Agent-based Retail Competition and Portfolio Optimization in Liberalized Electricity Markets: A Study Involving Real-World Consumers[☆]

H. Algarvio[a], F. Lopes[a]

[a]*LNEG−National Research Institute, Est. Paço do Lumiar 22, Lisbon, Portugal*

Abstract

The liberalization of energy markets brought full competition to the electric power industry. In the wholesale sector, producers and retailers submit bids to day-ahead markets, where prices are uncertain, or alternatively they sign bilateral contracts to hedge against pool price volatility. In the retail sector, retailers compete to sign bilateral contracts with end-use customers. Typically, such contracts are subject to a high-risk premium–that is, retailers request a high premium to consumers to cover their potential risk of trading energy in wholesale markets. Accordingly, consumers pay a price for energy typically higher than the wholesale market price. This article addresses the optimization of the portfolios of retailers, which are composed of end-use customers. To this end, it makes use of a risk-return optimization model based on the Markowitz theory. The article presents a simulation-based study conducted with the help of the MATREM (for Multi-Agent in Electricity Markets) system and involving 6 retailer agents, with different risk preferences, and 312 real-world consumers. The retailers select a pricing strategy and compute a tariff to offer to target consumers, optimize their portfolio of consumers using data from the Iberian market, sign bilateral contracts with consumers, and compute their target return during contract duration. The results support the conclusion that retail markets are more favourable to risk-seeking retailers, since substantial variations in return lead to small variations in risk. However, for a given target return, risk-averse retailers

[☆]This work has received funding from the EU Horizon 2020 research and innovation program under project TradeRES (grant agreement No 864276).
Email address: `hugo.algarvio@lneg.pt` (H. Algarvio)

consider lower risk portfolios, meaning that they may obtain higher returns in favourable and unfavourable situations.

Keywords: Electricity retailers, Portfolios of consumers, Risk-return optimization, The MATREM System, Trading strategies.

---

1. Introduction

The liberalization of energy markets brought full competition to the electricity supply industry (see, e.g., [1, 2, 3, 4]). Market participants have now the possibility to trade electricity in several different types of markets, notably mediated and bilateral markets [5, 6]. In mediated markets, participants can submit bids to electricity pools and/or power exchanges. Such markets are public, centralized markets, where buyers and sellers can trade energy indirectly. In bilateral markets, players can sign standard financial or physical contracts to hedge against the price volatility typical of mediated markets. Such markets are private, decentralized markets, that typically provide more flexibility but may be more expensive. Worthy to mention is also the possibility to sign tailored or customized bilateral contracts, in non-organized, decentralized markets, where buyers and sellers can privately negotiate the terms and conditions of the final agreements according to their own preferences. The trading parties can specify any contract terms they desire, but this flexibility comes frequently at a price, since negotiating and writing contracts may be expensive. Also, the network usage resulting from such contracts need to be approved by the system operator.

In terms of structure, power markets are typically divided into several sectors (or structural components), notably a wholesale sector and a retail sector. In the wholesale sector, competing generators offer their electricity output to retailers and possibly other players. In the retail sector, end-use customers have the possibility to choose their suppliers from competing electricity retailers and possibly other market participants [5]. Retailers operate in both wholesale and retail markets–they buy energy from producers and sell energy to end-use customers. Specifically, in retail markets, retailers compete to sign bilateral contracts with end-use customers, to cover their needs, resulting in a private portfolio to manage. And to satisfy such needs, retailers participate in wholesale markets, submitting bids to both day-ahead and intra-day markets, and also signing bilateral contracts with producers and possibly other market participants.

Nomenclature

Acronyms and Abbreviations

Agg	aggregation
AggRes	Agg of residentials
AggSCom	Agg of small commercials
CET	Central European Time
CfDs	Contracts for differences
CH	Calinski-Harabasz
CVaR	conditional VaR
DAM	day-ahead market
DR	demand-response
EM	electricity market
EROP	Equal Return Optimization
ERTMC	ER Tariff Market-Costs
ETOMaxR	Equal Tariff Optimization at a Maximum Return
ETOMinR	ETO at a Minimum Return
GDP	Gross Domestic Product
Ind	industrial
LCom	large commercial
LMP	Locational Marginal Pricing
MATREM	for Multi-Agent TRading in Electricity Markets
MIBEL	Iberian market of electricity
MTS	Multivariate Time Series
OMIE	the Spanish market operator
OMIP	the Portuguese market op.
OTC	over-the-counter
SMP	System Marginal Pricing
TOU	Time-of-use
VaR	value-at-risk

Symbols

$[\gamma]$	difference between costs
$[w]$	consumer weight
$[Cov]$	covariance
$[r]$	return
α	confidence level
$\chi_i, \beta_i, \delta_i$	regression variables
Δt	contract duration
ϵ_t	error
η_c	centroid mean
$\hat{r}$	expected return
λ	risk attitude
μ	expected return average
σ	standard deviation
C_h	retailer's cost
Cl_c	cluster
E_{t-1}	electricity consumption
I	investment
IR	intrinsic return
K_h	period discriminator
obj	k-means objective function
P_t	electricity price
$q_{j,h}$	consumer consumption
r	real return
r^*	cut-off return
R_f	risk free
R_i	retailer agent
R_p	risk premium
$RES\%_{t-1}$	renewable percentage
T_h	minimum tariff
$T_{j,h}$	tariff
U_j	consumer's cost
x	centroid of the cluster

Subscripts

c	cluster number
h	period of the tariff
i	period number
j	consumer number
t	current period
L, M, N	lags

Typically, retailers follow a “business as usual” strategy, meaning that they offer high tariffs to clients, which are equal for customers with similar consumption patterns. They usually try to attract as many customers as possible, signing bilateral contracts with them, and thus defining non-optimal portfolios of end-use consumers (in terms of risk and return). Also, they often consider a high risk premium, making the energy part of the tariff (retail price) substantially larger than the wholesale market price (see, e.g., [7, 8, 9]). The risk-premium depends on the attitude towards risk, which can be characterized as risk-averse, risk-seeking, or risk-neutral.

Risk-averse retailers tend to define stable portfolios, limiting their exposure to risk that might reduce profits significantly below their expectations. They may be willing to consider “small” risk premiums, allowing them to propose “reduced” tariffs to consumers. Risk-seeking retailers are, to a certain extent, the opposite of risk-averse retailers. They usually feel free to take significant risks in order to secure larger profits, but are not surprised by occasional large losses. In this sense, they may obtain advantage in retail competition, since a low variation in risk may be associated with a high variation in the expected return [8]. Risk-neutral retailers tend to focus on the expected return of portfolios, meaning that they do not care too much about uncertainty (risk).

This article addresses the optimization of the portfolios of retailers, which are composed of end-use consumers. Now, a thorough analysis of the literature reveals that the majority of existing pieces of work about portfolio optimization focus on energy producers [10, 11, 12, 13, 14]. There are also several articles about assets, focusing on optimization models to maximize profit [15, 16, 17]. And also some articles about the operation of retailers in energy markets, considering both spot markets and derivatives exchanges. For instance, Hatami et al. [18] developed a decision model for retailers that need to buy electricity to serve customers. The goals of retailers include the maximization of profit and the minimization of risk. The number of customers is pre-determined and no real consumption data is considered. Hatami et al. [19] extended this piece of work by considering interrupted contracts and a matrix that considers different load elasticities on each time-of-use (TOU) block. Kettenun et al. [20] studied optimal portfolios of forward contracts by considering retailers with different risk attitudes, facing both price risk and consumption risk. The authors concluded that risk-neutral retailers tend to be more concerned with price-related uncertainty, while risk-averse retailers tend to favour forward contracts to hedge against spot price volatility, thus being normally more concerned with the associated risk premium. They assumed, however, a strong correlation between the spot price and the demand of retailers. Guesmi et al. [21] presented a model to increase the return of retailers and minimize their price risk by considering other options than the day-ahead market, such as forward contracts, self-generating facilities and call or put options. Karandikar et al. [22] presented a strategic evaluation of the acquisition of bilateral contracts by retailers. Taking into account the market-clearing of day-ahead markets, the study selects the quantity of power acquired through bilateral contracts to guarantee a risk-constrained pay-off of an elastic load by quantifying risk using a "Risk Adjustment Recovery on Capital" methodology. Nojavan et al. [23] presented a robust optimization approach to minimize the energy acquisition costs of retailers in day-ahead markets, by considering forward contracts and demand-response (DR) programs. Results from the case study show that risk-averse retailers acquire more forward contracts as a risk mitigation measure, while the energy acquired from day-ahead markets has a significant reduction. Sekizaki et al. [24] presented a bi-level model to set the TOU tariffs that retailers propose to consumers and at the same time select the markets where they will purchase the energy between day-ahead and forward markets. The authors concluded that the consumers' response to the different blocks of the TOU tariffs is profitable for retailers. Charwand et al. [25] presented a risk management model where retailers consider multiple purchasing contracts to maximize their return taking into account the market price and load uncertainties of the cross-zonal dispatch where they trade, considering a portfolio draw-down risk over the planning horizon. Faia et al. [26] presented an optimization model for traders with the goal of maximizing their return considering their risk preference. The authors considered an hourly maximum fixed quantity of 10 MW that can be sold or bought trough day-ahead, balancing, bilateral and smart-grid markets. The authors concluded that risk-seeking traders have higher returns but also higher risks, so a balance between risk and return should be achieved.

Furthermore, a discussion about some of the authors own key pieces of work follows. Algarvio et al. [27] presented a deterministic optimization model to maximize the profit of a retailer agent, who buys energy in the day-ahead market and sells it to end-use consumers. The optimization problem takes into account the day-ahead prices, the consumption levels of consumers and the tariffs proposed to consumers. The model does not consider uncertainty, so, it is appropriate for risk-neutral retailers or past situations only (past periods of time) using observed data instead of forecasts. In [8], the authors tried to overcome this weakness by considering a model to optimize portfolios of retailers based on the Markowitz theory [28]. The Markowitz theory has been created to deal with the uncertainty related to an assets' portfolio and has been adapted to deal with the uncertainty related to the retailer's portfolio of end-use consumers. This piece of work focuses on the dual objective of maximizing return and minimizing risk, which involves the selection of specific (types) of customers and the distinction between similar customers (i.e., of the same type). The model is tested by considering three case studies and real-world data from the Iberian electricity market. The end-use customers were, however, hypothetical (clusters of consumers), belonging to the following specific types: industrial, commercial, residential and street lightning. Also, the retailer agents were risk-averse agents only, meaning that the other attitudes towards risk were not considered. Table 1 presents a literature review of models for optimizing the retailers portfolios of purchasing options and consumers.

Against this background, the purpose of this paper is twofold:

1. To adopt our model [8] and to extend it by considering the following: (i) a new trading strategy for retailers, (ii) forecast methods to predict both market prices and customer consumption, with the main objective of reducing errors, and consequently the differences between the expected and real returns and (iii) a formal model of retail competition.
2. To test the extended model by considering situations involving real-world consumers. Specifically, to present a study involving 6 retailers with different risk-attitudes, real data from the Iberian electricity market, and 312 consumers from Portugal.

These consumers are part of the portfolio of a Portuguese retailer (more information about them can be found at [29]). The time period of the study is as follows: from January 1, 2012 to December, 31 2013.[1] The simulation are performed with the help of the simulation tool MATREM (for Multi-Agent TRading in Electricity Markets) [30, 31].

Thus, the work presented here refines and extends our previous work on portfolio optimization as well as our work on risk management [32, 33].

[1] The real consumption data set can be found in an online repository in `https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014#`.

Table 1: Literature review on portfolio optimization of retailers

Reference	Time Period	Market Options	Purchase Optimization	Market price Risk	Consumers Optimization	Tariffs Type	Demand Risk	Risk Preferences
[8]	Long to mid-term	Day-ahead	No	Yes	Yes	TOU	No	Yes
[18]	Mid-term	1. Day-ahead 2. Forwards 3. Call option 4. Power plants	Yes	Yes	No	TOU	No	No
[19]	Mid-term	1-4. Previous 5. interrupted contracts	Yes	Yes	No	TOU	Elastic load	No
[20]	Long to Mid-term	Day-ahead and Forwards	Yes	Yes	No	–	Elastic load	Yes
[21]	Long to short-term	1. Day-ahead 2. Forwards 3. Call option 4. Put option 5. Power plants	Yes	Yes	No, fixed retail contracts	Fixed	No	No
[22]	Mid-term	Day-ahead and bilateral contracts	Yes	Yes	No	– –	Elastic load	No
[23]	Long to short-term	1. Day-ahead 2. Forwards 3. DR programs	Yes	Yes	No	–	Load curve	Yes
[24]	Mid-term	Day-ahead and Forwards	Yes	Yes	No	TOU	Yes	Yes
[25]	Long to short-term	1. Day-ahead 2. Forwards 3. Bilateral contracts 4. Power plants	Yes	Yes	No	Load	Cross-zonal	Yes
[26]	Mid to short-term	1. Day-ahead 2. Balancing 3. Bilateral contracts 4. Smart-grids	Yes	Yes	No	–	No	Yes
[27]	Mid to short-term	Day-ahead	No	No	Yes	TOU	No	No
This paper	**Long to mid-term**	**Day-ahead**	**No**	**Yes**	**Yes**	**TOU**	**Yes, real consumption**	**Yes**

In particular, and as noted, it extends our previous model based on the Markowitz theory by considering a new trading strategy for retailers, and also considers practical situations involving real-world consumers. By using real-world consumers, instead of clusters of consumers, there is possibility to model consumption uncertainty and analyse how the optimization model can deal with it in a real-world setting (thus, contrary of what was done in previous works). Furthermore, the portfolio optimization approach adopted in this paper focuses on the determination of the best share of consumers, differing largely from other approaches presented in the literature, which focus mainly on the determination of the best (sub-)markets to purchase a predefined quantity of electricity to feed a fixed quantity required by consumers (see Table 1).

The remainder of the paper is structured as follows. Section 2 describes the main features of the Iberian electricity market. Section 3 presents an overview of retail competition in electricity markets. Section 4 describes the extended risk-return optimization model based on the Markowitz theory, focusing an a trading strategy for retailers and a forecast method to predict electricity consumptions. Section 5 presents an overview of the MATREM system. Section 6 describes a simulation study to test the model in a real-world setting. Finally, concluding remarks are presented in section 7.

2. The Iberian Market

The Iberian wholesale market (MIBEL [34]) includes Portugal and Spain and involves a day-ahead market (DAM), an intra-day market and a derivatives market. The first two markets are managed by OMIE ([35]), the Spanish electricity market operator. The derivatives market allows private parties to trade standardized contracts and is managed by OMIP ([36]), the Portuguese electricity market operator. Also, Spain and Portugal have independent retail markets, but both countries share the same main retailers.

2.1. The Wholesale market

In the daily Iberian market, players submit hourly bids to trade electricity until 12:00 (CET time) of the day before the day of operation. Prices and volumes are computed using EUPHEMIA, a hybrid algorithm currently used in the European Price Coupling Region [37], based on the marginal pricing theory (see [38] for a complete overview). The algorithm simulates simple and complex bids and takes into account physical constraints of the cross-zonal capacity [39]. By defining the prices and volumes for each bidding zone, the algorithm may also define the flows between them. In case of market-splitting, the prices and volumes are determined for each zone individually.

The intra-day market involves six auction sessions, similar to the DAM, but with gate-closures between one and five hours ahead of real-time operation. The liquidity of this market is normally high (when compared to other European markets, such as Denmark or Germany). It is used by market participants to satisfy about 10% of the demand [40].

Derivatives market considers various types of standardized products, notably forwards, futures, options and contracts for differences (CfDs). Forward contracts are typically contracts subject to physical settlement. The parties take the obligation to buy or sell energy, in a standardized quantity and quality, at a predefined date and place, at a price agreed in the present. To a large extent, forward contracts allow sellers and buyers to financially hedge their exposure to price risk. However, sellers typically need to produce (or buy) the energy specified in the contracts at an uncertain future price, meaning that they still face a considerable price risk.

Futures contracts are similar to forward contracts, although they may be physical or financial (involving a financial settlement only). The parties define a price in the present (strike price) that during the contract will be subject to a finance settlement according to the spot index. When the spot index is higher than the strike price buyers receive the difference between them, otherwise are sellers who are compensated. Options include call options or put options. The former are financial contracts where buyers acquire the right, but not the obligation, to buy energy from sellers considering a standardized quantity of energy, at a future date, at a price set in the present. To this end, buyers pay a fee (premium). Similarly, put options are financial contracts where sellers acquire the right, but not the obligation, to sell energy by paying a fee (premium).

Contracts for differences involve mainly the negotiation of a strike-price for a specific quantity of energy during a specified period of time. The parties may receive or pay the difference between the spot price and the strike price during that period–that is, the settlement process involves the compensation of one party to another according to the strike price and the spot price.

Balancing markets in Portugal and Spain guarantee the secure operation of the power systems. They balance the difference between all physical agreements and real-time consumption and production of electricity [41]. The costs of these markets are passed to the players that deviate from their physical agreements, the balance responsibility parties.

2.2. Retail markets

Retail markets of electricity involve mainly the interaction between retailers and end-use customers with the aim of signing private bilateral contracts. To this end, retailers typically propose multi-part tariffs to consumers, which are composed by a fixed term (contracted power) and a variable term (energy used). They usually consider similar tariffs for consumers with similar consumption patterns. Such tariffs may involve different prices for different blocks of time (e.g., two-rate tariffs). Bilateral contracts are characterized by fixed prices and variable quantities (limited by the contracted power).

In the past, at the beginning of the Portuguese liberalization process, retailers proposed specific discounts to regulated tariffs. Currently, retailers consider mainly reference prices, and discounts are performed over such prices, resulting in a final energy price sometimes higher than the price of the regulated tariff. Also, retailers are essentially profit-seeking agents, following a business as usual strategy, meaning that retail prices are substantially higher than wholesale prices, being their typical markup in Europe around 20% [9, 42], *i.e.*, the retailers charge over the wholesale price.

The retail tariffs currently in place in Portugal are TOU rates. In Spain, tariffs may be both TOU or real-time pricing rates [43]. The latter are characterized by variable prices, typically considering the market price as the reference price, and therefore transferring part of the price risk to end-use customers.

2.3. The non-organised market

In the non-organised market, depending on the amount of time available and the quantities to be traded, buyers and sellers can resort to the following options of bilateral trading [2]: customized long-term contracts and trading "over-the-counter" (OTC).

Customized long-term contracts are very flexible, meaning that the parties can negotiate the energy quantity, the duration of the contract, and naturally the price of the energy. Contracts may account for different prices for different blocks of time (i.e., may consider two-rates, three-rates, etc.). In case of physical delivery, the seller commits to serve the quantity of electricity required by the buyer, and the buyer commits to pay the price defined in the contract.

OTC contracts involve standard and non-standard contracts that are negotiated privately (without using the Exchanges). These contracts consider small amounts of energy and are used when sellers and buyers refine their position as delivery time approaches. The only parameters that commonly have to be communicated to the market operator is the date (specific day(s) and hour(s)) for the electricity trading, such as the quantity and the input and output grid nodes. Then the system operator checks for the feasibility of the agreement and communicates to players the ratification or not of the contract.

Bilateral contracts are often considered very important to the efficient operation of competitive electricity markets. There are, however, several problems associated with a long-term bilateral contract. Chief among them is risk asymmetry: buyers face greater risks than sellers if they wait to transact in spot markets, so sellers can charge a risk premium for bilateral contracts [44]. Sellers have almost nothing to lose if they wait to transact in spot markets in which they will face bid-based clearing prices, the potential for windfall profits, and a very low risk because they cannot be forced to sell below the prices they offered. As a result, the gap between what buyers are willing to pay and what sellers are willing to accept, under long-term contracts, has been too great to bridge in many cases [45].

Although derivatives markets and private bilateral contracts are a form of risk hedging, they also carry risks, so it is important to compute the potential risks associated with them. To select the best options to trade electricity, sellers and buyers have to model their risk attitudes, which will be reflected on their decisions.

In this work the contracts negotiated between retailers and end-use consumers are private customized long-term contracts.

3. Retail Competition in Electricity Markets

Traditionally, in liberalized electricity markets, retailers persuade consumers by offering discounts to regulated tariffs (see Figure 1). This work considers retailer agents that follow the same behaviour. However, it also considers retailers that propose personalized tariffs to key consumers. Accordingly, consumers can choose the best tariff based on either the expected cost or the expected utility [46, 47].

Retailers follow a “strategic” process to persuade consumers to choose their tariffs and therefore to be included in their portfolios (see Figure 2). The

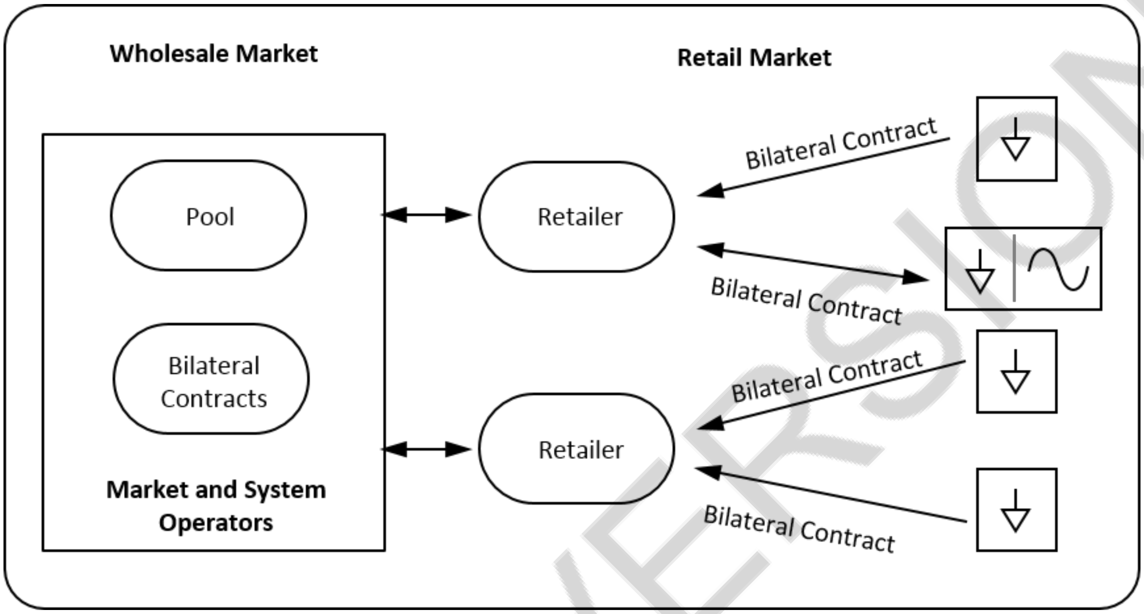


Figure 1: Retail competition in electricity markets.

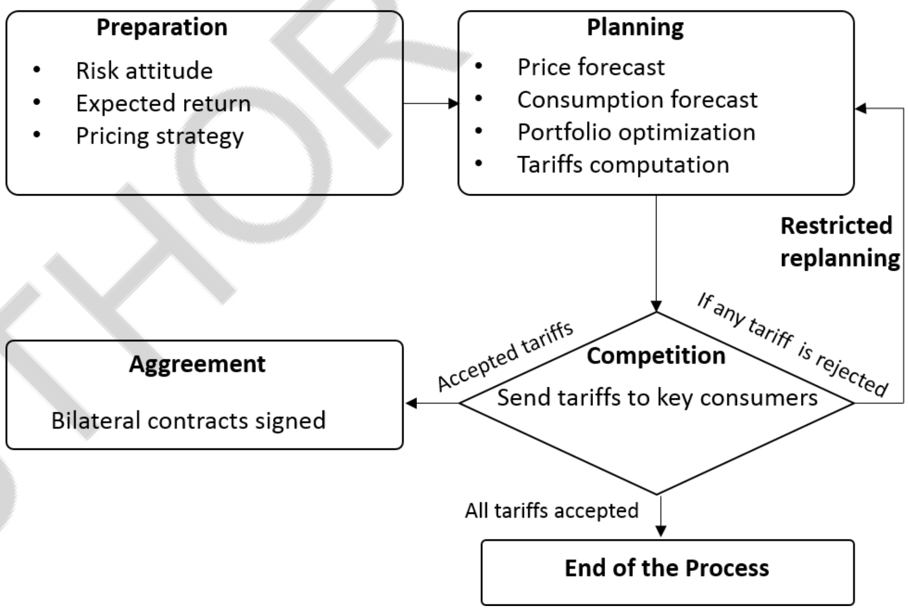


Figure 2: Strategic process of retailer agents.

process starts with a preparation phase, where retailers define the objectives, select a pricing strategy, and set some important parameters. The objectives include the selection of the target markets (where to buy and to sell energy), the definition of the expected return, and in some cases, the definition of the investment value (budget). The parameters involve mainly the adoption of an attitude towards risk. In the planning phase, retailers forecast both the energy price and the energy consumption taking into account the target markets, and then perform an optimization process to identify (or select) the key consumers to be included in their portfolios. After that, retailers basically send specific tariffs to consumers and interact with them with the main goal of signing bilateral contracts.

In case all consumers accept the proposed tariffs, the process ends with an agreement. Otherwise, retailers try to modify the composition of their portfolios. To this end, they perform a "new" optimization process, restricted by the fact that it takes into account the consumers that have already accepted the proposed tariffs.

Thus, consumers may either accept or not the proposed tariffs. To this end, they evaluate the tariffs they receive by computing a score (or utility) using either an additive or a multiplicative function [46, 47]. They can also make use of a cost function (and thus, choose the tariff that minimizes their expected cost). The cost function U_j of a consumer agent j takes the form:

$$U_j = \sum_{h=1}^{H} T_{j,h} \times q_{j,h} \tag{1}$$

where:

(i) $T_{j,h}$ is the prices of the tariff charged for consumer j at period h;

(ii) $q_{j,h}$ is the electricity consumption of the consumer j in period h.

In case of choosing the cost function, consumers may choose the tariff that minimizes their cost. Consumers may either accept a tariff or not. The acceptance of a tariff leads to a customized (or tailored) bilateral contract, which may account for different prices for different blocks of time (i.e., may consider two-rates, three-rates, etc.). Such contract may be considered very flexible, since the parties may discuss its terms and conditions, notably the energy price and the energy quantity. Failure to agree with a specific retailer (by rejecting the proposed tariff) may occur in two ways: (i) a consumer receives a better proposal from an opponent (another retailer), or (ii) the current tariff is better than the received tariff.

4. Risk Management and Portfolio Optimization

Retailer agents should select the best options to trade electricity–that is, they should select the markets (e.g., the day-ahead market in conjunction with the derivatives market) and define the bids to submit to each market. To this end, they should consider a risk management process, which typically includes three key phases [48, 49]: (i) risk assessment, (ii) risk characterization, and (iii) risk mitigation. In the risk assessment phase, retailers recognize the risk factors and identify the main deterministic and stochastic variables. Next, in the risk characterization phase, they make efforts to measure the risk using one or more methods, such as variance, correlation, regression, value at risk (VaR), and conditional VaR (CVaR). Finally, in the risk mitigation phase, they select the best set of products that allow them to reduce the risk.

4.1. Portfolio Optimization

In previous work [8], an optimization model has been proposed to select key consumers to be included in the portfolios of retailers, using the aforementioned risk management process. In the first phase, retailers face the following risk factors: market price volatility and consumption uncertainty (of customers in the portfolio). In the second phase, retailers consider the VaR to analyse how the previous risk factors affect the portfolios, which is given by the following expression:

$$VaR = -I \cdot r^* = I(\alpha\sigma\sqrt{\Delta t} - \mu\Delta t) \tag{2}$$

where:

(i) I is the investment made by a retailer (price to pay for the energy);

(ii) r^* is the cut-off return (the percentage of the investment at risk);

(iii) α, σ and μ are the confidence level, the standard deviation and the average of the expected return, respectively;

(iv) Δt is the time period under consideration (duration of the contract).

In the third phase, retailers consider their own risk attitude and the tariffs proposed to consumers to obtain the point that optimizes their risk-return ratio (which represents a share of consumers in their portfolio):

$$[w] = arg \max_{w_j \geq 0} \left([w]^T [\gamma] [\hat{r}] - \left(\frac{\lambda}{2} \right) [w]^T [Cov] [w] \right) \tag{3}$$

Subject to

$$\sum_{j=1}^{J} w_j = 1 \tag{4}$$

where:

(i) $[w]$ is the matrix containing the weight w_j of each consumer j in the portfolio;

(ii) $[\gamma]$ is the matrix containing the relative difference between the past (used data) and a future prediction of the arithmetic cost of electricity for each consumer j;

(iii) $[\hat{r}]$ is the matrix of the expected return of each consumer j;

(iv) λ is the risk attitude of the retailer;

(v) $[Cov]$ is the covariance matrix that relates the consumption between every consumer j.

The expected return is computed by taking into account the difference between the tariffs offered to consumers and the expected cost (for a particular quantity of electricity required by each consumer). This parameter may involve some uncertainty in relation to future prices of electricity, notably for retailers trading energy in day-ahead markets. However, in case retailers consider mainly forward contracts to buy electricity, the uncertainty is essentially related to the consumption of consumers (that is, the uncertainty associated with the price is reduced).

The covariance of the consumption of each consumer is important to select "complementary" consumers in order to avoid a high variation (uncertainty) in the expected consumption of the entire portfolio. The Markowitz efficient frontier is obtained by considering the conditions (risk factors) of the market(s) defined in the first phase of the risk management process, as well as the risk analysis carried out in the second phase and the optimized points obtained in the third phase. Retailers obtain the efficient frontier from the different points. It is worth noting that an optimized point is efficient if no other point can overcome its value in terms of risk (VaR) or return.

4.2. Background

Conceptually, Algarvio et al. [8] concluded that risk-averse retailers using a profit-seeking strategy may have an advantage in retail markets. The conclusion was obtained using the Markowitz theory (see Figure 3).

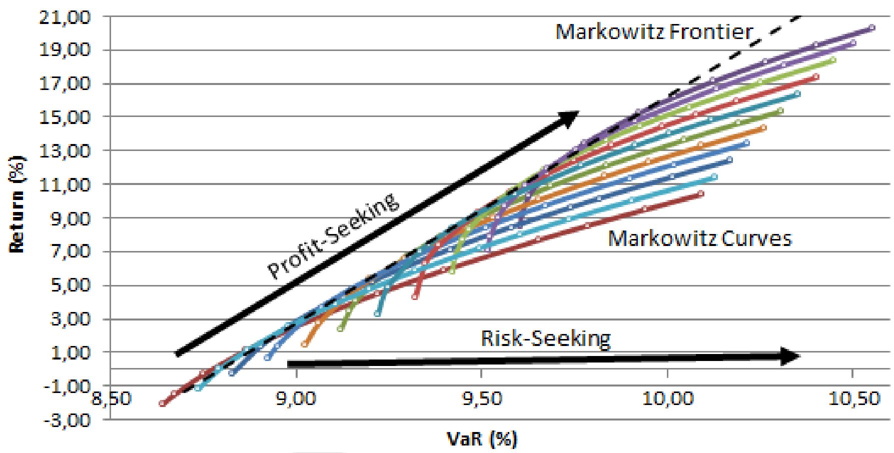


Figure 3: Markowitz curves and frontier

In Figure 3, each Markowitz curve corresponds to a different tariff. Considering the same share of consumers, for a higher target return of the retailer, then a higher tariff (profit-seeking) will be computed. Each point in each Markowitz curve corresponds to a portfolio of consumers, obtained using the optimization problem, taking into account the risk-attitude of the retailer. So, in each Markowitz curve, a higher risk-seeking attitudes leads to a portfolio that gives a higher expected return and VaR (risk-seeking).

However, by obtaining the efficient points of all Markowitz curves, there is the possibility to obtain the Markowitz efficient frontier (black dashed line). Those points are obtained in the portfolios of moderate risk-averse retailers, which are composed mainly of high shares of street lightning, moderate shares of small commercial, and small shares of industrial clusters.

The case studies of [8] only test the optimization model for a moderate risk-averse retailer, using clusters of consumers. However, in retail competition, a risk-seeking retailer can get higher returns by proposing lower tariffs (i.e., in Figure 3, it is possible to verify that the last point of the first dark-red Markowitz curve has a higher return than the initial points of all curves). So, risk-seeking retailers may have an advantage when competing for the same consumers. Thus, the theoretical advantage of risk-averse retailers in retail markets should be tested using retailers with different risk attitudes, by simulating retail competition for real consumers.

4.3. Extensions to the Model: Trading Strategy and Forecast Methods

The model depends on the tariffs proposed to each consumer. Such tariffs involve a fixed payment for power (contracted capacity fee) and a price per unit of electricity (variable fee). Both fees are divided into several parts, but the most important for the return of retailers is the energy part [50]. Accordingly, retailers may set an expected return tax ($\hat{r}$) for each consumer, the markup, which is given by the following expression:

$$\hat{r} = R_F + R_P \tag{5}$$

where R_F is the risk-free (deposits) of global markets and R_P is the risk-premium, that depends on several factors, such as the risk associated with the market prices and the consumption volatility.

Now, the most common tariffs for household consumers include tariffs that present a flat rate as well as tariffs that account for the value and cost of electricity in different days (week, weekends and holidays) and periods of a 24 hour day, such as two-rate tariffs (peak and off-peak), three-rate tariffs (peak, mid-peak and off-peak), and four-rate tariffs (peak, mid-peak, off-peak and super off-peak). Commercial and industrial consumers connected to high voltage or very-high voltage grids may also choose more refined tariffs (e.g., a hour-wise tariff, involving different prices for each hour).

The model presented in [8] includes several pricing strategies for retailers. Some of these strategies are adopted in this work, namely the "Equal Return OPtimization" strategy (EROP), the "Equal Tariff Optimization at a Minimum Return" strategy (ETOMinR), and the "Equal Tariff Optimization at a Maximum Return" strategy (ETOMaxR). The EROP strategy defines the minimum price (tariff) that retailers may offer to consumers to receive an equal return (target) from each of them. The ETOMinR strategy defines the minimum price that guarantees to retailers the target return (at least) from each consumer. And the ETOMaxR strategy computes the minimum price that at best gives to retailers the maximum target return from each consumer. This paper extends the model with a new pricing strategy, namely the “Equal Return Tariff based on Market-Costs (ERTMC)”. It reflects the expected costs of retailers with each consumer (in every period of the day associated with a particular tariff). This strategy incentives consumers to respond to TOU tariffs, adjusting their tariff by considering the expected market prices plus a premium in the blocks of prices proposed to consumers. So, consumers that have the majority of their consumption during off-peak periods will be compensated by a reduction in their costs with electricity, otherwise they can experience an increase in their costs. This strategy is formally described as follows:

$$T_{j,h} = \frac{(\hat{r}+1)\cdot\ \sum_{j=1}^{J}\sum_{h=1}^{H} q_{j,h}C_h}{\sum_{h=1}^{H} q_{j,h}} \tag{6}$$

where:

(i) $T_{j,h}$ is the prices of the tariff charged for consumer j at period h;

(ii) $\hat{r}$ is the retailer’s expected return;

(iii) C_h is the retailer’s expected cost per period h;

(v) $q_{j,h}$ is the electricity consumption of the consumer j in period h.

By using the Calinski-Harabasz (CH) criterion, it is possible to obtain the optimal number of clusters of the real data by considering the consumption profile of each consumer [51]. It computes the Euclidean distance between the clusters and compares it with the internal sum of squared errors for each cluster. Also, by using the k-means clustering algorithm, it is possible to divide consumers by their consumption segment identified by the CH criterion and compute their segment typical load profile. This algorithm is a robust model that minimizes the distance between each point to the centre of its respective cluster:

$$obj = min \sum_{c=1}^{K} \sum_{x \in Cl_c} \|x - \eta_c\|^2 \tag{7}$$

where:

(i) obj is the value of the k-means objective function;

(ii) c is the cluster number inside the total number of cluster, K ;

(iii) x is the centroid of the cluster Cl_c with a mean μ_c in their points;

To feed the model with a future prediction of the electricity consumption, there is a need to use a forecast method. This method consists in a multivariate time series (MTS) that uses the electricity consumption (E), the wholesale prices of electricity (P), and the gross domestic product (GDP).

$$\hat{E}_t = \sum_{i=1}^{L} \chi_i E_{t-1} + \sum_{i=1}^{M} \beta_i P_{t-1} + \sum_{i=1}^{N} \delta_i GDP_{t-1} + \epsilon_t \tag{8}$$

where:

(i) $\hat{E}_t$ consists in the forecast of the electricity consumption for year t;

(ii) L, M and K are the lags (number of previous periods);

(iii) χ_i, β_i and δ_i are regression variables.

(iv) ϵ_t is the error from random events.

To compute a future prediction of the arithmetic cost of electricity for each consumer, a forecast method was adapted from [8]. This method is similar to the previous one, but uses the share of renewable energy associated with electricity production (RES%) instead of the GDP, and the retail price of electricity, instead of the wholesale price.

Figure 4 presents the complete optimization model of each retailer. It uses the historical electricity wholesale and retail market prices, consumption, renewable share in the electricity mix, and the GDP to compute the expected wholesale market prices and the consumers' consumption. Next, considering the target return and the risk attitude, the retailer computes the expected costs with each consumer and selects a pricing strategy that computes the tariff to offer to each consumer. Then, the retailer enters into the retail competition phase by offering the computed tariffs to the target consumers indicated by the portfolio optimization. If all consumers accept the suggested tariffs, the process ends with the signature of bilateral contracts. Otherwise, consumers who reject their tariffs, are removed from the optimization process, and the others sign bilateral contracts with the retailer, entering into the

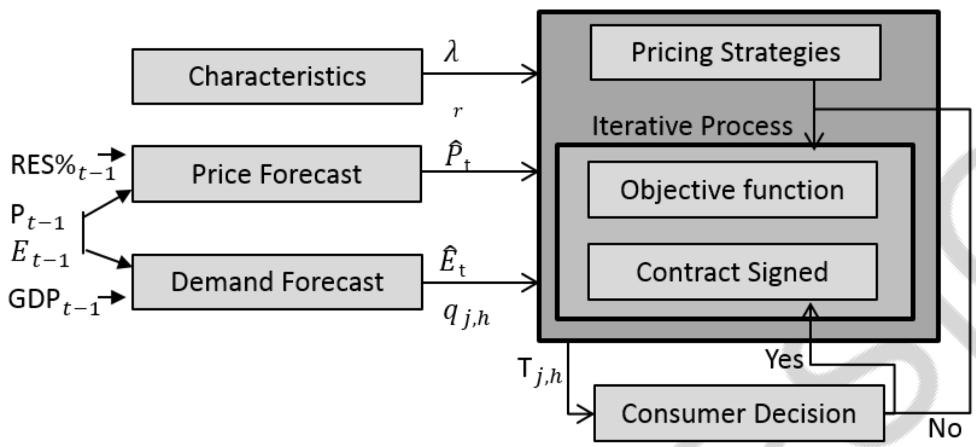


Figure 4: Retailer's optimization model

portfolio with their respective weight. In the end, the retailer enters into an iterative process until all target consumers accept the tariffs or no one remains to be part of the portfolio.

5. The MATREM System: An Overview

MATREM is a simulation tool based on intelligent agents for analysing the behaviour and outcomes of electricity markets. The tool supports a day-ahead market, a short-term market (an intra-day market) and a balancing market. Also, the tool supports a futures market for trading standardized bilateral contracts. Furthermore, it supports a marketplace for negotiating tailored (or customized) bilateral contracts. A detailed description of the system is presented in [31]. A classification of the system according to various dimensions associated with both electricity markets and intelligent agents can be found in [5]. This section gives an overview of MATREM.

The day-ahead market (DAM) is a central market where the entire Iberian electricity generation and demand can be traded on an hourly basis. Accordingly, a market operator agent collects all bids for a given hour h and sorts them according to the price (see, e.g., [43]). Next, the aggregated supply and demand curves are defined. The supply and demand are then matched by adding up all volumes. The market price is determined by the last unit necessary to satisfy the demand. The traded volume is determined as the sum of all demand bids that are satisfied at the market clearing price.

The intra-day market is a short-term market and typically involves several auction sessions. It is used to make adjustments in the positions of participants as delivery time approaches. Both the day-ahead and the intra-day markets are based on the marginal pricing theory. Two pricing mechanisms are supported: system marginal pricing (SMP) and locational marginal pricing (LMP).

The balancing market is a market for primary, secondary and tertiary reserves. For the particular case of tertiary reserve, a system operator agent determines the needs of the power system, collects the bids from the market participants, and determines the market prices by considering a simplified version of the system marginal pricing algorithm. Two computer simulations are performed, one for determining the price for up-regulation, and another for computing the price for down-regulation.

The futures market is an organized market for both financial and physical products, that may span from days to years. Typically, such products hedge against the financial risk (i.e., price volatility) inherent to day-ahead and intra-day markets. Market participants enter orders involving either bids to sell or buy energy in an electronic trading platform. The platform then matches the bids likely to interfere with each other

The tool also allows to negotiate tailored (or customized) long-term bilateral contracts, specifically forward contracts and contracts for difference(see, e.g., [33]). The terms and conditions of such contracts are flexible and can be negotiated privately to meet the objectives of two parties. To this end, the agents are equipped with a negotiation model that handles two-party and multi-issue negotiation. The negotiation process involves basically and iterative exchange of offers and counter-offers. We also wish to highlight that MATREM supports coalitions of end-user customers. In this way, two or more customers can intentionally form a coalition to strengthen their bargaining positions. The coalition may then interact and negotiate with a retailer agent in search for superior outcomes [52].

The target platform for the MATREM system is a 32/64-bit microcomputer running Microsoft Windows. The system supports generating companies, retailers, aggregators, coalitions of consumers, traditional consumers, market operators and system operators. All market entities are modelled as software agents.

6. Case Study

This section presents a study involving 6 retailers and 312 consumers from Portugal, corresponding roughly to 5% of the total demand of the country. The retailers want to invest in the Iberian electricity market. Their target are the 312 real-world consumers, that are connected to the mid voltage grid.

The study is conducted with the help of the MATREM system, meaning that the retailers and the consumers are modelled as software agents–that is, computer systems capable of autonomous action and able to meet their design objectives. The retailer agents are equipped with the portfolio optimization model described in section 4. The study period has the duration of 24 months: from January 1, 2012 to December 31, 2013.[2]

By using the Calinski-Harabasz criterion and the k-means clustering algorithm in Matlab, it is possible to divide the data set in five classes of consumption: aggregation of residentials (AggRES), aggregation of small commercials (AggSCom), large commercials (LCom), industrials (Ind) and others (aggregation of different types of consumers).

The study consider data from 2012–2013 and assumes that retailers start operating in the Portuguese market in 2013, meaning that in the planning phase they use real data from MIBEL and active consumers up to 2012 [35]. Then, after obtaining the optimized portfolios, retailers get the real results from 2013. Table 2 presents the main characteristics of retailers. In particular, for each retailer, R_i, i=1,...,6, the table shows the attitude towards risk, λ, the return, the price strategy, the type of tariff, and the possibility to perform a selective choice of consumers–that is, whether or not a particular retailer considers different types of tariffs to persuade specific consumers.

Most retailer agents consider a 3-rate tariff, which is defined for a 24 hour day as follows:

- Peak price: from 9 a.m. to 12 a.m. and from 6 p.m. to 9 p.m.;
- Mid-peak price: from 7 a.m. to 9 a.m., from 12 a.m. to 6 p.m., and from 9 p.m. to 12 p.m.;
- Off-peak price: from 12 p.m. to 7 a.m.

[2]This data set can be found in an online repository in `https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014#`.

Table 2: Retailers Characteristics

Retailer	Risk Preference	λ	Minimum Return (%)	Maximum Return (%)	Pricing Strategy	Tariff Type	Portfolio Optimization	Different Tariffs
R_1	High aversion	90	3.6		EROP	3-rate	Yes	Yes
R_2	Moderate aversion	70	3.6	12	ETOMaxR	3-rate	Yes	No
R_3	Small aversion	40	7.2		EROP	Single	Yes	Yes
R_4	Small seeking	20	7.6		ERTMC	3-rate	Yes	Yes
R_5	Moderate seeking	5	4		ETOMinR	3-rate	Yes	No
R_6	High seeking	–	6		ETOMinR	3-rate	No	No

The consumers are grouped into five groups. Each group contains the following consumers: Ind (10 consumers), LCom (11 consumers), AggSC (189 consumers), AggRes (71 consumers), and other (31 consumers). The study involves two main parts. The first part is devoted to computing the optimized portfolios of the retailer agents as well as the tariffs to propose to consumers (see next subsection). To this end, the retailers make use of the aforementioned forecast methods to get predictions of both the market prices and the consumer consumptions. Armed with this information, and equipped with the portfolio optimization model, the retailers then determine the optimized portfolios, define the tariffs, and compute the value at risk and the expected return (for the year 2013). The second part of the study analyses the results obtained with the optimization model (see subsection 4.1). Specifically, the retailer agents consider both the real market prices published by MIBEL and the real consumption data for the 312 consumers. By taking into account this information, and also considering the optimized portfolios and the tariffs to propose to consumers, obtained in the first part of the study, they then determine the "real" return (for the year 2013). In a next step, a systematic comparison is made between the expected return and the "real" return. Finally, some conclusions are drawn from the simulations performed.

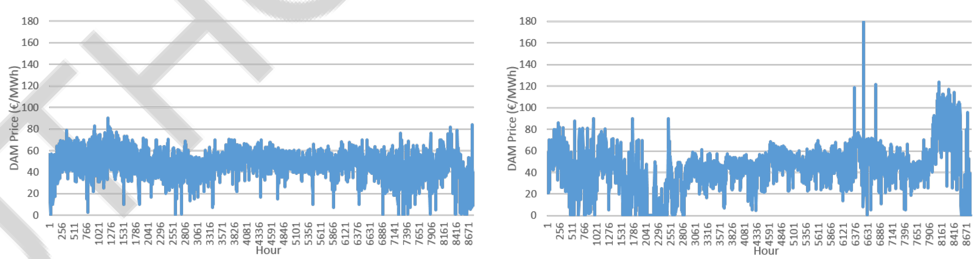
6.1. Optimal Portfolios of Retailers

As indicated earlier, the retailer agents propose specific tariffs to end-use customers with the main aim of signing bilateral contracts with them. The tariffs include two main terms: a fixed term, related to the contracted power, and a variable term, associated mainly with the energy consumed, but considering also the grid access and the global use of the system. Apart from the energy consumed, the other parts of the tariffs are fixed and set by decision of the Government, typically in strict accordance with the Regulator. Accordingly, this work considers that the part of the tariffs that can be negotiated is only the energy part. Table 3 presents the reference energy-part of the tariff in the retail market for each level of grid connection in 2013 [53]. Consumers accept the best tariff according to a cost function that computes their expected cost with electricity, considering the tariff that have been proposed to them and their expected consumption, as described in section 3.

Table 3: Energy part of the Portuguese reference tariff in 2013

Voltage Level	Tariff (€/MWh)		
	off-peak	mid-peak	peak
High voltage	46.75	65.10	76.40
Medium voltage	48.85	67.90	80.10
Low voltage commercial	55.00	73.00	83.60
Low voltage residential	58.20	73.00	84.10

Figure 5 presents the market prices published by MIBEL in 2012 and 2013 [35]. The price of the energy in the day-ahead market was highly volatile, meaning that price risk is indeed a key risk faced by retailers. The other key risk is the consumption uncertainty of the target consumers.



(a) (b)

Figure 5: Daily Iberian market prices published by MIBEL in the years 2012(a) and 2013(b).

Now, prior to the definition of the optimized portfolios, the retailer agents analyse the price volatility in the day-ahead market as well as the reference tariff in place in the retail market. The energy part of the Portuguese reference tariff during 2013 is shown in Table 3. In this year, this part of the tariff corresponded roughly to 40% of the variable term.

As noted above, retailers consider predictions of both market prices and energy consumptions in the computational simulations. A preliminary analysis of the results obtained with the forecast methods outlined in subsection 4.3 indicates a decrease around 4.83% in market prices, and an increase of 0.36% in energy consumption. A subsequent comparison of the real data in the years 2012 and 2013 indicates, however, a decrease of 9.2% in wholesale market prices and a decrease of 1.37% in energy consumption. Thus, from the point of view of retailers, this is an interesting situation, since they predicted a lower decrease in wholesale market prices. Accordingly, the return resulting from the simulations is expected to be lower than the "real" return.

Tables 4 and 5 summarize the results of the first part of the study. Table 4 shows the various consumers in the portfolios of the 6 retailers and the value at risk. The portfolios of retailers R_1 to R_5 were computed by making use of the optimization model. For instance, the optimized portfolio of retailer R_1 includes 5 consumers, leading to a VaR of 3.18%. The portfolios of retailers R_2, R_3, R_4 and R_5 include 22, 13, 32 and 13 consumers, respectively. Retailer R_6 proposed high tariffs to consumers, and as a result, it managed all consumers not included in the portfolios of retailers R_1 to R_5. Accordingly, its portfolio includes 228 consumers, a rather high value (when compared to the number of consumers in the other portfolios).[3]

The obtained portfolios can be considered optimal taking into account the available consumers and their choice in the retail competition. High return-seeking and risk-averse retailers propose higher tariffs to consumers, which can decrease portfolio efficiency, in the sense that consumers are likely to accept the tariffs proposed by other retailers, decreasing the efficiency of their portfolios. All the tariffs proposed by the first two retailers were accepted by consumers, although the other retailers also compete for those consumers. The consumers in the initial portfolio of retailers R_3 and R_4(the most efficient) reject the proposals, while retailer R_5 signs a contract with one

[3]The initial (optimal) and final portfolios of all retailers are presented in [54], an on-line repository. For each retailer, the first column corresponds to the optimal portfolio, while the second column corresponds to the final portfolio.

Table 4: Portfolios and expected return and VaR of each retailer.

Final Portfolio	R_1	R_2	R_3	R_4	R_5	R_6
AggRes		3	3		1	65
AggSCom	3	9	10	25	10	131
Ind		3		2		3
LCom		1		1	2	9
Others	2	6		4		20
Expected Return (%)	3.75	3.95	7.54	7.93	7.79	9.95
VaR (%)	3.42	3.78	3.99	4.13	4.19	4.59

Table 5: Portfolio of R_1: the tariffs and the energy share of each consumer.

Consumer	Type	Tariff (€/MWh)			Energy
		off-peak	mid-peak	peak	share (%)
c_3	Other	37.17	63.18	79.61	1.80
c_{81}	Other	34.09	57.96	73.03	27.14
c_{83}	AggSCom	31.74	53.96	67.99	4.65
c_{289}	AggSCom	31.03	52.75	66.46	36.11
c_{299}	AggSCom	30.99	52.68	66.37	30.03

of the consumers indicated in the initial portfolio. Naturally, R_6 only signs contracts with consumers that are not approached by the other retailers, since it is the retailer that proposes higher tariffs.

To some extent, Table 4 shows that retailers tend to not choose both residential consumers (since the uncertainty associated with their consumption is high) and large commercial consumers (because their consumption patterns are similar to the ones of small commercial consumers, which typically increase the risk inherent to portfolios). The table also indicates that risk-averse retailers–that is, retailers R_1 to R_3–tend to define portfolios with a reduced number of consumers, involving a low value at risk.

Table 5 shows the tariff proposed by the retailer agent R_1 to the five consumers of the portfolio.[4] This agent offers the cheapest tariff. In practical terms, the tariffs offered by all agents are interesting and competitive, since they are more attractive than the reference tariff proposed by the Regulator. The most expensive tariff is offered by the agent R_2, which involves the following prices: 48.69 €/MWh (off-peak price), 62.11 €/MWh (mid-peak price) and 67.05 €/MWh (peak price).

6.2. Return of Retailers

Table 6 and Figure 6 summarize the results of the second part of the study. The table shows that the expected return of the retailer agents is lower than the "real" return. As indicated above, this is an expected result, since the decrease of both wholesale market prices and energy consumption was higher than predicted. The analysis of Tables 4 and 6 shows that the expected return increases with the VaR. For instance, the VaR of retailer R_1 is 3.18%, and the expected return is 3.75%, and the VaR of retailer R_6 is 4.59%, and the expected return 9.95%. Interestingly, the "real return" does not follow a similar pattern. Indeed, the expected return of retailers R_5 and R_6 is higher that the expected return of retailers R_3 and R_4, respectively, but the same is not true for the "real" return.

Tables 4 and 6 show that the difference between the expected and the "real" return tends to decrease with the VaR–for retailers R_1 and R_6 the absolute value of this difference is 3.07 and 1.63, respectively (see Figure 6).

[4]The tariff of retailer R_1 is the most attractive to customers, meaning that the tariffs of the other retailers present higher rates. Since the portfolios of these retailers involve a rather large number of consumers, we present the tariff of R_1 only. The tariffs of the other retailers can be seen in the online repository previously mentioned.

Table 6: Expected and real return of each retailer in 2013 and consumption variability in relation to 2012.

Retailer	Expected Return (%)	"Real" Return (%)	Intrinsic variation of Return (%)	Consumption Variability (%)
R_1	3.75	6.82	81.87	-5.43
R_2	3.95	7.25	83.54	-8.76
R_3	7.54	10.84	43.77	-4.84
R_4	7.93	11.85	49.43	-7.50
R_5	7.79	9.28	19.13	-6.75
R_6	9.95	11.58	16.38	-2.22

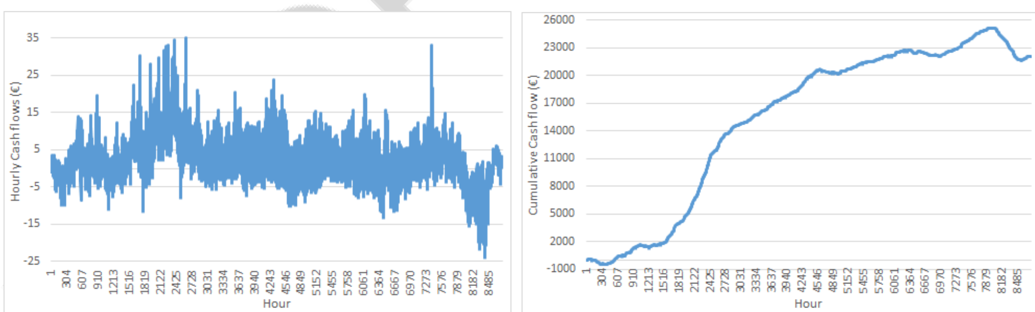
There is an exception, however, which is the case of retailer R_4. We believe this is due to the composition of the portfolio of this retailer, particularly to the (relatively high) number of small commercial consumers (of type AggSC). For each retailer R_i, we have computed the intrinsic variation of return IR, considering the real return, r, and expected return, $\hat{r}$, as follows:

$$IR = \frac{r - \hat{r}}{\hat{r}} \times 100 \quad (9)$$

Figure 6: Retailers expected and real returns.

Figure 6 summarizes the main results of the study. From Table 6 and Figure 6, the reader may observe a tendency between the risk preference and the increase in return of retailers. While high risk-aversion retailers substantially increase their return, small risk-aversion retailer and risk-seeking retailers moderately increase their return, and high risk-seeking retailers slightly increase their return. Risk-seeking retailers may have advantage in retail competition by offering more competitive tariffs, but risk-aversion retailers may have better outputs in case of favourable and not favourable situations. Indeed, it was proven that in case of wholesale market prices higher than expected, which is not good for retailers, the return of risk-averse retailers has small losses [8]. Furthermore, the presented article also proven that in case of wholesale market prices lower than expected, which is good for retailers, risk-averse retailers have substantially higher increases in their return when comparing with risk-seeking retailers. Risk-averse retailers that use strategies to obtain moderate returns can offer more competitive tariffs than profit-seeking retailers with a risk-seeking preference, and at the same time having more stable portfolios.

Figure 7 presents the cash flow of retailer R_1 during 2013 (a) and the corresponding cumulative cash flow (b). For this agent, the value of the cash flow is negative in 2895 hours (about 33% of the total number of hours), meaning that there is a large potential to consider demand response programs. Also, the cumulative cash flow is negative during the first months of the year and, at the end of the year, there is a considerable loss for R_1.



(a) (b)

Figure 7: Cash flow (a) and cumulative cash flow (b) of retailer agent R_1 during 2013

Overall, actual competitive retail markets seem to be more favourable to risk-seeking retailers. However, for a given target return, risk-averse retailers can take some advantage from actual markets, since their portfolios are stable, limiting their exposure to risk, and thus enabling them to get a high profit when pursuing a profit-seeking strategy.

7. Conclusion

This article presented an overview of the optimization model described in [8] and extended it by considering: (i) a new trading strategy for retailers, (ii) forecast methods to predict both market prices and customer consumption, and (iii) a formal model for retail competition. The extended model was tested in a real-world setting, involving 6 retailers with different risk-attitudes, real data from the Iberian electricity market, and 312 consumers from Portugal. The simulation study was conducted with the help of the MATREM system. The scenario is positive from the point of view of retailers, since the real wholesale market prices were lower than the predictions obtained with the forecast method. Specifically, the study involved an expected decrease around 4.83% in market prices, when the real decrease was about 9.2%. Accordingly, we found an expected return for retailer agents lower than the "real" return.

The results indicated that actual competitive retail markets seem to be favourable to risk-seeking retailers, who can typically offer lower tariffs to target consumers, and sign mutually advantageous bilateral contracts with them (probably overcoming retail competition). However, for a given target return, risk-averse retailers have more stable portfolios, so if they pursue profit-seeking strategies, they will get higher returns in both favourable and unfavourable scenarios. Furthermore, substantial variations in return lead to small variations in risk, so the retail market of electricity is favourable for profit-seeking retailers. To conclude, while risk-seeking retailers may have advantage in retail competition by proposing better tariffs, risk-averse retailers will have better returns from their portfolios in (positive and negative) unexpected situations.

At present, the main risk factors faced by retailers operating in competitive retail markets are the pool price volatility and the consumption variability (of the clients that compose their portfolios). Accordingly, the mitigation of these risk factors allows retailers to propose more competitive tariffs to target consumers. Also, encouraging consumers to enrol in demand response programs in strict collaboration with retailers will help improve the efficiency and reliability of retail markets.

References

[1] S. Hunt, G. Shuttleworth, Competition and Choice in Electricity, Chichester, England: Wiley, 1996.

[2] D. Kirschen, G. Strbac, Fundamentals of Power System Economics, Wiley, Chichester, 2004.

[3] F. Lopes, H. Coelho, Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation and Emerging Designs, Springer International Publishing, Cham, 2018.

[4] G. Strbac, D. Papadaskalopoulos, N. Chrysanthopoulos, A. Estanqueiro, H. Algarvio, F. Lopes, L. de Vries, G. Morales-Espaa, J. Sijm, R. Hernandez-Serna, *et al.*, Decarbonization of Electricity Systems in Europe: Market Design Challenges. IEEE Power and Energy Magazine 19.1, pp. 53– 63, 2021.

[5] F. Lopes, Electricity Markets and Intelligent Agents Part I: Market Architecture and Structure, in: F. Lopes, H. Coelho, (eds.), Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation and Emerging Designs, pp. 2348, Springer International Publishing, Cham, 2018.

[6] M. Shahidehpour, H. Yamin, Z. Li, Market Operations in Electric Power Systems, Chichester, England: Wiley, 2002.

[7] S. Gabriel, A. Conejo, M. Plazas, S. Balakrishnan, Optimal price and quantity determination for retail electric power contracts, IEEE Trans. Power Syst., vol. 21, no. 1, pp. 180187, Feb. 2006.

[8] H. Algarvio, F. Lopes, J. Sousa, J. Lagarto, Multi-agent electricity markets: Retailer portfolio optimization using Markowitz theory, Electric Power Systems Research 148, pp. 282–294, 2017.

[9] H. Algarvio, The Role of Local Citizen Energy Communities in the Road to Carbon-Neutral Power Systems: Outcomes from a Case Study in Portugal. Smart Cities 4, pp. 840–863, 2021.

[10] R. Bessa, M. Matos, Optimization models for an EV aggregator selling secondary reserve in the electricity market, Electric Power Systems Research 106, 36–50, 2014.

[11] P. Zhong, W. Zhang, B. Xu, A risk decision model of the contract generation for hydropower generation companies in electricity markets, Electric Power Systems Research 95, pp. 90–98, 2013.

[12] M. Kazemi, B. Mohammadi-Ivatloo, M. Ehsan, Risk-based bidding of large electric utilities using Information Gap Decision Theory considering demand response, Electric Power Systems Research 114, pp. 86–92, 2014.

[13] R. Faia, T. Pinto, Z. Vale, J. Corchado, An Ad-Hoc Initial Solution Heuristic for Metaheuristic Optimization of Energy Market Participation Portfolios, Energies 2017, 10(7), 883.

[14] H. Algarvio, F. Lopes, J. Sousa, J. Lagarto, Power Producers Trading Electricity in both Pool and Forward Markets, in: 3rd International Workshop on Intelligent Agent technology, Power Systems, and Energy Markets (IATEM-14), IEEE Computer Society Press.

[15] R. Teive, R. Guder, C. Sebba, Risk management in the energy trading activity: An approach by using multi objective genetic algorithm and multi criteria theory, Proc. IEEE/PES, pp.504–510 2010.

[16] R. Teive, T. Lange, G. Arfux, A. Queiroz, L. Rosa, A Decision Support System for Energy Trading and Portfolio Optimization, Journal of Energy & Power Engineering, Vol. 5 Issue 4, p349, April 2011

[17] T. Pinto, Z. Vale, I. Praça, E. Pires, F. Lopes, Decision Support for Energy Contracts Negotiation with Game Theory and Adaptive Learning, Energies 2015, 8, 9817–9842.

[18] A. Hatami, H. Seifi, and M. Sheikh-El-Eslam, Optimal selling price and energy procurement strategies for a retailer in an electricity market, Electric Power Systems Research 79, pp. 246–254, 2009.

[19] A. Hatami, H. Seifi, and M. Sheikh-El-Eslam, A Stochastic-Based Decision-Making Framework for an Electricity Retailer: Time-of-Use Pricing and Electricity Portfolio Optimization, IEEE Trans. Power Syst. vol. 26, no. 4, pp. 1808–1816, November 2011.

[20] J. Kettunen, A. Salo, D. Bunn, Optimization of Electricity Retailers Contract Portfolio Subject to Risk Preferences, IEEE Trans. Power Syst. vol. 25, no. 1, pp. 117–128, February 2010.

[21] K. Guesmi, R. Boroumand, S. Goutte, T. Porcher, Potential benefits of optimal intra-day electricity hedging for the environment: The perspective of electricity retailers. Energy Policy vol. 132: pp. 1120–1129, 2019.

[22] R. Karandikar, S. Khaparde, S. Kulkarni, Strategic evaluation of bilateral contract for electricity retailer in restructured power market. International Journal of Electrical Power & Energy Systems, vol. 32(5):457–63, 2010.

[23] S. Nojavan, R. Nourollahi, H. Pashaei-Didani, K. Zare, Uncertainty-based electricity procurement by retailer using robust optimization approach in the presence of demand response exchange. International Journal of Electrical Power & Energy Systems, vol. 105:237–48, 2019.

[24] S. Sekizaki, I. Nishizaki, Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers. International Journal of Electrical Power & Energy Systems, vol. 105:877–93, 2019.

[25] M. Charwand, M. Gitizadeh, P. Siano, A new active portfolio risk management for an electricity retailer based on a drawdown risk preference. Energy, vol. 118:387–398, 2017.

[26] R. Faia, T. Pinto, Z. Vale, J. Corchado, Portfolio optimization of electricity markets participation using forecasting error in risk formulation. International Journal of Electrical Power & Energy Systems 129, 106739, 2021.

[27] H. Algarvio, F. Lopes, J. Sousa, J. Lagarto, A Trader Portfolio Optimization of Bilateral Contracts in Electricity Retail Markets, in: 25th Database and Expert Systems Applications (DEXA), pp. 114–118, IEEE, 2014.

[28] H. Markowitz, Foundations of Portfolio Theory, The Journal of Finance 46(2), pp. 469–477, JSTOR, 1991.

[29] F. Rodrigues, A. Trindade, Load forecasting through functional clustering and ensemble learning, Knowledge and Information Systems 57(1), pp. 229–244, 2018.

[30] F. Lopes, H. Coelho, Electricity Markets and Intelligent Agents. Part II: Agent Architectures and Capabilities, in: F. Lopes, H. Coelho, (eds.), Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation and Emerging Designs, Series: Studies in Systems, Decision and Control, Vol. 144, pp. 49-77, Springer, Cham, 2018.

[31] F. Lopes, MATREM: An Agent-based Simulation Tool for Electricity Markets, in: F. Lopes, H. Coelho, (eds.), Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation and Emerging Designs, pp. 189–225, Springer International Publishing, Cham, 2018.

[32] H. Algarvio, F. Lopes, Risk Management and Bilateral Contracts in Multi-agent Electricity Markets, in: Highlights of Practical Applications of Heterogeneous Multi-Agent Systems, pp. 297–308, Springer Verlag, 2014.

[33] F. Lopes, H. Algarvio, J. Santana, Agent-Based Simulation of Electricity Markets: Risk Management and Contracts for Difference, in: Agent-Based Modeling of Sustainable Behaviors, pp. 207–225, Springer Verlag 2017.

[34] MIBEL, Description of the operation of the mibel. MIBEL Regulatory Council Tech. Rep. 2009, p. 240. http://www.erse.pt/eng/electricity/MIBEL/Documents/Description_Operation_MIBEL.pdf (Accessed on 08-06-2021).

[35] OMIE, The day-ahead MIBEL curves. https://www.omie.es/en/market-results/daily/daily-market/daily-hourly-price (Accessed on 08-06-2021).

[36] OMIP, Power Derivatives. https://www.omip.pt/en/content/power-derivatives-portfolio (Accessed on 08-06-2021)

[37] A. Sleisz, P. Sores, D. Raisz, Algorithmic properties of the all-European day-ahead electricity market, in: 11th International Conference on the European Energy Market (EEM), 2014.

[38] H. Algarvio, F. Lopes, A. Couto, A. Estanqueiro, J. Santana, Effects of Regulating the European Internal Market on the integration of Variable Renewable Energy. WIREs Energy and Environment, 8(6):e346, 2019.

[39] H. Algarvio, F. Lopes, J. Santana, Simple and Linear Bids in Multi-agent Daily Electricity Markets: A Preliminary Report, in: 15th International Conference on Distributed Computing and Artificial Intelligence (DCAI'18), Springer, 2018.

[40] ACER, Annual Report on the Results of Monitoring the Internal Electricity and Gas Markets in 2016, Electricity Wholesale Markets Volume. October 2017. `http://www.acer.europa.eu/Official_documents/Acts_of_the_Agency/Publication/ACER%20Market%20Monitoring%20Report%202016%20-%20ELECTRICITY.pdf` (Accessed on 08-06-2021).

[41] H. Algarvio, F. Lopes, A. Couto, A. Estanqueiro, Participation of Wind Power Producers in Day-ahead and Balancing Markets: An Overview and a Simulation-based Study. WIREs Energy and Environment, 8(5):e343, 2019.

[42] ACER, ACER Market Monitoring Report 2019 Energy Retail and Consumer Protection Volume, 2020. `https://www.acer.europa.eu/Official_documents/Acts_of_the_Agency/Publication/ACER%20Market%20Monitoring%20Report%202019%20-%20Energy%20Retail%20and%20Consumer%20Protection%20Volume.pdf` (accessed on 08-06-2021).

[43] F. Lopes, H. Algarvio, Demand Response in Electricity Markets: An Overview and a Study of the Price-Effect on the Iberian Daily Market, in: F. Lopes, H. Coelho, (eds.) Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-based Simulation, and Emerging Designs, SSDC, vol. 144, pp. 265–303, 2018, Springer, Cham.

[44] H. Algarvio, F. Lopes, J. Santana, Bilateral Contracting in Multi-agent Energy Markets: Forward Contracts and Risk Management, in: High-

lights of Practical Applications of Agents, Multi-Agent Systems, and Sustainability, pp. 260–269, Springer Verlag 2015.

[45] E. Hausman, R. Hornby, A. Smith, Bilateral Contracting in Deregulated Electricity Markets, Report to the American Public Power Association, Synapse Energy Economics (April 2008).

[46] R. Keeney, H. Raiffa, Decisions with Multiple Objectives: Preferences and Value Tradeoffs, Cambridge University Press, NY, USA, 1993.

[47] P. Goodwin, G. Wright, Decision Analysis for Management Judgment, John Wiley & Sons Ltd, Chichester, England, 2004.

[48] T. Aven, O. Renn, Risk management and governance: concepts, guidelines and applications, Berlin. Heidelberg: Springer, 2010.

[49] P. Hopkin, Fundamentals of risk management: understanding, evaluating and implementing effective risk management, 2nd ed. London: Kogan Page, 2012.

[50] ERSE, Portuguese Energy Regulator, Tariffs and Prices. `http://www.erse.pt/eng/electricity/tariffs/Paginas/default.aspx` (Accessed on 08-06-2021).

[51] T. Calinski, J. Harabasz, A dendrite method for cluster analysis. Commun. Stat., vol. 3, no. 1, p. 27, 1974.

[52] H. Algarvio, F. Lopes and J. Santana, Coalitions of End-Use Customers in Retail Electricity Markets: A Real-World Case Study Involving Five Schools for Children, in: International Conference on Practical Applications of Agents and Multi-Agent Systems, pp. 312–320, Springer Verlag 2018.

[53] ERSE, Tarifas e Preços para a Energia Elétrica e Outros Serviços em 2012 e Parâmetros para o período de Regulação 2012-2014, December 2011. `https://www.erse.pt/media/omfjwdlf/p%C3%A2rametros-reg-2012-2014.pdf` (Accessed on 08-06-2021).

[54] H. Algarvio, Retailers' Portfolio of Consumers, Harvard Dataverse, V1, 2021, `https://doi.org/10.7910/DVN/WFQ5V0` (Accessed on 08-06-2021).