)}(e_{i,j}^{(t)},\mathbf{e_{-i}^{(t)}},p_j^{(t)})$ for the given electricity consumption of the rest users, i.e., $\mathbf{e_{-i}^{(t)}}$. An one-to-one relation exists between $r_i^{(t)}$ and $e_{i,j}^{(t)}$, and thus the best response electricity consumption in response to $\mathbf{e_{-i}^{(t)}}$ that maximizes $U_i^{(t)}(e_{i,j}^{(t)},\mathbf{e_{-i}^{(t)}},p_j^{(t)})$ is also unique and is equal to $e_{i,j}^{(t)*} = E_{-i}^{(t)} \cdot \hat{r}_i^{(t)} = E_{-i}^{(t)} s_i^{'-1}(a_i^{(t)} \cdot p_j^{(t)})$. If $e_{i,j}^{(t)*} > d_i^{(t)}$ customer $i, i \in \mathbb{I}$ does not request for $e_{i,j}^{(t)*}$. In this case, since $e_{i,j}^{(t)*}$ is the unique maximizer of $U_i^{(t)}$, then $U_i^{(t)}$ is an increasing function of $e_{i,j}^{(t)}$ in $e_{i,j}^{(t)} \leq d_i^{(t)} \leq e_{i,j}^{(t)*}$ for fixed $\mathbf{e_{-i}^{(t)}}$. Therefore, the best response to $\mathbf{e_{-i}^{(t)}}$ is the maximum value of customer's electricity consumption, i.e., $BR_i(\mathbf{e_{-i}^{(t)}}) = d_i^{(t)}$. This implies that for $\tau < \gamma_i^{(t)} \cdot p_j^{(t)} \leq s_i^{'}(0)$, $BR_i(\mathbf{e_{-i}^{(t)}}) = min\{d_i^{(t)}, E_{-i}^{(t)} \cdot s_i^{'-1}(\gamma_i^{(t)} \cdot p_j^{(t)})\}$. For $\gamma_i^{(t)} \cdot p_j^{(t)} > s_i^{'}(0)$, we have $\frac{\partial U_i^{(t)}}{\partial e_{i,j}^{(t)}} < 0$, thus $U_i^{(t)}$ is a decreasing function of $e_{i,j}^{(t)}$. In this case, the imposed price by the companies is extremely high for customers to afford it, thus $BR_i(\mathbf{e_{-i}^{(t)}}) = 0, \forall i \in \mathbb{I}$.

Appendix B

Proof of Theorem 3

Given customers' optimal consumption response that is determined in the first stage of the DRM optimization problem, the profit function of each power company $j, j \in \mathbb{J}$ is written as follows:

$$\begin{aligned} P_j^{(t)}(E_j^{(t)}, p_j^{(t)}) = (1 - f_j^{(t)}) \cdot p_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \left[E_{-i}^{(t)} (\frac{k}{\gamma_i^{(t)} \cdot p_j^{(t)}} - \frac{1}{\lambda}) \right] \\ - c_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \left[E_{-i}^{(t)} (\frac{k}{\gamma_i^{(t)} \cdot p_j^{(t)}} - \frac{1}{\lambda}) \right] \end{aligned} \tag{B.1}$$

Considering the first order derivative of $P_j^{(t)}$ with respect to $p_j^{(t)}$, we have:

$$\frac{\partial P_j^{(t)}(E_{-i}^{(t)}, p_j^{(t)})}{\partial p_j^{(t)}} = -\frac{1}{\lambda}(1 - f_j^{(t)}) \cdot \sum_{i \in \mathbb{I}} E_{-i}^{(t)} + \frac{c_j^{(t)} \cdot k}{p_j^{(t)^2}} \cdot \sum_{i \in \mathbb{I}} \frac{E_{-i}^{(t)}}{\gamma_i^{(t)}} \tag{B.2}$$

As a result, the critical points of the profit function $P_j^{(t)}(E_{-i}^{(t)}, p_j^{(t)})$ are as follows:

$$p_j^{(t)*} = \left[\frac{k \cdot \lambda \cdot c_j^{(t)} \cdot \sum_{i \in \mathbb{I}} \frac{E_{-i}^{(t)}}{\gamma_i^{(t)}}}{(1 - f_j^{(t)}) \cdot \sum_{i \in \mathbb{I}} E_{-i}^{(t)}} \right] \tag{B.3}$$

Appendix B. Proof of Theorem 3

The second order derivative of the profit function $P_j^{(t)}$ is given as follows:

$$\frac{\partial^2 P_j^{(t)}(E_{-i}^{(t)}, p_j^{(t)})}{\partial {p_j^{(t)}}^2} = -2 \cdot c_j^{(t)} \cdot \frac{k}{{p_j^{(t)}}^3} \cdot \sum_{i \in \mathbb{I}} \frac{E_{-i}^{(t)}}{\gamma_i^{(t)}} \tag{B.4}$$

As observed by Eq. B.4, it holds true that $\frac{\partial^2 P_j^{(t)}(E_{-i}^{(t)}, p_j^{(t)})}{\partial {p_j^{(t)}}^2} < 0$, thus the $p_j^{(t)*}$ as determined in Eq. B.3 maximizes the company's $j, j \in \mathbb{J}$ profit function $P_j^{(t)}$.

References

[1] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—the new and improved power grid: A survey," *IEEE communications surveys & tutorials*, vol. 14, no. 4, pp. 944–980, 2011.

[2] V. C. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, and G. P. Hancke, "A survey on smart grid potential applications and communication requirements," *IEEE Transactions on industrial informatics*, vol. 9, no. 1, pp. 28–42, 2012.

[3] W. Wang, Y. Xu, and M. Khanna, "A survey on the communication architectures in smart grid," *Computer networks*, vol. 55, no. 15, pp. 3604–3629, 2011.

[4] J. Swift, J. Carey, and D. O'Connor, "Market monitor: Electric industry restructuring,"," *Division of Energy Resources, Office of Consumer Affairs and Business Regulation, MA, USA*, pp. 1–6, 2002.

[5] D. Nelson, K. Anderson, and B. Marquez, "Report to the 84th texas legislature: scope of com-petition in electric markets in texas," *Public Utility Commission of Texas, Austin*, pp. 1–142, 2015.

[6] T. Kastrinogiannis, E.-E. Tsiropoulou, and S. Papavassiliou, "Utility-based uplink power control in cdma wireless networks with real-time services," in *International Conference on Ad-Hoc Networks and Wireless*, pp. 307–320, Springer, 2008.

[7] D. Fudenberg and J. Tirole, "Game theory mit press," *Cambridge, MA*, p. 86, 1991.

[8] E. E. Tsiropoulou, T. Kastrinogiannis, and S. Papavassiliou, "Uplink power control in qos-aware multi-service cdma wireless networks," *Journal of Communications*, vol. 4, no. 9, pp. 654–668, 2009.

[9] C. U. Saraydar, N. B. Mandayam, D. J. Goodman, *et al.*, "Efficient power control via pricing in wireless data networks," *IEEE transactions on Communications*, vol. 50, no. 2, pp. 291–303, 2002.

[10] E. E. Tsiropoulou, G. K. Katsinis, and S. Papavassiliou, "Utility-based power control via convex pricing for the uplink in cdma wireless networks," in *2010 European Wireless Conference (EW)*, pp. 200–206, IEEE, 2010.

[11] E. Altman and Z. Altman, "S-modular games and power control in wireless networks," *IEEE Transactions on Automatic Control*, vol. 48, no. 5, pp. 839–842, 2003.

[12] E. E. Tsiropoulou, G. K. Katsinis, and S. Papavassiliou, "Distributed uplink power control in multiservice wireless networks via a game theoretic approach with convex pricing," *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, no. 1, pp. 61–68, 2011.

[13] T. Alpcan, T. Başar, R. Srikant, and E. Altman, "Cdma uplink power control as a noncooperative game," *Wireless Networks*, vol. 8, no. 6, pp. 659–670, 2002.

[14] E. E. Tsiropoulou, P. Vamvakas, G. K. Katsinis, and S. Papavassiliou, "Combined power and rate allocation in self-optimized multi-service two-tier femtocell networks," *Computer Communications*, vol. 72, pp. 38–48, 2015.

[15] M. R. Musku, A. T. Chronopoulos, and D. C. Popescu, "Joint rate and power control with pricing," in *GLOBECOM'05. IEEE Global Telecommunications Conference, 2005.*, vol. 6, pp. 5–pp, IEEE, 2005.

[16] E. E. Tsiropoulou, P. Vamvakas, and S. Papavassiliou, "Joint utility-based uplink power and rate allocation in wireless networks: A non-cooperative game theoretic framework," *Physical Communication*, vol. 9, pp. 299–307, 2013.

[17] M. R. Musku, A. T. Chronopoulos, D. C. Popescu, and A. Stefanescu, "A game-theoretic approach to joint rate and power control for uplink cdma communications," *IEEE Transactions on Communications*, vol. 58, no. 3, pp. 923–932, 2010.

[18] E. E. Tsiropoulou, P. Vamvakas, and S. Papavassiliou, "Joint customized price and power control for energy-efficient multi-service wireless networks via s-modular theory," *IEEE Transactions on Green Communications and Networking*, vol. 1, no. 1, pp. 17–28, 2017.

[19] E. E. Tsiropoulou, P. Vamvakas, and S. Papavassiliou, "Energy efficient uplink joint resource allocation non-cooperative game with pricing," in *2012 IEEE*

Wireless Communications and Networking Conference (WCNC), pp. 2352–2356, IEEE, 2012.

[20] H. Zhang, Y. Zhang, Y. Gu, D. Niyato, and Z. Han, "A hierarchical game framework for resource management in fog computing," *IEEE Communications Magazine*, vol. 55, no. 8, pp. 52–57, 2017.

[21] E. E. Tsiropoulou, G. K. Katsinis, P. Vamvakas, and S. Papavassiliou, "Efficient uplink power control in multi-service two-tier femtocell networks via a game theoretic approach," in *2013 IEEE 18th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*, pp. 104–108, IEEE, 2013.

[22] S.-Y. Lien, Y.-Y. Lin, and K.-C. Chen, "Cognitive and game-theoretical radio resource management for autonomous femtocells with qos guarantees," *IEEE Transactions on Wireless Communications*, vol. 10, no. 7, pp. 2196–2206, 2011.

[23] E. E. Tsiropoulou, G. K. Katsinis, A. Filios, and S. Papavassiliou, "On the problem of optimal cell selection and uplink power control in open access multi-service two-tier femtocell networks," in *International Conference on Ad-Hoc Networks and Wireless*, pp. 114–127, Springer, 2014.

[24] S. Barbarossa, S. Sardellitti, A. Carfagna, and P. Vecchiarelli, "Decentralized interference management in femtocells: A game-theoretic approach," in *2010 Proceedings of the Fifth International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 1–5, IEEE, 2010.

[25] P. Vamvakas, E. E. Tsiropoulou, and S. Papavassiliou, "Dynamic provider selection & power resource management in competitive wireless communication markets," *Mobile Networks and Applications*, vol. 23, no. 1, pp. 86–99, 2018.

[26] E. E. Tsiropoulou, A. Kapoukakis, and S. Papavassiliou, "Energy-efficient subcarrier allocation in sc-fdma wireless networks based on multilateral model of bargaining," in *2013 IFIP Networking Conference*, pp. 1–9, IEEE, 2013.

[27] P. Vamvakas, E. E. Tsiropoulou, M. Vomvas, and S. Papavassiliou, "Adaptive power management in wireless powered communication networks: A user-centric approach," in *2017 IEEE 38th Sarnoff Symposium*, pp. 1–6, IEEE, 2017.

[28] E. E. Tsiropoulou, A. Thanou, and S. Papavassiliou, "Modelling museum visitors' quality of experience," in *2016 11th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP)*, pp. 77–82, IEEE, 2016.

[29] C. Heitzenrater and A. Simpson, "Misuse, abuse and reuse: Economic utility functions for characterising security requirements," in *2016 11th International Conference on Availability, Reliability and Security (ARES)*, pp. 572–581, IEEE, 2016.

[30] J. E. Navarro-Barrientos, "Risk propensity and proportion of investment for agents using power utility functions," in *2016 International Conference on Control, Decision and Information Technologies (CoDIT)*, pp. 444–449, IEEE, 2016.

[31] M. Dolecki, P. Karczmarek, A. Kiersztyn, and W. Pedrycz, "Utility functions as aggregation functions in face recognition," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1–6, IEEE, 2016.

[32] W. M. Bateman, A. Amaya, and J. Fenstermaker, "Securing the grid and your critical utility functions," in *2017 IEEE Rural Electric Power Conference (REPC)*, pp. 29–37, IEEE, 2017.

[33] L. Maghrabi, E. Pfluegel, and S. F. Noorji, "Designing utility functions for game-theoretic cloud security assessment: a case for using the common vulnerability scoring system," in *2016 International Conference On Cyber Security And Protection Of Digital Services (Cyber Security)*, pp. 1–6, IEEE, 2016.

[34] E. E. Tsiropoulou, J. S. Baras, S. Papavassiliou, and G. Qu, "On the mitigation of interference imposed by intruders in passive rfid networks," in *International Conference on Decision and Game Theory for Security*, pp. 62–80, Springer, 2016.

[35] C. Heitzenrater, J. King-Lacroix, and A. Simpson, "Motivating security engineering with economics: A utility function approach," in *2016 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, pp. 352–359, IEEE, 2016.

[36] A.-H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE transactions on Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010.

[37] B. Chai, J. Chen, Z. Yang, and Y. Zhang, "Demand response management with multiple utility companies: A two-level game approach," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 722–731, 2014.

[38] P. Palensky and D. Dietrich, "Demand side management: Demand response, intelligent energy systems, and smart loads," *IEEE transactions on industrial informatics*, vol. 7, no. 3, pp. 381–388, 2011.

[39] C. Ibars, M. Navarro, and L. Giupponi, "Distributed demand management in smart grid with a congestion game," in *2010 First IEEE International Conference on Smart Grid Communications*, pp. 495–500, IEEE, 2010.

[40] M. Erkoc, E. Al-Ahmadi, N. Celik, and W. Saad, "A game theoretic approach for load-shifting in the smart grid," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 187–192, IEEE, 2015.

[41] N. Yaagoubi and H. T. Mouftah, "A comfort based game theoretic approach for load management in the smart grid," in *2013 IEEE Green Technologies Conference (GreenTech)*, pp. 35–41, IEEE, 2013.

[42] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 884–892, 2012.

[43] W. Shi, N. Li, X. Xie, C.-C. Chu, and R. Gadh, "Optimal residential demand response in distribution networks," *IEEE journal on selected areas in communications*, vol. 32, no. 7, pp. 1441–1450, 2014.

[44] Y. Xu, N. Li, and S. H. Low, "Demand response with capacity constrained supply function bidding," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1377–1394, 2015.

[45] M. Yu and S. H. Hong, "A real-time demand-response algorithm for smart grids: A stackelberg game approach," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 879–888, 2015.

[46] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable demand response management in the smart grid: A stackelberg game approach," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 120–132, 2013.

[47] K. Alshehri, J. Liu, X. Chen, and T. Başar, "A stackelberg game for multi-period demand response management in the smart grid," in *2015 54th IEEE Conference on Decision and Control (CDC)*, pp. 5889–5894, IEEE, 2015.

[48] G. Fragkos, P. A. Apostolopoulos, and E. E. Tsiropoulou, "Escape: Evacuation strategy through clustering and autonomous operation in public safety systems," *Future Internet*, vol. 11, no. 1, p. 20, 2019.

[49] D. Sikeridis, E. E. Tsiropoulou, M. Devetsikiotis, and S. Papavassiliou, "Wireless powered public safety iot: A uav-assisted adaptive-learning approach towards energy efficiency," *Journal of Network and Computer Applications*, vol. 123, pp. 69–79, 2018.

[50] P. A. Apostolopoulos, E. E. Tsiropoulou, and S. Papavassiliou, "Game-theoretic learning-based qos satisfaction in autonomous mobile edge computing," in *2018 Global Information Infrastructure and Networking Symposium (GIIS)*, pp. 1–5, IEEE, 2018.

[51] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[52] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-time demand response model," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 236–242, 2010.

[53] S. Shao, M. Pipattanasomporn, and S. Rahman, "Demand response as a load shaping tool in an intelligent grid with electric vehicles," *IEEE Transactions on Smart Grid*, vol. 2, no. 4, pp. 624–631, 2011.

[54] M. Zugno, J. M. Morales, P. Pinson, and H. Madsen, "A bilevel model for electricity retailers' participation in a demand response market environment," *Energy Economics*, vol. 36, pp. 182–197, 2013.

[55] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *2010 First IEEE International Conference on Smart Grid Communications*, pp. 415–420, IEEE, 2010.

[56] S. Wang, S. Bi, and Y.-J. A. Zhang, "Demand response management for profit maximizing energy loads in real-time electricity market," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6387–6396, 2018.

[57] S. Bahrami, M. H. Amini, M. Shafie-Khah, and J. P. Catalao, "A decentralized renewable generation management and demand response in power distribution networks," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, pp. 1783–1797, 2018.

[58] J. Li, G. Ma, T. Li, W. Chen, and Y. Gu, "A stackelberg game approach for demand response management of multi-microgrids with overlapping sales areas," *Science China Information Sciences*, vol. 62, no. 11, p. 212203, 2019.

[59] A. S. Farsangi, S. Hadayeghparast, M. Mehdinejad, and H. Shayanfar, "A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs," *Energy*, vol. 160, pp. 257–274, 2018.

[60] R. Lu, S. H. Hong, and M. Yu, "Demand response for home energy management using reinforcement learning and artificial neural network," *IEEE Transactions on Smart Grid*, 2019.

[61] R. Godina, E. Rodrigues, E. Pouresmaeil, J. Matias, and J. Catalão, "Model predictive control home energy management and optimization strategy with demand response," *Applied Sciences*, vol. 8, no. 3, p. 408, 2018.

[62] Y. Yao, X. He, T. Huang, C. Li, and D. Xia, "A projection neural network for optimal demand response in smart grid environment," *Neural Computing and Applications*, vol. 29, no. 6, pp. 259–267, 2018.

[63] S. K. Desai, A. Dua, N. Kumar, A. K. Das, and J. J. Rodrigues, "Demand response management using lattice-based cryptography in smart grids," in *2018 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, IEEE, 2018.

[64] H. M. Ruzbahani and H. Karimipour, "Optimal incentive-based demand response management of smart households," in *2018 IEEE/IAS 54th Industrial and Commercial Power Systems Technical Conference (I&CPS)*, pp. 1–7, IEEE, 2018.

[65] A. Jindal, M. Singh, and N. Kumar, "Consumption-aware data analytical demand response scheme for peak load reduction in smart grid," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 11, pp. 8993–9004, 2018.

[66] E. S. Parizy, H. R. Bahrami, and S. Choi, "A low complexity and secure demand response technique for peak load reduction," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3259–3268, 2018.

[67] C. Abreu, D. Rua, P. Machado, J. P. Lopes, and M. Heleno, "Advanced energy management for demand response and microgeneration integration," in *2018 Power Systems Computation Conference (PSCC)*, pp. 1–7, IEEE, 2018.

[68] W.-Y. Chiu, J.-T. Hsieh, and C.-M. Chen, "Pareto optimal demand response based on energy costs and load factor in smart grid," *IEEE Transactions on Industrial Informatics*, 2019.

[69] P. Luo, X. Wang, H. Jin, Y. Li, and X. Yang, "Load management for multiple datacenters towards demand response in the smart grid integrating renewable energy," in *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence*, pp. 140–144, ACM, 2018.

[70] X. Kou, F. Li, J. Dong, M. Starke, J. Munk, T. Kuruganti, and H. Zandi, "A distributed energy management approach for residential demand response,"

tech. rep., Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States), 2019.

[71] R. Lu, S. H. Hong, and X. Zhang, "A dynamic pricing demand response algorithm for smart grid: reinforcement learning approach," *Applied Energy*, vol. 220, pp. 220–230, 2018.

[72] L. Chen, N. Li, S. H. Low, and J. C. Doyle, "Two market models for demand response in power networks," in *2010 First IEEE International Conference on Smart Grid Communications*, pp. 397–402, IEEE, 2010.

[73] N. Li, L. Chen, and S. H. Low, "Optimal demand response based on utility maximization in power networks," in *2011 IEEE power and energy society general meeting*, pp. 1–8, IEEE, 2011.

[74] S. Datchanamoorthy, S. Kumar, Y. Ozturk, and G. Lee, "Optimal time-of-use pricing for residential load control," in *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 375–380, IEEE, 2011.

[75] C. Chen, S. Kishore, and L. V. Snyder, "An innovative rtp-based residential power scheduling scheme for smart grids," in *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 5956–5959, IEEE, 2011.

[76] Z. Fan, P. Kulkarni, S. Gormus, C. Efthymiou, G. Kalogridis, M. Sooriyabandara, Z. Zhu, S. Lambotharan, and W. H. Chin, "Smart grid communications: Overview of research challenges, solutions, and standardization activities," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 21–38, 2012.

[77] P. Vytelingum, S. D. Ramchurn, T. D. Voice, A. Rogers, and N. R. Jennings, "Trading agents for the smart electricity grid," in *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: volume 1-Volume 1*, pp. 897–904, International Foundation for Autonomous Agents and Multiagent Systems, 2010.

[78] D. Sikeridis, E. EleniTsiropoulou, M. Devetsikiotis, and S. Papavassiliou, "Self-adaptive energy efficient operation in uav-assisted public safety networks," in *2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, pp. 1–5, IEEE, 2018.

[79] R. D. Yates *et al.*, "A framework for uplink power control in cellular radio systems," *IEEE Journal on selected areas in communications*, vol. 13, no. 7, pp. 1341–1347, 1995.

[80] P. Vamvakas, E. E. Tsiropoulou, and S. Papavassiliou, "On controlling spectrum fragility via resource pricing in 5g wireless networks," *IEEE Networking Letters*, vol. 1, no. 3, pp. 111–115, 2019.

[81] P. Vamvakas, E. E. Tsiropoulou, and S. Papavassiliou, "Dynamic spectrum management in 5g wireless networks: A real-life modeling approach," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, pp. 2134–2142, IEEE, 2019.

[82] A. R. Hota, S. Garg, and S. Sundaram, "Fragility of the commons under prospect-theoretic risk attitudes," *Games and Economic Behavior*, vol. 98, pp. 135–164, 2016.

[83] G. Hardin, "Extensions of" the tragedy of the commons"," *Science*, vol. 280, no. 5364, pp. 682–683, 1998.