PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

MANAGEMENT OF CHARGING STATION OF ELECTRIC VEHICLES UNDER ADVANCE RESERVATION SCHEMES

RODRIGO CRISTÓBAL BERNAL SOTO

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
DANIEL OLIVARES QUERO

Santiago de Chile, December 2019

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A mis padres

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ABSTRACT

As electric vehicles (EVs) surpassed the 3 million-vehicle threshold in 2017, charging stations (CS) are becoming a growing necessity to allow EV charging while parked away from home. In addition, by harnessing the inherent flexibility of the charging process, CS can also provide services to the grid, such as frequency and voltage regulation. However, given that full-charge using state-of-the-art technology can take a minimum of nearly 30 minutes, drivers may face queues and uncertainty on the availability of charging sockets. To address this issue this work presents a model to determine the optimal management of CS using advance reservations. In the model, CS are assumed to participate in the energy and regulation markets, in addition to providing charging services to EV users. On the other hand, EV users are modeled using Satisficing and Stochastic Satisficing decision models. The optimal management strategies are characterized by different charging tariffs and reservation fees, and their impact is analyzed in terms of the resulting charging profiles and welfare of EV users.

Keywords: Charging Station Management, Electric Vehicles, Reservation Schemes.

RESUMEN

Los vehículos eléctricos ya han sobrepasado el umbral de más de 3 millones de unidades en el 2017, esto tiene una directa implicancia en la importancia que las estaciones de carga comienzan a tener para cargarlos mientras se encuentran fuera del hogar. Adicionalmente, y tomando en cuenta la inherente flexibilidad que el proceso de carga posee, las estaciones de carga pueden proveer servicios a la red, tales como regulación de frecuencia y tensión. No obstante, dado que para lograr una carga total usando la tecnología disponible puede tomar un mínimo de $\approx$30 minutos, los conductores pueden verse enfrentados a tiempos de espera, filas e incertidumbre sobre la disponibilidad de estaciones de carga. Conforme a lo anterior, este trabajo presenta un modelo para determinar la gestión óptima de la estación de carga a través del uso de esquemas de reserva. En este modelo, se asume que la estación de carga puede participar en el mercado de energía y regulación, además de proveer servicios de carga. Por otra parte, los usuarios de vehículos eléctricos son modelados a través de modelos de desición del tipo ”*Satisficing*” simple y estocástico. Las estrategias de gestión son caracterizadas por tarifas de carga y reservas, y su impacto es analizado en términos del perfil de carga y bienestar de los usuarios.

Palabras Claves: Gestión de estaciones de carga, vehículos eléctricos, esquemas de reserva.

1. INTRODUCTION

1.1. Context

EVs surpassed the 3 million-vehicle threshold in 2017, and are expected to reach up to 228 millions by 2030 (IEA) (2017). This unprecedented growth brings important challenges in terms of charging infrastructure and coordination, with significant impact in electricity distribution networks. Furthermore, since full charge of an EV can take a significant amount of time, drivers may face queues and uncertainty over availability of charging services.

The uncoordinated charging of EVs can have a negative impact in the distribution networks, such as overloading of feeders and transformers, voltage deviations and imbalance, among others. One alternative to face these issues is to upgrade the distribution network infrastructure; however this involves significant investment. A second alternative, with much lower costs, is the use of coordinated charging strategies that maximize the utilization of existing distribution assets, by taking advantage of the inherent flexibility of the EV charging process.

Additional benefits for the distribution network can be obtained with the use of so-called V2G strategies Habib et al. (2015). In particular, V2G and coordinated charging strategies can help the operation of the DN, and the grid in general, by providing active power regulation, voltage support, load balancing, and harmonic currents filtering services, among others.

Industries that face somewhat similar challenges to allocate demand to a limited number of resources (e.g., restaurants, airlines, hotels) widely use advance reservations (AR) as a resource management scheme Charbonneau & Vokkarane (2012). AR plays a significant role in improving the provisioning quality of a resource manager and predictable behaviour of grid resources Mumtaz Siddiqui (2010). Furthermore, AR benefits both users and service provider by reducing the uncertainty of being served and improving resource management, respectively.

The straightforward communication between EVs and the CS is already a reality thanks to IoT technologies and the use of smart applications, such as ChargePoint. These applications provide EVs users with information about available charging sockets, prices and location of CSs. In Cao et al. (2017) a communications framework for on-route EV charging is presented, which allows users to optimize decisions on where to charge. Other well-known applications associated with parking services, such as SpotHero, ParkWhiz and JustPark, also allow users to compare parking alternatives and make reservations in advance.

Previous work on AR for CSs has concentrated in the development of tools for the minimization of travel times and route optimization Gerding et al. (2013); Liu et al. (2016), as well as the optimal allocation of vehicles in the CSs Timpner & Wolf (2014). Also, dynamic pricing schemes have been recently analyzed in Latinopoulos et al. (2017), where reservation decisions are evaluated within a risky-choice modelling framework.

In this work we study the adaptation and implementation of AR schemes to the context of CS for EVs. In specific, we model the participation of a CS in a whole-sale electricity market and its associated ancillary services market by means of scheduling the charging of available EVs. The later requires a detailed analysis and modeling of the users' decision making process in order to anticipate their individual behaviour. In this regard, Game Theory (more precisely poisson games Myerson (1998b,a)) and Decision Theory are used to model decisions of EV users on whether to make an AR or not, and which CS to choose.

The main contributions of this work are the following:

(i) AR schemes are adapted to the context of CS for EVs.

(ii) A simplified demand model is proposed for the CS, which considers a *satisficing* behaviour of EV users.

(iii) An optimization model is developed to calculate the optimal charging tariffs and reservation fees of a CS that maximizes revenues from charging services and electricity market participation.

1.2. Literature Review

1.2.1. Flexibility in Power Systems

In Lannoye et al. (2012), the concept of flexibility in power systems is defined as the ability of a system to deploy its resources to respond to changes in net load, where net load is defined as the remaining system load not served by variable generation. In this regard, the resources that can supply flexibility services can be categorized in four types:

(i) Flexibility in generation: this service has been the most used during the past 60 years RWE (2009), supplying power ramps and switching on/off power plants when needed to face mostly demand variations.

(ii) Flexibility in transmission: this type of flexibility is given mainly by HVDC systems and FACTS devices, which give more control in terms of stability and power management. Additionally, interconnections can be used as exportable flexibility between different areas Bucher et al. (2016).

(iii) Flexibility in demand: this service can be provide through Demand Response which is defined as a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time Qdr (2006).

(iv) Flexibility in storage: the storage of energy in periods when the energy cost is low allows to reduce the total operation cost particularly in demand peaks Akinyele & Rayudu (2014). Also storage can provide additional services that improve power system reliability and power quality Divya & stergaard (2009).

The particular features of EVs make them suitable to provide flexibility services Zhang & Kezunovic (2016) using them for charging (demand) or for saving energy and discharging when needed (storage), .

1.2.2. Integration of Electric Vehicles in the Distribution Network

The integration of EVs in the distribution Network is becoming a technical issue due to the fast and massive penetration of this kind of elements. An uncoordinated charging, particularly in peak hours, has a negative effect related with overloading of feeders and transformers in the Distribution Network. The grid is not prepared for these changes, mainly because it was built and planned for unidirectional power flow and residential consume where the loads are located throughout the feeder. Additionally, the massive charge and discharge of EVs can produce many other technical problems. There are several works that have investigated these impacts on the distribution grid Green II et al. (2011). Main impacts reported are itemized next.

- Supply-demand matching: users tend to charge EV's after work time so uncontrolled domestic charging will increase the peak load. Proposed solutions rely on smoothing the load curve and avoid creating new peak demands. A smart control system would need to be programmed or incentives created for customers to distribute charging throughout the day. An EV can be charged with different rates depending on the voltage level at which is plugged in. In Standard (2010) three different rates of charging are presented, which are the ones that are typically used in United States, these charging levels are summarized in the next table.

Table 1.1. Charge method electrical ratings (United States)

Level of Charging	Use	Power [kW]
Level 1	Residential 1 phase charger (120 V_{AC})	1.4 to 1.9
Level 2	Primary dedicated 1 phase charger (208 to 240 V_{AC})	4 to 19
Level 3	DC Comercial fast charger (600 V_{DC})	Up to 100

- Voltage profile: EV's impact is network-specific, and depends strongly on their distribution within the network. Two extreme conditions could lead to violation of voltage limits: EV's charging during maximum load time, or EV's generating during minimum load scenarios. Moderate EV's penetration could be manage by OLTC.
- Malfunction of network protection: EV interface devices may be designed to minimize or even eliminate the effects of EVs on the network fault level and protection system. Suitable electronic devices can be used to plug EV's into DN's.
- Phase imbalance: three phase supply points may not be available, particularly in some residential distribution grids. Single phase interface is more practical. When few EV's are charging the diversity is low so the imbalance increase but the lower total load reduces the voltage imbalance. When more EV's are charging the diversity increases so the imbalance is low.
- Power quality: EV interface devices employ power electronic converters and these are highly non-linear devices due to their operating principles and the presence of switching power semiconductor elements.This make manufacturers to attend this issue by improving converters and filters to produce a good power quality (mainly with regard to harmonics and power factor), both in charging and regeneration modes.

1.2.3. Vehicle-to-Grid technology

EV technology may offer many advantages to the grid if the charging and discharging is performed in a coordinated and intelligent manner. The main benefits can be the increased efficiency of charging, and decrease in the associated CO2 emissions. The particular features of the EV technology offers an advantage known as Vehicle-to-Grid (V2G) which is essentially the ability of a vehicle to make possible direct flow of power into the distribution network Habib et al. (2015). This concept is a specific way of enhancing the flexibility of the system by the charging and discharging of EVs' batteries while the vehicle is parked.

To implement V2G technology a special power electronic interface and software are required; however, many of the charging kits currently available in the market already allow this feature Kempton et al. (2001).

The main applications of V2G technology which can help to increase the performance, reliability and efficiency of the distribution network, and the system as a whole, are Habib et al. (2015):

(i) Active power regulation
(ii) Provide virtual inertia
(iii) Support reactive power
(iv) Load balancing
(v) Reduce utility operating cost and overall cost of service
(vi) Peak load shaving
(vii) Improve load factors
(viii) Reduced gas emissions
(ix) Tracking of variable renewable energy resources

Many of these applications can be used for providing ancillary services such as frequency and voltage control among others. Hence, V2G gives the opportunity of generate extra revenue to EV owners and CS operators. On the other hand, V2G implementation may produce higher battery degradation due to extensive charging/discharging (reducing battery life and its storage capacity), and requires investment in new electric and communications infrastructure.

1.2.3.1. Charging Strategies

The charging coordination can provide benefits to the distribution network and mitigate some problems that were presented before. In Sioshansi et al. (2010) the impacts of a coordinated integration of 230 EVs in the Ohio Network are analyzed. This work shows a reduction in the imbalance between generation and demand whilst decreasing in a 70% the use of conventional vehicles and CO2 emissions.

There are mainly 2 paths for achieving a proper integration of EVs. The first require lot of investment to enhance the distribution network (protections devices, capacity of lines and transformers, devices to provide voltage regulation, etc.) and to improve the charging facilities (by installing new charging sockets and measurement devices) and the second consist on applying a coordinated charging strategy that takes advantage of the EVs charging features (e.g storage) Lopes et al. (2010).

The coordination of EVs must have a strong communication and control system with standarized protocols. The literature refers to two main architectures which are centralized and decentralized systems "Modeling Coordination in Organizations and Markets" (1987). The difference between these categories lies on the level in which the charging decision is made.

A centralized strategy compute the charging decision in a high level knowing the state of all variables involved. This approach has the advantage of having a reliable charging control and also it can be easily integrated to the most used control schemes in power systems. However, these kind of architectures require a massive management of information and data in order to assure a proper performance.

On the other hand, a decentralized strategy takes the charging decision in a low level, that is, each EV take the charging decision independently. Most of these approaches are based on price signals with different pricing methods such as time-of-use or dynamic pricing, among others.

There is also a third control architecture, called hierarchical, which mixes both centralized and decentralized schemes by aggregating EVs and controlling them in a high level. The selection of a proper strategy depends directly on the size of the problem and the available resources.

In the next figure the three architectures are depicted in a simple manner Vay & Andersson (2012). This figure gives a notion of the dimension of the problem for each scheme, being the centralized the one which requires the most computational resources.

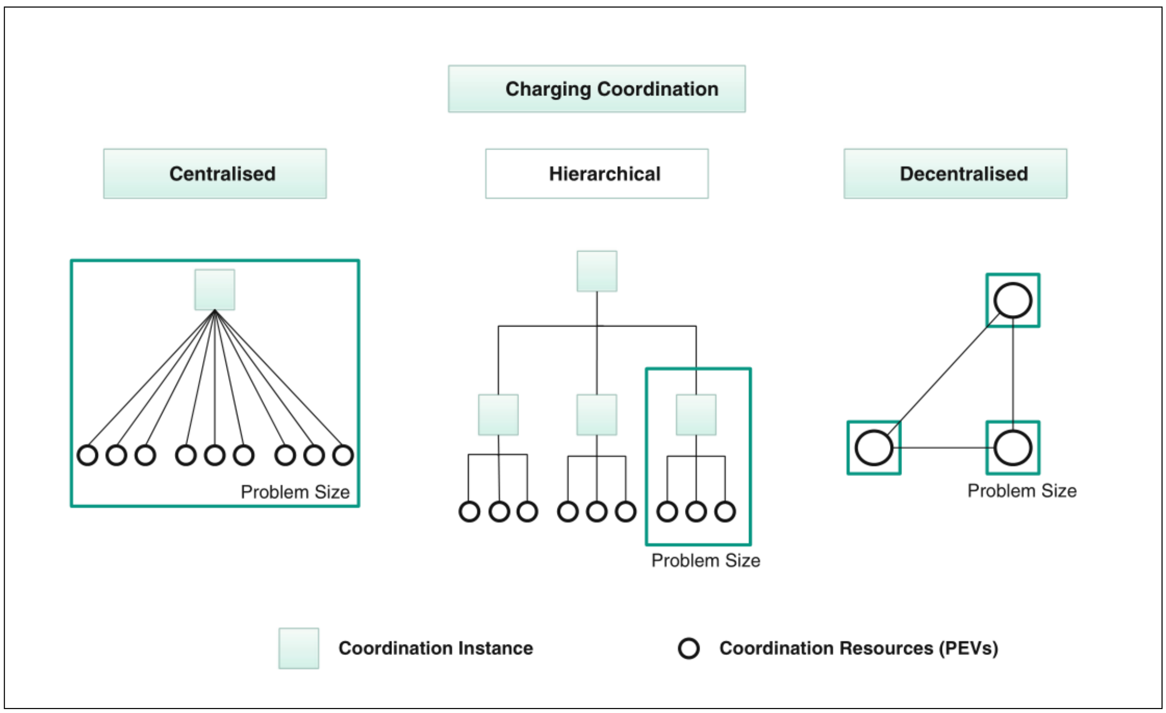


Figure 1.1. Coordination architectures and problem dimensions.

In Lopes et al. (2010) a local and centralized control scheme is used in order to reduce the impacts on the voltage and power unbalance in a microgrid. A battery is used as the main supply and as support EVs are charged in a coordinated manner. Other work that shows the technical impact of a coordinated and centralized charge is presented in Clement-Nyns et al. (2010), however in a distribution network, where an stochastic approach is included in the loads and a dynamic and quadratic programming is used to solve the optimization problem.

The work presented in Tushar et al. (2014) tries to maximize the use of resources of generation of a microgrid through a minimization of the power imported from the grid or other external microgrids, this is an input signal for a decentralized charging strategy for EVs. This paper models variable resources, such as wind and solar plants, and the load (with its respective appliances) with an stochastic approach. A comparison between the cases with and without EVs shows a remarkable improvement in the imported power.

Other work with a decentralized charging strategy is presented in Jian et al. (2013) where the impacts of the total load variability are considerably reduced by minimizing the variation of each household individually through the charge and discharge of the EV battery. The latter is modeled as a quadratic non linear problem and solved with a proposed heuristics method.

A novel approach for decentralized strategies is proposed in Hamid & Barria (2016), where a relation between energy and fluid particles is made to model the charging behaviour of multiple EVs in a distribution network. This work shows that the voltage and power variations are significantly reduced with the proposed strategy.

In Rajakaruna et al. (2015) an approach based on Model Predictive Control (MPC) is proposed in order to control the charge and discharge of the EV Battery. In this work a Load Area (LA) in which there are solar power plants and parked EV (used as storage) available. The aim of the Load Area Controller (LAC) proposed is to reduce the variations between load and generation, taking into account the minimum energy requirements of each EV. The LAC also helps with the integration of renewable resources and educing the overall operational costs

Another model that uses MPC model is proposed in Wenzel et al. (2016), where this controller is tested in an Air Force EV float of the United States. This work proof that this kind of control can be suitable for real time applications and signal tracking such as an Automatic Generation Control signal.

2. FRAMEWORK

This chapter presents a framework for advance reservations and decision models.

2.1. Advance Reservations AR

This work makes use of the AR games framework in order to formulate the proposed reservation scheme. The main feature of this framework is that it allows the modeling of strategic behavior of users in systems that support reservations.

AR games are a type of non-cooperative game with a random number of players, and can be classified as Poisson games; thus, they are characterized by the properties of independent actions and environmental equivalence Myerson (1998b). Moreover, Poisson games are guaranteed to have at least one equilibrium when the types of users and the decisions are finite, and the utility function is bounded.

AR games are characterized by a number of servers, N, and a number of users requesting a server, D, both integer values. Requests for servers are made with a rate λ, and are allocated in a first-reserved-first-allocated fashion; then, users that do not make an AR are allocated randomly. Users decide whether to make an AR or not based on their own lead-time and the reservation fee, where the lead-time is the time elapsing between moment in which the users realize they require the service, and their arrival to the server. The random realizations of demand and lead-times for each slot are independent. In a general AR scheme, the provider sets a fee C for making a reservation that is only charged if the user is finally served, which may or may not be guaranteed.

A common assumption in AR is that each user follows a threshold strategy, which has been shown to be the best response of users given any initial belief Simhon et al. (2015). According to such strategy, users will make reservations if and only if their lead-time is larger than a threshold value.

It has been shown that the expected revenue for the provider is higher when information about available servers is not made available to users Simhon & Starobinski (2015); however, in this work we assume that such information is made public. We also assume that the users' rate of arrival is known to the CS and to the other users, which is a condition for the use of *Poisson Games*; however, *Extended Poisson Games* can be applied in the cases where such parameter is unknown Myerson (1998a).

This work also considers that the information of the state of the world is known, this means that every player knows the rate of arrivals of other player. Extended Poisson Games can be used if the state of the world is unknown, where the expected population sizes and player's utility function may depend on this state

To the best of the authors' knowledge, the existing literature on AR games Simhon & Starobinski (2016, 2014); Simhon et al. (2015); Simhon & Starobinski (2015) only focuses on schemes that feature one time-slot and one type of user; however, the framework can be extended for its application to more realistic CS systems, with multiple (or continuous) time-slots and types of users. In particular, this work extends the use of AR schemes to CS with one type of user and a continuum of arrival times.

2.2. Decision Models

Demand for charging sockets varies with prices, location of the CS, reservation fees (if any), sockets' charging modes, among other factors. In order to account for these decision criteria, consumers' decision on where to charge is modelled using Decision theory Bermudez (2009). Random Utility Theory (RUT) behavioural models are the most widely used theoretical paradigm for modelling choices among discrete alternatives Cascetta (2009); Ortuzar & Willumsen (2011). RUT models assume that individuals act rationally by choosing, within all available alternatives, the one associated with the higher net utility. These models were first studied by H. Block Pawl & Sets (1992) and McFadden McFadden (1973) and later choice models based in this theory as MNL were formulated by T. Domencich A. Domencich & McFadden (1975). Among these models, mixed logit models (MLM) are largely used in the literature related to EVs and CS Zoepf et al. (2013); Jabeen et al. (2013); Sun et al. (2015); Xu et al. (2017), because it provides a convenient way to model heterogeneity across individuals. However, MNL and other choice models Ge et al. (2017) are also used to consider different types of decision makers. The decisions covered in these works are such as charging or not at the end of a trip, charging preferences among charging at home, work, and public stations, preferred charging time, charging depending on the initial SOC and location.

Most of the existing literature on decision models assume that consumers behave as welfare maximizing agents (i.e., the *homo economicus* paradigm); however, there are works on behavioral economics Henrich et al. (2001); Frank (2016); Kluver et al. (2014), psychology Todd & Gigerenzer (2003a); Yamagishi et al. (2014) and biology Fehr & Fischbacher (2003) that don't share the same assumptions. Howerver, satisficing theory, introduced by Herbert A. Simon Simon (1955, 1956) postulates that consumers decisions are determined by an aspiration level, which can be different from consumer to consumer. The idea behind this approach is that consumers normally lack either sufficient information or time to make welfare maximizing decisions which involves computational capacity, choice models described before such as RUT and Elimination By Aspects Tversky (1972b,a) among others, involve the examination of all alternatives. Thus, satisficing theory considers a simplified decision process, where consumers are satisfied with any solution that yields a welfare exceeding their aspiration level.

2.2.1. Random Utility Maximization Models

This models are the richest and by far the most widely used theoretical paradigm for modelling choices among discrete alternatives, many application on transport modelling and theory are widely detailed in Cascetta (2009) and Ortuzar & Willumsen (2011). Choice models in literature related with electric vehicles are mainly focused on mixed logit models Zoepf et al. (2013), Jabeen et al. (2013), Sun et al. (2015), Xu et al. (2017)

because it provides a convenient way to model heterogeneity across individuals. However, MNL and other choice models Ge et al. (2017) are also used to consider different types of decision makers. The decisions covered in these works are such as charging or not at the end of a trip, charging preferences among charging at home, work, and public stations, preferred charging time, charging depending on the initial SOC and location.

Random utility theory postulates that individuals act rationally by choosing, within all available alternatives, the one associated to the higher net utility. As the modeler is an observer she doesn't possess complete information about the user, thus the utility U_i^q is structured as the sum of measurable attributes V_i^q and terms that reflects idiosyncrasies, particular preferences, errors, etc. ϵ_i^q (q index of alternative).

Expression (2.1) shows the proposed utility function of each user. It considers charging tariff, cost of reservation and location.

$$U_i^q = \theta_{i,\rho} \cdot \rho_q \cdot E_i + \theta_{i,C} \cdot C_i^{AR} + \theta_{i,q,d} \cdot d_i^q + \epsilon_i^q \tag{2.1}$$

In this work, all users have decided to charge in a charging station. Under this assumption, a MLM is proposed as a discrete location choice mechanism. This can be achieved by assuming that the random residuals ϵ_i^q are distributed IID as Gumbel. Thus, the choice probabilities are given by expression (2.1).

$$P_i^{q_0} = \frac{\exp\left(\beta \cdot V_i^{q_0}\right)}{\sum_q \exp\left(\beta \cdot V_i^q\right)} \tag{2.2}$$

2.2.1.1. Elimination by Aspects

This decision model is focused on evaluating attributes of all alternatives and eliminate those who doesn't meet a certain criteria, starting with the most important attribute to the decision maker. This work is introduced by Tversky in 1972 Tversky (1972b) and Tversky (1972a), and was later used as an heuristic elimination algorithm by Categorization Todd & Gigerenzer (2003b). When is applied, decision makers will reduce the number of alternatives considering only the most important ones. One alternative is evaluated at a time until just a couple of alternatives remain. For example, someone who is looking for a place to live may first compare different places on the basis of location, eliminating all places of a specific area. The person may then reduce the choice set further by setting a price threshold, followed by number of rooms, etc, until only one option remains.

2.2.2. Satisfyicing Theory

Satisficing theory, introduced by Herbert A. Simon Simon (1955) postulates that consumers decisions are determined by an aspiration level, which can be different from consumer to consumer. In general, people tend to make their decisions by achieving a certain level of satisfaction rather than optimizing. In this cases the revenue requirements are represented by an inequality that must be satisfied. Once this requirement is achieve, it isn't necessary to determine whether there is an alternative that has a higher revenue.

The theory postulates that as in actual human decision-making, alternatives are often examined sequentially. This is opposite to most global models of rational choice, where all alternatives are evaluated before a choice is made. When alternatives are examined sequentially, is very possible to chose the first satisfactory alternative that is evaluated Simon (1956).

An assumption of this model postulates that information gathering isn't costless. This means that when people find it easy to discover satisfactory alternatives, their aspiration level rises; as he finds it difficult to discover satisfactory alternatives, his aspiration level falls. The higher the information cost is, the simpler the cognitive process may become. However, there are simplifications and heuristics that allow reducing the amount of alternatives (e.g. Elimination By Aspects Tversky (1972b))

The main advantages of Satisficing theory are:

- It doesn't require an utility function to choose between alternatives.
- It hasn't a maximization problem.

- It doesn't consider the attributes of alternatives conjointly, but rather considers them independently.

2.2.2.1. Stochastic Satisficing

The Stochastic Satisficing theory is proposed in Gonz & Ortúzar (2017) where it is shown that this model allows variable or constant marginal rates of substitution and enables the explicit characterization of non-compensatory behaviours. In this work the model is tested on synthetic data and then on real data showing that is a good characterization of Satisficing behaviour for simple datasets.

In this model, the acceptability of an alternative i (A_{iq}) evaluated by individual q is given by the acceptability of each component of the acceptability vector. This vector is composed with the attributes or the combination of attributes.

$$Pr(A_{iq} = 1) = \prod_{\forall k \in K} Pr(a_{kiq} = 1) \tag{2.3}$$

In this equation, it is assumed that the acceptance of each attribute k is independent, then the probability of choosing this alternative is given by the product of each attribute acceptability.

Another assumption of this model is related with the behaviour when an acceptable alternative is found. In this matter, the individual can continue searching for other alternatives with a certain probability, which can decrease as the searching continues.

The Stochastic Satisficing model contemplates three simplifications:

(i) The probability of starting with a particular alternative is assumed equally for all alternatives and is chosen randomly.
(ii) The probability of the transition between alternatives when are inspected is considered equally between all alternatives.

(iii) The length of the search after finding an acceptable alternative is simplify. Therefore, it is assumed that the first acceptable alternative is chosen.

As it was mentioned before, the acceptability of an alternative is based on the acceptability of each alternatives attributes. Each individual q has a set of acceptability thresholds for each attribute $f^{'}$. Where $f^{'}$ represents the aspirational level for the specific attribute k and it can be assumed as a function for each individual. The acceptability of an attribute a_{kiq} in terms of its quantity or level is denoted as x_{kiq}.

The difference between the acceptability level of an attribute and its threshold can be assumed as a logistic distribution and equation 2.3 can be reformulated as:

$$Pr(a_kiq = 1) = \frac{exp(\lambda_{kiq}(x_{kiq} - f^{'}_{kiq}))}{1 - exp(\lambda_{kiq}(x_{kiq} - f^{'}_{kiq}))} \tag{2.4}$$

where λ_{kiq} is a scale factor that represents the impact of x_{kiq} in the probability of accepting attribute k. Thus a higher value of λ_{kiq} is related with a higher sensibility to changes in the attribute. The next Figure shows how the threshold and the scale factor affect the acceptability of an attribute Gonz & Ortúzar (2017).

$$a_{kiq} = \begin{cases} 1 & if\ x_{kiq} > f^{'}_{kiq} \\ 0 & \text{otherwise} \end{cases} \tag{2.5}$$

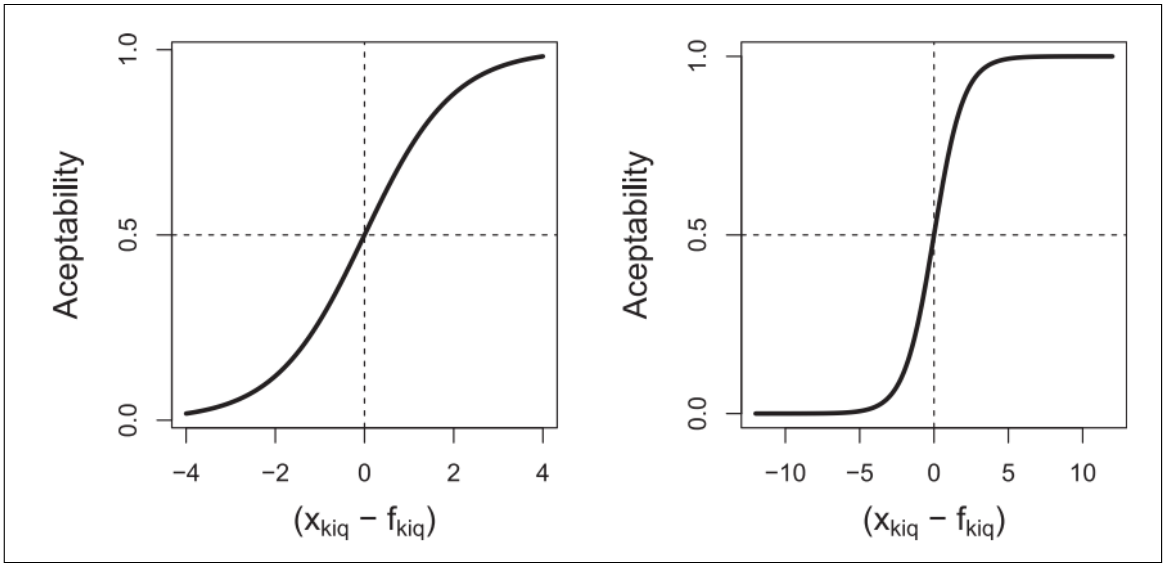


Figure 2.1. Acceptability function versus different scale factors and attribute-threshold differences .

3. MODEL

This chapter presents an optimization model formulated as a Mixed-Integer Lineal Problem (MILP) is developed to calculate the optimal charging tariffs and reservation fees of a CS that maximizes revenues from charging services and electricity market participation.

3.1. Nomenclature

This section presents the description of all sets, parameters and variables used to formulate the optimization model.

3.1.1. Sets

$\mathcal{I}$	Set of EVs $i \in \{i_0, \ldots, i_j\}$
$\mathcal{T}$	Set of time $t \in \{t_0, \ldots, t_l\}$
$\mathcal{S}$	Set of servers $s \in \{s_0, ..., s_q\}$

3.1.2. Parameters

E_i	Energy required by electric vehicle i
$\rho^{DA}(t)$	Day-ahead market price at time t
$\rho^{down}(t)$	Price for energy delivered as downward reserve at time t.
$\rho^{up}(t)$	Price for energy delivered as upward reserve at time t.
$\gamma^{down}(t)$	System deviation sign at time t, 1 when the system needs downward reserve and 0 otherwise.
$\gamma^{up}(t)$	System deviation sign at time t, 1 when the system needs upward reserve and 0 otherwise.
$\rho^{down}_{cap}(t)$	Price for available downward reserve capacity at time t
$\rho^{up}_{cap}(t)$	Price for available upward reserve capacity at time t
$\rho_e(t)$	Charging tariff in the rest of the system in time t

P_i^{max}	Maximum charging rate of vehicle i
η_i^+	Charging efficiency of vehicle i
$T_i(T)$	Vehicle charging state parameter, $(0,1]$ when the vehicle i need to charge in time t, 1 if the vehicle need to charge the entire interval and 0 if the vehicle doesn't need to charge.
SOC_i^0	Battery initial state of charge of vehicle i
SOC_i^f	Battery final state of charge of vehicle i
d_i^o	Distance of vehicle i to its nearest charging station
d_i^{cs}	Distance of vehicle i to the charging station under study
κ_d	Distance weight factor
Δt	Duration of each time interval
N	Total number of charging facilities in the charging station
M	A very large number
$P_{i,s}^{AR'}$	Probability of vehicle i of being served if s servers are in use

3.1.3. Variables

$\rho(t)$	Charging tariff in time t
$C^{AR}(t)$	Reservation fee for time t
$E^{DA}(t)$	Energy purchased in the day-ahead market for the charging station in time t
$E^{down}(t)$	Energy purchased in the spot market if downward reserve is needed in time t
$E^{up}(t)$	Energy purchased in the spot market if upward reserve is needed in time t
$\hat{P}^{down}(t)$	Downward reserve capacity bid in time t
$\hat{P}^{up}(t)$	Upward reserve capacity bid in time t
$Av(t)$	Availability of vehicles in time t
$P_{av}(t)$	Maximum charging power available at time t
R_i	Profit for the energy charged to vehicle i

C_i^{AR}	Reservation fee charged to vehicle i
D_i	Charging decision binary variable, 1 if the vehicle i chooses to charge in the charging station, o otherwise.
S_i	Service state binary variable, 1 if the vehicle i is served in the charging station, 0 otherwise.
AR_i	Advance reservation decision, 1 if the vehicle i chooses to reserve, 0 otherwise
m_i	Number of servers in use that vehicle i observes
$\epsilon_i^+(t)$	Charged energy to vehicle i in time t
$SOC_i(t)$	Battery state of charge of vehicle i in time t
$X_{i,k}$	Auxiliary SOS1 binary variable for vehicle i if s servers are in use
$Z_{i,k}$	Auxiliary variable which denotes the charging tariff of vehicle i if s servers are in use.

In this section, an optimization model formulated as a Mixed-Integer Lineal Problem (MILP) is developed to calculate the optimal charging tariffs and reservation fees of a CS that maximizes revenues from charging services and electricity market participation.

3.2. Objective Function

The objective function (3.1) consists in maximizing the charging station revenue, and is divided in seven parts: i) income for selling the energy to the EVs; ii) income for the reservation of each EV served ; iii) cost of buying energy in the day ahead market; iv) cost of charging the EV with downward reserve; v) income for having downward reserve capacity available; vi) income for having upward and reserve capacity available; vii) income for providing upward reserve.

$$\max \begin{pmatrix} \sum_{i \in I} R_i + \sum_{i \in I} C_i^{AR} \\ -\sum_{t \in T} \rho^{DA}(t) \cdot E^{DA}(t) \\ -\sum_{t \in T} \rho^{down}(t) \cdot E^{down}(t) \cdot \gamma^{down}(t) \\ +\sum_{t \in T} \rho^{down}_{cap}(t) \cdot \hat{P}^{down}(t) \cdot \gamma^{down}(t) \\ +\sum_{t \in T} \rho^{up}(t) \cdot E^{up}(t) \cdot \gamma^{up}(t) \\ +\sum_{t \in T} \rho^{up}_{cap}(t) \cdot \hat{P}^{up}(t) \cdot \gamma^{down}(t) \end{pmatrix} \tag{3.1}$$

3.3. Market Constraints

The aggregation of EVs clusters allows the CS to participate in whole-sale electricity markets. Moreover, the inherent charging features of EVs make the EV Aggregator a suitable regulation provider for the ancillary services market. In Bessa et al. (2012); Sortomme & El-Sharkawi (2012); Jin et al. (2013), the EV Aggregator acts as a commercial middleman between electricity market and EV owners. Similarly to these works, in this paper the CS participates in a day-ahead, real-time and a regulation market.

On one hand, the day-ahead market bids cover all 24 h of the next day where the market closure occurs in the morning of th next day (≈ 10 h). On the other hand, the regulation market allows upward and downward reserve separated bids for each hour of the day. The Aggregator presents capacity bids and the amount of reserve contracted is settled at the market clearing price. Accordingly, constraints (3.2b) to (3.2g) sets market rules to trade energy and regulation services in the electricity market for all time $t \in \mathcal{T}$. T

$$\sum_i \epsilon_i^+(t) \leq E^{DA}(t) + E^{down}(t) - E^{up}(t) + \frac{P^{down}(t)}{\Delta T} \cdot pf(t) - \frac{P^{up}(t)}{\Delta T} \cdot pf(t) \tag{3.2a}$$

$$Av(t) \cdot P^{max} = Pav^{max}(t) \tag{3.2b}$$

$$Av(t) = \sum_{i \in I} T_i(t) \cdot S_i \tag{3.2c}$$

$$\frac{E_{DA}(t)}{\Delta T} + \frac{E^{down}(t)}{\Delta T} + P^{down}(t) \leq Pav^{max}(t) \tag{3.2d}$$

$$P^{up}(t) \cdot \Delta T + E^{Down}(t) \leq E_{DA}(t) \tag{3.2e}$$

$$P^{down}(t) \leq M \cdot \gamma^{down}(t) \tag{3.2f}$$

$$P^{up}(t) \leq M \cdot \gamma^{up}(t) \tag{3.2g}$$

The constraint (3.2a) ensures that all the energy that is sold to charge EVs is trade in the electricity market, (3.2b) and (3.2c) define the maximum power available at time t, (3.2d) and (3.2e) ensure that the downward reserve doesn't exceed the maximum available capacity and that the upward reserve bids are equal or below the electrical energy bid in the day-ahead market. The last two constraints (3.2f) and (3.2g) guarantee that upward and downward reserve are bid when is possible.

The next constraints are valid for all vehicles $i \in \mathcal{I}$,

$$-M \cdot S_i \leq R_i \leq M \cdot S_i \tag{3.2h}$$

$$-M \cdot (1 - S_i) \leq R_i - \rho(t) \cdot E_i \leq M \cdot (1 - S_i) \tag{3.2i}$$

To face the nonlinearity of multiplying the variables S_i and ρ in the objective function Big M constraints are used. This problem arises from the necessity of charging only vehicles who are served. Expressions (3.2h) and (3.2i) create a new variable R_i that takes value only when the vehicle is served.

As the CS is supplied by the distribution network, electrical energy and reserve bids may be constrained by the DSO. During peak hours and a stressed feeder, provide downward reserve may be dangerous for the system Clement-Nyns et al. (2010).

3.4. Battery Constraints

The next constraints represent the charging dynamics of EV's batteries.

$$SOC_i(t+1) = SOC_i(t) + {\epsilon^+}_i(t) \cdot \eta^+, \; \forall\, i \in I, t \in T \tag{3.3a}$$

$$SOC_{0i} = SOC_i(t_0), \qquad \forall\, i \in I \tag{3.3b}$$

$$SOC_{f_i} \leq SOC_i(t_f), \qquad \forall\, i \in I \tag{3.3c}$$

$$\frac{{\epsilon^+}_i(t)}{\Delta T} \leq P_i^{max} \cdot T_i(t) \cdot S_i, \qquad \forall\, i \in I, t \in T \tag{3.3d}$$

Constraint (3.3a) is a linear simplification of the charging pattern of the vehicle i. Where only charging is allowed and the state of charge SOC_i in time t is given by the energy in $t-1$ and the charged energy in this period. The boundary conditions are given by constraints (3.3b) and (3.3c). The last expression sets the maximum charging rate, which can be limited by the capacity the EV or the CS.

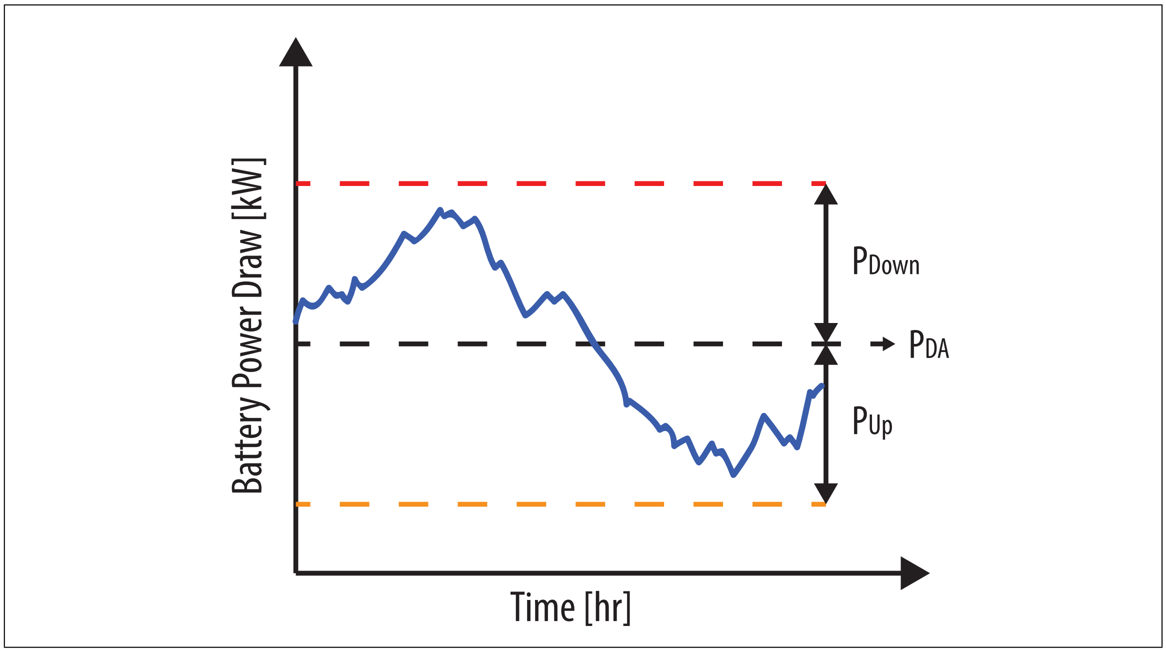


Figure 3.1. Graphical depiction of a battery power draw for regulation.

3.5. Demand constraints

On one hand, the aspiration level of each user is represented by U_i^o, which is the utility of being served in the nearest charging station from vehicle i. On the other hand, the utility of being served in the studied CS is denoted by U_{cs}. The details of the utility expressions are presented next.

$$U_o = \rho_e \cdot E_i + \kappa_d \cdot d_o$$

$$U_{cs} = \rho . E_i + \kappa_d \cdot d_{cs} + C_i^{AR}(t)$$

With these expressions we can build the equations of the Satisficing Demand model for all users.

$$U_i^{cs} - U_i^{o} \leq M \cdot D_i \tag{3.4a}$$

$$U_i^{o} - U_i^{cs} \leq M \cdot (1 - D_i) \tag{3.4b}$$

Expressions (3.4a) and (3.4b) are Big M constraints that model the charging decision for all vehicles $i \in \mathcal{I}$. If the utility of being served in the charging station under study U_i^{cs} is higher than the aspiration level U_i^{o}, then the vehicle chooses to charge in CS.

3.6. Advance Reservation Constraints

For simplicity a continuous time and one type of user formulation is proposed in this work. This is made because arrivals and departures are in a continuous fashion and a simple rate tariff is applied (e.g. only fast charging). A shows a multiple types of users and time slots modelling formulation, this appendix helps understand the basic steps in order to achieve a continuous formulation.

Additionally, the rate of arrivals is the same for all time and is revealed to the users. Note that not all drivers affect directly the decision of a single user, a specified range that considers the staying time ΔT and the leadtime t is taken into account to face this issue.

In a continuous time formulation the arrivals are in a continuous fashion. For this case we will consider that users are statistically equal, this means that vehicles with same characteristics follow the same threshold strategy. This implies that if users with leadtime t and staying time ΔT make an AR for time t_{arr}, then all users with leadtime $t + \alpha$ are going to make AR for being served in $[t_{arr}, t_{arr} + \Delta T]$, for $\alpha \in \mathbb{R}_0^+$. And if he is better off not making AR then all users with leadtime $t - \beta$ are not going to make an AR for being served in $[t_{arr}, t_{arr} + \Delta T]$, for $\beta \in \mathbb{R}_0^+$. A threshold user is then defined as the user whose utility is equal whether taking the decision of making a reservation (AR) or not (AR') and her leadtime is denoted as t^*.

As ΔT and the utility of being served is different for each user a threshold user is difficult to find for the charging station owner. However, each user decides to make an AR or not based on the same utility principle. The utility function of users who take decision AR_i and served is given by $(U_i^s - C)$, where U_i^s is the utility of being served and C is the reservation cost. This expression is valid only when there are available servers, otherwise the service cannot be provide by the CS and the utility becomes zero. For a user who takes the decision AR_i', the utility function is given by the utility of being served U_i^s multiplied by the actual probability of being served, $\mathbb{P}(S_i|AR_i')$:

$$\mathbb{P}(S_i|AR_i') = \mathbb{P}_{AR_i'} = \mathbb{P}(\tilde{D} < N|\tilde{D} \geq n), \tag{3.5}$$

using Bayes' theorem we obtain

$$\mathbb{P}_i^{AR'} = \frac{\mathbb{P}(n \leq \tilde{D} < N)}{1 - \mathbb{P}(\tilde{D} < n)}.$$

Equation 3.5 denotes the probability of being served without making AR given the number of free servers. Where $\tilde{D}$ is the demand for the charging service in a specific studied time ΔT, N is the total number of servers (charging facilities) and n represents the occupied servers (being in use and reserved). The probability $\mathbb{P}$ is assumed as a Poisson distribution with rate λ_i.

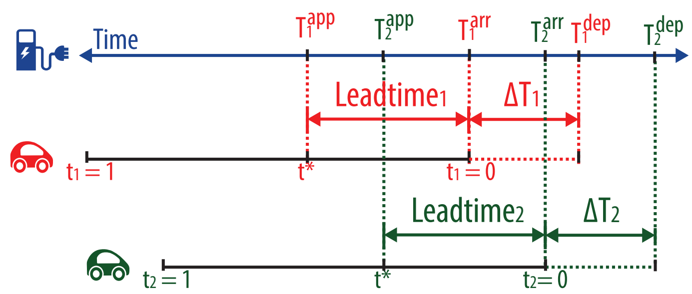
$$\mathbb{P}(k) = e^{\lambda_i} \frac{\lambda_i^k}{k!}$$

The expression for λ_i is given by

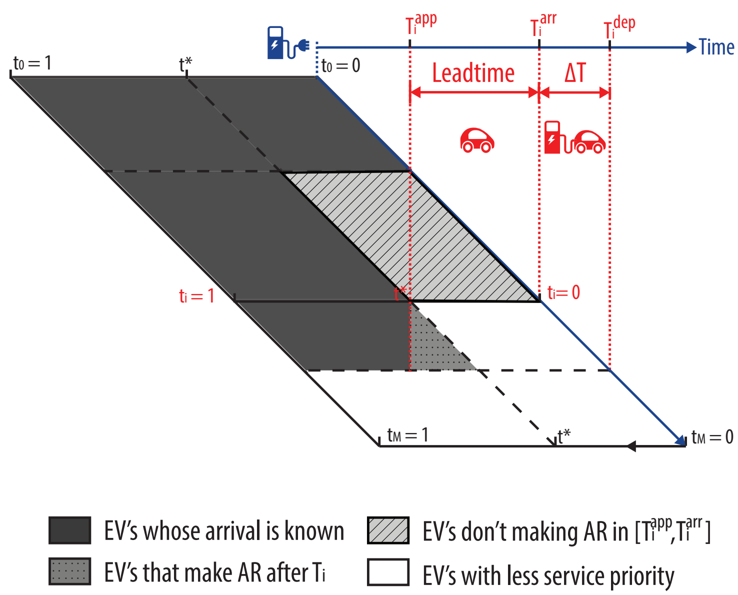
$$\lambda_i = \begin{cases} \lambda(t)\left(t_i^2 + \frac{\Delta T^2}{2}\right) & \text{if } \Delta T_i \leq t_i \leq (1 - \Delta T_i), \\ \lambda(t)\left(t_i^2 + \frac{\Delta T^2}{2} - A_1\right) & \text{if } t_i < \Delta T_i, (1 - \Delta T,) \\ \lambda(t)\left(t_i^2 + \frac{\Delta T^2}{2} - A_2\right) & \text{if } t_i > \Delta T_i, (1 - \Delta T), \\ \lambda(t)\left(t_i^2 + \frac{\Delta T^2}{2} - A_1 - A_2\right) & \text{if } (1 - \Delta T_i) < t_i < \Delta T_i. \end{cases}$$

where $A_1 = \frac{(\Delta T_i - t_i)^2}{2}$, $A_2 = \frac{(\Delta T - (1 - t_i))^2}{2}$ and $\Delta T \leq 1$.

For a better understanding of the expression for λ_i, a graphical depiction is shown in Figure 3.2. Figure 3.2(a) illustrates the arrivals, leadtime, departures and staying time for two EVs, in this example a parking overlap can be observed between T_2^{arr} and T_1^{dep}, during this time both vehicles are being charged in the CS. Figure 3.2(b) shows a theoretical continuous of possible arrivals of EVs (from 0 to M) that can be served in the CS, with an emphasis in the vehicle i. The darkest area represents vehicles whose arrival is known, i.e., users that have decided to make an AR or have arrived before T_i^{app}. The gray area filled with lines represents EVs that doesn't reserve but will arrive before vehicle i. The gray area filled with dots represents vehicles that might reserve and will arrive within $[T_i^{app},\ T_i^{app} + \Delta T]$. Finally, the white area represents vehicles with less service priority.



(a) Charging example for two vehicles.



(b) Charging example for M vehicles

Figure 3.2. Arrival, leadtime, staying time and departure characteristics for two 3.2(a) and M 3.2(b) vehicles.

Aggregation Poisson property allows to formulate an expression for λ_i. This expression covers the arrivals of individuals before the studied user in a specific time and users who make AR for the same time but with arrivals before the studied user.

The AR decision for each user is done by evaluating the utility of making the reservation or not, this is based on the expected number of users who arrive at the CS in the required time. Equation (3.6) compares both utilities.

$$\begin{aligned} U_i^{AR'} &= U_i^{AR} \\ \mathbb{P}_i^{AR'} \cdot U_i^s &= \mathbb{P}_i^{AR} \cdot (U_i^s - C). \end{aligned} \tag{3.6}$$

As $\mathbb{P}_i^{AR'} = 1$, the expression becomes:

$$\mathbb{P}_i^{AR'} \cdot U_i^s = U_i^s - C.$$

Figure 3.3 shows the probability function $\mathbb{P}_i^{AR'}$ given a set of parameters. $\mathbb{P}_i^{AR'}$ is a non-increasing function of the leadtime, as leadtime increases, the probability that more users are served in the required time also increases. All the $N - 1$ curves start at one because the probability that vehicles arrive and use the remaining free servers is one for a leadtime equals to zero.

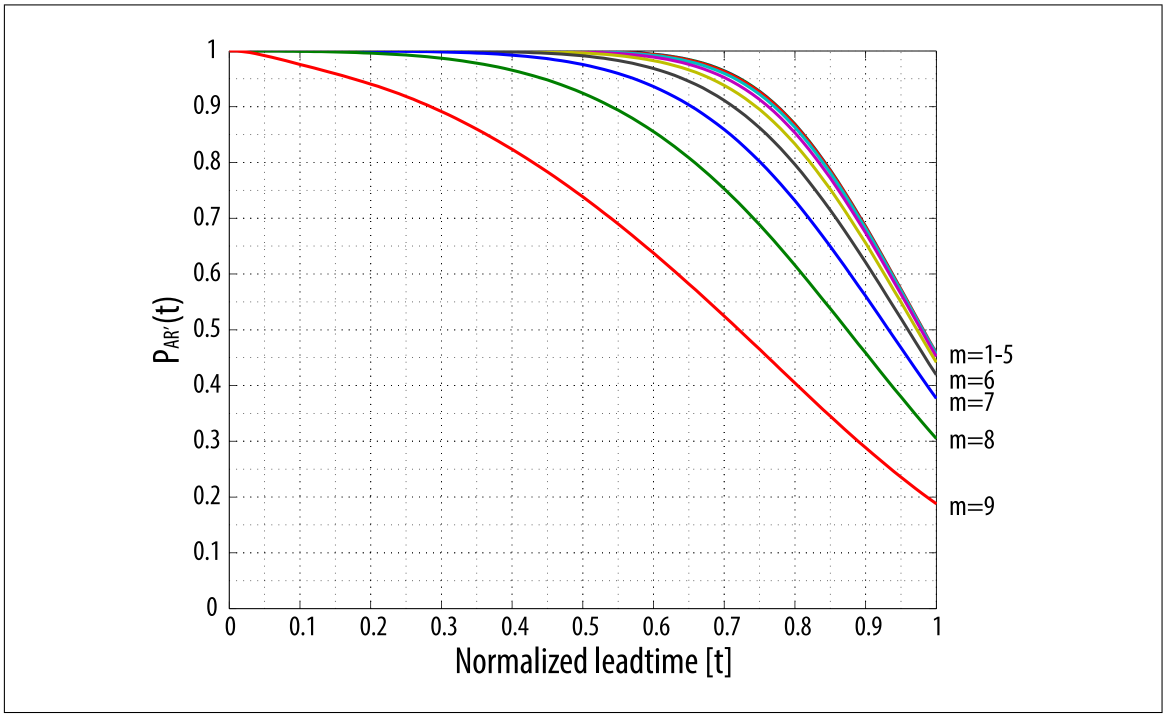


Figure 3.3. Function $\mathbb{P}_i^{AR'}$ as a function of the leadtime t for different servers in use m, given $\lambda = 10$ and $\Delta T = 0.2$

U_i^s denotes the utility of being served and can be written as the sum of two terms. The first one covers the utility of buying the required energy and is given by $E_i[\rho_i^w - \rho]$, the willingness to pay per unit of energy ρ_w is represented as ρ_e. The second term covers the utility related to the distance to the CS and is given by $\kappa_d(d_i^o - d_i^{cs})$. Thus, equation 3.6 can be reformulated as:

$$\begin{aligned} &P_i^{AR'}\left[E_i[\rho_e - \rho] + \kappa_d(d_i^o - d_i^{cs})\right] \\ &= E_i(\rho_e - \rho) + \kappa_d(d_i^o - d_i^{cs}) - C + U_i^u. \end{aligned} \tag{3.7}$$

In the right side the term U_i^u is added in order to cover the utility that a user gives for clearing the uncertainty of being served, this term will be analyzed later.

Finally, the next constraints model the advance reservation decision for all vehicle $i \in \mathcal{I}$ and time $t \in \mathcal{T}_i$.

$$\begin{aligned} &\mathbb{P}_i^{AR'}\left(E_i \cdot \rho_e(t) + \kappa_d(d_i^o - d_i^{cs})\right) - U_u \\ -E_i \cdot \sum_{s \in \mathcal{S}} &P_{i,s}^{AR'} \cdot Z_{i,s} - \kappa_d(d_i^o - d_i^{cs}) - E_i[\rho_e(t) - \rho] \\ &\leq M(1 - AR_i) - C^{AR}(t) + M'(1 - D_i) \end{aligned} \tag{3.8a}$$

$$\begin{aligned} &-\mathbb{P}_i^{AR'}\left(E_i \cdot \rho_e(t) + \kappa_d(d_i^o - d_i^{cs})\right) \\ &+E_i \cdot \sum_{s \in \mathcal{S}} P_{i,s}^{AR'} \cdot Z_{i,s} + U_u + \kappa_d(d_i^o - d_i^{cs}) \\ +E_i[\rho_e(t) - \rho] &\leq M(AR_i) + C^{AR}(t) + M'(1 - D_i) \end{aligned} \tag{3.8b}$$

Constraints (3.8a) and (3.8b) are Big M constraints that represent equation (3.6) and compare the utilities of making a reservation or not for all vehicle $i \in \mathcal{I}$ and time $t \in \mathcal{T}_i$. If a user's utility of choosing a reservation is higher, then the decision variable AR_i takes the value of one. These constraints are valid only if the user decides to charge in the charging station under study ($D_i = 1$).

$$-M \cdot AR_i \leq C_i^{AR}(t) \leq M \cdot AR_i \tag{3.8c}$$

$$-M(1 - AR_i) \leq C_i^{AR}(t) - C^{AR}(t) \leq M(1 - AR_i) \tag{3.8d}$$

As the variable R_i, C_i^{AR} is created to face the nonlinearity of multiplying the variables $C^{AR}(t)$ and AR_i in the objective function. Big M constraints (3.8c) and (3.8d) are used to charge the reservation fee only to the EV's who make an AR.

3.7. Additional Constraints

The constraints (3.9a) to (3.9c) are used to represent the nonlinearity function probability for all vehicle $i \in \mathcal{I}$ being served without making a reservation if $s \in \mathcal{S}$ servers are in use.

$$\mathbb{P}_i^{AR'} = \sum_{s \in \mathcal{S}} P_{i,s}^{AR'} \cdot X_{i,s} \tag{3.9a}$$

$$0 = \sum_{s \in \mathcal{S}} s \cdot X_{i,s} - m_i \tag{3.9b}$$

$$1 = \sum_{s \in \mathcal{S}} X_{i,s} \tag{3.9c}$$

These constraints are build to formulate an Special Order Set of type 1 (SOS1).

$$-M \cdot X_{i,s} \leq Z_{i,s} \leq M \cdot X_{i,s} \tag{3.9d}$$

$$-M(1 - X_{i,s}) \leq Z_{i,s} - \rho \leq M(1 - X_{i,s}) \tag{3.9e}$$

Constraints (3.9d) and (3.9e) are valid $\forall i \in \mathcal{I}$ and $s \in \mathcal{S}$. These Big M constraints are used to face the nonlinearity of variable multiplication between ρ and $X_{k,i}$ presented in the AR decision constraints (3.8a) and (3.8b).

Constraints (3.9f) to (3.9k) are made for all vehicle $i \in \mathcal{I}$. (3.9f) and (3.9g) are logic expressions that ensures that if a vehicle doesn't chooses to charge in the charging station, then she cannot be served, neither make a reservation in this station.

$$AR_i \leq S_i \tag{3.9f}$$

$$S_i \leq D_i \tag{3.9g}$$

$$\sum_{k\in\mathcal{I}_i^A} AR_k + \sum_{k\in\mathcal{I}_i^B} AR_k$$

$$+\sum_{k\in\mathcal{I}_i^C} V_k - N \leq M \cdot (1 - S_i) + M' \cdot (1 - D_i) \tag{3.9h}$$

$$N - \sum_{k\in\mathcal{I}_i^A} AR_k - \sum_{k\in\mathcal{I}_i^B} AR_k$$

$$-\sum_{k\in\mathcal{I}_i^C} V_k \leq M \cdot S_i + M' \cdot (1 - D_i) \tag{3.9i}$$

$$\sum_{k\in\mathcal{I}_i^A} AR_k + \sum_{k\in\mathcal{I}_i^D} V_k$$

$$-N \leq M \cdot (1 - AR_i) + M' \cdot (1 - D_i) \tag{3.9j}$$

$$N - \sum_{k\in\mathcal{I}_i^A} AR_k - \sum_{k\in\mathcal{I}_i^D} V_k \leq M \cdot AR_i + M' \cdot (1 - D_i) \tag{3.9k}$$

$$-M \cdot (1 - S_i) \leq \sum_{k\in\mathcal{I}_i^A} AR_k - \sum_{kin\mathcal{I}_i^D} V_k - m_i \leq M \cdot (1 - S_i) \tag{3.9l}$$

For constraints (3.9h) to (3.9j) four sets are defined: $\mathcal{I}_i^A$, $\mathcal{I}_i^B$, $\mathcal{I}_i^C$ and $\mathcal{I}_i^D$. The first and second one denotes the set of vehicles who require being served when user i needs to, and decide to charge before and after user i. The third and fourth sets cover the vehicles who arrive before user i and appear before and after user i. These three Big M constraints ensures the priority of service of vehicles who make an AR and those who arrive first.

4. RESULTS AND DISCUSSION

In this section we analyze the AR schemes management structure by comparing the performance of the AR model with a first-come-first-served FCFS management structure. FCFS structure can be modelled as an AR scheme with a large cost of reservation for each time slot. Thus, FCFS is a lower bound of the AR maximization problem. As the solution of using an AR scheme is always equal or higher than a FCFS the comparison between the two structures is analyzed in terms of the management of charging tariff, AR cost, driver decisions making and welfare.

At the end of this section a Stochastic Satisficing demand model is proposed to compare the modelling of drivers' decisions considering the uncertainty in the demand. This model tries to undertake different behaviours that depends on personal tastes, idiosyncrasy and not measurable attributes.

The model is built as an MILP optimization problem and is solved in the python-based open software Pyomo, where Gurobi is used as solver. A 1% MIP gap is selected.

4.1. Simulation Setup

A test case is built with 60 vehicles and 10 CSs randomly distributed spatially where the CS in study is located in the centre of a normalized area. Six time slots of one hour each is analyzed, arrivals and departure are allowed during all the studied time. The maximum time that a vehicle is allowed to make an advance reservation is 12 hours before the required time-slot.

The CS in study is equipped with 5 charging sockets with fast charging allowed (≈50kW). If a vehicle is not served in this CS, then it is assumed that is served in another CS with a charging tariff of ρ_e per kWh. Parameters such as location or arrival time are set randomly. However, these parameters can be estimated from historical data.

On one hand, the real time price profile follows a sinusoidal shape to simulate a real price variation in time. On the other hand, the profile for the day-ahead prices is normalized and set to 1 per kWh to simplify and generalize the calculation. Up regulation and Down regulation is allowed in the first half and the second half of the simulation time respectively.

The distance disutility parameter κ_d is set to 5 per unit of distance. The calculation of this parameter takes into account an average efficiency of 5 km per kWh, the cost of getting to the CS and come back, and an extra disutility for the total charging time.

4.2. Study Cases

This section describes three Case Studies built to evaluate the management performance of the proposed AR model.

- **Study Case 1 - Fixed charging tariff**: in this Case Study the charging tariff is fixed in order to induce situations of interest such as positive and negative values of the reservation fee.
- **Study Case 2 - Variable charging tariff:** unlike the previous case, this Case Study the charging tariff is a variable optimized in order to maximize the CS owner profit.
- **Study Case 3 - Flexible EVs**: the focus of this Case Study is the evaluation of the EV's flexibility in the CS's profit. The flexibility here is assumed as a longer staying time, but with a constant charging requirement.

4.3. Results and Discussion

This subsection discusses comparisons between the results of the Study Cases described before in terms of the charging tariff, AR cost, market participation and welfare.

The owner of the CS has four main revenue streams in managing the CS:

- Ancillary Services Market: the owner of the CS is allowed to provide up or down regulation capacity for each hour if is available.
- Day-ahead and real-time Market Arbitrage: as EVs can be a flexible load, buying and selling energy in both of these markets gives to the owner of the CS a tool to profit with the price variability.
- Charging Tariff: the CS owner can profit if the Charging Tariff per energy sold is higher than the energy bought in the electricity market.
- Reservation Scheme: the CS owner offers to the drivers the opportunity of reducing the uncertainty of being served for a reservation fee.

The next subsections discuss how the CS owner use these four instances through the management of its resources.

4.3.1. Charging Tariff and Reservation Cost

The charging tariff has a direct relation with the charging demand. Figure 4.1 shows a demand curve for charging services in the Case Study 1 with a Satisficing model, which is used to represent driver's charging choices. It can be observed that demand decreases as the charging tariff increases, drivers that are willing to pay more for each kWh are those who are closer to the CS. A saturation of the available sockets of the charging station in ≈36 EVs can be observed when the charging tariff is fixed at $0,9[\$/kWh]$.

Most of the existing charging tariff are fixed rates and time-of-use tariffs for the different charging levels. The CS owner can adjust the charging tariff according to the market prices and charging demand. It is reasonable to decrease the charging tariff if the market provides incentives for being able to provide ancillary services or if the energy market prices are low. On the other hand, the owner of the CS will increase the charging tariff if the demand is inelastic or if prices allows a proper arbitrage of the energy trade in the market. Additionally, incentives such as reservations, can be offered to motivate drivers to charge even if the tariff is high.

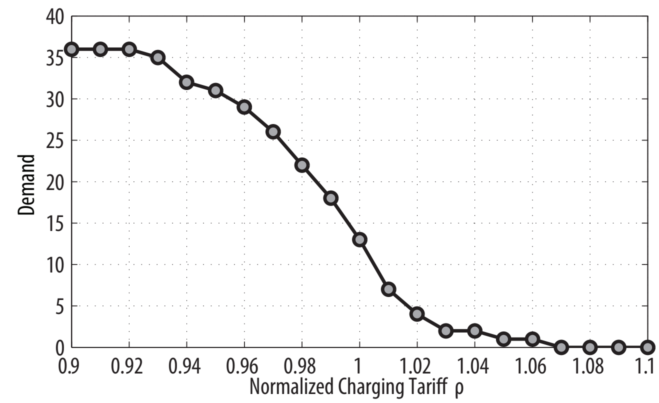


Figure 4.1. Demand curve as a function of the charging tariff using a Satisficing model for drivers charging choice model.

Figure 4.2 shows the available power (red line) and the actual charging power (blue line) of the EVs for an optimized fixed charging tariff (Case Study 2) with an AR and a FCFS scheme. The dashed lines denote the FCFS case and the solid lines the AR scheme case. It can be observed that in hours 4, 5 and 6, the AR structure has more power available than the FCFS scheme, this is because in these hours the reservation cost is settled in negative values in order to incentive drivers to charge during this period. A low positive cost of reservation in the firsts hours produces a similar drivers' charging response for a FCFS and a AR schemes. This is mainly because the charging tariff is not low enough to incentive drivers to come and charge. In this particular case the optimized charging tariff for an AR scheme is $\rho^*_{AR} = 1.003$ and is similar to the FCFS structure $\rho^*_{FCFS} = 1$.

As it was shown in Figure 4.2 the reservation cost is used as a price signal for vehicles to charge in opportune periods. To achieve a proper response two strategies can be followed. The first one decreases charging prices in order to increase the expected demand, with an elevated demand an AR scheme ensures that users take advantage of low charging tariffs. The second strategy increases the charging price and incentives users to charge in specific periods with a negative cost of AR. This strategy can be applied in periods when charging is not profitable for the CS owner.

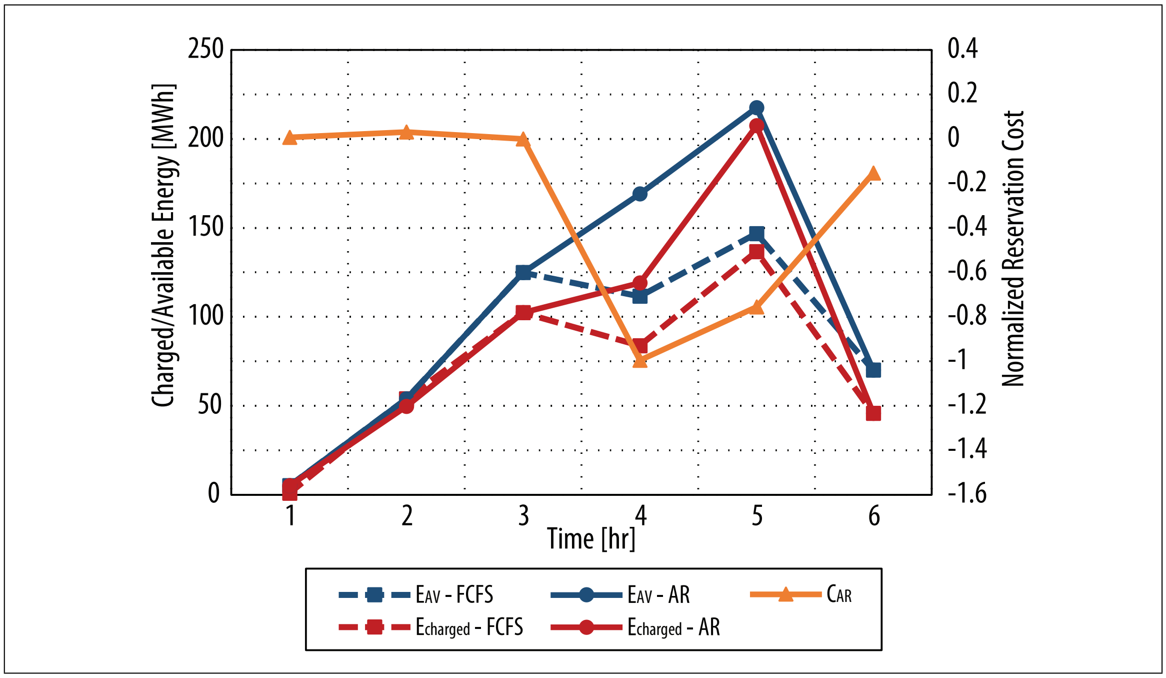


Figure 4.2. Charging profiles and power availability of electric vehicles for a fixed tariff ρ_e and an optimized tariff ρ.

To study these strategies Figure 4.3 shows a boxplot of the reservation as a function of the charging tariff for the Case Study 1. If the charging tariff is set low (0.9 per kWh) more drivers are motivated to charge, in this cases the reservation fee takes a positive value. As the charging tariff increases the reservation cost decreases, moreover, it becomes negative.

An optimized positive value of the reservation fee indicates that drivers give more importance to clear the uncertainty of being served in the CS with a low charging tariff. On the other hand, a negative value of the reservation indicates that an additional incentive has to be set to counteract the charging tariff prices and distance.

4.3.2. Driver's Charging Characteristics

This subsection describes the charging behaviour using a Satisficing decision model. An analysis on the features of vehicles that decide to charge an those who decide to make an AR is made.

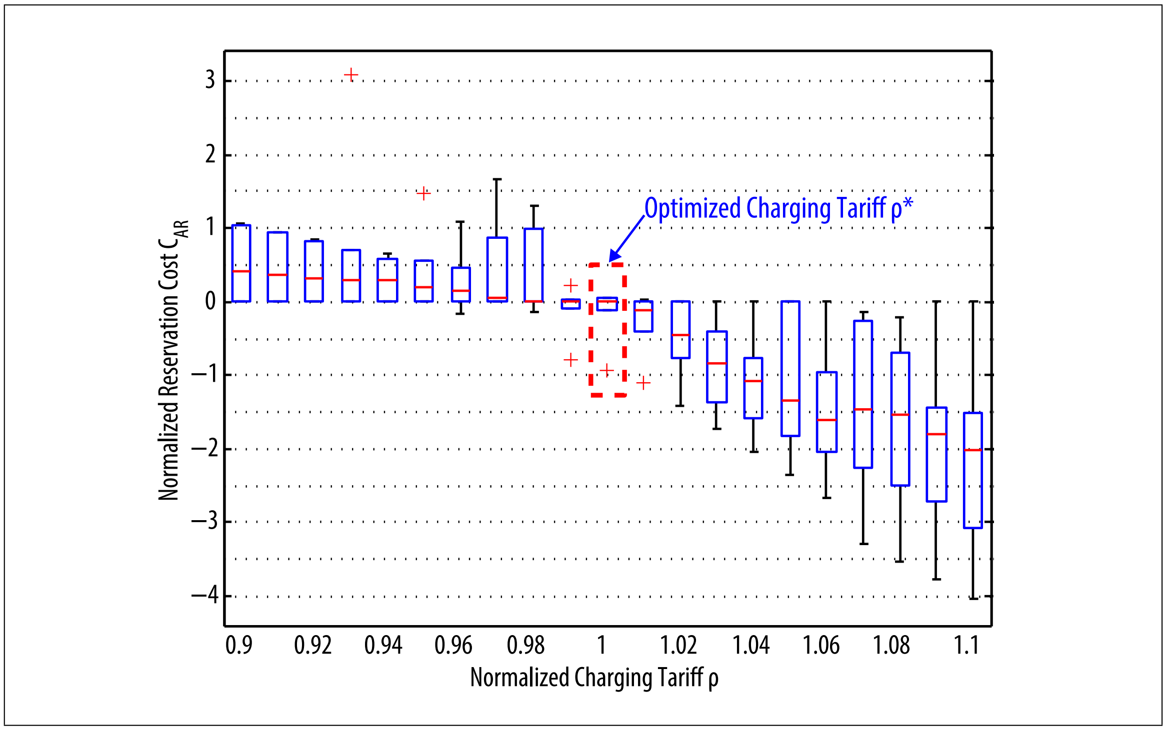


Figure 4.3. Reservation cost boxplot as the charging tariff increases.

In this work the amount of energy required, distance, arrival time, leadtime and willingness to pay are presented as the main features for the driver to take his charging decision. Charging tariff and AR cost are directly related with the willingness to pay of the driver, however this attributes are managed by the CS owner.

Figure 4.4 shows vehicles that decide to charge in the studied CS for the Case Study 2, each circle represent an electric vehicle, the ones that are filled with blue, red or green decide to charge in the CS when using structure AR, FCFS or in both cases respectively. The vertical axis denotes the distance difference between the CS and the distance that satisfy a minimum aspiration level for each driver, which in this work is considered as d_o. The horizontal axis denotes the leadtime.

To calculate the drivers' utility a ρ_e price is settled for all CSs except the studied one, in which a charging tariff ρ is optimized.

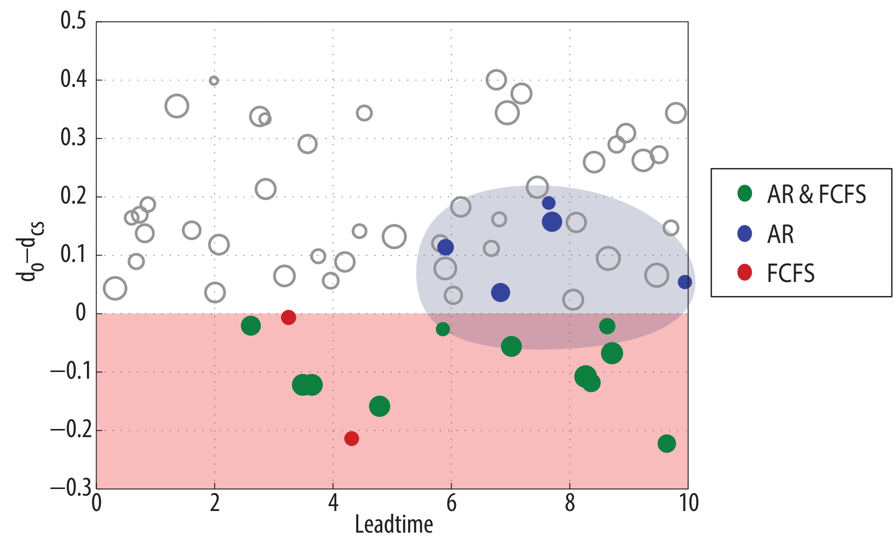


Figure 4.4. Charging decision as a function of the distance to the CS, leadtime and arrival time.

For a FCFS structure, EVs inside the red area decide to charge in the studied CS. Moreover, if a FCFS structure is used and the optimized charging tariff ρ is similar to ρ_e, the red area encloses all vehicles whose aspiration level is surpassed.

Having a long leadtime increase the uncertainty of being served if an AR is not made. However, if the driver takes the decision of making an AR that uncertainty is reveal and cleared. Thus, drivers whose leadtime are longer are more probable to be served when an AR scheme is used. This can be straightforwardly from Figure 4.4, in which the blue area encloses vehicles whose leadtimes are high and decide to charge even if they are distant to the CS.

The difference between the available power and the actual charging profile is given by the flexibility that drivers possess. Being parked more time that the required to charge the battery, gives to the CS owner the flexibility of charging when is opportune.

Figure 4.5 shows the objective function as the flexibility increases for Case Study 3. In this case, the flexibility is defined as the extra staying time that a driver is parked in the CS without an additional energy requirement. Initially the objective function increases with

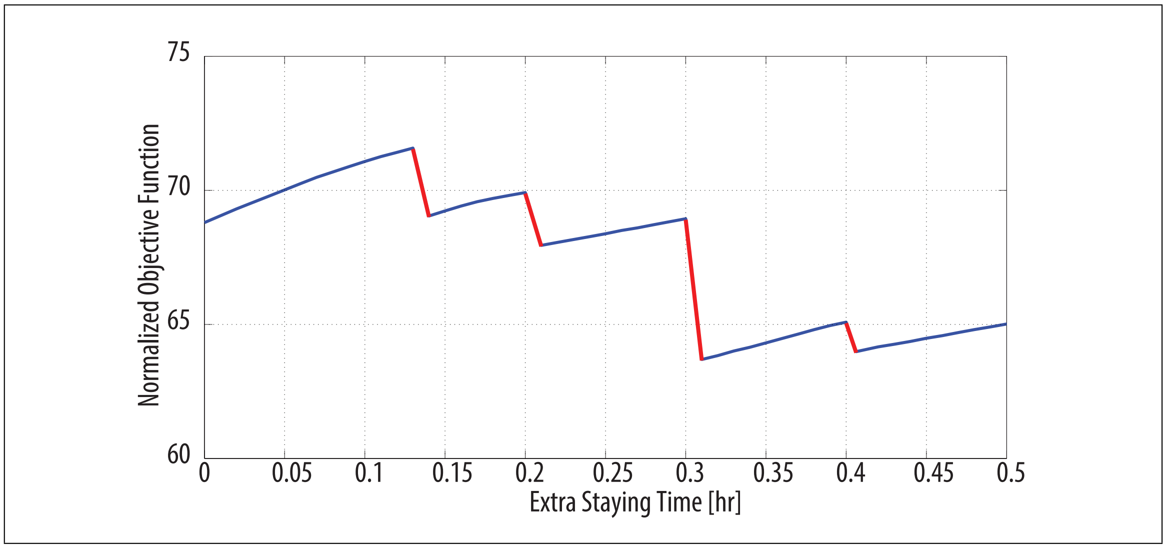


Figure 4.5. Objective function as the drivers' flexibility increases.

the flexibility of the drivers. This is because the CS owner can manage the resources that has available freely. A step down in the profit can be observed if the extra staying time keeps on increasing, because being in the CS for a long time takes away the opportunity for an other vehicle to charge.

4.3.3. Welfare

The total welfare takes into account the CS welfare, which is directly related with his profit, and consumer's welfare, which covers individual drivers utilities in terms of charging tariff per energy bought, reservation cost and distance to the CS. The latter expression is presented next:

$$\mathcal{W}_C = \sum_{i \in \mathcal{I}} (\rho_e - \rho) \cdot E_i + (d_i^o - d_i^{cs}) \cdot \kappa_d - C_i. \tag{4.1}$$

As expression (4.1) does not consider an extra profit if the driver makes a reservation and is served, an extra parameter that contemplates the value of clearing the uncertainty of being served U_i^u is added to the consumer's welfare expression for EVs who make AR and are served. U_i^u can be associated with the difference between the consumers' welfare who

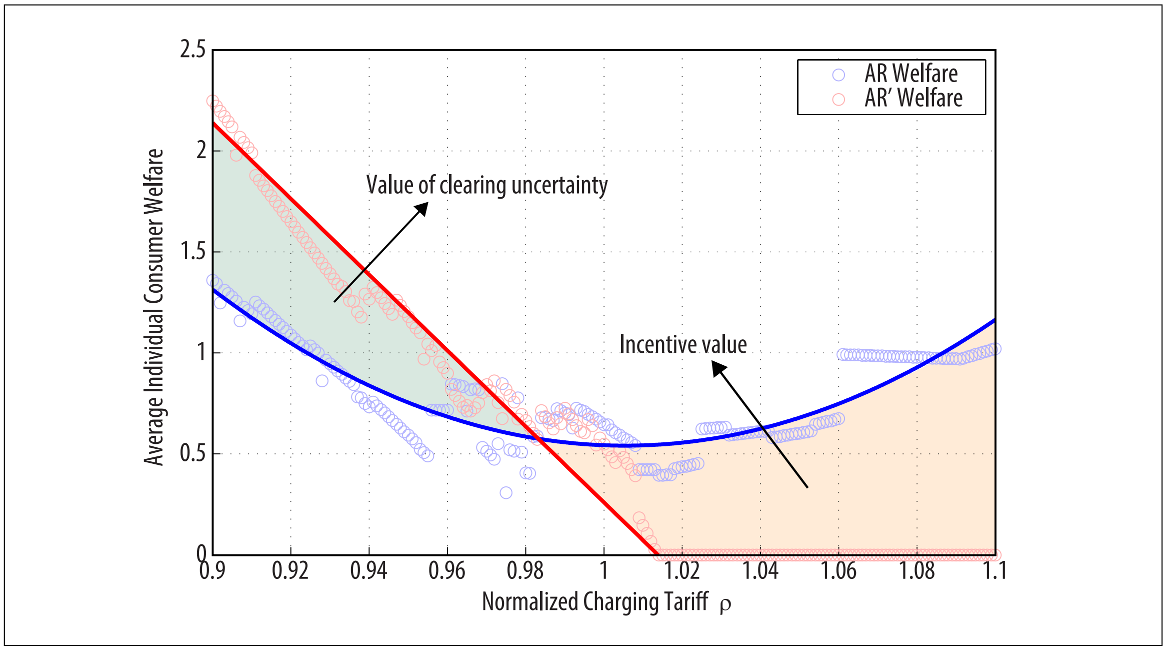


Figure 4.6. Average individual consumer welfare for EVs who make a reservation and those who don't.

make an AR and those who don't. This value increases as the charging tariff decreases, this is related to the fact that demand also increases and the uncertainty of being served with it.

In Figure 4.6 the average individual Consumer's Welfare is presented as a function of the normalized charging tariff in Case Study 1 for EVs who make an AR (in blue) and those who don't (in red). For a better understanding, a trend line is plotted in both cases.

On one hand, the value of the uncertainty, which is represented as the difference between the consumers' welfare of EVs who make an AR and those who don't is depicted in a light green area. On the other hand, the incentive value for EV's to charge in the CS is presented in a light orange area. Both values are quite related with the reservation fee presented in Figure 4.3.

Another value that expression (4.1) does not consider is the disutility that drivers perceive if they do not reserve and are not served in the required CS. However, this value can be computed through real data and then added to the consumer's welfare.

4.3.4. Stochastic Satisficing Sensibility

In this subsection, a Stochastic Satisficing model Gonz & Ortúzar (2017) is used as a demand model instead of the normal Satisficing theory to face the uncertainty within drivers' charging decision. Unlike normal Satisficing theory, the Stochastic Satisficing model undertakes the decision of charging as a probability. The probability function represents the acceptability of each driver, which is modeled as a logit function. The shape of the curve is related to the unpredictable behavior of drivers, the more the uncertainty is cleared, the more the probability gets closer to a step.

If the decision is now considered as a probability the model becomes a non-linear problem hard to solve. In order to make this problem solvable and for simplicity some assumptions are taken into account:

- The charging tariff ρ is fixed and equal to ρ_e. In this case, the results of the non Stochastic approach are used as an input.
- The logit model is adjusted considering that with a normalized price 0.9 and a normalized distance 0.1, a vehicle has a probability 0.9 of deciding to charge in the CS. Whilst with a normalized price of 1 and the same distance 0.1, the probability of deciding to charge decreases to 0.5.
- A marginal substitution rate of cost/distance κ_d is approximated as $1/5$.
- The logit model of the Stochastic Satisficing formulation is linearized and approximated with a linear piecewise function with an error less than a 10%.
- Only negative values of the AR cost are considered.

A model of the drivers' unpredictable behavior has a direct impact on the expected demand. In this case there is not a particular set of vehicles that decide to charge in the CS, furthermore, all drivers might charge but with a given probability that depends on measurable (distance, charging tariff and reservation cost) and unmeasurable (uncertainty) conditions. The grey arrows in Figure 4.7 show how the availability of EVs changes compared with the nonstochastic approach. The Stochastic Satisficing model tends to

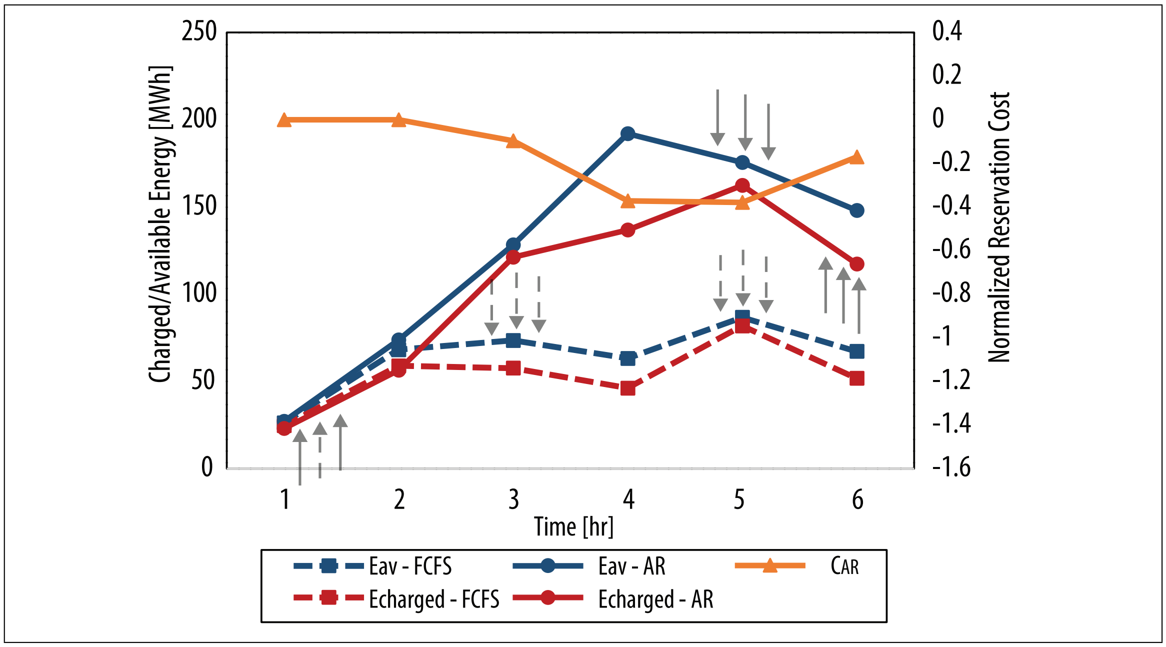


Figure 4.7. Charging profiles and Energy availability with a Stochastic Satisficing approach.

smooth the CS charging profiles through time. However, price incentives with the AR structure still make a notable difference between these two schemes.

On one hand, the stochastic approach reduces a $\approx 47\%$ the profit of the CS for the FCFS scheme, because the demand is smoothed and, in this particular case, more vehicles charge in times when is not profitable and less in profitable periods. On the other hand, the revenue of the CS considering an AR scheme remains similar (approximately a difference of a 6% in the total revenue), this gives an insight of the impact of the reservation fee on the charging profile of the CS, that regardless of the demand model a similar revenue is achieved.

Additionally, is important to mention that the reservation fee in the stochastic and non-stochastic approach have a similar shape. However, in the stochastic approach differences on the reservation value can be attributed to the parameter tune on the logit model of the demand.

5. CONCLUSIONS

This work has modeled an EV Aggregator (EV charging station) and its interaction with the electricity markets and individual EV users in order to determine the optimal pricing and management strategy using of AR schemes. EV users' decision making process is modelled using Satisficing Theory.

A unique charging tariff is determined throughout the studied time, together with a dynamic reservation fee. The reservation fee can be set to positive or negative values depending on the CS objectives: An incentive to charge at a desired time, or an extra cost for securing a specific charging time and socket.

The value that EV users assign to clearing the uncertainty of being served is estimated, together with the incentives, in the form of negative reservation fees, required by EVs to choose the CS at certain periods of time.

It is shown that EV's flexibility, in terms of longer staying times in the CS facilities, can have positive or negative effects on the CS revenues due to a trade-off between charging flexibility and charging socket availability.

The AR scheme to manage CS for EVs is compared with traditional FCFS, showing a superior performance in terms of CS revenues and management of available resources.

The Stochastic Satisficing model, which faces the drivers unpredictable behavior, has a direct impact on the expected demand. On one hand, by using this approach, the revenue for the FCFS scheme is significantly reduced. This is explained because the demand is smoothed, more vehicles charge when is not profitable and less vehicles charge in prof-itable periods. On the other hand, the revenue of the CS considering an AR scheme re-mains similar, this gives an insight of the impact of the reservation fee on the charging-profile of the CS, that regardless of the demand model a similar revenue is achieved.

REFERENCES

A. Domencich, T., & McFadden, D. (1975). *Urban Travel Demand: A Behavioral Analysis*. Amsterdam: North-Holland.

Akinyele, D., & Rayudu, R. (2014). Review of energy storage technologies for sustainable power networks. *Sustainable Energy Technologies and Assessments*, *8*, 74 - 91. Retrieved from `http://www.sciencedirect.com/science/article/pii/S2213138814000708` doi: https://doi.org/10.1016/j.seta.2014.07.004

Bermudez, J. (2009). *Decision theory and rationality*. Oxford New York: Oxford University Press.

Bessa, R. J., Matos, M. A., Soares, F. J., & Lopes, J. A. P. (2012, March). Optimized bidding of a ev aggregation agent in the electricity market. *IEEE Transactions on Smart Grid*, *3*(1), 443-452. doi: 10.1109/TSG.2011.2159632

Bucher, M. A., Chatzivasileiadis, S., & Andersson, G. (2016, March). Managing flexibility in multi-area power systems. *IEEE Transactions on Power Systems*, *31*(2), 1218-1226. doi: 10.1109/TPWRS.2015.2413387

Cao, Y., Wang, N., Kamel, G., & Kim, Y. (2017, Sept). An electric vehicle charging management scheme based on publish/subscribe communication framework. *IEEE Systems Journal*, *11*(3), 1822-1835. doi: 10.1109/JSYST.2015.2449893

Cascetta, E. (2009). *Transportation Systems Analysis: Models and Applications* (2nd ed.). New York, NY, USA: Springer. doi: 10.1007/978-0-387-75857-2

Charbonneau, N., & Vokkarane, V. M. (2012, Fourth). A survey of advance reservation routing and wavelength assignment in wavelength-routed wdm networks. *IEEE Communications Surveys Tutorials*, *14*(4), 1037-1064. doi: 10.1109/SURV.2011.111411.00054

Clement-Nyns, K., Haesen, E., & Driesen, J. (2010, Feb). The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems*, *25*(1), 371-380. doi: 10.1109/TPWRS.2009.2036481

Divya, K., & stergaard, J. (2009). Battery energy storage technology for power systemsan overview. *Electric Power Systems Research*, *79*(4), 511 - 520. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0378779608002642` doi: https://doi.org/10.1016/j.epsr.2008.09.017

Fehr, E., & Fischbacher, U. (2003). The nature of human altruism. *Nature*, *425*(6960), 785–791. doi: 10.1038/nature02043

Frank, R. H. (2016). If Homo Economicus Could Choose His Own Utility Function, Would He Want One with a Conscience? , *77*(4), 593–604.

Ge, Y., Mackenzie, D., & Keith, D. R. (2017). Gas anxiety and the charging choices of plug-in hybrid electric vehicle drivers. *Transportation Research Part D*(August), 0–1. Retrieved from `http://dx.doi.org/10.1016/j.trd.2017.08.021` doi: 10.1016/j.trd.2017.08.021

Gerding, E. H., Stein, S., Robu, V., Zhao, D., & Jennings, N. R. (2013). Two-sided online markets for electric vehicle charging. In *Proceedings of the 2013 international conference on autonomous agents and multi-agent systems* (pp. 989–996). Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems. Retrieved from `http://dl.acm.org/citation.cfm?id=2484920.2485076`

Gonz, F., & Ortúzar, J. D. D. (2017). The Stochastic Satisficing model : A bounded rationality discrete choice model. (October), 1–14. doi: 10.1016/j.jocm.2017.11.002

Green II, R. C., Wang, L., & Alam, M. (2011). The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook. *Renewable and sustainable energy reviews*, *15*(1), 544–553.

Habib, S., Kamran, M., & Rashid, U. (2015). Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks a review. *Journal of Power Sources*, *277*, 205 - 214. Retrieved from http://www.sciencedirect.com/science/article/pii/S0378775314020370 doi: https://doi.org/10.1016/j.jpowsour.2014.12.020

Hamid, Q. R., & Barria, J. A. (2016, March). Congestion avoidance for recharging electric vehicles using smoothed particle hydrodynamics. *IEEE Transactions on Power Systems*, *31*(2), 1014-1024. doi: 10.1109/TPWRS.2015.2412653

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., & Mcelreath, R. (2001). American Economic Association In Search of Homo Economicus : Behavioral Experiments in 15 Small-Scale Societies. *The American Economic Review*, *91*(2), 73–78.

(IEA), I. E. A. (2017). Global ev outlook 2017, beyond two million electric cars. Retrieved from https://www.iea.org/publications/freepublications/publication/$Global_EV_Outlook_2017$.pdf

Jabeen, F., Olaru, D., Smith, B., Braunl, T., & Speidel, S. (2013). Electric Vehicle Battery Charging Behaviour : Findings From a Driver Survey. *Australasian Transport Research Forum 2013 Proceedings*, 1 – 15.

Jian, L., Xue, H., Xu, G., Zhu, X., Zhao, D., & Shao, Z. Y. (2013, Aug). Regulated charging of plug-in hybrid electric vehicles for minimizing load variance in household smart microgrid. *IEEE Transactions on Industrial Electronics*, *60*(8), 3218-3226. doi: 10.1109/TIE.2012.2198037

Jin, C., Tang, J., & Ghosh, P. (2013, March). Optimizing electric vehicle charging with energy storage in the electricity market. *IEEE Transactions on Smart Grid*, *4*(1), 311-320. doi: 10.1109/TSG.2012.2218834

Kempton, W., Tomic, J., Letendre, S., Brooks, A., & Lipman, T. (2001). Vehicle-to-grid power: battery, hybrid, and fuel cell vehicles as resources for distributed electric power in california.

Kluver, J., Frazier, R., & Haidt, J. (2014). Behavioral ethics for Homo economicus, Homo heuristicus, and Homo duplex. *Organizational Behavior and Human Decision Processes*, *123*(2), 150–158. Retrieved from `http://dx.doi.org/10.1016/j.obhdp.2013.12.004` doi: 10.1016/j.obhdp.2013.12.004

Lannoye, E., Flynn, D., & O'Malley, M. (2012, May). Evaluation of power system flexibility. *IEEE Transactions on Power Systems*, *27*(2), 922-931. doi: 10.1109/TPWRS.2011.2177280

Latinopoulos, C., Sivakumar, A., & Polak, J. W. (2017). Response of electric vehicle drivers to dynamic pricing of parking and charging services : Risky choice in early reservations q. *Transportation Research Part C*, *80*, 175–189. Retrieved from `http://dx.doi.org/10.1016/j.trc.2017.04.008` doi: 10.1016/j.trc.2017.04.008

Liu, H., Niu, M., & Wang, W. (2016, Dec). Reserving charging strategy for electric vehicles based on combined model of road-charging station-electric vehicle. In *2016 ieee 2nd annual southern power electronics conference (spec)* (p. 1-6). doi: 10.1109/SPEC.2016.7846050

Lopes, J. P., Polenz, S. A., Moreira, C., & Cherkaoui, R. (2010). Identification of control and management strategies for lv unbalanced microgrids with plugged-in electric vehicles. *Electric Power Systems Research*, *80*(8), 898 - 906. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0378779610000039` doi: http://dx.doi.org/10.1016/j.epsr.2009.12.013

McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior.* doi: 10.1108/eb028592

Modeling coordination in organizations and markets. (1987). *Management Science*, *33*(10), 1317-1332. Retrieved from http://dx.doi.org/10.1287/mnsc.33.10.1317 doi: 10.1287/mnsc.33.10.1317

Mumtaz Siddiqui, T. F. a. (2010). *Grid resource management: On-demand provisioning, advance reservation, and capacity planning of grid resources* (1st ed.). Springer-Verlag Berlin Heidelberg. Retrieved from http://gen.lib.rus.ec/book/index.php?md5=DF46D04B72FB72A4DE49442B300BCA7E

Myerson, R. B. (1998a). Extended poisson games and the condorcet jury theorem. *Games and Economic Behavior*, *25*(1), 111 - 131. Retrieved from http://www.sciencedirect.com/science/article/pii/S0899825697906102 doi: http://dx.doi.org/10.1006/game.1997.0610

Myerson, R. B. (1998b). Population uncertainty and poisson games. *International Journal of Game Theory*, *27*(3), 375–392. Retrieved from http://dx.doi.org/10.1007/s001820050079 doi: 10.1007/s001820050079

Ortuzar, J. d. D., & Willumsen, L. G. (2011). *Modelling Transport* (4th ed.). Wiley. doi: 10.1002/9781119993308

Pawl, Z., & Sets, R. (1992). *Theory and Decision Library D:* (Vol. 9) (No. 1). Retrieved from http://dx.doi.org/10.1007/978-94-009-9394-5{_}18 doi: 10.1007/978-3-642-02865-6

Qdr, Q. (2006). Benefits of demand response in electricity markets and recommendations for achieving them. *US Dept. Energy, Washington, DC, USA, Tech. Rep.*

Rajakaruna, S., Ghosh, A., & Shahnia, F. (2015). Plug in electric vehicles in smart grids. *Springer*, *1*, 208-239. doi: 10.1109/TIE.2012.2198037

RWE. (2009, December). The need for smart megawatts power generation in europe facts & trends..

Simhon, E., Cramer, C., Lister, Z., & Starobinski, D. (2015, April). Pricing in dynamic advance reservation games. In *2015 ieee conference on computer communications workshops (infocom wkshps)* (p. 546-551). doi: 10.1109/INFCOMW.2015.7179442

Simhon, E., & Starobinski, D. (2014, March). Game-theoretic analysis of advance reservation services. In *Information sciences and systems (ciss), 2014 48th annual conference on* (p. 1-6). doi: 10.1109/CISS.2014.6814104

Simhon, E., & Starobinski, D. (2015, November). On the impact of sharing information in advance reservation systems. *SIGMETRICS Perform. Eval. Rev.*, *43*(3), 82–82. Retrieved from `http://doi.acm.org/10.1145/2847220.2847248` doi: 10.1145/2847220.2847248

Simhon, E., & Starobinski, D. (2016, March). A game-theoretic perspective on advance reservations. *IEEE Network*, *30*(2), 6-11. doi: 10.1109/MNET.2016.7437018

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 99–118.

Simon, H. A. (1956). Rational Choice and the Structure of the Environment. , *63*(3), 129–138.

Sioshansi, R., Fagiani, R., & Marano, V. (2010). Cost and emissions impacts of plug-in hybrid vehicles on the ohio power system. *Energy Policy*, *38*(11), 6703 - 6712. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0301421510005045` (Energy Efficiency Policies and Strategies with regular papers.) doi: http://dx.doi.org/10.1016/j.enpol.2010.06.040

Sortomme, E., & El-Sharkawi, M. A. (2012, March). Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Transactions on Smart Grid*, *3*(1), 351-359. doi: 10.1109/TSG.2011.2164099

Standard, S. (2010). Sae electric vehicle and plug-in hybrid electric vehicle conductive charge coupler.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2015). Charge timing choice behavior of battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *37*, 97–107. Retrieved from `http://dx.doi.org/10.1016/j.trd.2015.04.007` doi: 10.1016/j.trd.2015.04.007

Timpner, J., & Wolf, L. (2014, April). Design and evaluation of charging station scheduling strategies for electric vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *15*(2), 579-588. doi: 10.1109/TITS.2013.2283805

Todd, P. M., & Gigerenzer, G. (2003a). Bounding rationality to the world. *Journal of Economic Psychology*, *24*(2), 143–165. doi: 10.1016/S0167-4870(02)00200-3

Todd, P. M., & Gigerenzer, G. (2003b). Bounding rationality to the world. *Journal of Economic Psychology*, *24*(2), 143 - 165. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0167487002002003` (The Economic Psychology of Herbert A. Simon) doi: https://doi.org/10.1016/S0167-4870(02)00200-3

Tushar, M. H. K., Assi, C., Maier, M., & Uddin, M. F. (2014, Jan). Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances. *IEEE Transactions on Smart Grid*, *5*(1), 239-250. doi: 10.1109/TSG.2013.2290894

Tversky, A. (1972a). Choice by Elimination. *Journal of Mathematical Psychology*, *9*(4), 341–367. doi: 10.1016/0022-2496(72)90011-9

Tversky, A. (1972b). Elimination by aspects: A theory of choice. *Psychological Review*, *79*(4), 281–299. doi: 10.1037/h0032955

Vay, M. G., & Andersson, G. (2012, July). Centralized and decentralized approaches to smart charging of plug-in vehicles. In *2012 ieee power and energy society general meeting* (p. 1-8). doi: 10.1109/PESGM.2012.6344902

Wenzel, G., Negrete-Pincetic, M., Olivares, D., MacDonald, J., & Callaway, D. S. (2016, Jul). Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. In *Submitted to IEEE transactions on smart grids.*

Xu, M., Meng, Q., Liu, K., & Yamamoto, T. (2017). Joint charging mode and location choice model for battery electric vehicle users. *Transportation Research Part B: Methodological*, -. Retrieved from `http://www.sciencedirect.com/science/article/pii/S019126151630368X` doi: https://doi.org/10.1016/j.trb.2017.03.004

Yamagishi, T., Li, Y., Takagishi, H., Matsumoto, Y., & Kiyonari, T. (2014). In Search of Homo economicus. *Psychological Science*, *25*(9), 1699–1711. Retrieved from `http://journals.sagepub.com/doi/10.1177/0956797614538065` doi: 10.1177/0956797614538065

Zhang, B., & Kezunovic, M. (2016, May). Impact on power system flexibility by electric vehicle participation in ramp market. *IEEE Transactions on Smart Grid*, *7*(3), 1285-1294. doi: 10.1109/TSG.2015.2437911

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging Choices and Fuel Displacement in a Large-Scale Demonstration of Plug-In Hybrid Electric Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, *2385*, 1–10. Retrieved from `http://trrjournalonline.trb.org/doi/10.3141/2385-01` doi: 10.3141/2385-01

APPENDIX

A. APPENDIX A: EXTENDING AR GAMES

This appendix presents how to extend Advance Reservation (AR) games theory to a multiple types of user and time slots. Design principles are presented for a service provider who wants to adapt a reservation system. A general formulation is made and different simplified cases are presented to understand the influence on the AR costs of the time slot length, rate of servers per time required, rate of arrivals and flexibility of the user.

A.1. Multiple types of users and time slots

In this section a formulation of a system that supports AR with multiple type of users and time slots is presented. This is made for representing real systems where arrivals are in random fashion and players want to use different number of slots in different times. The formulation tries to be as general as it can to be adapted to different systems.

A Nash Equilibrium exists when there is no profitable deviation from any of the players, this only occurs if a threshold that guarantee a maximum profit for each player can be found. Thus, this equilibrium is reached when both the provider and users maximize their profit, knowing the strategy of all the other players. The strategy function maps the type t and lead time lt to an action $a \in \{AR, AR'\}$,

$$\sigma(\tau \mid t) = \begin{cases} AR & \text{for} \quad \tau > \tau_t \\ AR' & \text{for} \quad \tau \leq \tau_t \end{cases}, \qquad \forall t \in \mathcal{T}, \tag{A.1}$$

where $\mathcal{T}$ indicates the set of types $\{t_1, \ldots, t_2\}$.

All equilibrium strategies must be of threshold form Simhon & Starobinski (2016). The main reason is that if a user makes AR, the probability of being served is a non-decreasing function of her lead time, and if she doesn't, the probability of being served doesn't depend on her lead time.

The cost structure depends on the probability of being served by making a reservation π_{AR} and the probability of being served without making a reservation $\pi_{AR'}$. These expressions are given by

$$\pi_{AR|t} = \underbrace{\prod_{m=m_0}^{m_f}}_{A} \underbrace{\sum_{k=0}^{N-S_m}}_{B} \underbrace{\sum_{c\in\mathcal{C}^k}}_{C} \underbrace{\prod_{(i,t)\in\mathcal{T}^c}}_{D} \mathbb{P}(\lambda_t(1-\tau_t), i) = \prod_{m=m_0}^{m_f} P_1(m), \tag{A.2}$$

where the sum term A represent the time range that the user t requires, B term represents the servers per time slot required, C term denotes the combinations of types that sum k, D is used to calculate the weight of each combination and $\mathbb{P}(\lambda, n)$ is a Poisson cumulative distribution function

$$\mathbb{P}(\lambda, n) = e^{-\lambda}\frac{\lambda^n}{n!}.$$

$\pi_{AR'|t}$, the probability of being served by not making AR. Same as Eq. (A.2), but multiplied by two extra terms covering users who don't make AR.

$$\begin{aligned} \pi_{AR'|t} = \prod_{m=m_0}^{m_f} P_1(m) \cdot \Bigg[&\sum_{j=0}^{N-k-S_m-1} \sum_{c\in\mathcal{C}^j} \prod_{(i,t)\in\mathcal{T}^c} \mathbb{P}(\lambda_t\tau_t, i) \\ + \sum_{j=N-k-S_m}^{\infty} \sum_{c\in\mathcal{C}^j} \prod_{(i,t)\in\mathcal{T}^c} &\mathbb{P}(\lambda_t\tau_t, i) \cdot \left(\frac{\prod_{s=0}^{S_m}(N-k-s)}{(j+1)^{S_m}} \right) \Bigg]. \end{aligned} \tag{A.3}$$

The first of the two last terms in Equation A.3 covers the case in which the number of players not making a reservation is less than the available servers. The second term covers the case in which the number of players not making a reservation is higher than the available servers, multiplied by a proportion that distributes the chance of being served equally among the players that didn't make a reservation.

The AR cost curve is built on the assumption that a threshold user exists, this user is indifferent between the possible actions. For a threshold user take the action AR or AR' must yield to the same payoff. Therefore, the following expression holds

$$(U_t - C_t) \cdot \pi_{AR|t}(\tau_{t_0}, \ldots, \tau_{t_n}) = U_t \cdot \pi_{AR'|t}(\tau_{t_0}, \ldots, \tau_{t_n}), \qquad \forall t \in \mathcal{T}, \tag{A.4}$$

Where the left side of Equation A.4 shows the payoff by taking action AR and the right side the payoff by taking action AR'. An expression for the cost C_t as a function of the thresholds of each user can be derived from equation A.4,

$$C_t(\tau_{t_0}, \ldots, \tau_{t_n}) = U_t \cdot \left(1 - \frac{\pi_{AR'|t}(\tau_{t_0}, \ldots, \tau_{t_n})}{\pi_{AR|t}(\tau_{t_0}, \ldots, \tau_{t_n})}\right). \tag{A.5}$$

A brief summary of sets and index is shown in Table A.1.

Notation	Description
AR	Action of making an advance reservation
AR'	Action of not making an advance reservation
m	Time slot index, being m_0 the first time slot and m_f the last
k	Number of users choosing AR
N	Total number of available servers
S_m	Rate per slot required by user t in the time slot m
i	Auxiliar index to denote number of users of one type
$\mathcal{T}^c$	Set of i users of type t given by combination c
$\mathcal{C}^k$	Combinations of types that sum k
U_t	Utility of type t user when is served
n	Number of types of user

Table A.1. Notation summary

A.2. 2 types of users

This subsection discusses the impacts of adding an extra type of user on the expected revenue of the provider and AR cost for each type of user. The game is played between the uncertain population of 2 types of users and the CS owner. Two pricing structures are presented: Fixed Rate (FR) and Differentiated Rate (DR).

Figure A.1 shows the computed cost of AR for each user C_1 and C_2 for a system where $N = 12$ and the rate of arrivals of each user is $\lambda_{t_1} = 6$ and $\lambda_{t_2} = 3$.

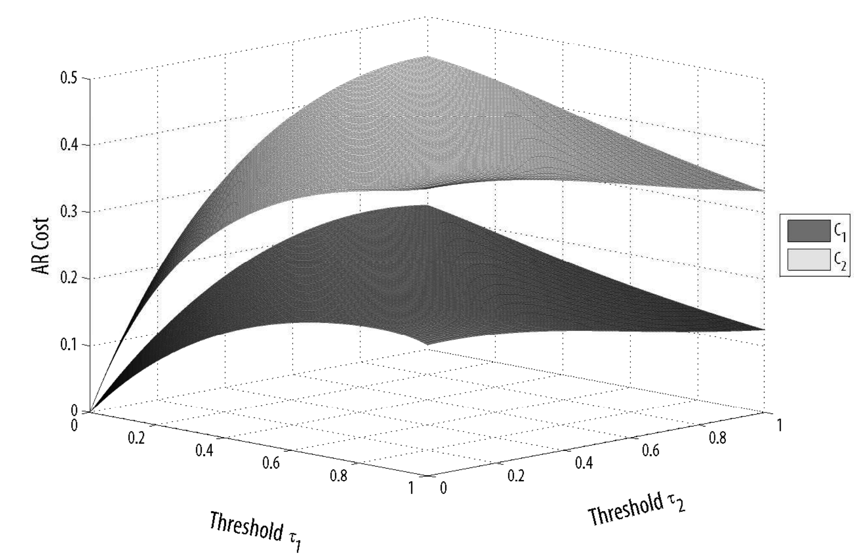


Figure A.1. Cost function with $N = 12$, $\lambda_{t_1} = 6$ and $\lambda_{t_2} = 3$.

As AR cost depends on the user's type, 2 pricing structures are presented next with its possible equilibrium states:

- **Fixed Rate (FR)**: this structure charges a fixed cost for every user regardless his type. FR supports 5 possible equilibria:
  (i) *None-make-AR*, this equilibrium is achieved when there is no threshold that leads to the cost of AR and all players are better off not making AR.

(ii) *None-1-some-2*, this equilibrium is achieved when some of type 2 users and none type 1 make AR, this means that the thresholds are $\tau_{t_1} = 1$ and $\tau_{t_2} \in (0, 1)$.

(iii) *None-1-all-2*, this equilibrium is achieved when all of type 2 users and none type 1 make AR, this means that the thresholds of each user are $\tau_{t_1} = 1$ and $\tau_{t_2} = 0$.

(iv) *Some-1-all-2*, this equilibrium is achieved when all of type 2 users and some type 1 make AR, this means that $\tau_{t_1} = \in (0, 1)$ and $\tau_{t_2} = 0$.

(v) *All-make-AR*, this equilibrium is achieved when all players are better off making AR.

To calculate the ranges within each equilibrium we will define some values to limit these ranges.

$$\overline{C_1^{FR}} = \max_{\tau_{t_1}} \{C_{t_1}(\tau_{t_1}, 0)\} \tag{A.6}$$

$$\overline{C_2^{FR}} = \max_{\tau_{t_2}} \{C_{t_2}(1, \tau_{t_2})\} \tag{A.7}$$

$$\underline{C_1} = \left[1 - \pi_{AR'|t_1}(1, 1)\right] \tag{A.8}$$

$$\underline{C_2} = \left[1 - \pi_{AR'|t_2}(1, 1)\right] \tag{A.9}$$

$$\underline{C} = \max \left\{\underline{C_1}, \underline{C_2}\right\} \tag{A.10}$$

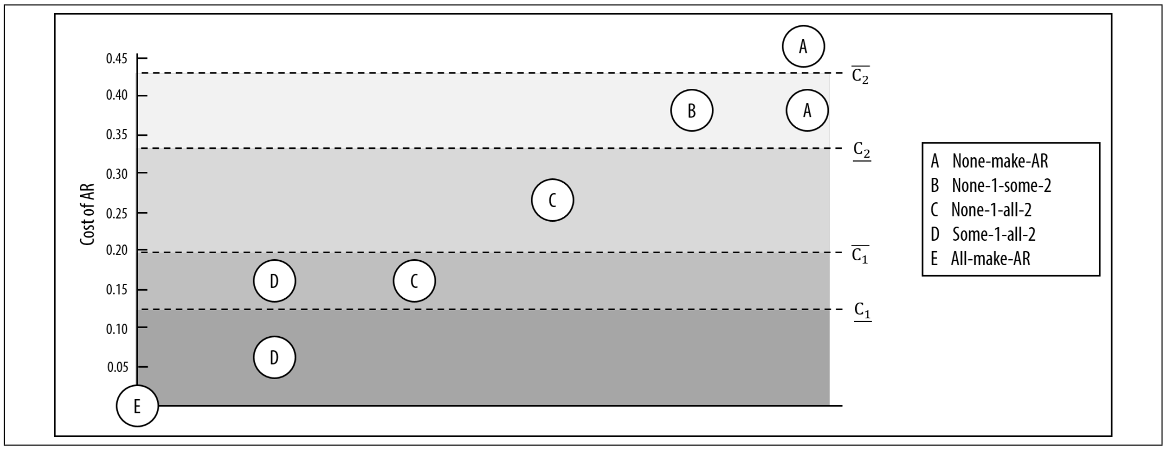


Figure A.2. Equilibria and its C ranges for FR structure.

For FR there isn't an state that support a threshold equilibrium (some-make-AR equilibrium for each type). This statement is interesting because it constraints the range in which both type of users make AR.

- **Differentiated Rate (DR)**: this structure charges a different cost depending on the type, C_{t_1} and C_{t_2} DR supports 5 possible equilibria:
  - (i) *None-make-AR*, this equilibrium is achieved when there is no threshold that leads to the costs of AR and all players are better off not making AR.
  - (ii) *None-1-some-2*, this equilibrium is achieved when some of type 2 users and none type 1 make AR. The difference between this equilibrium and the one in FR is that the threshold τ_{t_1} is not necessarily equal to 1.
  - (iii) *Some-1-none-2*, this equilibrium is achieved when none of type 2 users and some type 1 make AR. The difference between this equilibrium and the one in FR is that the threshold τ_{t_2} is not necessarily equal to 1.
  - (iv) *Some-make-AR*, this equilibrium is achieved when some of the user of each type make AR.
  - (v) *All-make-AR*, this equilibrium is achieved when all players are better off making AR.

These equilibria are reached under the assumption that there exist a threshold user for every type of user. To calculate the ranges of these equilibria is necessary to add two more limits

$$\overline{C_1^{DR}} = \max_{\tau_{t_1},\tau_{t_2}} \{C_{t_1}(\tau_{t_1},\tau_{t_2})\} \tag{A.11}$$

$$\overline{C_2^{DR}} = \max_{\tau_{t_1},\tau_{t_2}} \{C_{t_2}(\tau_{t_1},\tau_{t_2})\} \tag{A.12}$$

In this structure we can show that a threshold equilibrium exists, this means that for a given cost $C_1 \in [0, \overline{C_1}]$ (or $C_2 \in [0, \overline{C_2}]$) there exist a cost C_2 (or C_1) that yields to thresholds τ_1 and τ_2 for each user.

Lemma 0.1. *For a given DR structure there is a combination of thresholds* $\{\tau_{t_1}, \tau_{t_2}\} \in (0, 1)$ *that yields to costs of AR* $C_1(\tau_{t_1}, \tau_{t_2})$ *and* $C_2(\tau_{t_1}, \tau_{t_2})$*.*

Lemma 0.1 gives the provider the faculty to control the expected demand of AR by choosing the adequate cost for each type of user.

A.2.1. Revenue

AR with different types of users reveals an interesting problem of achieving the maximum revenue under strategic customer behaviour. This is because the pricing may differ from one type of user to another.

Let $D_{AR}(\tau_1, \tau_2)$ be a random variable denoting the number of users requesting AR under a threshold strategy $\{\tau_1, \tau_2\}$ and $d_{AR}(\tau_1, \tau_2)$ be a random variable denoting the number of reservation request of servers under a threshold strategy $\{\tau_1, \tau_2\}$. Then the expected value of the revenue for structure FR is given by

$$R^{FR}(\tau_1, \tau_2) = \begin{cases} C \cdot \mathbb{E}[D_{AR}(\tau)] & \text{for} \quad d_{AR}(\tau_1, \tau_2) \leq N \\ C \cdot N \cdot \mathbb{E}\left[\frac{D_{AR}(\tau_1, 1) + D_{AR}(1, \tau_2)}{d_{AR}(\tau_1, \tau_2)}\right] & \text{for} \quad d_{AR}(\tau_1, \tau_2) > N \end{cases} \tag{A.13}$$

The reason for taking a piecewise function is because the number of requests may exceed the number of available servers.

Figure A.3 shows the expected revenue in the range of equilibria B and D.

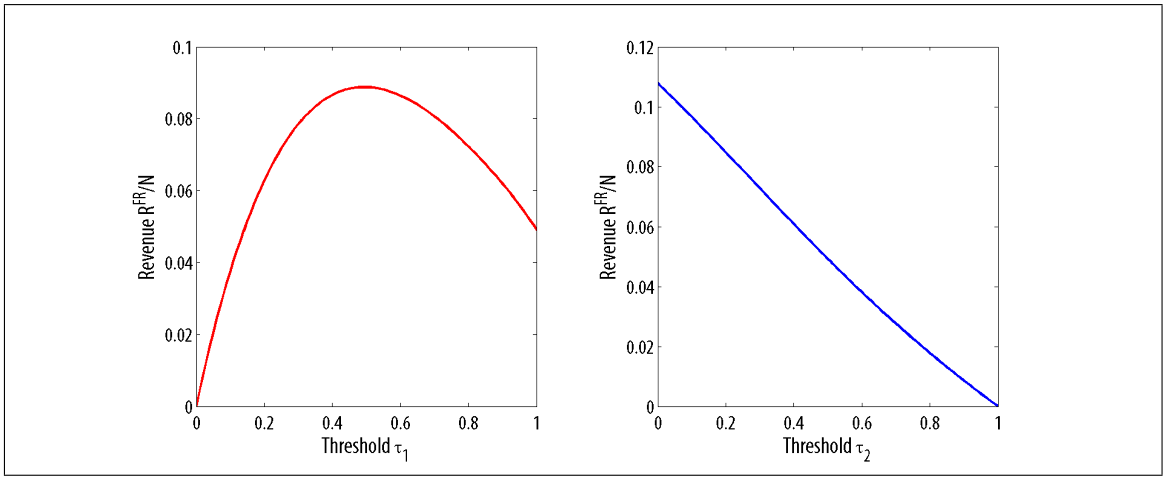


Figure A.3. FR structure expected revenue per server in the range of equilibria B and D for $N = 12$, $\lambda_1 = 6$ and $\lambda_2 = 3$: (a) B and (b) D.

Note that in this equilibria the expected revenue only depends in the threshold of one type of user.

The equilibria A and E yield to zero revenue because there isn't AR demand in A and there is zero AR cost on B. In equilibrium C the revenue is linearly dependent on the cost of reservation in the range $[\overline{C_1^{FR}}, \underline{C_2}]$.

The expected value of the revenue for structure DR is given by

$$R^{FR}(\tau_1, \tau_2) = \begin{cases} \sum_{t \in \mathcal{T}} \mathbb{E}\left[C_t \cdot D_{AR|t}(\tau_t)\right] & \text{for} \quad d_{AR}(\tau_1, \tau_2) \leq N \\ \sum_{t \in \mathcal{T}} \mathbb{E}\left[C_t \cdot \frac{D_{AR|t}(\tau_t)}{d_{AR}(\tau_1, \tau_2)}\right] & \text{for} \quad d_{AR}(\tau_1, \tau_2) > N \end{cases} . \tag{A.14}$$

Figure A.4 shows the expected revenue in a DR structure. The maximum revenue for these settings is 0.142, that is reached for $C_1 = 0.270$ and $C_2 = 0.388$, here a some-make-AR and none-make-AR equilibria can occur. To avoid the risk of none-make-AR the maximum permitted revenue is 0.107 and is reached for $C_1 = 0.125$ and $C_2 = 0.241$.

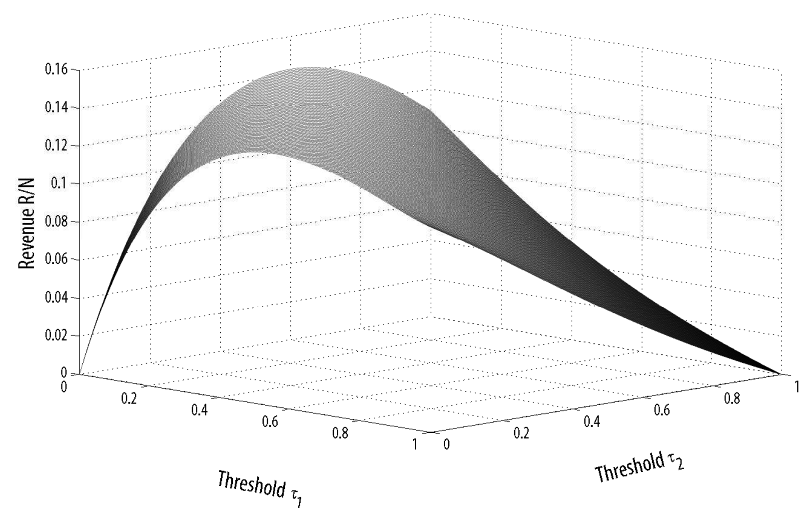


Figure A.4. Expected revenue per server in structure DR for $N = 12$, $\lambda_1 = 6$ and $\lambda_2 = 3$.

A.3. 2 time slots

This subsection discusses the impacts of adding an extra time slot. The game begins at time $n = 1$ and ends at $n = 2$. All users request only one server but if not served, then they wait until the next time slot. Users can arrive in time $n = 1$ and $n = 2$ with rates λ^1 and λ^2. The server duration, denoted by ΔT, is analysed as a design parameter in this system.

For establish an equilibrium the strategy function is modified and extend to cover multiple time slots formulation,

$$\sigma^n(\tau) = \begin{cases} AR & \text{for} \quad \tau > \tau_e \\ AR' & \text{for} \quad \tau \leq \tau_e \end{cases} \tag{A.15}$$

where the index $n \in [1,2]$ in this case denotes the time slot and τ the threshold.

For this analysis the threshold is the same for every user. However, there could be cases where the threshold of users requesting servers in each time slot is different.

A DR structure is used and three types of equilibria are found: all-make-AR, some-make-AR and none-make-AR. These are achieved when a certain action maximizes the profit of each user within a threshold strategy followed by all players.

All-make-AR occurs only if the utility of being served by making AR is always greater than the utility of being served without making AR. This is given by

$$\sum_{n\in\mathcal{N}} (U^{1,n} - C^1) \cdot \pi_{AR}^{1,n}(0) > \sum_{n\in\mathcal{N}} U^{1,n} \cdot \pi_{AR'}^{1,n}(0), \tag{A.16}$$

and

$$(U^{2,2} - C^2) \cdot \pi_{AR}^{2,2}(0) > U^{2,2} \cdot \pi_{AR'}^{2,2}(0), \tag{A.17}$$

where $\mathcal{N}$ is the set of time slots, in this case $\{1,\ 2\}$. Equation A.16 cover the first period and A.17 covers the second period. It is easy to deduce that for a negative C in both periods an all-make-AR equilibrium exists.

None-make-AR occurs only if the utility of being served by making AR is always lower than the utility of being served without making AR.

$$(U^{1,1} - C^1) \cdot 1 < \sum_{n\in\mathcal{N}} U^{1,n} \cdot \pi_{AR'}^{1,n}(1) \tag{A.18}$$

$$(U^{2,2} - C^2) \cdot 1 < U^{2,2} \cdot \pi_{AR'}^{2,2}(1). \tag{A.19}$$

The left side of equations A.18 and A.19 are multiplied by 1 just to note that if a user differ from the action of not making AR, then he is served with probability 1. From these equations we can find $\underline{C}^1$ and $\underline{C}^2$,

$$\underline{C}^1 = U^{1,1} - \sum_{n \in \mathcal{N}} U^{1,n} \cdot \pi^{1,n}_{AR'}(1) \tag{A.20}$$

$$\underline{C}^2 = U^{2,2} - U^{2,2} \cdot \pi^{2,2}_{AR'}(1). \tag{A.21}$$

If the cost of reservation for each period is higher or equal than $\underline{C}^1$ and $\underline{C}^2$, then there is at least one none-make-AR equilibrium.

Some-make-AR equilibrium is achieved when a virtual threshold user is indifferent between making an AR or not. A strategy with threshold τ is a some-make-AR equilibrium if and only if the next 2 equalities hold for a threshold user in period 1 and 2

$$\sum_{n \in \mathcal{N}} (U^{1,n} - C^1) \cdot \pi^{1,n}_{AR} = \sum_{n \in \mathcal{N}} U^{1,n} \cdot \pi^{1,n}_{AR'} \tag{A.22}$$

and

$$(U^{2,2} - C^2) \cdot \pi^{2,2}_{AR} = U^{2,2} \cdot \pi^{2,2}_{AR'}, \tag{A.23}$$

where the left terms of the above expressions denote the utility of a user who makes an AR and the right side the utility of not making an AR, in the first time slot A.22 and in the second A.23. At each time slot the utility and the probability of being served change, that's why there is a sum through the time slots.

An expression for C^1 and C^2 can be formulate from equations A.22 and A.23,

$$C^1(\tau, \Delta T) = \frac{\sum_{n \in \mathcal{N}} U^{1,n} \cdot \pi^{1,n}_{AR}(\tau) - \sum_{n \in \mathcal{N}} U^{1,n} \cdot \pi^{1,n}_{AR'}(\tau)}{\sum_{n \in \mathcal{N}} \pi^{1,n}_{AR}} \tag{A.24}$$

$$C^2(\tau) = U^{2,2} - U^{2,2} \cdot \pi^{2,2}_{AR'}(\tau). \tag{A.25}$$

The expressions for $\pi_{AR}^{n,n'}$ and $\pi_{AR'}^{n,n'}$ are presented in the appendix. It is important to note that $\pi_{AR}^{n,n'}$ is a non decreasing function of ΔT.

As seen in Section A.2 there are some cases where one type of user is better off not making AR as the other one make AR. In this section these particular cases are considered a type of some-make-AR equilibrium.

A.3.1. Revenue

With a DR structure revenue can be formulated as

$$R(\tau) = \sum_{n \in \mathcal{N}} C^n \cdot \mathbb{E}[\min\{D_{AR}^n(\tau), \bar{N}\}], \tag{A.26}$$

where C^n is the AR cost of each time slot, $\bar{N}$ is the maximum number of available servers per time slot. The reason for taking the minimum between $\bar{N}$ and $D_{AR}(\tau)$ is because the number of request may exceed the number of available servers.

An example is presented next to see how the revenue and costs of AR change as a function of ΔT. The settings are $N = 6$, $\lambda^1 = \lambda^2 = 6$ and users of each period follow the same strategy. The utility of being served in the second period by requesting AR in the first is represented as a quadratic function of ΔT of the form

$$U^{1,2} = U^{1,1} - \Delta T^2. \tag{A.27}$$

The utility, lead time and length of each period are normalized between $[0, 1]$.

For these settings it can be found a cost for reservation and a revenue, both function of the lead time and ΔT. The maximum revenue is $R(\tau)/N = 0.3953$ (see Figure A.5) and is achieved with a threshold $\tau = 0.2$ and $\Delta T = 0.49$, the fees corresponding to this threshold are $C_1 = 0.2043$ and $C_2 = 0.2898$ (see Figure A.6)

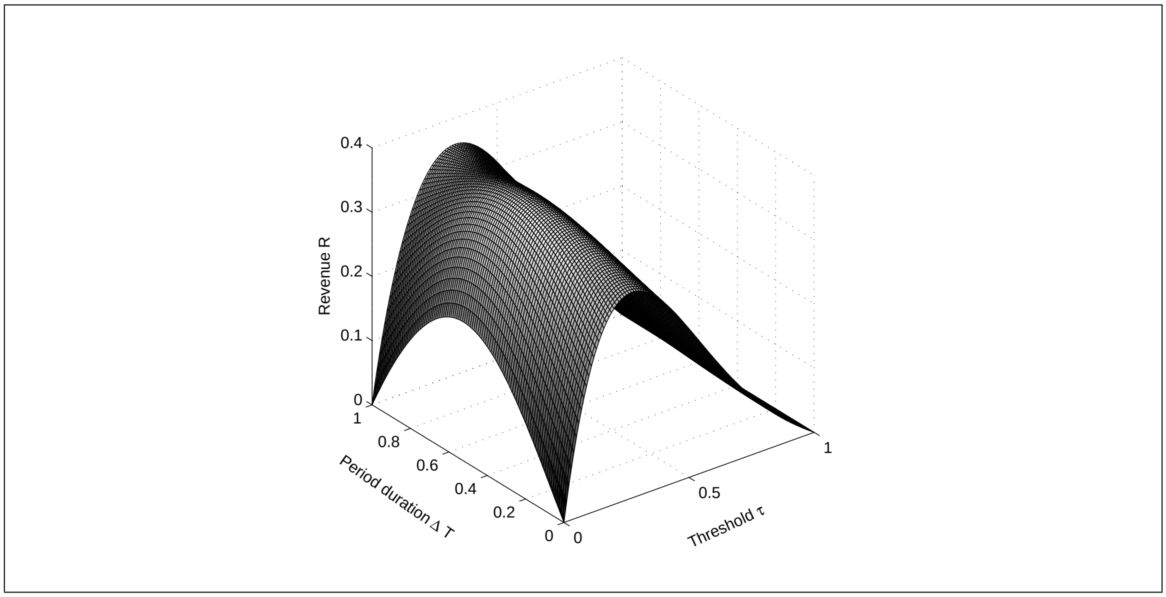


Figure A.5. Revenue of the CS owner for $N = 6$ and $\lambda^1 = \lambda^2 = 6$.

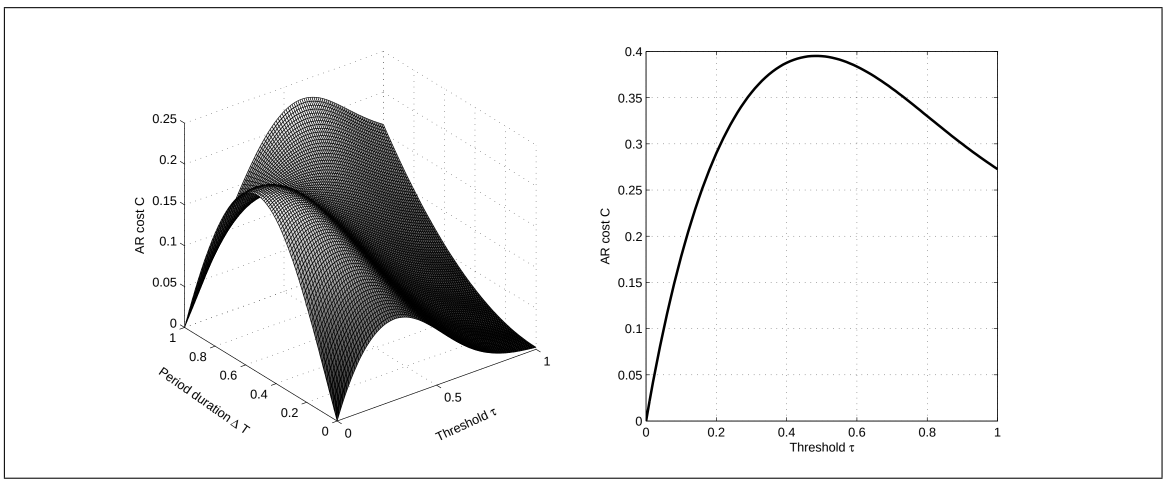


Figure A.6. Cost of AR for $N = 6$ and $\lambda^1 = \lambda^2 = 6$, where a) is the first period and b) the second.

Note that the cost C^2 (Figure A.6.b) is not a function of the time slot's length. This is because for a threshold user the lead time of a first period user is always grater than the lead time of the second one. Thus, the cost C^1 (see Figure A.6.a is a function of the period length.

For this point there is a some-make-AR and a none-make-AR equilibrium. Figure A.7 shows how the costs $\underline{C}^1$ and $\underline{C}^2$ change as ΔT increases. As was expected $\underline{C}^2$ doesn't depend on ΔT, but $\underline{C}^1$ is quadratic because of the utility function.

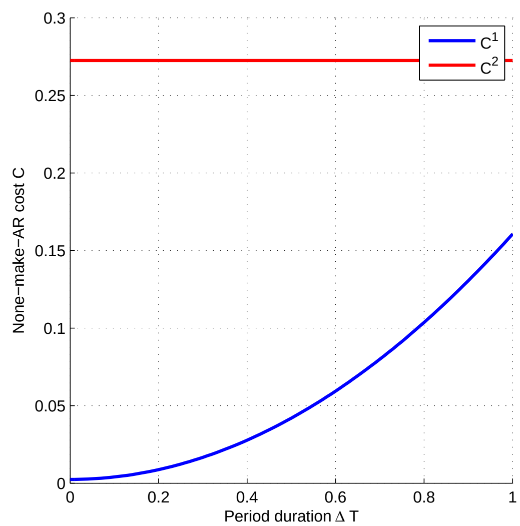


Figure A.7. Cost of none-make-AR equilibrium for $N = 6$ and $\lambda^1 = \lambda^2 = 6$.

A.4. 4 types of users and 2 time slots

This subsection presents a model of 4 types of users that differ on the time and servers requested. A DR structure as proposed in Section A.2 is used. This is because for all combinations of thresholds there is a differentiated cost of AR for each type of user, despite the fact that each type of user has its own threshold and rate of arrivals. This can be proved from Lemma 0.1. Thus, the same threshold is used for each user as a simplification for showing the main results.

Same equilibria as Section A.3 are found here for a DR structure. Note that in the some-make-AR equilibria it can be found types of user that are better of without making AR.

The main idea of this example is to analyse the impacts on AR pricing of the number of servers and the rate of servers per time requested. Figure A.8 shows the cost of reservation and the provider's revenue as the threshold increase.

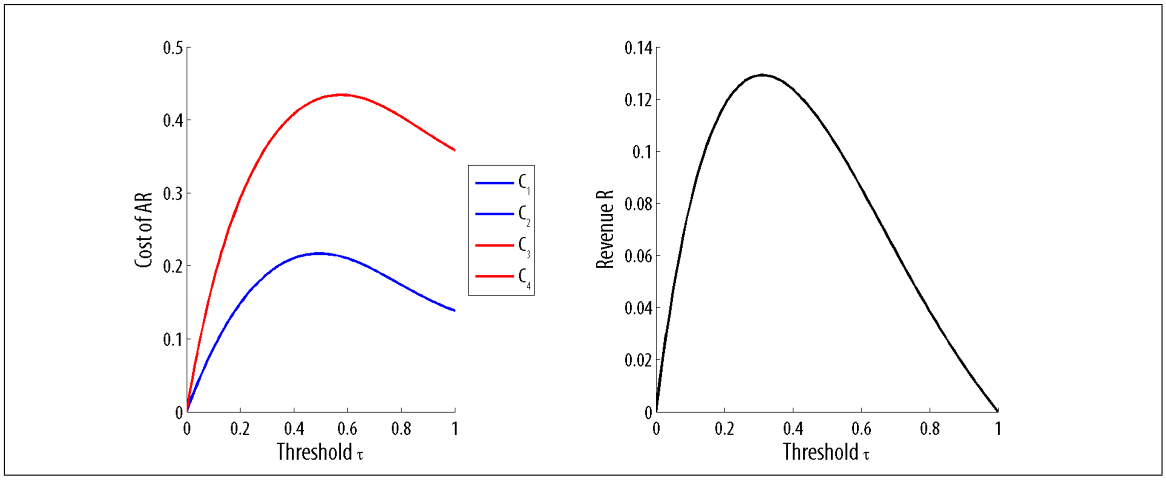


Figure A.8. For settings $N = 6$ and $\lambda_t = 6 \; \forall \; t \in \mathcal{T}$, (a) Cost of AR (b) Expected revenue per server.

In Figure A.8 it can be seen that the AR cost is the same for users of type 1 and 3 and for users of type 2 and 4, even if the total amount of servers requested is not the same.

Lemma 0.2. *In a multiple time and multiple type of users formulation, if there isn't a waiting time and a DR structure is applied, then the cost for AR for each type doesn't depend on the time requested but the rate of servers per time.*

One implication of this lemma is that pricing structures should focus on pricing by rate and not by the amount of time slot a user request.

Requesting servers through time only increase the AR cost for users that request servers after the current time slot, this is mainly because the AR cost is an increasing function of available servers.

Although the price is the same for users whose rate per servers require is equal, the probability of being served and the utility of a player who requires less servers is higher.