Bilateral Contracting in Liberalized Energy Markets: Contracts for Difference and Risk Management

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Abstract— The liberalization process of the power sector led to the existence of fully competitive wholesale and retail markets. The participating entities in these sectors compete with each other and have the common goal of maximizing their profits.

These market participants are exposed to risks associated with price volatility and uncertainties regarding production and consumption. The dissertation addresses the issue by conducting a study of financial products used to hedge against these risks, specifically the Contract for Difference (CFD).

This article starts with a contextualization of the subject, followed by the creation of a model to negotiate CFDs and the development of a group of strategies created with the intent of controlling the exposure of risk by each agent. Finally, a set of case studies have been completed in order to verify the capability of a CFD as a risk management tool and compare their performance with another type of bilateral contract.

Keywords— Risk Management, Bilateral Agreements, Contract for Difference, Autonomous Software Agents, Multi-Agent Systems.

I. INTRODUCTION

A. Sector Organization and Road to Liberalization

The power sector covers four main activities: the generation, transmission, distribution and retail of electricity. The way this sector has been organized has changed throughout the last century and it is customary to distinguish four main models of said sector: a regulated natural monopoly, single buyer, competition in the wholesale market, and competition in the wholesale and retail markets [1]. The technical challenges associated with the transmission of energy and the economies of scale in generation of electricity fostered the emergence of the regulated monopoly as the main model of organization at the beginning of the 20th century [2]. The regulated monopoly is characterized by the existence of a single vertically integrated company responsible for the aforementioned activities [3].

The introduction of competition in the power sector started inadvertently in the 1970’s when the increasing concern for the environment and the search for alternative energy sources led to the passing of the PURPA (Public Utility Regulatory Policies Act) in the United States in 1978, in which vertically integrated utilities were required to purchase electricity from independent generators, that competed with each other for the right to sell to the single buyer [2]. A growing belief that competition in the sector would be beneficial paved a way for liberalization. This happened through the introduction of policies by governments that, at first, created a fully competitive wholesale market by allowing the participation of more than one utility company (that kept the monopoly of its final customers) to be free to buy from whichever generator it wanted.

Finally, in some cases, the organization progressed towards a full liberalized sector by allowing the final customer to choose their own supplier of energy. This kind of model is currently implemented in Portugal and by the end of 2015 all of its electricity customers will have entered the liberalized retail market [4]. Also, the Portuguese electricity market is integrated with the Spanish to form the MIBEL (Iberian electricity market). The management of the Iberian derivatives market is the responsibility of the OMIP. The operator in charge of the spot market is the OMIE. Both operators own 50% of the OMIClear, that manages the clearing platform for the derivatives market and acts as central counterparty to all operations [5]. There is also a regulator for the Portuguese sector, called ERSE (Energy Services Regulatory Authority), whose responsibilities go from the approval of regulations and energy prices to the protection of consumer’s rights by guaranteeing that the law is enforced [6].

B. Energy Contracting: Spot Market and Bilateral Contracts

When the wholesale market of electricity is fully competitive there are two ways to purchase and sell electricity. The first one is through an electricity pool, on which the generators and retailers place their offers to sell or buy energy usually for the next day. This market acts as an auction and is supervised by a market operator who mediates the negotiations. When the aggregated production curve matches the aggregated load a market price is reached. Every generator that offered energy at a price lower than that market price will
be chosen to deliver its energy and will be paid the market price [7].

Market participants have another way to fulfill their needs, they can engage in bilateral contracts. A bilateral contract is an agreement between two parties where one of them makes the commitment to deliver energy and the other pays for it. The advantage of this type of agreement compared to resorting to the spot market is that, in these contracts, the terms (such as quantity of energy, price and maturity of contract) are custom-made to the parties’ needs. Bilateral contracts also help to mitigate the position of bigger producers’ power in the spot market by allowing buyers to no longer be dependent on them to fulfill their energy needs and look elsewhere for a better deal.

Another advantage of bilateral contracts is the support given by them to renewable energy. Renewable energy is characterized by having high capital costs and having its output heavily dependent on weather conditions, which are problems that other traditional energy sources don’t have. Potential investors require a guaranteed stream of future revenues in order to obtain financing for those resources, therefore if they engage in bilateral contracts to sell their output they have a guaranteed flow of revenue independent from the market situation [8].

C. The Need for Risk Management

One of the main issues with electricity is the inexistence of an economically viable way to store it, electricity has to be consumed within a tenth of a second of its generation. Therefore, the offer has to match the demand at all time to ensure the system’s efficiency and stability. This fact makes the market participants exposed to risks since they have to work with predictions regarding the load. There are financial risks related to high volatility of market prices due to fluctuation of the demand which can reach a peak in periods when the generation is insufficient. There are also risks regarding the volume of energy due to the inherent uncertainty regarding the demand and the generation. When these risks are not fully addressed the consequences can be devastating to the market participants.

One case that shows how dangerous these risks are, is the energy crisis that happened in California in 2000-2001. The reason behind the crisis was an inadequate legal framework. The purchase of energy through a power pool was made mandatory in 1998 [2] and there was a belief that the prices in the wholesale market were going to decrease due to the fully competitive nature of it. Meanwhile, the utility companies had their selling prices to customers “frozen” at a rather high price to compensate “stranded costs” The expectation was that generation expenses would be rather lower than this figure, and this would help to promptly realize such compensation, after that retail prices might be defrosted (and should decline) [9].

This model worked for a while, but during that time there wasn’t a relevant investment in new power plants and the demand kept growing. When a particularly hot summer hit California in 2000, the demand peaked and there was insufficient generation to meet the demand. The prices in the electricity pool grew 500% between 1999 and 2000 [10]. This led to a series of blackouts due to the high demand and some generators halted their production with fear of lack of credit from the utilities. Since the retail prices were frozen the customers never felt the rise in prices and kept the demand high [2].

The rise on the wholesale prices meant that utilities had no hedge against the spot price and were required to buy energy at very high prices and sell it at the “frozen” price, which made them accumulate debt. Meanwhile, some generators were making profits of 350% [9]. Ultimately, the government had to intervene and one of the measures applied to stabilize the prices was allowing the utilities to make long-term bilateral contracts. This case highlights the need for the existence of financial instruments that, when properly applied, can protect market participants from the volatility in prices.

D. Financial Instruments in Bilateral Contracting

The hedging of risk exposure is essential to electricity market participants, and many different financial instruments are used when two parties with opposite views are willing to exchange risk. The most common ones are futures contracts, forward contracts, option contracts and contracts for difference. These contracts can either require the physical delivery of electricity or have a purely financial settlement [11]. Currently, all these contracts are available in Portugal and the following descriptions refer to their terms in the Portuguese market of derivatives in the energy market, the OMIP.

Futures contracts include an obligation to buy or sell a specified quantity of energy at a certain future time for a certain price. These contracts have financial daily settlements between the agreed price and the variable spot market price for these contracts. The parties do not interact directly with one another, a central counterparty guarantees the fulfillment of obligations of both parties. The physical delivery is optional [12][13][14].

Forward contracts imply a commitment between parties to sell or buy a specific amount of electricity at a certain future time for a certain price. Unlike future contracts, forward contracts only have settlements on single a date, in which the energy is delivered and the payment is made [15]. In these cases there are no financial settlements and the physical delivery of energy is always required [16].

An option contract includes a right (not obligation) to buy or sell a specified quantity of an asset at a certain future time for a certain price [15]. A call option gives the agent the right to buy an asset and a put option gives him the right to sell it in a certain future time. In the option contracts available in the OMIP, the buyer has to pay a premium to seller in order to have those rights and that asset is a future contract [17].

E. Contracts for Difference

Finally, there’s the contract for difference (CfD) which is the derivative highlighted in this dissertation. In this type of contract there is no physical delivery of the energy by the seller. Both he and the buyer keep fulfilling their energy needs in the spot market throughout the duration of the contract [18]. They establish a bilateral agreement between them where they
negotiate an amount of energy for a fixed price called the strike price. Both parties also come to an agreement to have a reference price of which they will use to calculate the differences. If the reference price is higher than the strike price, then the seller will pay that difference to the buyer. But if the reference price is lower than the strike price then buyer pays an amount equal to the difference between the strike price and the reference price. A typical case of a CfD is shown on Figure 1. In some cases, the CfD can be a one way contract, when the difference payments are made only by one of the parties [15].

The contract for difference is present in the OMIP, with the name swap, and follows the same principles described above. It can have many durations, spanning from days to years [19]. The seller pays the strike for the notional quantity of energy and the buyer pays the reference price spot which is equal to the price for futures contracts with equivalent delivery period [20]. The settlement value between parties is calculated using the equation:

\[ DSV_d = H \times \sum_{i}^{n} \left[ FQ_i \times (SRP - SP_i) \right] \]  

(1)

Where:

i)\, DSV\_d is the delivery settlement value related to the d calculation day;

ii)\, H is the number of hours corresponding to the d calculation day;

iii)\, i is the transaction in the swap contract, on a d calculation day;

iv)\, n is the total number of transactions in swap contracts on a d calculation day;

v)\, SRP is the spot reference price for the d calculation day;

vi)\, SP\_i is the price of the swap contract transaction i, on a d calculation day;

vii)\, FQ\_i is the quantity of the swap contract transaction i, on a d calculation day, assuming a positive value in case of a buy and a negative value in case of a sell.

When DSV is positive, that amount is due by the seller to the buyer, and negative DSV values are due by the buyer to the seller.

F. Multi-Agent Systems

One of the main objectives of this dissertation is to provide a tool that models the current electrical sector where each participant is responsible for a specific set of activities and has to interact with different participants in order to fulfill their responsibilities. The liberalization of the sector increased its complexity and now there is a growing number of different market participants, each one of them have their own set of objectives, strategies and exposure to risk.

One way to model such a complex system is using autonomous software agents to represent each one of the participants. These agents are computer systems capable of flexible autonomous action in order to meet their design objectives. They can respond in a timely fashion to changes that occur in the environment, exhibit goal-directed behavior, and interact with other agents in order to reach their design objectives [22]. Each of these agents is characterized by a set of features such as [23]:

- Autonomy: an agent is an independent entity of the underlying system. It communicates and interacts with other agents, but makes its decision without external control by its peers or administrative agents;
- Heterogeneity: every single agent can be different and have its own characteristics;
- Adaptation: each agent should make decisions in order to adapt according to its current states and the changing conditions in its environment;
- Sociability: an agent should have the capability to communicate and exchange information, this feature provides it with a basic mechanism to interact with other agents or humans in order to reach its goals.

Also, each agent is equipped with some tools that will be useful in the negotiation process, such as [24]:

- A set of beliefs that represent the information that an agent has from itself and the market;
- A set of goals representing states to be achieved by the agent;
- A library of plan templates to be used in order to reach the goals;
- A set of plans for the execution of actions.

These agents interact with each other in a multi-agent system, which is ideally suited to represent problems that have multiple problem solving entities and multiple problem solving methods [22]. Multi-agent systems are loosely coupled networks of autonomous software agents that interact with the aim of solving problems that surpass their individual capabilities. Agent technology has been used to solve real-world problems in a range of industrial and commercial applications [25].

Nowadays, there is an increasing search for software tools that model the power market in order to provide information to support decision-making. One of them worth mentioning is the Market Complex Adaptive Systems (EMCAS), developed by the Argonne National Laboratory in the USA. The EMCAS includes a wide series of agents, including generation

![Diagram of a CfD](image)
companies, transmission companies, distribution companies, independent system operators or regional transmission organizations, consumers, and regulators and three types of markets including bilateral contracts, pool, and ancillary services. The agents go through a learning process by gathering information that creates price expectations and helps to support their internal decision models [26].

In Portugal, there is also a similar software being developed, called MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) where the agents (representing the main entities participating in the market) use different strategies during negotiations and are equipped with learning mechanisms that help them reach their goals [27].

II. ENERGY CONTRACTS AND BILATERAL NEGOTIATION

In the present dissertation, we define a bilateral contract in power markets as a social interaction between two agents (one seller/generator and a buyer/consumer) with the goal of defining the prices for a specific volume of energy. The negotiation process involves the exchange of offers and counter-offers between them, where there is the possibility of an agreement being reached but one of them, or even both can leave the negotiation. The negotiation can be divided in three different stages [28]. The first one is the pre-negotiation where the agents prepare and plan and define their objectives, negotiation limits and initial offers. This is followed by a problem resolution stage characterized by the interaction between agents, the use of strategies and the attempt to reach an agreement. Finally, and if an agreement is reached, there is an implementation phase where the contractual terms are put in practice.

A. Bilateral Negotiation Model

The negotiation model described in this section is based on the work done by Lopes et al. (2002; 2005) [29] [30] and Lopes & Coelho (2010 a; 2012) [31] [32].

Let \( A = \{a_1,a_2\} \) be the set of autonomous agents participating in the negotiation. Let \( \text{Agenda} = \{x_1, ..., x_k\} \) be the negotiation agenda that represents the set of issues to be deliberated during the negotiation. Each one of these issues is quantitative and is defined over a continuous domain \( D_n = [\text{min}_n, \text{max}_n] \). The price limits of each agent for an issue \( x_k \) is \( \text{lim}_k \).

One of the key elements of the negotiation is the adoption of a protocol that settles the rules by which the agents have to follow when they negotiate. In the present dissertation, an alternating offers protocol will be considered. The agents determine an allocation of the issues by alternately submitting proposals at times in \( T = \{1,2,\ldots\} \). This means that only one offer is submitted in each period \( t \in T \), with agent \( a_1 \) sending his offers at odd periods \( \{1,3,\ldots\} \) and the agent \( a_2 \) doing the same at even periods \( \{2,4,\ldots\} \). Both agents have the possibility to abandon the negotiation as a response to an offer made by the opponent.

The negotiation process starts with agent \( a_1 \) submitting his offer \( p_{1-t}^{l} \) to agent \( a_2 \) in the period \( t = 1 \). Agent \( a_2 \) receives the offer \( p_{1-t}^{l} \) and has three different ways to reply to it. Either he accepts it, or he rejects it and leaves the negotiation, or he rejects it but keeps negotiating. In the first two cases, the negotiation comes to an end. If \( p_{1-t}^{l} \) is accepted the agreement is implemented. If \( p_{1-t}^{l} \) is rejected and \( a_2 \) leaves, then the negotiation ends without an agreement. If the agents keep on negotiating, the negotiation goes to period \( t = 2 \), where \( a_2 \) submits his counter-offer \( p_{2-t}^{l} \). This process repeats itself until one of the outcomes mentioned before occurs.

Each offer is a vector of issue values sent by an agent \( a_i \in A \) to an agent \( a_j \in A \) in period \( t \in T \):

\[
P_{t-i,j}^{l} = (v_1, ..., v_n)
\]

where \( v_n, n = 1, ..., k \) is the value of an issue \( x_k \) in \( \text{Agenda} \).

The decision to accept or decline the offer depends on the rating that the agent gives to each issue taking into account his preferences. For each issue \( x_k \), the agents give them a weight \( w_k \), which is a number that represents the agent’s preference regarding \( x_k \). Each agent has a multi-issue utility function to rate offers:

\[
U_i(x_1, ..., x_n) = \sum_{k=1}^{n} w_k V_k(x_k)
\]

Where \( V_k(x_k) \) is the marginal utility function that gives the score \( a_i \) assigns to a value of an issue \( x_k \). This additive model will rate the offers, where each agent adds the values given to each one of the issues depending on their relative weight. An offer will be accepted when the utility given to the received offer is higher than the utility of the offer that the agent would be willing to counter-propose.

The work done in this dissertation, extends the model previously described. This model lacks procedures to properly simulate a contract for difference, as it ends right after the agreement is reached and the CfDs require the calculation of price differences.

In the specific case of the situation, the negotiation agenda is \( \text{Volume} = (\text{vol}_1, \text{vol}_2, \text{vol}_3) \), where each volume represents a consumption for one of the three parts of the day considered, according to the load profile: off-peak, mid-peak and on-peak. If the negotiation ends with an agreement, then the offer accepted by the parties \( p_{t-i,j}^{l} = (v_1, v_2, v_3) \) will give the strike prices:

\[
\text{Strike} = (\text{stk}_1, \text{stk}_2, \text{stk}_3)
\]

where:

i) \( \text{Strike} \) is the vector of strike prices (in €/MWh);
ii) \( \text{stk}_i \), \( i = 1,2,3 \), is the strike price for each of the volumes \( \text{vol}_i \).

CfDs also require that parties agree on a set of prices considered as references to use in the calculation of the differences. These reference prices can be defined as:

\[
\text{Reference} = (\text{ref}_1, \text{ref}_2, \text{ref}_3)
\]

where:
i) Reference is the vector of reference prices (in €/MWh);
ii) \( ref_i, i = 1,2,3 \), is the reference price associated to each part of the day where the \( vol_i \) is negotiated.

With the formalization of these vectors, the differences between these sets of prices can be calculated and the multiplication of these differences by the volumes in the agenda will give the financial compensation owe by the agents.

When the strike prices are smaller than the reference prices, the seller agent will pay the buyer. The total amount will be given by:

\[
\text{Difference}_{\text{seller}} = \sum_{i=1}^{3} (ref_i - stk_i) \times vol_i
\]

It will be the buyer’s turn to pay financial compensation when the strike prices are higher than the reference prices. The total amount will be given by:

\[
\text{Difference}_{\text{buyer}} = \sum_{i=1}^{3} (stk_i - ref_i) \times vol_i
\]

B. Strategies in Bilateral Contracting

The strategies used by agents in a negotiation can reflect a wide range of behaviors and lead to different outcomes. Usually, there are three groups of strategies that are used in negotiations [28] [31]:

• Concession making: negotiators reduce their aspirations in order to accommodate the opposing negotiators;
• Competing: negotiators maintain their aspirations and try to persuade the opposing negotiators to yield;
• Problem solving: negotiators try to find ways of reconciling their aspirations with the aspirations of the opposing negotiators.

The choice of an appropriate strategy is an important part of the pre-negotiation process and it takes into account the settings of the negotiation and the probability of success of such strategy. In this dissertation, the focus will be upon the group of concession making strategies. There is extensive research in this area that supports three reasonable conclusions about the effect of a single party’s demand level and rate of concession on the outcome of the negotiation worth mentioning [33]. The first one is that higher initial demands and slower concessions make an agreement less likely and less rapidly reached. Also, lower initial demands and faster concessions produce smaller outcomes for the negotiator employing them and larger outcomes to the other negotiator. The last one is that there is an inverted U-shaped relationship between the level of demand and the level of outcome. The model developed in the next section relies on these conclusions as the concession pattern was developed in order to recreate this relationship between the demands and the negotiation outcome.

III. BILATERAL CONTRACTING AND RISK MANAGEMENT

A. Introduction to Risk Management

One of the main advantages of bilateral agreements is that they allow each negotiator to control their exposure to risks. They hedge against the risk by adopting specific behaviors in the negotiation process that lead to outcomes that allow them to dodge the perils associated with price volatility. In this dissertation, the behavior of an agent throughout the negotiation will depend on his attitude towards risk and the model created will try to quantify this attitude. There are several ways to classify an agent behavior towards risk, in this dissertation the definition of a risk averse agent will be the one given by expected utility theory, that states that a person is risk-averse if he prefers the certain prospect with guaranteed outcomes to any risky prospect that may have better outcomes [34]. Accordingly, each agent will fit one of the following categories:

• Risk-Averse: an agent who prefers a setting where he is guaranteed to profit a certain amount, opposed to another setting where that profit can be bigger but there is a chance of not getting anything;
• Risk-Seeking: an agent who prefers a setting where there is a chance of making bigger profits (although they are not guaranteed) to another where a smaller amount of profit is guaranteed;
• Risk-Neutral: the agent doesn’t have a preference over the outcome of the negotiation and takes an intermediate stance compared to the two described above.

In the bilateral contracting developed in this dissertation, there is a limit to the number of offers exchanged between the parties until an agreement is achieved. Once this number is reached, the negotiation ends without a deal. A risk averse agent will show more flexibility during the negotiation in order to secure that the deal is done, and therefore, will concede to his opponent’s demands so that the negotiation does not end prematurely. If an agreement is reached, this agent will buy (sell) energy at a higher (lower) price compared to an agent that isn’t averse to risk.

A risk-seeking agent will be more rigid regarding his demands and will concede less to his opponent’s aspirations. By engaging in this behavior, he is risking that his demands reach the opponent’s negotiation limits and in that case the negotiation will end. Despite this, if the negotiation ends with an agreement, he will benefit from a better deal than a risk-averse agent would have in the same situation.

B. Utility as a Measure of the Agent’s Preferences

Utility is taken to be correlative to desire or want. In economy, utility is the price which a person is willing to pay for the fulfillment or satisfaction of his desire [35].

A person’s preferences regarding a given consumption set \( x \) can be represented using a utility function \( U(x) \) [7]:
i) \( U(x) > U(x') \) if a consumer prefers \( x \) to \( x' \);

ii) \( U(x) = U(x') \) if a consumer is indifferent between \( x \) and \( x' \);

If a person has preferences over consumption sets, then he can rank those preferences using a utility function.

In general, the way a person values a consumption set compared to another depends on the probability that the outcome associated with the consumption set will actually occur. For this reason, the utility function can be written taking into account the probabilities as well as the consumption levels.

For each consumption set \( x_1, x_2, \ldots, x_n \), there is a probability \( \pi_1, \pi_2, \ldots, \pi_n \) of the consumption sets occurring. The expected value (the average level of consumption that you would get) is given by [36]:

\[
u(x_1, x_2, \ldots, x_n, \pi_1, \pi_2, \ldots, \pi_n) = \pi_1 x_1 + \pi_2 x_2 + \cdots + \pi_n x_n \quad (8)\]

Considering that the consumption sets are mutually exclusive, only one of them can occur and, therefore, any decision to choose a consumption level is independent from the other outcome of the others. The utility function can be written in the following way:

\[
u(x) = \pi_1 u(x_1) + \pi_2 u(x_2) + \cdots + \pi_n u(x_n) \quad (9)\]

This says that utility can be written as a weighted sum of some function of consumption in each set, where the weights are given by the probabilities. When the utility function has this particular form we can refer to it as an expected utility function, or a von Neumann-Morgenstern utility function [37].

Besides having an additive form, von Neumann-Morgenstern utility functions also satisfy a set of axioms regarding a person’s preferences. Consider three lotteries \( u, v \) and \( w \), with each one of them having their own value of utility:

- Completeness: a person can rank two different lotteries (either one of them is preferred or there is no preference);
- Transitivity: preference is consistent across any three lotteries (if \( u \geq v \) and \( v \geq w \), then \( u \geq w \));
- Continuity: if \( x < w < v \) is true, then is a probability \( \alpha \) such that \( \alpha u + (1 - \alpha) v < w \);
- Independence: if a person has no preference between two outcomes, then she will not have any preference over two lotteries that offer those outcomes with the same probability. Also referred to as the axiom of substitution, because the lotteries can be replaced by each other: if \( u = v \) then \( \alpha u + (1 - \alpha) w = \alpha v + (1 - \alpha) w \).

With a von Neumann-Morgenstern utility function, one can rank and characterize an agents preferences. When an agent is risk-averse the utility function is concave, meaning that the utility of the expected value is greater than the expected utility of wealth. Likewise, for risk-seeking agents the expected utility of wealth is greater than the utility of the expected value of wealth, and the function is convex. For the intermediate case (risk-neutral), the utility function is linear. This can be seen in Figure 2. In general, the more concave the utility function, the more risk averse the consumer will be, and the more convex the utility function, the more risk loving the consumer will be [36].

C. Measuring an Agent’s Risk Aversion

With the development of the multi-agent simulator in mind, it is necessary to define a parameter to measure the attitude towards risk of an agent. It is not enough to classify them in one of the three categories previously described, since even two risk-averse agents need to be distinguishable from one another.

One approach that can be used is to quantify an agent’s attitude through the curvature of his utility function. This can be done by evaluating the function’s second derivative \( u''(x) \), it will be negative for a concave function, positive for a convex one and zero for a linear one.

John Pratt (1964) proposed the following equation to measure an agent’s risk aversion [38]:

\[
r(x) = \frac{-u''(x)}{u'(x)} \quad (10)\]

The absolute magnitude of \( u''(x) \) does not in itself have any meaning in utility theory, but one feature of \( u''(x) \) does have meaning, namely its sign, which equals that of \( -r(x) \). A negative (positive) sign at \( x \) implies unwillingness (willingness) to accept risk for the consumption set \( x \). Also, a negative (positive) sign for all \( x \) implies strict concavity (convexity) and, therefore, aversion (propensity) to accept risk.

Pratt’s work will be used as the basis to measure an agent’s risk aversion: let \( \lambda \) be a parameter correlated with \( r(x) \), with \( \lambda \in [-1, 1] \) and his value one can classify the agent’s attitude towards risk. Given the domain for which \( \lambda \) is defined and using Platt’s sign stipulation, an agent can be classified according to Table 1.
Table 1 - Agent classification according to the attitude towards risk

<table>
<thead>
<tr>
<th>Level of Risk Aversion</th>
<th>Value of $\alpha (x)$</th>
<th>Interval for $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk-Averse</td>
<td>$\alpha (x) &gt; 0$</td>
<td>$\lambda \in [0,1]$</td>
</tr>
<tr>
<td>Risk-Neutral</td>
<td>$\alpha (x) = 0$</td>
<td>$\lambda = 0$</td>
</tr>
<tr>
<td>Risk-Seeker</td>
<td>$\alpha (x) &lt; 0$</td>
<td>$\lambda \in [-1,0]$</td>
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D. Strategies Using Risk Management

In this dissertation, the measure of risk aversion ($\lambda$) is used in the conception of a new group of strategies for the simulator. This group belongs to the family of concession making strategies, that models the negotiator’s initial offers and rate in which they concede to their opponents demands, and in this case it will happen depending on the negotiator’s attitude towards risk (that fits one of the three categories).

The strategies created will reformulate the value of the issues being deliberated (in this case, energy prices) in each round according to (for the seller and the buyer, respectively) [39]:

\[
P_{i+1} = P_i + C_f (\text{lim} - P_i) \quad (11)
\]

\[
P_{i+1} = P_i + C_f (P_i - \text{lim}) \quad (12)
\]

where:

i) $P_{i+1}$ is the price for period $i$;

ii) $C_f$ is the concession factor;

iii) $\text{lim}$ is the price limit established by the agent.

The concession factor $C_f$ is a parameter that varies, in percentage, between 0 and 100. If the concession factor is null, then the agent submitting the offer will not concede at all. If it is 100, then the agent makes a full concession to the opponent’s demand and can accept a price considered his limit.

In the specific case considered in this dissertation, the concession rate will be fixed throughout the negotiation. The concession factor will depend on the agent’s attitude towards risk, the bigger the flexibility in the negotiation the bigger the concession factor is. This implies that a risk-averse agent will make concession at a bigger rate and, therefore, his concession factor will have to be bigger than the one of a risk-seeking agent that shows unwillingness to concede and shows less flexibility in the negotiations.

The value of the concession factor will be given by an exponential function where the measure of risk aversion ($\lambda$) plays a major role. It is important to note that, despite all of them having $\lambda$ that varies from -1 to 1, in order to keep the simulation as close to a real negotiation as possible, exponential functions that give values for the concession factor smaller than 5% and bigger than 25% were discarded, as those values do not represent a reasonable stance in a real negotiation.

These exponential functions have the following structure:

\[
C_f = C_{fn} e^{c \times \lambda} \quad (13)
\]

where:

i) $\lambda$ is the value of the agent’s risk aversion;

ii) $C_{fn}$ is the concession factor for a risk-neutral agent ($\lambda = 0$);

iii) $c$ is a constant that shapes the function’s curvature.

Table 2 shows the functions considered and Figure 3 shows their values. In order to choose one of them, they were compared with one another in terms of the reasonability of their outcomes.

Table 2 - Exponential functions considered

<table>
<thead>
<tr>
<th>Series</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0,15e^{0,4\lambda}$</td>
</tr>
<tr>
<td>2</td>
<td>$0,1e^{0,55\lambda}$</td>
</tr>
<tr>
<td>3</td>
<td>$0,12e^{0,55\lambda}$</td>
</tr>
<tr>
<td>4</td>
<td>$0,1e^{0,6\lambda}$</td>
</tr>
<tr>
<td>5</td>
<td>$0,13e^{0,6\lambda}$</td>
</tr>
</tbody>
</table>

After much deliberation, the chosen exponential function was $C_f = 0,1e^{0,55\lambda}$, that gives values for the concession factor defined for $[0,057; 0,17]$.
IV. CASE STUDIES

A. Software Used and User Interface

Three case studies were done in order to access the capability of the contracts for difference as a risk management tool and to compare their performance with a forward contract. The simulations done in each one of them were made using the JADE (Java Agent Development Framework) platform, which is written in Java programming language.

The software developed in this dissertation allows the user to simulate an array of different situations. The interface between the user and the software is done by using a set of windows where he can choose the options he wishes to simulate.

The user can, at first, choose the type of contract he wishes to simulate (either a Forward, a Two-way CfD or a One-Way CfD). After that, the agents are created. In this version of the simulator it is only possible to create a seller agent (representing a generator) and a buyer agent (representing a utility company). The pre-negotiation ensues, with the selection of the load profile (Industrial, Commercial, Residential or User Defined), followed by the characterization of each agent initial offers and negotiation limits. Then, the user has to choose which strategy is used (one of the options is the one described in the previous section and the one chosen for the simulations in the following sections, called Risk Preference Concession) and the agent’s attitude towards risk (Risk-Averse, Risk-Neutral or Risk-Seeker). This process ends with the agents agreeing on a deadline.

After this, the negotiation starts and either it ends without an agreement and the user is informed of the reasons for such an outcome, or it ends successfully and a window will inform the user about the results.

B. Presuppositions for the Simulations

In these case studies, the agents negotiate three different prices, corresponding to the off-peak, mid-peak and on-peak periods of the day. The hours of the day belonging to each period are shown in Table 3 and are taken from the timetables for large customers in Portugal [40].

<table>
<thead>
<tr>
<th>Period</th>
<th>Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-Peak</td>
<td>00:00-07:00h</td>
</tr>
<tr>
<td>Mid-Peak</td>
<td>07:00-14:00h 17:00-00:00h</td>
</tr>
<tr>
<td>On-Peak</td>
<td>14:00-17:00h</td>
</tr>
</tbody>
</table>

The amount of energy negotiated is based on a typical industrial consumer, provided by Xcel Energy\(^1\). The prices used to create the initial offers and limits were obtained by analyzing the data from the MIBEL in particular the prices for the Portuguese spot market for weekdays from May to October 2013, and doing the average for each period of the day. The seller had prices 10% higher as an initial offer and 9% lower for the limit, and the buyer started at prices 5% lower and his limit was 4% higher. Those prices are shown in tables 4 and 5.

<table>
<thead>
<tr>
<th>Period</th>
<th>Initial Offer (€/MWh)</th>
<th>Price Limit (€/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-Peak</td>
<td>42,70</td>
<td>35,33</td>
</tr>
<tr>
<td>Mid-Peak</td>
<td>52,12</td>
<td>48,08</td>
</tr>
<tr>
<td>On-Peak</td>
<td>58,58</td>
<td>48,69</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Period</th>
<th>Initial Offer (€/MWh)</th>
<th>Price Limit (€/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-Peak</td>
<td>36,88</td>
<td>40,37</td>
</tr>
<tr>
<td>Mid-Peak</td>
<td>50,20</td>
<td>54,95</td>
</tr>
<tr>
<td>On-Peak</td>
<td>50,83</td>
<td>55,64</td>
</tr>
</tbody>
</table>

C. Simulations and Results

Three different case studies were conducted, each one of them had the characteristics shown in Table 6.

<table>
<thead>
<tr>
<th>Case</th>
<th>Type of Contract</th>
<th>Seller’s Attitude</th>
<th>Buyer’s Attitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Two-way CfD</td>
<td>Risk-Averse ((\lambda=1))</td>
<td>Risk-Seeking ((\lambda=-1))</td>
</tr>
<tr>
<td>2</td>
<td>Two-way CfD</td>
<td>Risk-Neutral ((\lambda=0))</td>
<td>Risk-Seeking ((\lambda=-1))</td>
</tr>
<tr>
<td>3</td>
<td>Forward</td>
<td>Risk-Averse ((\lambda=1))</td>
<td>Risk-Neutral ((\lambda=0))</td>
</tr>
</tbody>
</table>

The reason why those attitudes were given is due to the nature of such contracts. Since the CFs only have financial settlements, we’ve considered that agents that seek this kind of deal do it for financial reasons and not just to satisfy their energy needs, so unlike the ones engaging in forward contracts they have a non-neutral attitude. The buyer is always risk-seeking because he is in a position where he can search the market for better because if he doesn’t strike a deal with one generator he can easily look for a new one. It was decided to change the attitude of the generator to see the consequences of assuming opposing attitudes.

The results presented in this section shows a case where the agents negotiate a strike price for the three periods of the day and those prices would be used for a three month contract for the months of June, July and August 2014. The prices used as reference for calculating the differences were obtained, again, from the MIBEL but this time regarding the time period of the contract and are shown in Table 7.

The volume of energy is also the same for each case, and the load profile chosen was one of an industrial consumer with

\(^1\) Available at: http://www.xcelenergy.com/
a consumption of: 184,75 kWh in off-peak, 581,21 kWh in mid-peak and 309,87 kWh in on-peak.

All the negotiations ended successfully, with the agreement being reached after 6, 14 and 9 rounds for each case, respectively. The results are presented in Table 8.

Table 7- Reference prices for the contract

<table>
<thead>
<tr>
<th></th>
<th>Off-Peak</th>
<th>Mid-Peak</th>
<th>On-Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference Prices June (€/MWh)</td>
<td>46,99</td>
<td>57,83</td>
<td>57,77</td>
</tr>
<tr>
<td>Reference Prices July (€/MWh)</td>
<td>41,12</td>
<td>53,06</td>
<td>53,76</td>
</tr>
<tr>
<td>Reference Prices August (€/MWh)</td>
<td>44,85</td>
<td>54,01</td>
<td>54,36</td>
</tr>
</tbody>
</table>

Since the prices in 2014 were higher than those in 2013, the strike prices negotiated for cases 1 and 2 were lower than the reference prices. Therefore, the seller agent had to pay the differences to the buyer, with a total amount of 259,58€ for Case 1, and 177,6€ for Case 2. For Case 3, the prices of the agreement were also lower than the market prices.

It’s important to remember that the agents who participate in a CfD still have to go to the spot market to fulfill their needs, and they buy and sell there at the market price. Their effective cost of energy is the market price adding or subtracting the differences (depending on who pays who). For Case 3, the cost of energy is the price of the agreement. The effective costs for the three cases are shown in Figure 4.

### Table 8- Negotiation’s results

<table>
<thead>
<tr>
<th></th>
<th>Off-Peak</th>
<th>Mid-Peak</th>
<th>On-Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strike Prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 1</td>
<td>37,78</td>
<td>51,42</td>
<td>52,07</td>
</tr>
<tr>
<td>(€/MWh)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strike Prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 2</td>
<td>38,73</td>
<td>52,72</td>
<td>53,38</td>
</tr>
<tr>
<td>(€/MWh)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prices Case 3</td>
<td>38,7</td>
<td>52,68</td>
<td>53,34</td>
</tr>
<tr>
<td>(€/MWh)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

It is possible to draw some interesting conclusions from the results. First of all, it is possible to conclude that CfDs are very useful financial tools to hedge against price volatility. The buyer agent effectively protected himself from the rise of prices by receiving payments from the seller, and in the best case (Case 1) entering a CfD saved him 259,58€. Although the seller is on the losing side of the contracts, he can safeguard his interests, which brings us to the second conclusion.

The seller can maximize his profit if he has a risk-seeking attitude during the negotiations, as it is clearly shown by comparing the prices between Case 1 and Case 2.

A third conclusion is also worth mentioning. Even though a seller is on the losing side of a CfD, this type of contract can be more beneficial than a forward contract, just as long as the seller assumes a risk-seeking attitude that ensures that the payment he makes in CfDs to the seller is less than the difference between the price on the forward contract and the market price.

![Figure 4- Effective cost of energy for each case and for the spot market](image-url)
REFERENCES


