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ADAPTIVE LEARNING IN AGENTS BEHAVIOUR:
A FRAMEWORK FOR ELECTRICITY MARKETS SIMULATION

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ABSTRACT

Electricity markets are complex environments with very particular characteristics. A critical issue regarding these specific characteristics concerns the constant changes they are subject to. This is a result of the electricity markets' restructuring, which was performed so that the competitiveness could be increased, but it also had exponential implications in the increase of the complexity and unpredictability in those markets scope.

The constant growth in markets unpredictability resulted in an amplified need for market intervenient entities in foreseeing market behaviour. The need for understanding the market mechanisms and how the involved players' interaction affects the outcomes of the markets, contributed to the growth of usage of simulation tools. Multi-agent based software is particularly well fitted to analyze dynamic and adaptive systems with complex interactions among its constituents, such as electricity markets.

This dissertation presents ALBidS – Adaptive Learning strategic Bidding System, a multiagent system created to provide decision support to market negotiating players. This system is integrated with the MASCEM electricity market simulator, so that its advantage in supporting a market player can be tested using cases based on real markets' data.

ALBidS considers several different methodologies based on very distinct approaches, to provide alternative suggestions of which are the best actions for the supported player to perform. The approach chosen as the players' actual action is selected by the employment of reinforcement learning algorithms, which for each different situation, simulation circumstances and context, decides which proposed action is the one with higher possibility of achieving the most success.

Some of the considered approaches are supported by a mechanism that creates profiles of competitor players. These profiles are built accordingly to their observed past actions and reactions when faced with specific situations, such as success and failure.

The system's context awareness and simulation circumstances analysis, both in terms of results performance and execution time adaptation, are complementary mechanisms, which endow ALBidS with further adaptation and learning capabilities.

Keywords:

Adaptive Learning; Artificial Intelligence; Decision Support Systems; Electricity Markets; Multiagent Simulation

RESUMO

Os mercados de electricidade sofreram um processo de reestruturação que originou um aumento considerável da competitividade neste sector e, consequentemente, criou novos desafios na operação das entidades nele envolvidas. De forma a ultrapassar estes desafios é essencial para os profissionais uma compreensão detalhada dos princípios destes mercados e de como gerir os seus investimentos num ambiente tão dinâmico e competitivo. A crescente necessidade de entender estes mecanismos e a forma como a interacção das entidades envolvidas afecta os resultados destes mercados levou a uma grande procura de ferramentas de software, nomeadamente simulação, para analisar possíveis resultados de cada contexto de mercado para as várias entidades participantes. Os sistemas multi-agente são adequados à análise de sistemas dinâmicos e adaptativos com interacções complexas entre os seus constituintes, e portanto, várias ferramentas de modelação dirigidas para o estudo dos mercados reestruturados de electricidade usam este tipo de técnicas.

Tirando partido destes simuladores, é possível estudar vários tipos de mercados e a interacção entre as entidades neles envolvidas. No entanto, todos estes simuladores apresentam lacunas no que diz respeito ao apoio à decisão a essas entidades, nomeadamente na gestão dos seus investimentos. Um aspecto tão relevante como é a utilização de todo este suporte de simulação para permitir aos agentes de mercado realmente aprenderem com a experiência de mercado e desenvolveram capacidades para analisar contextos de negociação e adaptar automaticamente os seus comportamentos estratégicos de acordo com as circunstâncias, não é considerado na amplitude que é requerida. É neste âmbito que esta dissertação contribui, utilizando técnicas de inteligência artificial para oferecer um apoio relevante e eficaz às decisões estratégicas das empresas envolvidas nestes tipos de negociação.

O principal objectivo deste trabalho é dotar essas entidades de capacidades que lhes permitam apresentar comportamentos inteligentes e adaptativos na sua actuação nos mercados de electricidade de forma a serem capazes de atingir os seus objectivos da melhor forma possível, sendo capazes de reconhecer e actuar em conformidade com os contextos em que estão inseridas.

De forma a atingir este objectivo, foi desenvolvido o sistema ALBidS – *Adaptive Learning strategic Bidding System* (sistema de aprendizagem adaptativa para licitações estratégias). Este sistema está implementado como um sistema multi-agente independente, em que cada agente é responsável pela execução de uma abordagem estratégica diferente. Este sistema está integrado com o simulador MASCEM, para que seja possível testar e validar as contribuições dadas num contexto de simulação de mercados já implementado e consolidado. Sendo este simulador uma ferramenta que simula mercados de electricidade permitindo a utilização de informação obtida a partir de mercados de electricidade reais, garante-se, assim, também que as conclusões retiradas deste trabalho são apoiadas por experimentação baseada em casos reais ou quase reais.

A definição das estratégias de oferta dos agentes de mercado é baseada na aprendizagem adaptativa por parte das entidades, considerando o histórico do sistema, através da informação disponível, incluindo informação recolhida durante a utilização do próprio sistema multi-agente. Para isso são propostos e testados vários algoritmos e metodologias de aprendizagem e análise de dados, para que conjuntamente contribuam para que os agentes possam tomar as melhores decisões em cada momento de acordo com o contexto identificado.

Um contributo importante do trabalho está na proposta destes algoritmos, na sua combinação e na obtenção de conhecimento relativo à utilização criteriosa dos algoritmos considerados em função do contexto, utilizando o conceito de *context awareness*. A análise destes contextos é efectuada por um mecanismo desenvolvido para esse efeito, analisando as características específicas de cada dia e período de negociação.

São estudados e analisados vários algoritmos baseados em abordagens diversas, para que seja possível contemplar formas distintas de resolver problemas, dependendo de circunstâncias concretas. Entre estas abordagens, podem referir-se: redes neuronais artificiais dinâmicas; teoria de jogos; médias/regressões lineares; abordagens económicas, tendo em conta a análise macroeconómica e sectorial, e também a análise interna das empresas no que diz respeito aos seus investimentos e perspectivas de crescimento; algoritmos de Inteligência Artificial (IA), como os algoritmos *Roth-Erev* e o *Q-Learning* de aprendizagem por reforço; uma abordagem baseada na teoria do determinismo, em que são analisadas todas as variáveis intervenientes na obtenção dos resultados pelo simulador; e outras propostas de algoritmos de aprendizagem e análise de dados específicos para determinadas situações, bem como a combinação de algoritmos de tipos diversos.

Numa camada superior aos algoritmos mencionados foi implementado um mecanismo de aprendizagem por reforço, baseado em estatísticas e em probabilidades, que é responsável por escolher em cada altura a proposta de licitação que dá mais garantias de sucesso. Com o passar do tempo, vão sendo actualizadas as estatísticas, através da análise dos resultados de cada proposta. Este mecanismo permite que em cada momento sejam escolhidos os algoritmos que estão a ter os melhores resultados para cada situação e contexto. Ao serem considerados vários algoritmos, de naturezas completamente distintas, consegue-se uma maior probabilidade de haver sempre algum a oferecer bons resultados.

Existe também a possibilidade de se definir as preferências e parametrizações relativas a cada algoritmo individualmente, e também de se definirem preferências relativas ao desempenho dos algoritmos no que diz respeito à eficiência computacional, permitindo que o utilizador escolha a relação eficiência/probabilidade de sucesso, de acordo com as suas preferências. O sistema excluirá então, automaticamente, os algoritmos que usualmente requerem um maior tempo de processamento, quando esse tempo não corresponde a soluções proporcionalmente melhores. Desta forma, garante-se que o sistema estará a utilizar o seu tempo de processamento em abordagens que oferecem melhores respostas no menor tempo possível.

Como apoio ao funcionamento adequado das estratégias implementadas foi criado um mecanismo de definição de perfis dos agentes competidores. Desta forma é possível obter previsões acerca das acções esperadas dos outros agentes participantes no mercado, tendo em conta as suas acções passadas e as reacções verificadas quando confrontados com situações específicas, como o sucesso ou o falhanço.

Palavras-chave:

Aprendizagem Adaptativa; Inteligência Artificial; Mercados de Energia Eléctrica; Simulação Multi-Agente; Sistemas de Apoio à Decisão

NOMENCLATURE

A	Action
a	First cost coefficient
AD	Offers action domain
a_i^R	Reported first cost coefficient
$amount$	Price change amount (cent.€/kWh)
b	Second cost coefficient
b_i^R	Reported second cost coefficient
C	Confidence Value
$C1$	Social factor
$C2$	Cognitive factor
$capacity_available$	Available production capacity (MW)
Cap_i^L	producer i's reported lower real-power production limit (MW)
Cap_i^L	True lower production limit for producer i (MW)
Cap_i^U	producer i's reported upper real-power production limit (MW)
Cap_i^U	True upper production limit for producer i (MW)
C_i	Cooling parameter
$Cost_i$	Player i costs (€)
D	Day
$Decrement$	Risk decrement
$degree$	Weight of a learning case
Dif_i	Difference between a strategy's prediction and the actual market price (cent.€/kWh)
E	Observed evidence
E_i	Energy amount (MW)
e_i	Experimentation parameter
$energy_sold$	Sold amount of power (MW)
$exper$	Experience
$exper'$	New experience
FC	Fixed costs (€)
G_b	Best global position of a particle
int	Interval
$learningRate$	Learning rate
M	Offers action domain cardinality
m'	Selected action
MC_i	Marginal cost function of producer i (€)
MCi	Unavailability or forced outage rate
min	Minimum considered bid value (cent.€/kWh)
n	Number of plays
$New\ Decrement$	Updated risk decrement

newValue	Updated value of the Q-Learning function
np	Number of possible bided prices
numb	Number of considered possible bids
number_of_bids	Number of bids
number_of_scenarios	Number of scenarios
O	Market offer
O_i	Possible Outcomes
oldValue	Q-Learning function's old value
P	Bid price (cent.€/kWh)
p	Producer's actual production (MW)
$P(O_i\|E,A)$	Conditional probability
$P_{0\ldots n}$	Possible bids
$p_{1\ldots n}$	Weighted average weights
P_b	Best individual position of a particle
$p_{im}(D)$	Probability of producer i choosing action m in day D
P_{market}	Market price (cent.€/kWh)
price	Price (cent.€/kWh)
probc	Probability
probc'	New probability
$Profit_{im'}(D)$	Profits attained by producer i in day D, in response to its choice of supply offer m' (€)
Profits	Obtained Profits (€)
Q	Q-Learning function
q_{im}	Propensity of generator i for action m
r	Reward or cost
R1	Random number between 0 and 1
R2	Random number between 0 and 1
$RCap^L$	Reported lower production limit (MW)
$RCap^U$	Reported upper production limit (MW)
recency	Experimentation parameter
ref	Reference point
Reinf	Reinforcement amount
reinfValue	Value of the reinforcement
r_i	Recency parameter
$RIMax_i^L$	Lower range-index parameter for ADi construction
$RIMax_i^U$	Upper range-index parameter for ADi construction
$RIMin_i^C$	Capacity range-index parameter for ADi construction
Risk_factor	Risk assumed by the player
s	State
S	Reported supply offer
SS_i	Slope-start control parameter for ADi construction

Contexts are an important factor in what concerns the adaptation of the approaches to be chosen as the final action to be performed in the market by the supported player. A mechanism to analyse and define different market negotiating contexts is presented in section 3.5, hence providing the means for the chosen actions to be adapted and chosen depending of the different circumstances that are encountered at each moment.

The ALBidS system integrates several very distinct approaches in what concerns market negotiations, and prices forecast. These approaches, implemented and tested independently before their integration in ALBidS are presented in section 3.7 – Strategy Agents. Each of these strategies is introduced with an overview on the context of each approach. Afterwards, the details on these approaches implementations are described and the necessary experimental findings are presented, in order to test each approach's adequate performance, and prove the adequacy to its purpose [Pinto *et al.*, 2011b].

In order to support some of these approaches, a competitor player's profile definition mechanism has been implemented, with the point of creating adequate player profiles to be used by the ALBidS strategies which require such profiles for their execution [Pinto *et al.*, 2011c]. This mechanism is presented in section 3.8.

Additionally, a mechanism with the purpose of managing the balance between the efficiency and the effectiveness of the system has been developed (presented in section 3.9), so that the ALBidS system can be able to adapt to different simulation circumstances. This mechanism provides the means for the system to adapt its execution time depending on the purpose of the simulation, *i.e.*, if the expected results from ALBidS are as best as it is able to achieve, or, on the other hand, if the main requirement is for the system to be executed rapidly, since the purpose of the considered simulation is to analyse issues other than player's optimal performance in the electricity market [Pinto *et al.*, 2011d]. The Efficiency/Effectiveness Management mechanism manipulates the strategies both externally and internally. From the system's perspective this mechanism contributes by deciding which tools are used at each moment for each circumstance; depending on their observed performance in terms of efficiency and effectiveness. This way this mechanism can choose to exclude certain strategies when they are not fulfilling the ALBidS' requirements for the case in matter. The strategies chosen to be executed are also manipulated internally, so that they can adapt their individual results quality/execution time balance to the needs of the current simulation.

The details regarding ALBidS' internal design, its multiagent architecture, and its integration with MASCEM [Praça *et al.*, 2003], are presented in section 3.2. This section is supported and extended by sections 3.3 and 3.4, which respectively present the ALBidS facilitator built to support this system's agents communications independently of the rest of the simulation [Pinto *et al.*, 2011e]; and the ALBidS user interface which supports the interaction with the user, and the respective feedback from the system, regarding the presentation of the events that occur throughout a simulation, and consequent results. Figure 1.2 presents the ALBidS' integration with the MASCEM simulator.

agent has only partial knowledge of other agents and makes his own decisions based on his partial knowledge of the system. Methodologies for strategic bidding in electricity markets [Figueiredo *et al.*, 2005], [Wellman *et al.*, 2007], [Amjady *et al.*, 2010], [Vale *et al.*, 2011a] can help players making more successful decisions but they must be combined together with dynamic behaviour strategies able to take advantage from the knowledge concerning past experience and other players.

There are several experiences that sustain that a multiagent system with adequate simulation abilities is suitable to simulate Electricity Markets [Harp *et al.*, 2000], [Koritarov, 2004], [Zimmermann *et al.*, 2004], [Migliavacca, 2007], [Li and Tesfatsion, 2009], considering the complex interactions between the involved players. It is important to note that a Multi Agent System is not necessarily a simulation platform but simulation may be of crucial importance for electricity markets study, namely concerning scenarios comparison, future evolution study and sensitive analysis.

Simulator for Electric Power Industry Agents (SEPIA) [Harp *et al.*, 2000] is a Microsoft Windows platform oriented simulator. It is based on a Plug and Play architecture, allowing users to easily create simulations involving several machines in a network, or in a single machine, using various processing units. SEPIA allows specifying the number of participating agents, as well as their behaviours, interactions, and changes during the simulation. The simulation developments can be followed and oriented by mechanisms for that purpose.

The Electricity Market Complex Adaptive System (EMCAS) [Koritarov, 2004] uses an agent based approach with agents' strategies based on learning and adaptation. Different agents are used to capture the restructured markets heterogeneity, including generation, demand, transmission, and distribution companies, independent system operators, consumers and regulators. It allows undertaking Electricity Markets simulations in a time continuum ranging from hours to decades, including several Pool and Bilateral Contracts markets.

Power Web [Zimmermann *et al.*, 2004] is a Web-based market simulator, allowing the various participants to interact from very distinct zones of the globe. It is a rather flexible system that allows the definition of simulations with a large set of scenarios and rules. This simulator includes a centralized agent, acting as an independent system operator, to guarantee the reliability of the system, according to a defined group of entities, acting in various markets. It also allows users to enter an open market, competing against producers controlled by other users or computational algorithms.

The Short – Medium run Electricity Market Simulator (SREMS) [Migliavacca, 2007] is based on game theory and is able to support scenario analysis in the short-medium term and to evaluate market power, in some situations. Some of its main features are: short-medium run (a time horizon of one month or multiples of it) simulation of electricity markets based on game theory, calculating price-makers optimal hourly bids; inelastic load, defined hour by hour and zone by zone; tree-like network with interzonal transit limits; monthly scheduling of reservoir hydro pumping storage plants; highly realistic representation of thermal plants; possible quota appointed to physical bilateral contracts, depending on producers share and risk attitude. It is particularly suitable to study the Italian electricity market.

Agent-based Modelling of Electricity Systems (AMES) [Li and Tesfatsion, 2009] is an open-source computational laboratory for the experimental study of wholesale power markets restructured in accordance with

However, it is still premature to take definitive conclusions. Therefore, tools allowing the study of different market models' performance prove to be a real added value.

The electricity market can be seen as a multiagent decision problem, where each market player is represented by an autonomous agent. Just as agents, the electricity markets players have their own objectives, and certain autonomy. Agents can behave as buyers, sellers, aggregators, intermediaries, traders, or market and system operators. Multiagent systems, particularly multiagent based simulation, proved to be an adequate way to develop tools that allow, not only to analyse the market's performance as a whole, but also the individual behaviour of the several entities.

In this sense, some works have arisen, which confirm the adequate applicability of agents and multiagent systems to the study of electricity markets. Some of the most important works in this scope have been presented, highlighting their main characteristics, and pointing out their main limitations. These limitations are mostly directed to the lack of machine learning capabilities that allow them to effectively provide support to market entities. To overcome these limitations is the main goal of this work; by developing an adaptive tool which is able to provide effective support to market negotiating players, by adapting to different circumstances and negotiation contexts, hence providing players with the most adequate acting support for each situation.

Chapter 3 presents ALBidS, an adaptive learning system equipped with artificial intelligence techniques, context analysis tools, and adaptation capabilities, able to endow market players with strategic acting capabilities, hence providing them competitive advantage in the market. This enables the contribution regarding the requirements that market players have, resulting from the electricity markets restructuring; and also concerning the limitations that the existing market simulators present.

Each MASCEM negotiating agent bids in the market for each period of each day. The information regarding all the agents' bids is stored in the **Bids** table. This data includes the indication of the success that each bid got on the market. These bids are subject to an error, which is especially relevant in the case of bids resulting from strategies based on forecasting techniques. The error is saved in the **ErrorData** table. This information is used by several strategies which require the competitors' log of actions to support the self strategy's action proposal. These tables are dependent on a ScenarioID, indicating the scenario that the simulator is running. When a new simulation is started, the user is able to choose to continue an existing scenario, with a specific number of agents, with already set characteristics, or, on the other hand, to create a new scenario, defining all the MASCEM simulation options. When ALBidS is being used for a previously existing scenario, it is able to use the simulation data that was saved before to support the strategic behaviour. The scenario dependent data includes the statistics used by the Main Agent to choose among the proposed bids, and also the historic market prices, saved in the **MarketData** table. This table is filled with the historic market prices, which may be from different markets relevant to the required studies. This historic data is used as reference for the market price forecasts, and it is updated, depending on the scenario, with the prices resulting from the simulation, this way it is kept updated with the actual market prices.

When designing the ALBidS system, high importance had to be given to defining its architecture, as it is one of the first decisions and steps to take when one pretends to develop a computer system. The architecture depends on the characteristics of the system, and will influence all its conception. Choosing the MVC (Model-View-Controller) architecture (Figure 3.2) ensured the independence between the data (model), the user interface (view), and the business layer (controller).

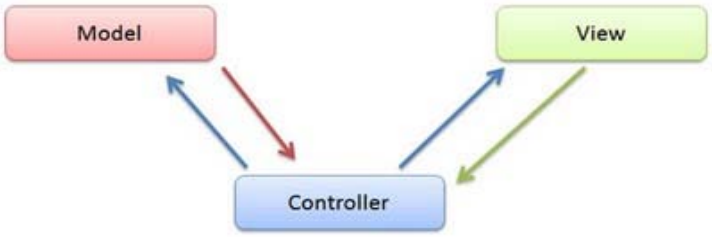


Figure 3.2 – Interaction between the MVC architecture components.

ALBidS is integrated with the MASCEM simulator through the *MainGUI* class, the class that is responsible for the ALBidS user interface (presented in section 3.4) and for creating the ALBidS model classes. The *MainGUI* class contains an instance of the *AlbidsController* class, which is responsible for making the connection with the rest of the ALBidS system, manipulating the domain objects and the system's agents (Figure 3.3).

After all user decisions are made, and the simulation is started, the ALBidS interface displays the graphs presenting the simulation data. As the ALBidS system is responsible for "feeding" the graphs, it was found necessary to send the graphs instances by parameter from the interface to the core ALBidS system, at the time of the simulation beginning request. This way the graphs can be directly manipulated by ALBidS.

When a simulation is started, the user interface changes its aspect, hiding the input options presented at first and giving place to the simulation data graphs. When the window changes its appearance, it keeps presenting one tab per MASCEM agent, and for each of those, one tab concerning each context or period.

There are two types of graphs: the global stats graphs, providing a global view of the simulation; and the strategy individual graphs, presenting the information regarding each of the strategies. The graphs are grouped in panels, once again separated by tabs. This second mode of the interface is showed in Figure 3.15.

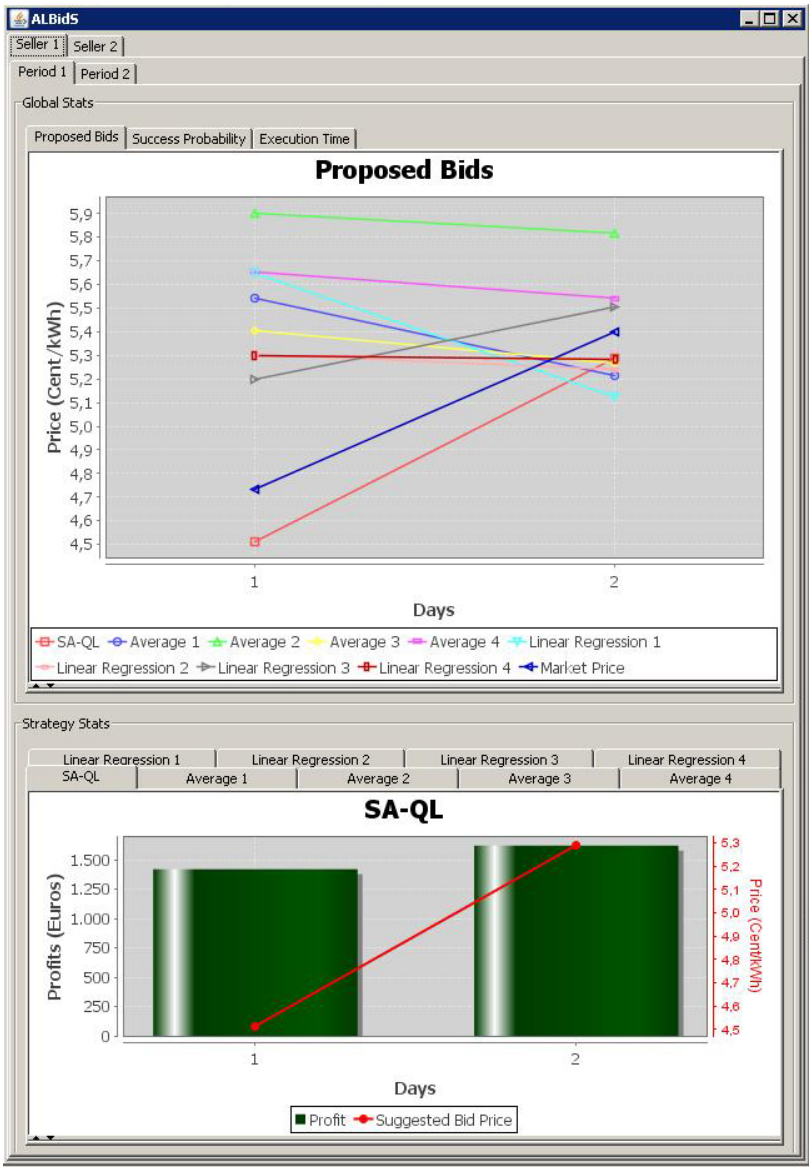


Figure 3.15 – ALBidS interface module for simulation results display.

Regarding day 1, in which all strategies present equal confidence value, Average 1 was chosen as the algorithm's response, and consequently was able to achieve incomes, only by chance, because in this case the choice was made randomly, and it just "got lucky" in being chosen.

Figure 3.24 presents the confidence values of the same three strategies, in the same exact scenario, but this time with Linear Regression 1 being attributed a weight of 100%, while the other two strategies receiving only half of that value. This test intends to show the influence of the weight value.

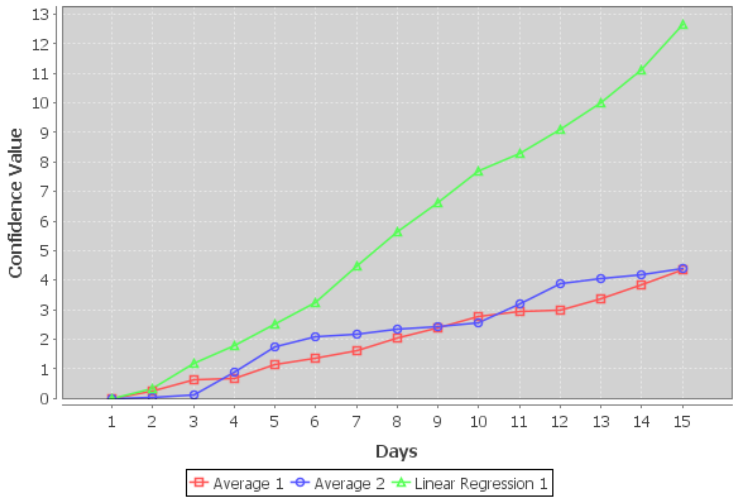


Figure 3.24 – Strategies' confidence values with Linear Regression 1's higher weight.

Figure 3.24 shows that the difference between the confidence value of the Linear Regression1 and the confidence values of the other strategies is much higher than in the first test (Figure 3.22). It detached faster from the rest because it was attributed a higher weight.

The third test considers a much higher number of proposing bid's strategies. Figure 3.25 presents the confidence values of these strategies to the Simple Reinforcement Learning Algorithm.

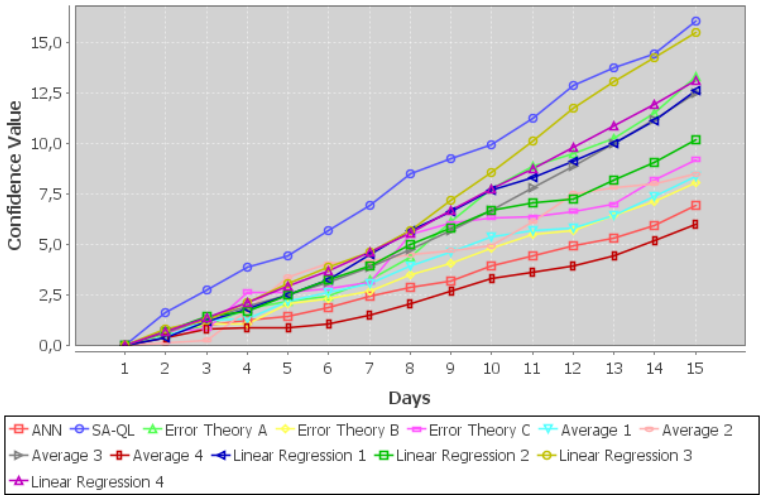
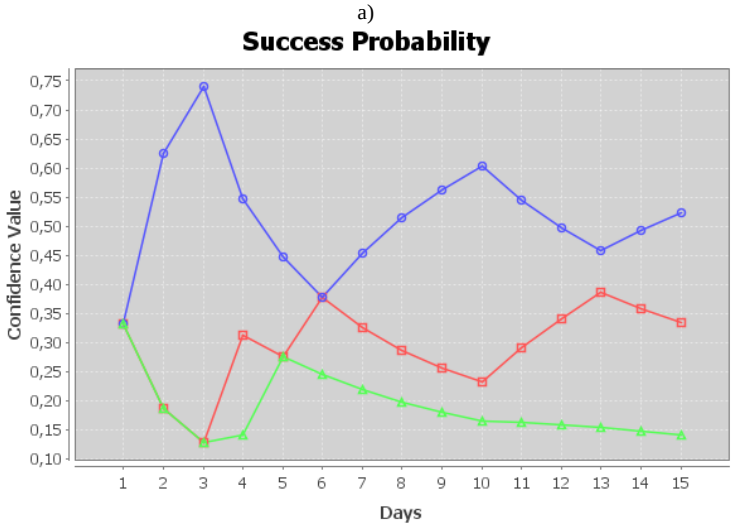


Figure 3.25 – Strategies' confidence values in the third test.

From Figure 3.24 the evolution of the confidence values of the several strategies can be seen. This shows the capability of the Simple Reinforcement Learning Algorithm in considering a high number of alternative strategies.

a)



b)

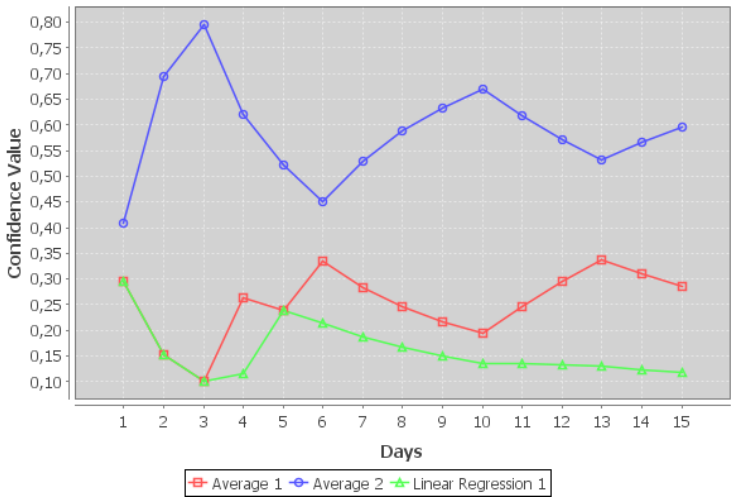


Figure 3.31 – Seller agents' success probability for an Average 2 weight: a) equal to the other strategies, b) double of the other strategies'.

Analysing Figure 3.31 it is visible that when the Average 2 strategy is assigned a higher weight value, this strategy's confidence values detach faster from the others. This detachment reflected an isolation of Average 2 as presenting the best confidence values for all days.

Figure 3.32 presents the results, in incomes, achieved by ALBidS use of the Average 2, in both simulations.

Comparing the graphs presented in Figure 3.42, it is visible that the simulation using the proposed method with SA was clearly the most profitable for Seller 2 for this period.

In both simulations the initial periods were unsuccessful, as expected, due to the initial inexperience of the method. As experimentation progresses, the results start to be positive. However, it is obvious, analyzing these results, that in the second simulation, as time progresses and the temperature of SA decreases, forcing the method to choose the best options at an earlier time, the results start to improve much earlier, around day 28. In the approach without SA these results only start to appear around day 42.

These results are a consequence of the convergence time of each method, as presented in Figure 3.43:

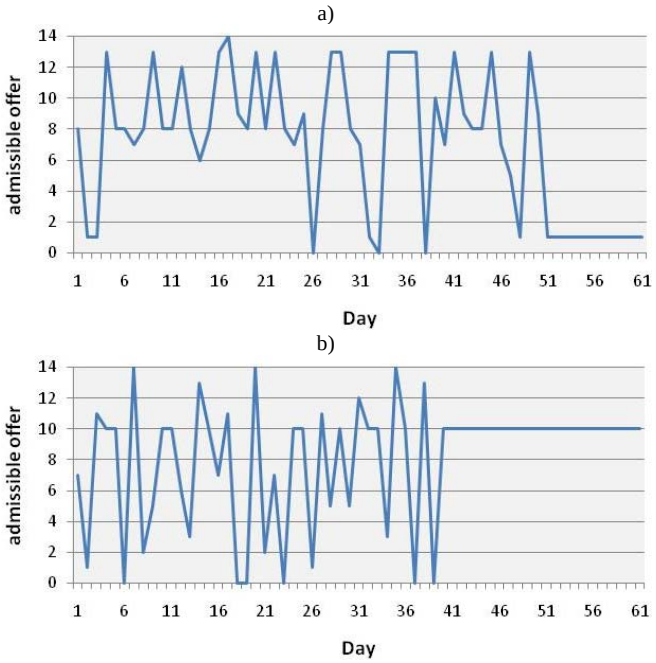


Figure 3.43 – Offer chosen by Seller 2 in the first period of the considered 61 days, using the proposed method: a) without SA, b) with SA.

Both approaches went through an experimentation period, after which they eventually converged to an offer, as supported by Figure 3.43. It is visible that the method without SA took longer to converge.

Comparing Figure 3.43 a) with Figure 3.42 a) it can be concluded that day 51 is the day when the method without SA stabilized for admissible offer 1, coinciding with the day when it started obtaining incomes in a more regular way.

Comparing Figure 3.43 b) with Figure 3.42 b) it is visible that the method with SA stabilized around day 39; however in what concerns the obtained incomes, it still meant a failure in some days after that, as well as success in many days before that point. This means that the offer in which it converged is a more risky offer than in the other approach, translating into more incomes when it is able to sell, comparing to the other approach, but also meaning that this offer is not capable of obtaining incomes in every day.

Note that a certain offer that performs well in a certain day does not guarantee success in all days. There are safer offers, which guarantee incomes in almost all cases, but being incapable of achieving the highest possible gain in each

The dynamic feed-forward neural network trained with the historic market prices, presented in sub-section 3.7.4, is used as a reference value to forecast market prices, which afterwards will be adjusted by using the proposed approaches,

The first test concerns Error Theory A strategy, comparing its prediction with the value received by the auxiliary strategy, to which the expected error is applied. In this comparison there is presented the actual market price, so one can check the quality of the prediction strategy. Figure 3.59 presents a chart with the results of this test.

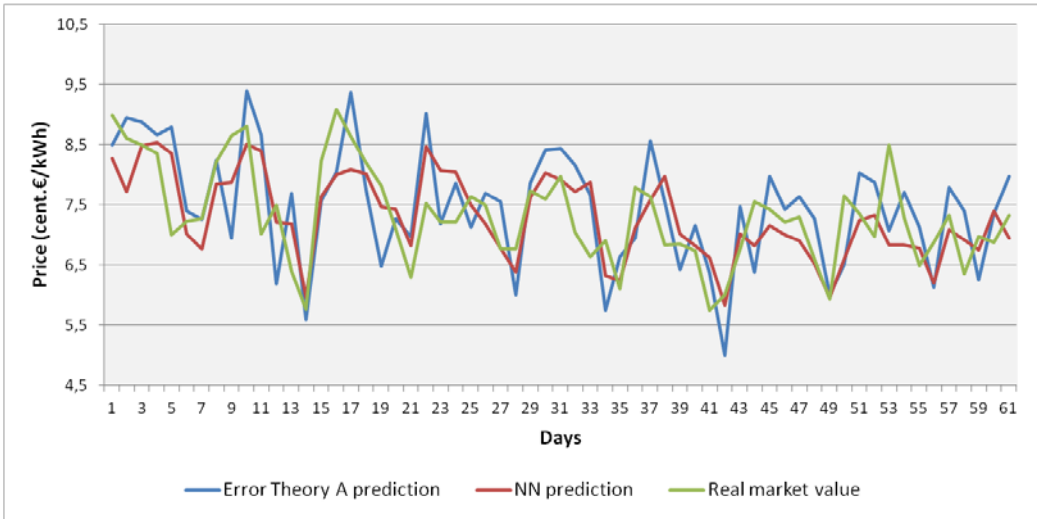


Figure 3.59 – Results of the test on Error Theory A strategy.

As can be seen from the chart presented in Figure 3.59, the calculation and application of the expected error, using the Error Theory A strategy, is very close to the actual market value, such as the auxiliary strategy. The comparison of the MAPE for both predictions is presented in the final of this sub-section.

In the second test, the same process was taken for Error Theory B. Figure 3.60 presents a chart with the test results.

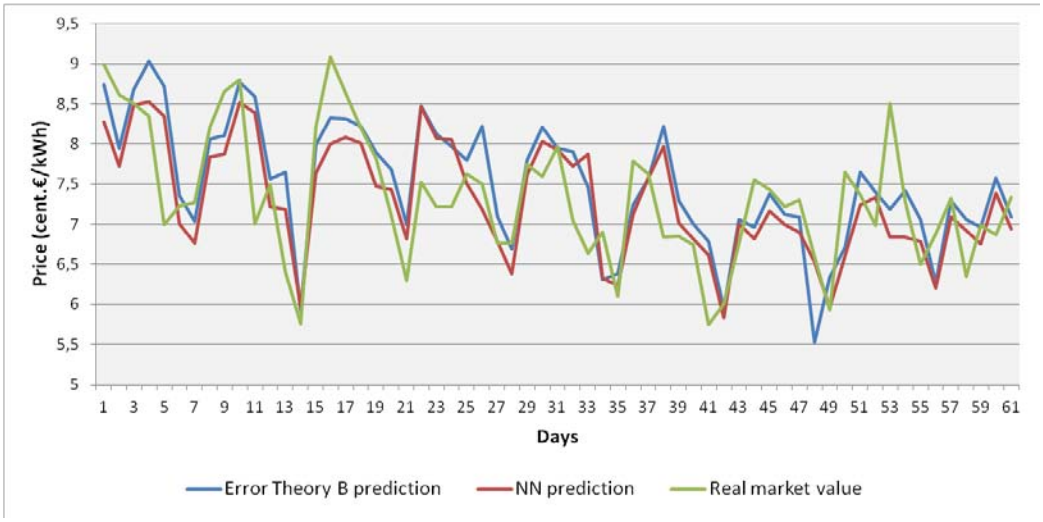


Figure 3.60 – Results of the test on Error Theory B strategy.

In this second test, one can see that the Error Theory B strategy had worst results when compared with Error Theory A strategy, for the tested starting day and period.

Finally, the third test is similar to the previous ones, but it is applied to Error Theory C strategy. These test results are presented in Figure 3.61.

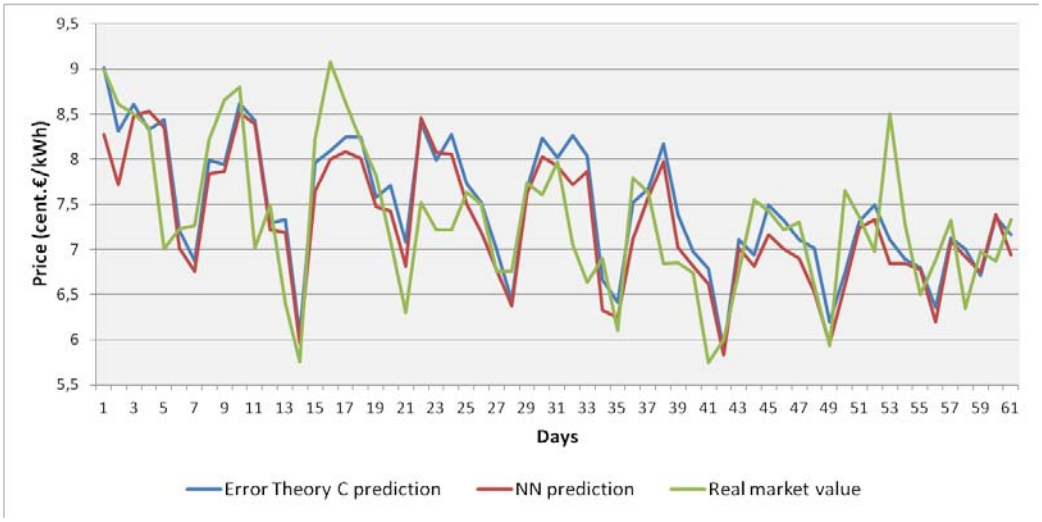


Figure 3.61 – Results of the test on Error Theory C strategy.

Analyzing the results of the third test, it seems that the Error Theory C strategy, concerning the tested start day and time, has a better performance than the Error Theory strategy B, regarding the level of proximity of the forecast with the actual values of the market, but worst than Error Theory strategy A. These results are supported by Table 3.5, which presents the comparison of the MAPE values of the presented forecasts.

Table 3.5 – MAPE comparison of each proposed strategy with the auxiliary strategy.

	Error Theory A	*Error Theory B*	*Error Theory C*
Forecasting strategy	0,064907955	0,06651243	0,065098301
Auxiliary forecast strategy (NN)	0,066845633		

In spite of the three strategies having got better results than the auxiliary strategy, Error Theory A proves to be the best of the three strategies, for the day and period used in the tests, as can be seen by the MAPE values, which relate the actual market value to the predictions of the auxiliary strategy, and the presented approaches.

The observed results are motivating, since all the approaches were able to adjust the NN forecasted values, and generate predictions closer to the actual goal. This was achieved by considering the prediction of the forecasting error that was expected.

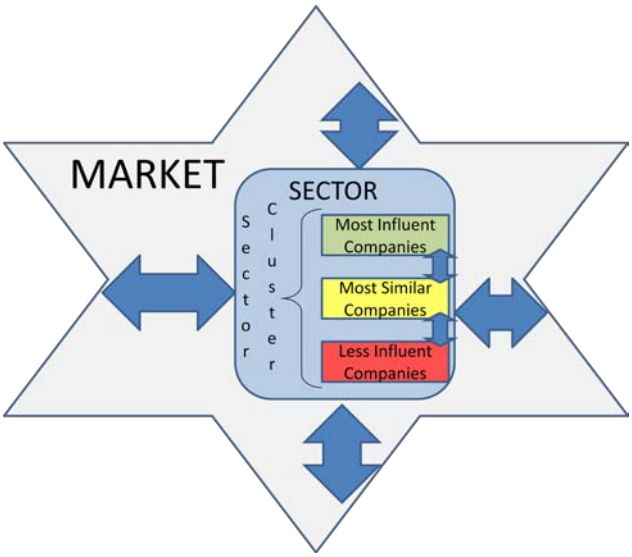


Figure 3.62 – External/Sectorial Analysis.

In order to define the sub-sectors inside the electricity market sector, a clustering mechanism is used to group the companies that act in the electricity market, in different groups, according to their characteristics. The clustering is performed using the K-Means algorithm provided by MATLAB. The companies are grouped according to their similarity in what concerns their dimension (amount of produced energy), the prices they are practicing recently (the most recent bid prices), and the average price they presented for the last month and year.

The clustering mechanism groups the companies into three different clusters; one representing the most influential companies, one representing the most similar companies to the one ALBidS is supporting, and one representing the less influent companies over the market.

Once the clustering is finished, the average bid price of the companies grouped in the same cluster as the supported one, is determined as the sector reference price, as it is used as reference for the situations in which the decision was to act towards equilibrium. The only situation in which this may not apply is when the supported company is placed in a highly competitive cluster, with high risking prices. In this case it is used the lower from the cluster reference or market price forecast as reference value.

Concerning both reference values (sector reference price in case of equilibrium, or market price in case of risking), they are subject to a decrement before being defined as the bid price for the supported player. This decrement is based on a *risk factor*, chosen by the user, with the purpose of guaranteeing that the final bid price is located below the reference, regardless of which.

The *risk factor* is a value between 0 and 1, and the higher the value is, the smaller is the decrement, meaning a higher proximity to the used reference values, and therefore increasing the risk to which it is subject. The initial decrement is calculated as in (3.63).

$$Decrement = 1 - Risk\ factor \tag{3.63}$$

If the decision in a certain moment is acting towards equilibrium, the decrement stays fixed at this value. Otherwise, if decision is risking for a continuous number of periods, the decrement lowers according to (3.64),

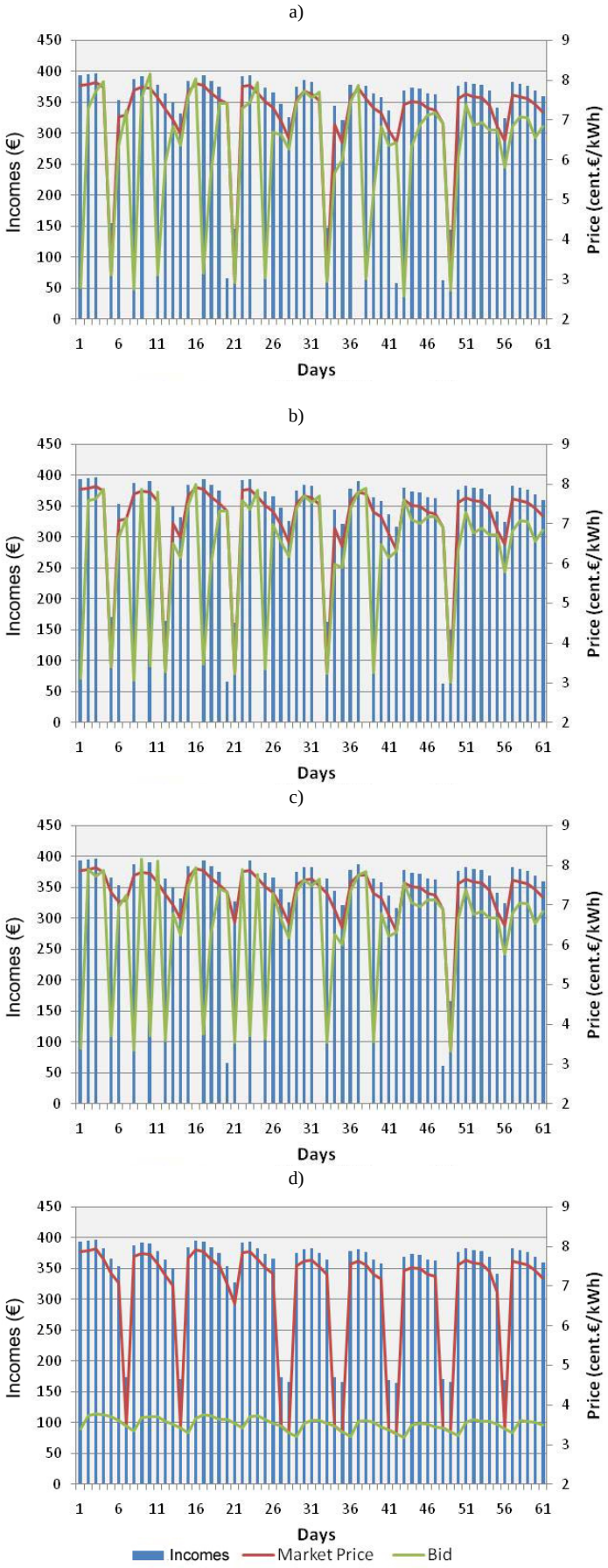


Figure 3.63 – Incomes obtained by Seller 2 in the twelfth period of the considered 61 days, with: a) a risk of 0.2, b) a risk of 0.5, c) a risk of 0.8, d) equilibrium.

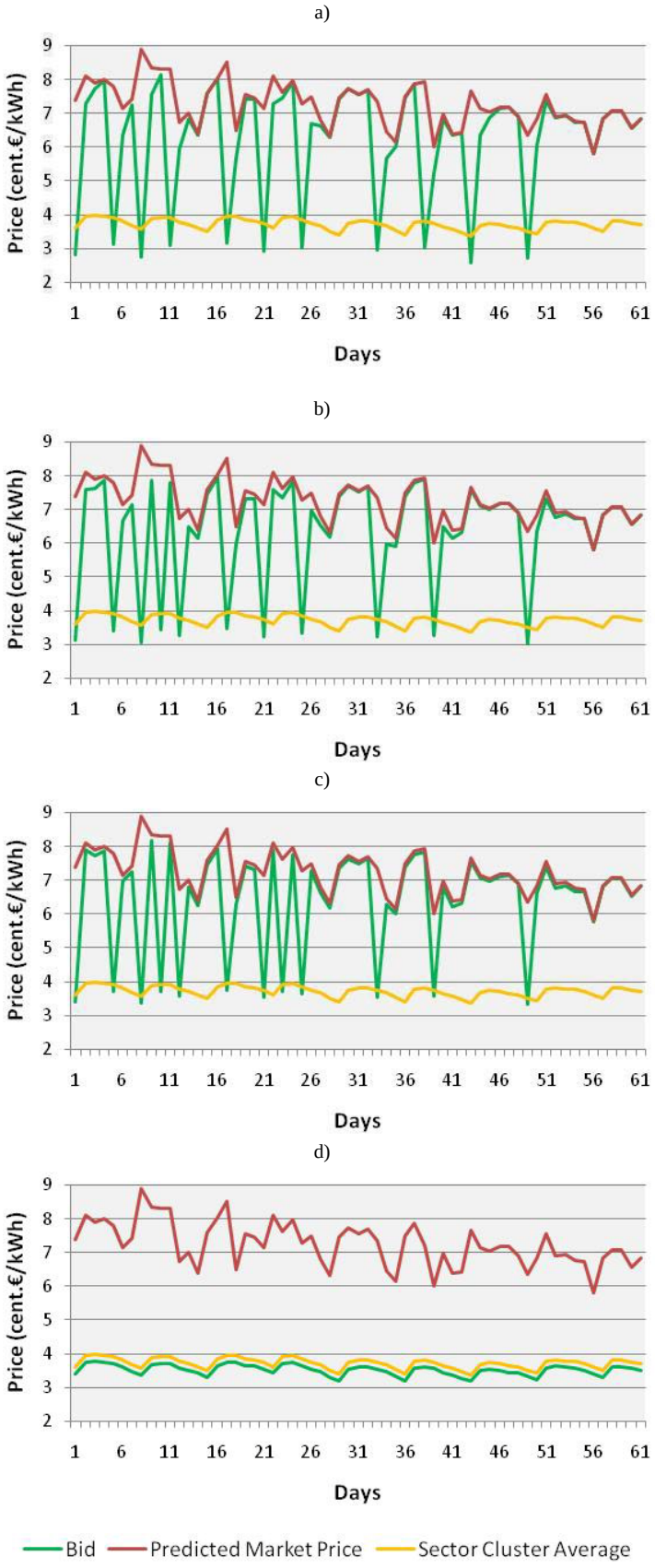


Figure 3.64 – Seller 2's bid comparison with the reference values in the twelfth period of the considered 61 days, with: a) a risk of 0.2, b) a risk of 0.5, c) a risk of 0.8, d) equilibrium.

The graphs in Figure 3.64 show that Seller 2's bid is always located below a reference value, either the forecasted market price, when assuming a higher risk, or the cluster reference value when going for equilibrium. In the fourth test, as the player uses the equilibrium approach at all times, the bid is always closely below the cluster reference value. Regarding the first three tests, it depends on the recent results. When comparing Figure 3.64 with Figure 3.63 it is visible that the cluster reference value is used after the periods in which the player got worst results. Comparing the bids among these first three tests, it is visible that the higher the risk of the approach, the closer the bid value gets to the reference values. Figure 3.65 presents the differences of the bids in each case, from the used reference value.

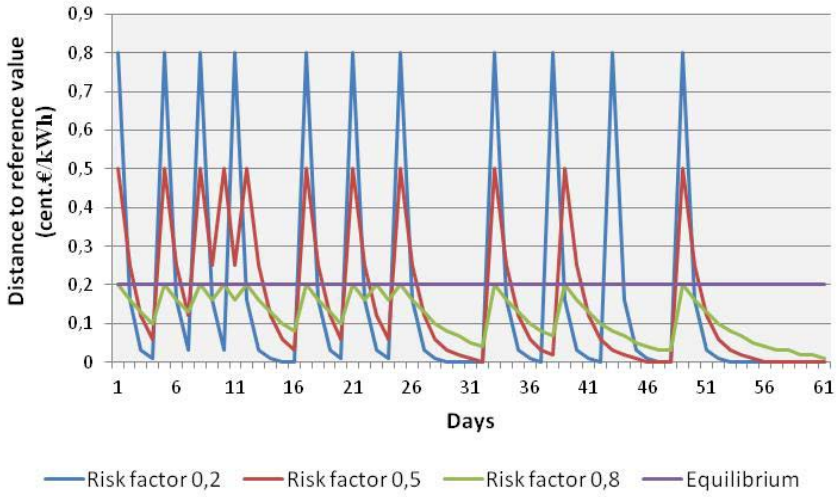


Figure 3.65 – Difference between the reference value and Seller 2's bid in the three considered cases.

In the first case, using a risk factor of 0.2, the bid value is located much lower than the references, as shown in Figure 3.65, presenting an average difference of 0,18 cent.€/kWh. In the second case, the differences are intermediate, with an average of 0.16 cent.€/kWh. Regarding the third case, where the risk factor is defined as 0.8, the bid comes very close the reference values, being the difference average of 0.11 cent.€/kWh. Finally, in what concerns the equilibrium approach, the difference is constant, being maintained at 0.2 cent.€/kWh in all situations.

The tests presented in this sub-section allowed demonstrating the adequacy and advantage of using the proposed approach, as it proved being able to provide high incomes to the supported player. Additionally, the combination of risk with equilibrium depending on the internal and external analysis of a company has been demonstrated.

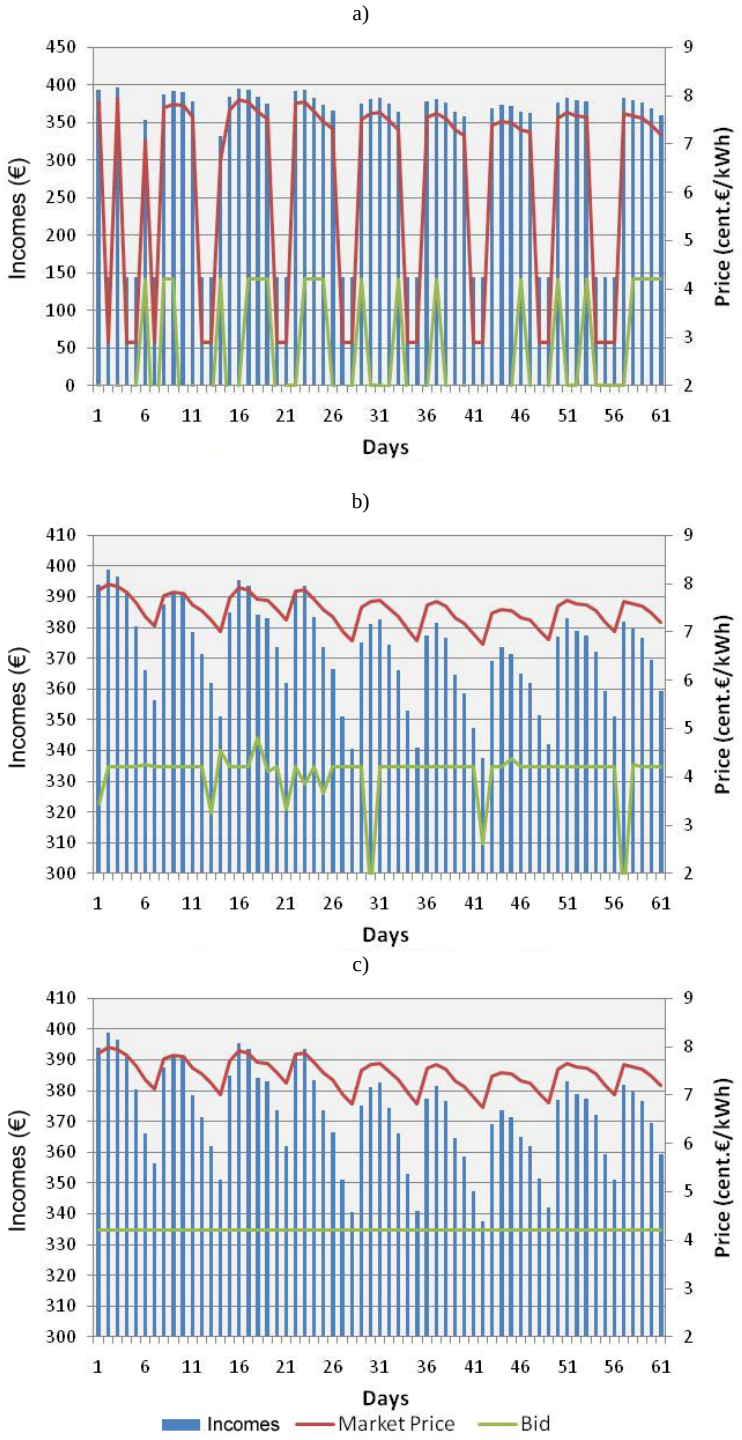


Figure 3.67 – Incomes obtained by Seller 2 in the twelfth period of the considered 61 days, with an effectiveness preference percentage of: a) 0%, b) 50%, c) 100%.

The graphs in Figure 3.67 show that Seller 2 was able to obtain incomes in all days in the three simulations. This proves the methods' high adequacy for supporting the player's actions when negotiating in the market, independently of the processing times that the method is obliged to respect.

Additionally, when comparing the income amounts along the days in the three cases, it is visible that the second and third simulations are very similar, meaning that the reduction of the players' profiles definition quality is not critical for the method's performance for a 100% to 50% preference on effectiveness.

Figure 3.68 presents the incomes obtained by Seller 2 in the first simulation, and a comparison between the proposed bid and the market price.

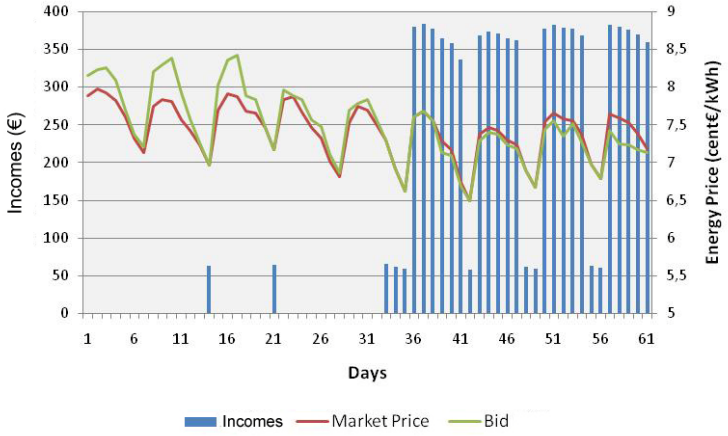


Figure 3.68 – Results of the Simple Metalearner.

Analyzing Figure 3.68 it is visible that this strategy starts by achieving bad results, which start to improve with the passing of the days. This is due to some supporting strategies' worst suggestions at the start, while they do not have the experience to learn adequately yet. As this metalearner considers all suggestions in a similar way, the good outputs that some strategies may be presenting are muffled by the bad ones. As the time progresses and the strategies start to learn and provide best individual results, the metalearner's results improve as well. Figure 3.69 presents a comparison between the metalearner's bid price and the supporting strategies' bid proposals.

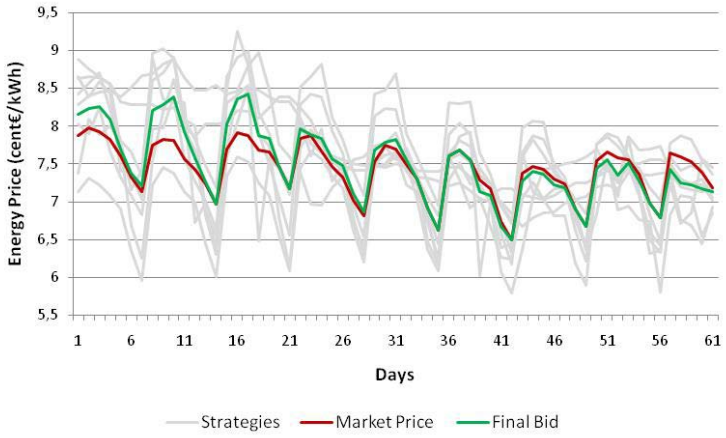


Figure 3.69 – Simple Metalearner's and supporting strategies' bids.

Figure 3.69 shows that, in the first days, the strategies' proposals present a high variance among each other, and so the metalearner's bid varies much as well. In the later days, the proposals start to converge and improve their quality, and consequently, the metalearner's bid gets closer to the market price.

The consideration of all suggestions in an equal way results in a bad performance of the Simple Metalearner especially in the first days. This is why the use of the Weighted Metalearner is important. This method considers adequate weights to instigate the attribution of higher importance to the strategies that are presenting best results at each time. Figure 3.70 presents the results of Seller 2 using the Weighted Metalearner.

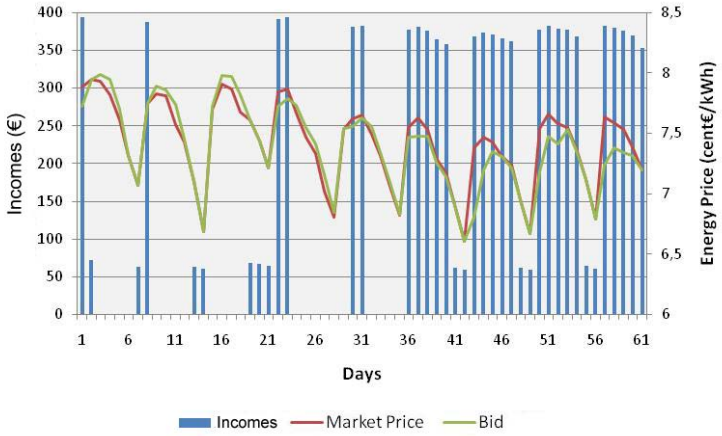


Figure 3.70 – Results of the Weighted Metalearner.

Figure 3.70 shows that, in spite of these results following the same tendency as the Simple Metalearner, with bad results at first, and a visible improvement over time, it could achieve good results in some early days, proving the advantage of attributing higher weights to the most appropriate supporting strategies' proposals. Figure 3.71 presents the development of the supporting strategies' confidence values, which determine the weights each one will be attributed.

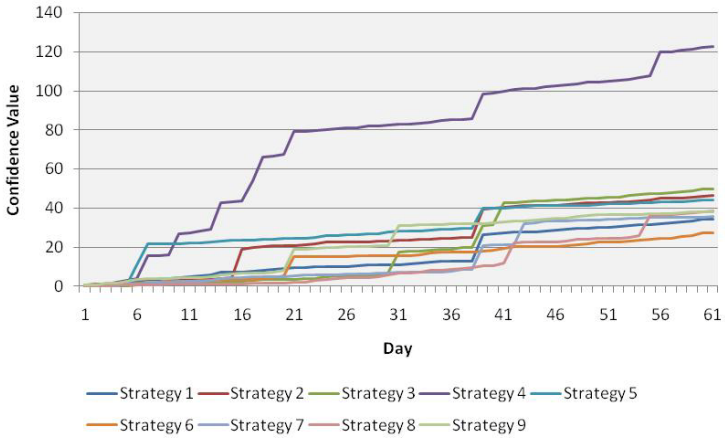


Figure 3.71 – Supporting strategies' confidence values.

From Figure 3.71 it is visible that *Strategy 4* detaches from the others. This means that this strategy is the one that influences the most the final bid from the Weighted Metalearner. Its influence increases over time. Figure 3.72 shows how this metalearner's bid follows the *Strategy 4*'s responses, in comparison with the rest of the supporting strategies.

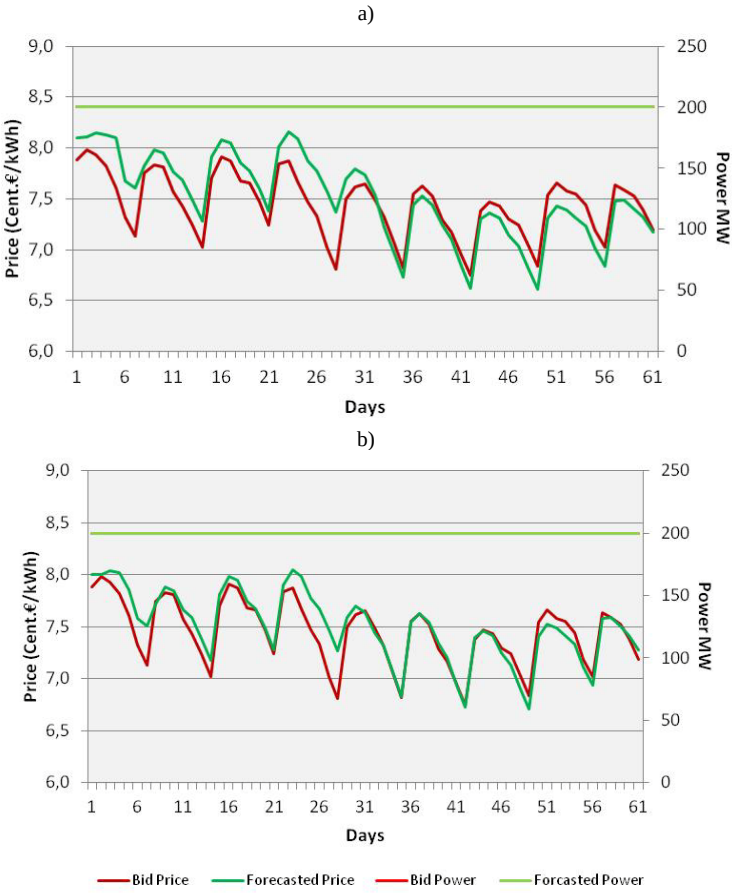


Figure 3.73 – Predicted and actual bid prices and powers, regarding Buyer 5, for an efficiency preference of: a) 100%, b) 0%.

Figure 3.73 shows that Buyer 5's bid price prediction was more accurate when the preference was attributed totally to the effectiveness of the method. This was an expected result, as in this case the Player Profile Definition mechanism has at its disposal a higher number of profile definition strategies, providing a larger number of results, which grants a higher chance of being more accurate. However, for this case, the differences, in spite of being noticed, are not that big. In what regards the power prediction, as it is fixed in a constant amount, it created no difficulty of prediction in none of the cases, with both achieving an expected 100% accuracy.

The differences in performance when considering a higher or lower preference for efficiency or effectiveness are dependent on the evolution of the considered supporting strategies' individual performance. The way the strategies perform affects the reinforcement they will be attributed by the reinforcement learning algorithm. This reinforcement defines the chances of each strategy's response being chosen as the final prediction. The evolution of the stats each strategy presented for the reinforcement learning algorithm, in both cases of the considered efficiency/effectiveness preference percentage is presented in Figure 3.74.

a)

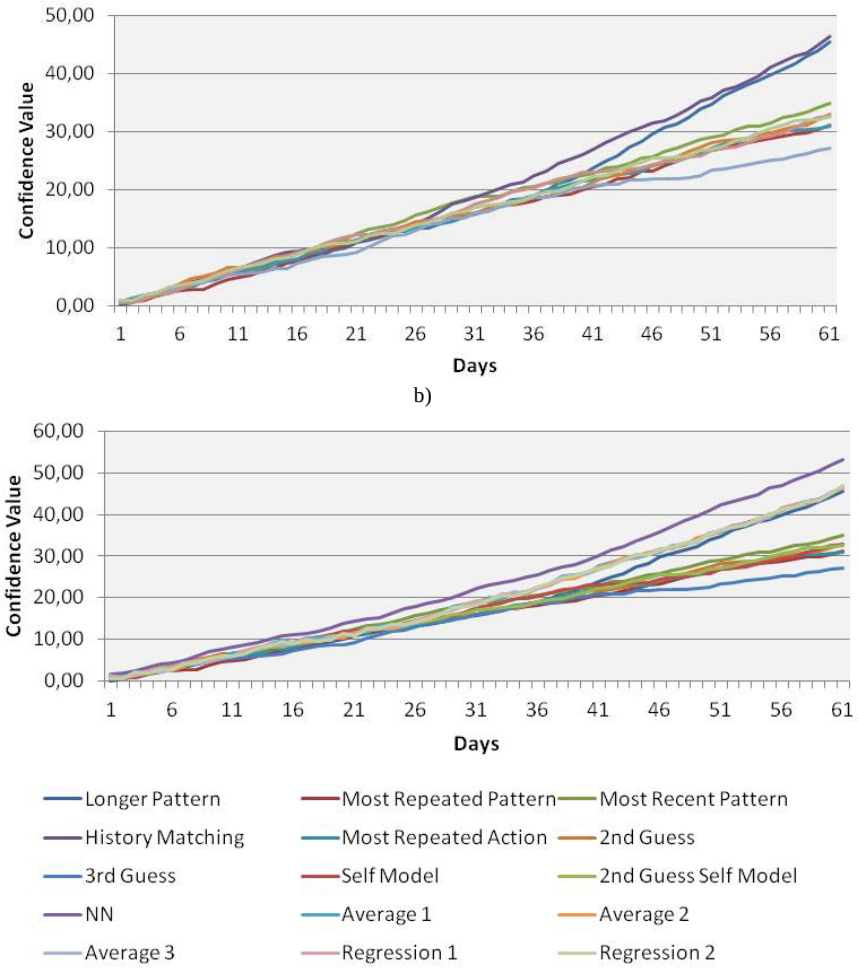


Figure 3.74 – Strategies' stats, for an efficiency preference of: a) 100%, b) 0%.

With the exclusion of the NN, the average, and the regression strategies, for the case with 100% preference for the efficiency, the Player Profile Definition mechanism strategies that presented higher stats were the *longer pattern*, and the *history matching*.

Regarding the case with full preference for the effectiveness, the strategy that most detached from the rest was the NN. The fact that different strategies got the bests results for the two cases explains why the results for the two cases are distinct.

The tests for the prediction of VPP 2 actions include both the prediction of the bid price, and of the bid power. The results regarding the tests on VPP 2's bid price prediction, for both preference percentages for efficiency, are presented in Figure 3.75.

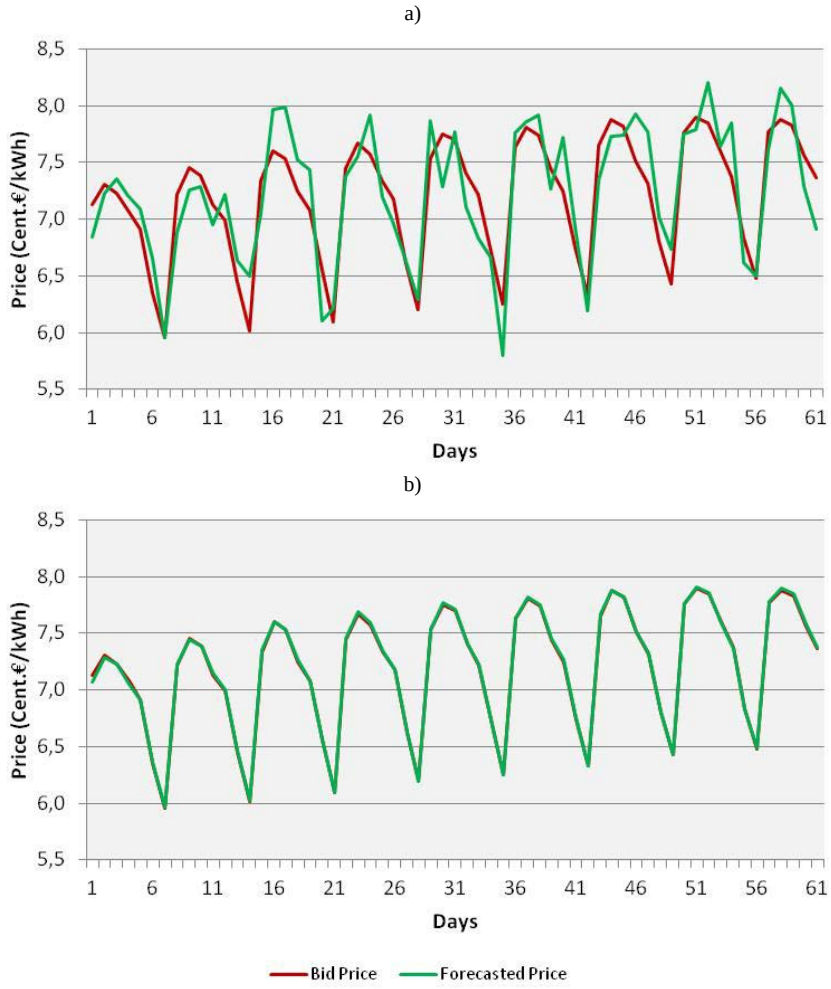


Figure 3.75 – Predicted and actual bid price of VPP 2, for an efficiency preference of: a) 100%, b) 0%.

Figure 3.75 shows that the bid price prediction for this agent was once again more accurate when the preference was attributed totally to the effectiveness of the method. The results concerning VPP 2 are more evident than the ones regarding Buyer 5, with the difference between the forecasted and actual bid prices being highly reduced from the case with 100% preference for efficiency to the case with 0% preference.

These differences are shown in Table 3.15, which presents the MAPE values of Buyer 5 and VPP 2's bid price and power predictions, for several values of preference for the efficiency/effectiveness balance.

Analyzing Figure 3.76, it is visible that the predictions of VPP 2 bid power are much worse than the predictions of its bid price. Regarding the prediction performance, when comparing the cases with full preference for efficiency and for effectiveness, an evident improvement is verified in the case with 0% preference for efficiency.

The stats of the different strategies regarding the prediction of the VPP bid price are presented in Figure 3.77.

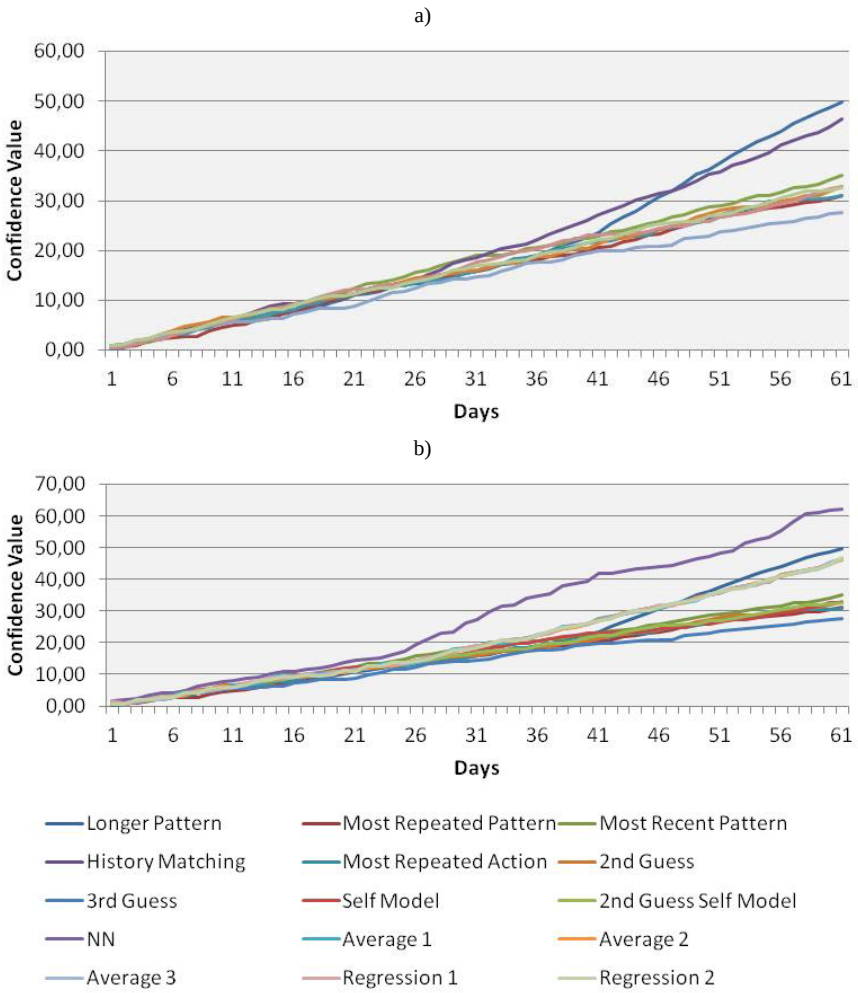


Figure 3.77 – Strategies' stats, for an efficiency preference of: a) 100%, b) 0%.

From Figure 3.77, it is visible that in the case of 100% preference for efficiency, the strategies presenting higher confidence values are the *Longer Pattern*, and the *History Matching*, such as occurred in the Buyer 5's bid prediction case. In the case of 100% preference for the effectiveness of the method, the NN maintains its leadership, followed by the *Longer Pattern* and *Regression 2* strategies.

The strategy presenting the lower confidence values is the *3rd Guess*. This occurs because of the characteristics of the predicted player. It defines its bid depending on its production, which is based on environmental resources, while this strategy is directed to the prediction of players' actions, whose bids are defined based on intelligent decision making, rather than on natural environmental events. When confronted with other types of opponents, this strategy can prove to be very useful. This is the main advantage of considering several different approaches to predict an action, having, at all times, strategies prepared to deal with different scenarios they may come across with.

consider. This provides the means for the system to increase its chances of always be provided with at least one adequate answer, even when the majority of the approaches fails in the accomplishment of its purposes.

This fact is extended to the other mechanisms which complement the system, *i.e.* the Context Analysis mechanism, the Player Profile Definition mechanism, and the Efficiency/Effectiveness Management mechanism. Once again, it is important to accentuate the importance of the case studies presented in Chapter 4, in their purpose of supporting the influence and advantage of these mechanisms, by displaying further tests with the whole ALBidS system's mechanisms fully integrated.

Finally, regarding the main entity in the ALBidS system – the Main Agent, it also proved to efficiently accomplish its purposes, showing its ability to choose the most appropriate actions for the supported player to take, by using the reinforcement learning algorithms at its disposal, and taking advantage on the complementary mechanisms that aim to enlarge ALBidS' capabilities of adaptation and providing of intelligent decision support.

The ALBidS system as a whole is tested and challenged in real data based scenarios, which are presented in Chapter 4. These case studies aim at guaranteeing the adequate coordination between the several mechanisms of this system, and proving its suitability in solving the issues it is designed to overcome.

In the first day the income using the ALBidS system is located below the value of the income using the regression approach. That is because the confidence values for all algorithms have been initialized with equal values, and so the selection of the answer is made by chance. The selected algorithm answer originated a low income.

In the second day, after the reinforcement learning algorithm is updated, it chooses the strategy that had the greater success in the first day. Obviously the one that got the best reward, and it is visible that the income is located above both the other comparison strategies, as well as it happens on the third day.

In the fourth day its value is below the results of the NN; the algorithm is still selecting the other algorithm that got the best results in the first 3 days.

In the fifth day the value is equal to the NN, and it follows that trend until day 10, in spite of its lower values in days 9 and 10. In day 11 the chosen algorithm is no longer the NN, as the third simulation's value is higher than the ones of the other two considered strategies. Other algorithm passed the NN as the best result of confidence as a result of the NN worst results in days 9 and 10.

In the last two days of the simulation, the selected algorithm is the regression, catching its high value tendency still on time to get two good final results. This is due to the low weight value of past experience; otherwise this algorithm would not be chosen, for its weaker performance in the first days.

Figure 4.3 presents the total amount of incomes obtained by Seller 2 in this period, using each of the three approaches.

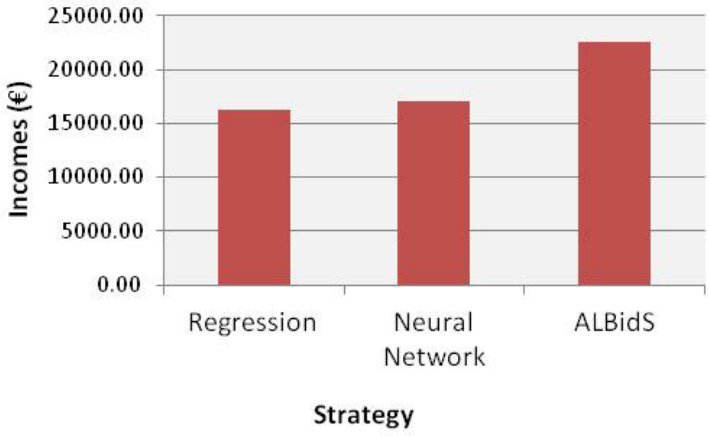


Figure 4.3 – Total incomes obtained by Seller 2 in the first period using each of the three approaches.

From Figure 4.3 it is evident that from the considered approaches, ALBidS was the one that, by far, was able to provide the best results for Seller 2 in the considered period.

Figure 4.4 presents the evolution of Seller 2 incomes in the thirteenth period of the day (to represent a period in the middle of the day, along the same 14 days, using each of the three considered methods.

similar initialization of the strategies' stats, and consequent random selection of the answer. The selected agent's answer originated a low income, which was not from either the NN or the regression's responses.

In the second day ALBidS chose the suggestion of the algorithm that got the best reward, and it can be seen that the income is equal to the one obtained by the NN for the same day. From this day forward the selected values remained always equal to the NN's proposals, taking advantage on this method's good results along the days for this period. This selection is verified even in the last two days, when the NN's results were null and the regression's higher. This is because of the value of confidence that the NN gained in the reinforcement learning algorithm over the passage of the days, due to its overall good performance. In spite of the regression getting good results in the last two days, it was not enough for it to overcome the NN confidence, even with the low value of the past experience weight attributed to the learning algorithm, to grant higher influence to the most recent results.

Figure 4.5 presents the total amount of incomes obtained by Seller 2 in the thirteenth period, for the fourteen considered days, using each of the three approaches.

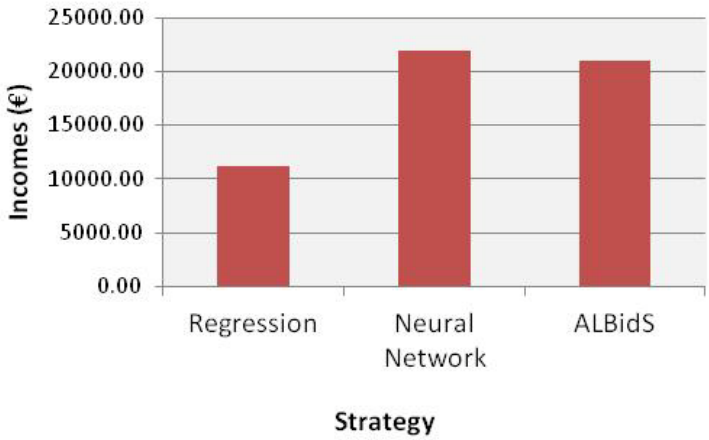


Figure 4.5 – Total incomes obtained by Seller 2 in the thirteenth period using each of the three approaches.

As presented in Figure 4.5 the simulation using ALBidS resulted on very similar results concerning the incomes of Seller 2, comparing to the one where the NN is used. This is due to what was analysed before, ALBidS having supported its decisions on the NN's suggestions throughout all days except for the first day. The first day, in which no data was still available for ALBidS' to support its choosing, was the reason behind the small discrepancy between the both simulations total results for this period.

Finally, the total amount of incomes obtained by Seller 2 considering all the 24 periods of the 14 considered days, can be compared, as presented in Figure 4.6.

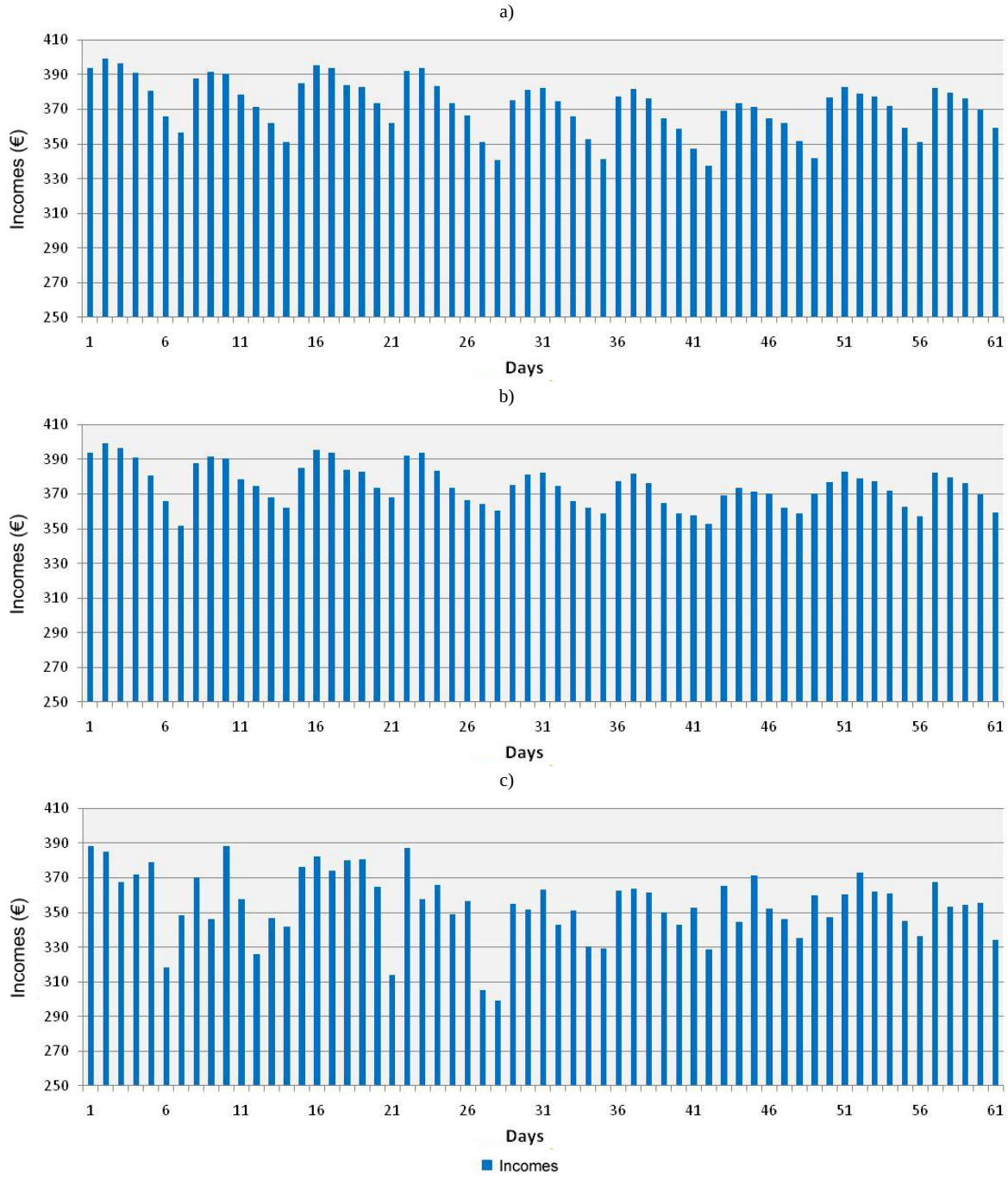


Figure 4.10 – Incomes obtained by Seller 2 in the twelfth period of the considered 61 days, in: a) the first simulation, b) the second simulation, c) the third simulation.

Analyzing the chart presented in Figure 4.10 a), the pattern concerning the weekend days results is clearly visible. The achieved incomes are always much lower on weekends than during working days. This tendency is softened slowly over the days, but never completely. This is due to the consideration of all days in the same way, not taking into account the different characteristics that weekend days present.

This is visible by analyzing Figure 4.10 b), which by considering weekend days as a different context, and consequently treating these days independently from the rest, manages to get better results on weekends, with no degradation of the results of the business days. Looking closely at this graph, it is visible that the results improvement on weekends starts on the second weekend and continues improving until the end of the simulation

days. Regarding the first weekend (days 6 and 7) presents weak results, since the strategies stats for this context are still in an initial point, *i.e.*, as initialized. This is easily visible by Figure 4.11, which presents the comparison of the incomes of Seller 2 in the first and second simulations.

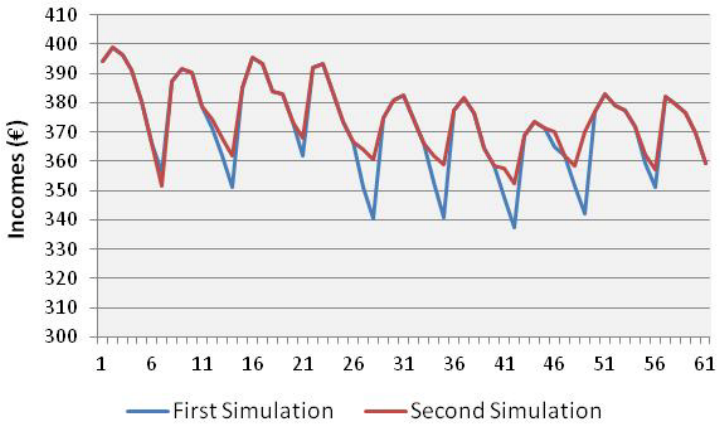


Figure 4.11 – Incomes obtained by Seller 2 in the first and second simulations, for the twelfth period of the considered 61 days.

Concerning the third simulation, since the full preference is given to the efficiency of the method and not on its effectiveness, the results are much more unstable. However, it is still possible to see in Figure 4.10, the weekends' worst results pattern in the beginning of the simulation, which is softened throughout the days, to the point that at the end it is almost imperceptible. This is due to the context definition, even with a low preference for effectiveness.

The comparison of the total incomes achieved by Seller 2 in the three simulations, in the total of the 61 days for the considered period is presented in Figure 4.12.

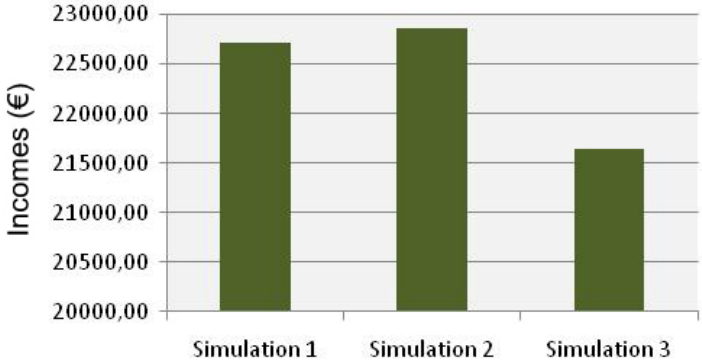


Figure 4.12 – Total Incomes obtained by Seller 2 in the twelfth period of the considered 61 days.

These results show the advantage of using context analysis to define the negotiating behaviour, since the simulation that used it – Simulation 2 is the one that achieved higher incomes. Regarding the third simulation, its preference for efficiency over effectiveness originated the achievement of worst incomes. However, this is compensated by the advantage in processing time, as presented in Table 4.1.

As presented in Figure 4.14, the two players' bids are always very close, and constantly changing whose is above and whose is below. It is even difficult to analyze their performance, so many are the changes in their behaviour, to make it unpredictable, anticipating the other's actions, and reacting to the environment. In fact, in order to understand which of the two performed better, it is necessary to take a look at their obtained incomes, which are presented in Figure 4.15. Note that the range of the graph may be misleading, since the axes' range had to be small, in order to be able to properly show the differences.

Figure 4.15 – Seller 2 and Seller 3's incomes in the twelfth period of the considered 61 days.

A better visualization of this equilibrium can be achieved by analysing Figure 4.16.

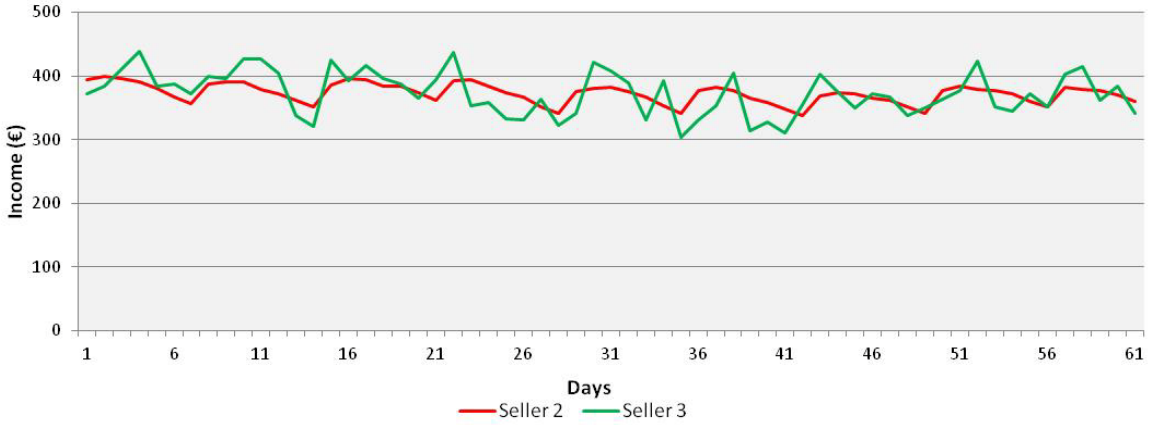


Figure 4.16 – Comparison between Seller 2 and Seller 3's incomes in the twelfth period of the considered 61 days.

As can be seen by Figure 4.16, the total incomes of both considered players concerning this period are very close, resulting from the constant variations and reaction in both players' actions. The closeness in both players' results is supported by Figure 4.17.

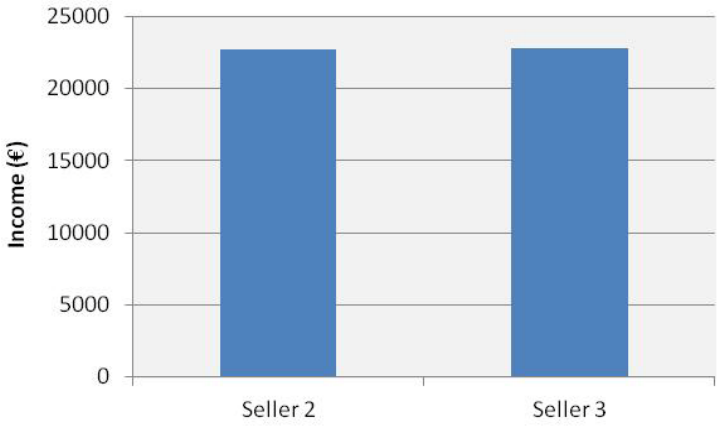


Figure 4.17 – Seller 2 and Seller 3's total incomes in the twelfth period of the considered 61 days.

From Figure 4.17 the difference between both players' achieved incomes is almost imperceptible. In fact the results for this period are as close as: Seller 2: 22,710.24 €; Seller 3: 22,756.36 €.

The results equilibrium is a constant factor, not only for the period in matter, but for all. Figure 4.18 presents the total incomes achieved by both players in the total of the 24 hourly periods of the 61 considered days.

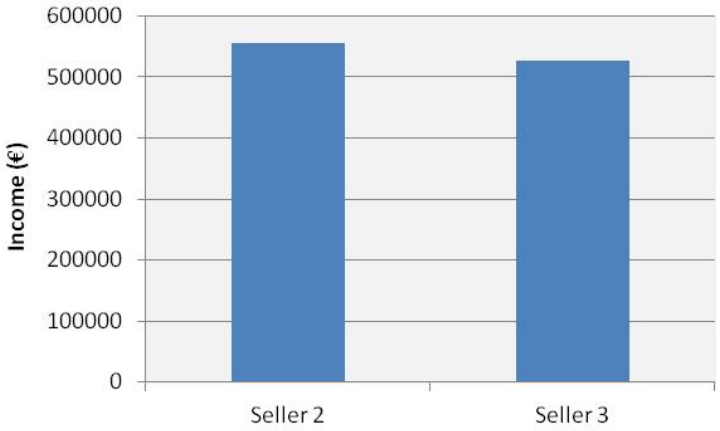


Figure 4.18 – Seller 2 and Seller 3's incomes in the total of the 24 periods of the considered 61 days.

Analyzing Figure 4.18 the remark goes for the equilibrium of both players' achieved incomes. The total income results for all periods are: Seller 2: 555,040.21 €; Seller 3: 526,152.74 €. The two players' equilibrium through competition was expected. However, such close results can be surprising, even though the two players were equipped with the same exact tools.

The most relevant conclusion to take from this test is that a player using ALBidS can, in fact, deal with the competition of intelligent opposition, and still be able to adequately achieve high incomes and adapt its behaviour to anticipate changes, react to other's plays, and make its own behaviour as unpredictable as possible.

Market Research: The AMES Test Bed", *Journal of Energy Markets*, vol. 2, no. 2, pp. 111-128, 2009

[Liu *et al*., 2005] Liu, Z. *et al*., "Electricity Price Forecasting Model Based on Chaos Theory", *The 7th International Power Engineering Conference*, 2005

[Liu *et al.*, 2008] Liu, W. *et al*., "An Information Theoretic Approach of Designing Sparse Kernel Adaptive Filters", *Transactions on Neural Networks*, vol. 20, no. 12, pp. 1950-1961, 2008

[Luck *et al.*, 2005] Luck, M. *et al*., "Agent Technology: Computing as Interaction (A Roadmap for Agent Based Computing)", *University of Southampton*, 2005

[Madureira and Pereira, 2010] Madureira, A. and Pereira, I., "Self-Optimization for Dynamic Scheduling in Manufacturing Systems", *Technological Developments in Networking, Education and Automation*, pp. 421-426, Springer Netherlands, 2010

[Matos, 2007] Matos, F., "Mercados Ambientais e Certificados Verdes", *Workshop Sistemas de Energia - Instituto Superior de Engenharia de Lisboa*, 2007

[Meeus *et al*., 2005] Meeus, L. *et al*., "Development of the Internal Electricity Market in Europe", *The Electricity Journal*, vol. 18, no. 6, pp. 25-35, 2005

[Mellor, 1986] Mellor, D., "Fixed Past, Unfixed Future", *Contributions to Philosophy: Michael Dummett*, pp. 166-86, 1986

[Menon *et al.*, 1999] Menon, A. *et al.*, "Antecedents and Consequences of Marketing Strategy Making", *Journal of Marketing - American Marketing Association*, vol. 63, no. 2, pp. 18-40, 1999

[Michalski, 1980] Michalski, R., "Pattern Recognition as Rule-Guided Inductive Inference", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 2, no. 4, pp. 349-361, 1980

[Migliavacca, 2007] Migliavacca, G., "SREMS-electricity market simulator based Game Theory and incorporating network constraints", *IEEE Power Tech*, Lausanne, Swiss, 2007

[Minsky, 1961] Minsky, M., "A Selected Descriptor-Indexed Bibliography to the Literature on Artificial Intelligence", *IRE Transactions on Human Factors in Electronics*, vol. 2, no. 1, pp. 39-55, 1961

[Minsky, 1986] Minsky, M., "The Society of Mind", *Simon and Schuster*, 1986

[Neumann *et al.*, 2003] Neumann, J. *et al.* "The essence of game theory", *IEEE Potentials*, vol. 22, no. 2, 2003

[Nicolaisen *et al.*, 2001] Nicolaisen, J. *et al*., "Market power and efficiency in a computational electricity market with discriminatory double-auction pricing", *IEEE Transactions on Evolutionary Computation*, vol. 5, no. 5, pp. 504-523, 2001

[Oliveira *et al*., 2009] Oliveira, P. *et al*., "MASCEM – An Electricity Market Simulator providing Coalition Support for Virtual Power Players", *International Conference on Intelligent System Application to Power Systems*, 2009

[Olsson and Soder, 2008] Olsson, M. and Söder, L., "Modeling Real-Time Balancing Power Market Prices Using Combined SARIMA and Markov Processes", *IEEE Transactions on Power*

Systems, vol. 23, no. 2, 2008

[Osborne and Martin, 2004] Osborne, A. and Martin, J., "An introduction to game theory", *Oxford University Press*, 2004

[Owen, 1995] Owen, G., "Game Theory", *Academic Press*, 1995

[Oxford, 2011] *Oxford dictionary*,New York Oxford Press

[Padovitz *et al.*, 2010] Padovitz, A. *et al*., "Multiple-Agent Perspectives in Reasoning About Situations for Context-Aware Pervasive Computing Systems," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 38, no. 4, pp. 729-742, 2008

[Pal, 2010] Pal, R., "Context-Sensitive Probabilistic Boolean Networks: Steady-State Properties, Reduction, and Steady-State Approximation", *IEEE Transactions on Signal Processing*, vol. 58, no. 2, pp. 879-890, 2010

[Panait and Luke, 2005] Panait, L. and Luke, S., "Cooperative Multi-Agent Learning: The State of the Art", *Autonomous Agents and Multi-Agent Systems*, pp.387-434, 2005

[Pereira, 2010] Pereira, I., "Aspectos de Aprendizagem em Optimização", *Master of Science thesis in Computer Science – Knowledge-based and Decision Support Technologies*, Polytechnic of Porto, Portugal, 2010

[Pinto *et al*., 2009] Pinto, T. *et al*., "Multi-Agent Based Electricity Market Simulator with VPP: Conceptual and Implementation Issues", *IEEE PES General Meeting*, 2009

[Pinto *et al.*, 2011a] Pinto, T. *et al.*, "Multiagent System for Adaptive Strategy Formulation in Electricity Markets", *IEEE Symposium Series on Computational Intelligence - IEEE Symposium on Intelligent Agents - SSCI-IA*, 2011

[Pinto *et al.*, 2011b] Pinto, T. *et al.*, "Cost Dependent Strategy for Electricity Markets Bidding Based on Adaptive Reinforcement Learning", *International Conference on Intelligent System Application on Power Systems - ISAP*, 2011

[Pinto *et al.*, 2011c] Pinto, T. *et al.*, "Strategic Bidding Methodology for Electricity Markets using Adaptive Learning", *Modern Approaches in Applied Intelligence*, vol. 6704, pp. 490-500, 2011

[Pinto *et al.*, 2011d] Pinto, T. *et al.*, "Bid Definition Method for Electricity Markets Based on an Adaptive Multiagent System", *Advances on Practical Applications of Agents and Multiagent Systems*, Springer Berlin / Heidelberg, vol. 88, pp. 309-316, 2011

[Pinto *et al.*, 2011e] Pinto, T. *et al*., "A new approach for multi-agent coalition formation and management in the scope of electricity markets", *Energy*, vol. 36, no. 8, pp. 5004-5015, 2011

[Pinto *et al.*, 2011f] Pinto, T. *et al*., "Multi-Agent Negotiation for Coalition Formation and Management in Electricity Markets", *Negotiation and Argumentation in MAS*, Bentham Science Publishers Ltd., 2011

[Porter, 1979] Porter, M., "How Competitive Forces Shape Strategy", *Harvard business Review*, 1979

[Porter, 2008] Porter, M., "The Five Competitive Forces that Shape Strategy", *Harvard Business*

[Wand *et al*., 2008] Wang, B. *et al*., "Prediction of Power System Marginal Price Based on Chaos Characteristics", *IEEE International Conference on Industrial Technology*, pp. 21-24, 2008

[Weiss, 2010] Weiss, G., "Multiagent Systems: a modern approach to distributed artificial intelligence", *MIT Press*, 2010

[Wellman *et al.*, 2007] Wellman, P. *et al*., "Autonomous Bidding Agents: Strategies and Lessons from the Trading Agent Competition", *MIT Press*, 2007

[Wilamowski and Yu, 2010] Wilamowski, B. and Yu, H., "Neural Network Learning Without Backpropagation", IEEE Transactions on Neural Networks, vol. 21, no. 11, pp. 1793-1803, 2010

[Winnie, 1996] Winnie, J., "Deterministic Chaos and the Nature of Chance", *The Cosmos of Science - Essays of Exploration*, University of Pitsburgh Press, pp. 299–324, 1996

[Winston, 1992] Winston, P., "Artificial Intelligence", *Addison- Wesley*, pp. 15-228, 1992

[Wooldridge, 2002] Wooldridge, J., "Econometric Analysis of Cross Section and Panel Data", *Cambridge MIT Press*, Cambridge, 2002

[Wooldridge, 2002] Wooldridge, M., "An Introduction to Multiagent Systems", *Wiley*, New York, 2002

[Zambonelli *et al.*, 2004] Zambonelli, F. *et al*., "Towards a Paradigm Change in Computer Science and Software Engineering: A Synthesis", *The Knowledge Engineering Review*, vol. 18, no. 4, 2004

[Zhao *et al.*, 2008] Zhao, J. *et al*., "A Statistical Approach for Interval Forecasting of the Electricity Price", *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 267-276, 2008

[Zhifeng *et al.*, 2009] Zhifeng, Q. *et al*., "Comparison of Two Learning Algorithms in Modelling the Generator's Learning Abilities", *15th International Conference on Intelligent System Applications to Power Systems – ISAP*, vol. 1, no. 6, pp.8-12, 2009

[Zimmermann *et al*., 2001] Zimmermann, H. *et al*., "Multi-agent modeling of multiple FX-markets by neural networks", *IEEE Transactions on Neural Networks*, vol. 12, no. 4, pp. 735-743, 2001

[Zimmermann *et al.*, 2004] Zimmermann, R. *et al*., "PowerWeb: a tool for evaluating economic and reliability impacts of electric power market designs", *IEEE PES Power Systems Conference and Exposition*, vol. 3, pp. 1562-1567, 2004

[Zimmermann *et al*., 2005] Zimmermann, H. *et al*., "Dynamical consistent recurrent neural networks", *IEEE International Joint Conference on Neural Networks*, vol. 3, pp. 1537- 1541, 2005