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INTELLIGENT TRADING AGENT FOR POWER TRADING THROUGH WHOLESALE MARKET

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Inteligentni programski agent za trgovanje električnom energijom posredstvom veleprodajnog tržišta

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Abbreviations

ICT	*Information and Communications Technology*
PowerTAC	*Power Trading Agent Competition*
RES	*Renewable Energy Sources*
EU	*European Union*
RD&D	*Research, Development and Demonstration*
SG	*Smart Grid*
EISA	*Energy Independence and Security Act*
NIST	*National Institute of Standards and Technology*
AMI	*Advanced Metering Infrastructure*
DER	*Distributed Energy Resources*
EMCAS	*Electricity Market Complex Adaptive Systems*
MAIS	*Multi Agent Intelligent Simulator*
ACE	*Agent-based Computational Economics*
MCP	*Market Clearing Price*
MCV	*Market Clearing Volume*
LMP	*Locational Marginal Price*
ZMCP	*Zonal Market Clearing Price*
TSO	*Transmission System Operator*
MSE	*Mean Squared Error*
NRMSE	*Normalized Root Mean Squared Error*
MPE	*Mean Percentage Error*
MAPE	*Mean Absolute Percentage Error*
ARMA	*Autoregressive Moving Average*
WCR	*Wholesale Clearing Rate*
KPI	*Key Performance Indicator*

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Introduction

Liberalization and decentralization of energy market has resulted in major changes in its structure and dynamics, thus creating a regulated and competitive market environment. To enable further improvements, most of traditional power grids are introducing novel Information and Communications Technology (ICT) solutions, progressively transforming into evolved systems called *smart grids*. Smart grids enable more efficient energy usage, better communication between the entities on the market as well as real-time balancing of energy supply and demand. There is also a possibility for implementing advanced software solutions to provide a support for trading on the modern energy market. Hence, there is a need for a risk-free environment in order to test software solutions developed for modern energy markets.

Power Trading Agent Competition (PowerTAC) is an agent-based competitive simulation which models a modern energy market, where competing entities (brokers) offer energy services to customers through tariff contracts and must serve those customers by trading in a wholesale market. One of the competitors in PowerTAC 2013 is CrocodileAgent 2013, developed at University in Zagreb. The main focus of this paper is optimizing CrocodileAgent's trading in the wholesale market, in order to improve its general performance.

Background and motivation for designing and improving trade mechanisms in evolved wholesale energy market are described in the first chapter. Architecture of smart grids and their characteristics are described in the second chapter. Third chapter defines structure and mechanisms on today's wholesale market, altogether with forecasting methods used on the market. Fourth chapter describes competitive environment and integrated mechanisms of PowerTAC competition, used as a test environment for new improvements of intelligent software agent CrocodileAgent 2013 described in the final chapter. Final chapter also presents results of CrocodileAgent's performance evaluation.

1. Background and motivation

Since the discovery of the light bulb, electricity has made a huge impact in developing a modern society. Today, it is hard to imagine a life without it. Electric companies provide every factory and household with a supply of electric energy and they used to serve various areas from which consumers had to buy their electric energy. Traditional energy market was centralized in order to ensure security of supply and efficient production of electric energy. Efficiency was achieved through economics of scale[1]. The power sector had a highly vertically integrated market structure[2] with a little competition, but during last two decades huge changes of electricity market's structure have taken place all around the world. The architecture of a traditional energy market is depicted in Figure 1.

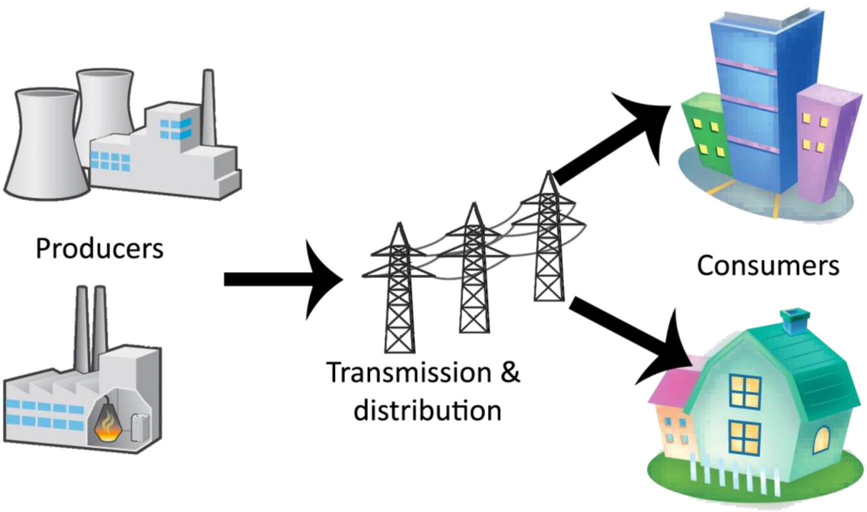

Figure 1: Architecture of a traditional energy market

[1] The increase in efficiency of production as the number of goods being produced increases.

[2] Vendors offer goods and services specific to an industry, trade, profession, or other group of customers with specialized needs.

In order to promote competition, traditional structure of energy market has been replaced by deregulated, competitive structure, where consumers are free to choose their provider. Electricity exchanges and pools have been organized in order to enable and enhance trading in these new markets. A power exchange, though, is not a necessary entity in a deregulated power market. In fact, in most countries the most of the deals are made on a bilateral basis, on the so-called over-the-counter (OTC) market[3]. Establishment of power exchanges has promoted competition and contributed to the high trading activity, but the main value can be expressed through providing updated, independent and good-quality market information which can enhance quality of trading and provide base for further evolution of electricity market. In a modern, competitive power market electricity can be traded at market prices, which as a consequence has an increased amount of risk borne by electric utilities, power producers and marketers. In order to successfully manage a company in the modern market there is a need for using statistical analysis and educated guesswork, which involves developing dedicated statistical techniques and managing huge amounts of data for modeling, forecasting and pricing purposes.

The second aspect of electricity market's evolution can be expressed through strong need to increase number of renewable energy sources (RES, hereafter) in order to increase sustainability. Non-renewable energy sources were exploited for over two centuries, however, often with undesirable side effects such as pollution and other damage to the natural environment. In the second half of the 20th century, building of nuclear power plants grew in popularity, relieving some demands on limited fossil fuel reserves, but at the same time, raising safety and political problems [2]. Even though the RES technologies are constantly developing, exploitation of non-renewable is growing and will continue in the near future, resulting in the environment pollution. As a response, there is a need to establish a sustainable energy policy in order to integrate both renewable and non-renewable technologies and to minimize utilization of fossil sources.

[3] Over-the-counter trading is done directly between two parties, without any supervision of an exchange.

In the European Union (EU, hereafter) there is a goal to join liberalization of electricity sector and reduction of greenhouse gas emission in order to modernize the energy policy. EU officially started its renewable energy policy through launching of Research, Development and Demonstration (RD&D) programs from 1974 onwards [2]. In 1974, Madrid Conference laid the basis for the first objectives for renewable energy at EU level, later formalized in the RES-E whitepaper “Energy for the future – renewable sources of energy”. According to the Kyoto Protocol[4], commits to reduce emission of greenhouse gases by 8% during period 2008-2012 in comparison to levels in 1990. Regarding that commitment, the 2010 target for electricity was set at 22.1 % as a share of electricity produced from RES within the EU. Promotion of renewable sources should lead in the long term to electricity systems based on renewables to a larger extent than today. But increasing the share of renewable sources in the electricity technology mix requires strong and efficient regulatory policy support.

According to Renewables 2012 report [3], there is substantial growth of 16.7% in contribution of RES to global energy consumption in 2010. As it is depicted in Figure 2, modern RES are accounted for 8.2% in this total, and that share has increased over last years as a result of technology evolution [3].

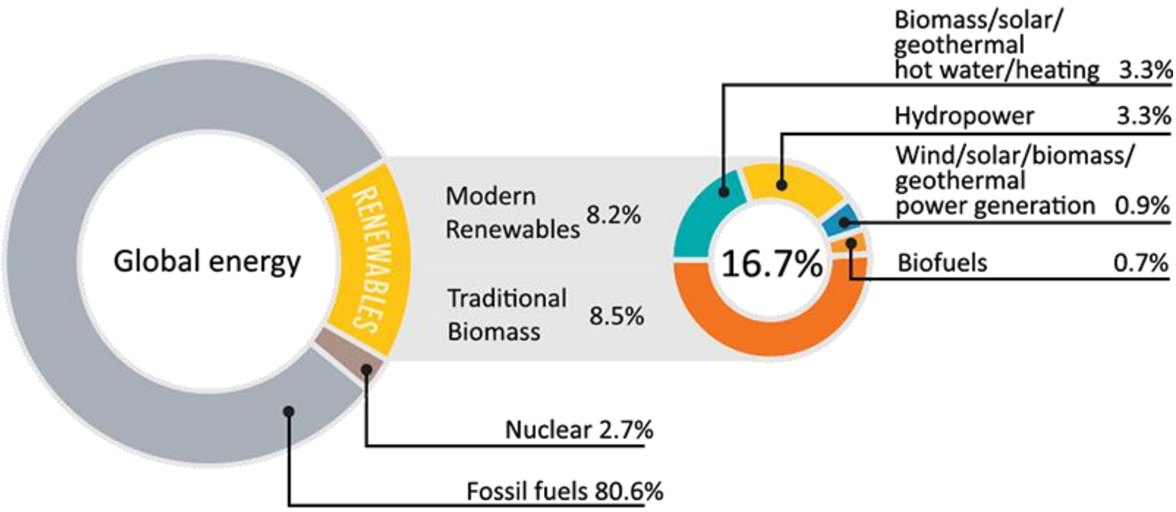

Figure 2: Energy distribution in 2010

[4] International treaty that sets binding obligations on industrialized countries to reduce emissions of greenhouse gases.

Share of energy from traditional biomass has declined to 8.5%. Total of 3.3% of global energy consumption was supplied by hydropower, and its supply rate is growing substantially. All other modern renewables provided approximately 4.9% of energy consumption. During 2011, the growth of modern renewables continued in all sectors: *heating*, *cooling*, *power* and *transport*. *Wind* and *solar photovoltaics* accounted for almost 40% and 30% of renewable capacity, respectively, followed by a hydropower which contributed to renewable capacity with almost 25%. By the end of 2011 renewables contributed with more than 25% to total global power capacity (estimated at 5,360 GW in 2011) and supplied an estimated 20.3% of global electricity. As Figure 3 shows, the fastest-growing RES is solar, which at the end of 2011 had annual growth of 74%.

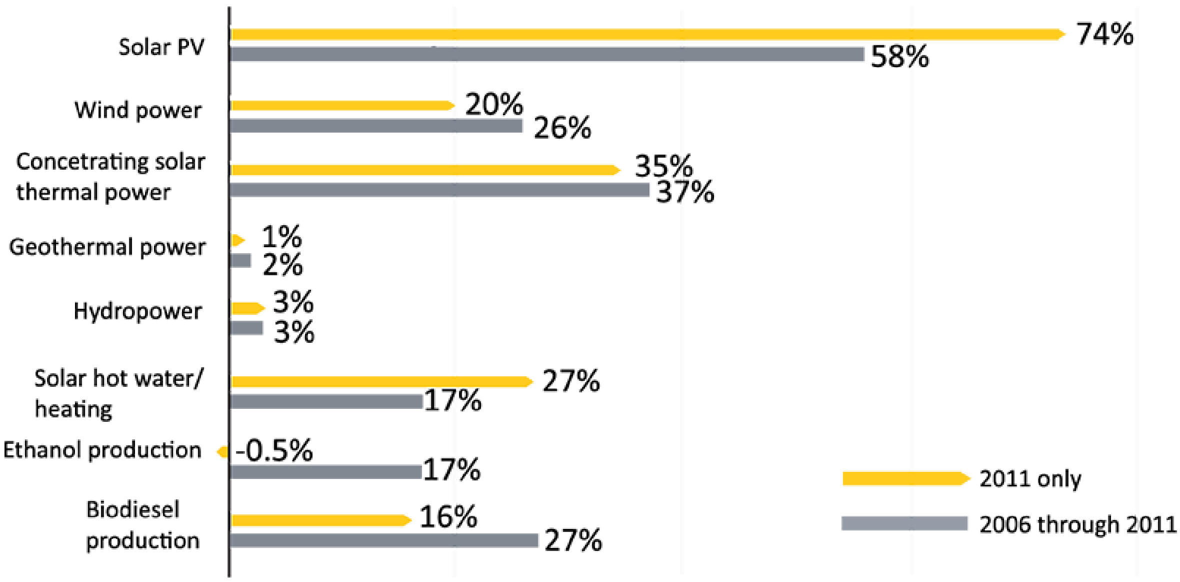

Figure 3: Renewable energy sources through last 5 years

As a result of decentralization and liberalization of electricity market, and increasing trend of using RES, it is necessary to transform existing power grid in order to provide better control and satisfy increasing demand for electricity. One of the solutions is to create synergy of already evolved power grid and information and communications technology (ICT, hereafter) layer in order to create advanced energy network called *smart grid*.

2. Smart grid

The term “Smart Grid” (SG, hereafter) refers to a modernization concept of the electricity delivery system so it monitors, protects and automatically optimizes the operation of the modernized power grid, from the central and distributed generator through the high-voltage transmission network and the distribution system, to industrial users and building automation systems, to energy storage installations and to end-use consumers and their thermostats, electric vehicles, appliances and other household devices [4]. The Energy Independence and Security Act of 2007[5] (EISA), which directed the National Institute of Standards and Technology[6] (NIST) to coordinate development of this framework and roadmap, states that national policy supports the creation of a Smart Grid [5]. SG is characterized by a two-way flow of electricity and information in order to create automated and distributed energy delivery network. It provides the power grid with benefits of distributed computing and communications in order to deliver the real-time information and maintain balance of supply and demand in the power grid. Using modern information technologies, the SG is capable to deliver electric power more efficiently and to respond to various conditions and events [6]. Figure 4 shows the general architecture of modern a SG. Generally, the SG is able to respond to various events that occur anywhere in the grid, such as power generation, transmission, distribution, and consumption, and adopt the corresponding strategies in order to maintain load balance and to supply energy to end-users. For instance, once a voltage transformer failure event occurs in the distribution grid, the SG may automatically change the power flow to recover the power delivery service.

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[5] Act of Congress concerning the energy policy of the United States.

[6] http://www.nist.gov, measurement standards laboratory, otherwise known as a National Metrological Institute (NMI), which is a non-regulatory agency of the United States Department of Commerce.

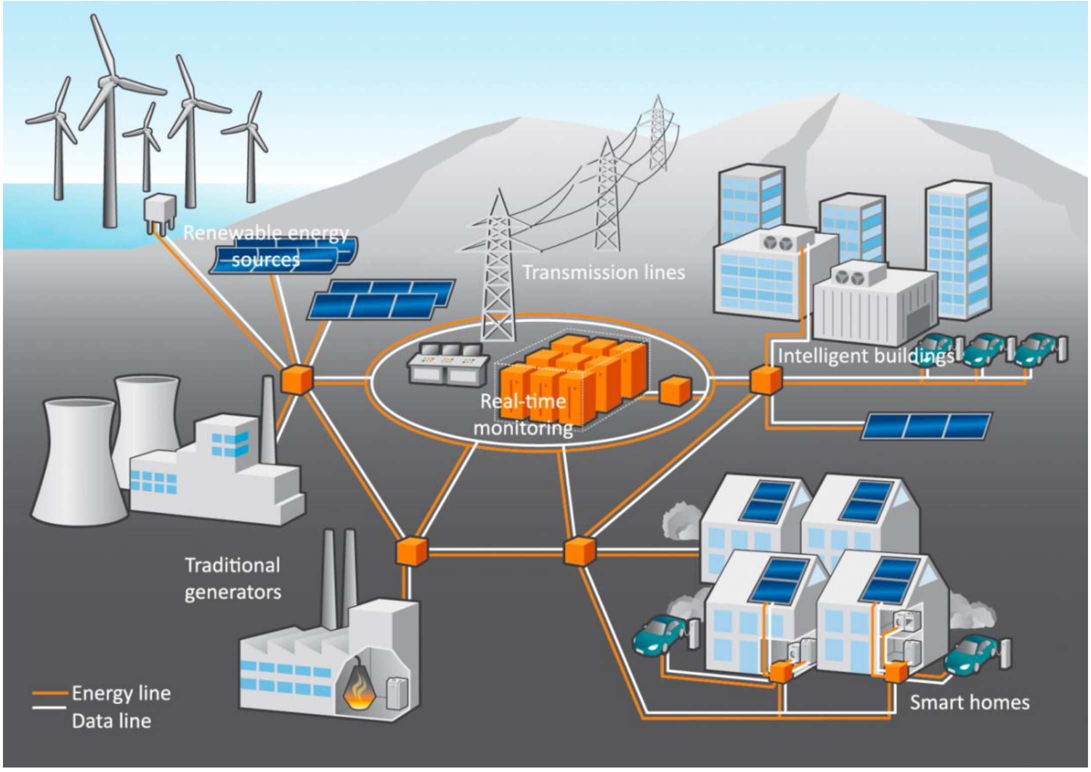

Figure 4: General architecture of a modern smart grid

Evolution of ICT and its integration into modern SG provided solid base for two-way communication between entities in SG, in order to maintain balance through the whole power grid. ICT is the main component of the future Internet, and one of most important part of the future Internet is Internet of energy, which is simply a term that describes intelligent, evolved, modern and transformed power grid, or shortly – SG. A SG extends a traditional power grid with additional functionalities provided by ICT layer. Multi-layered smart grid architecture along with its functionalities and correspondent flows is depicted in Figure 5.

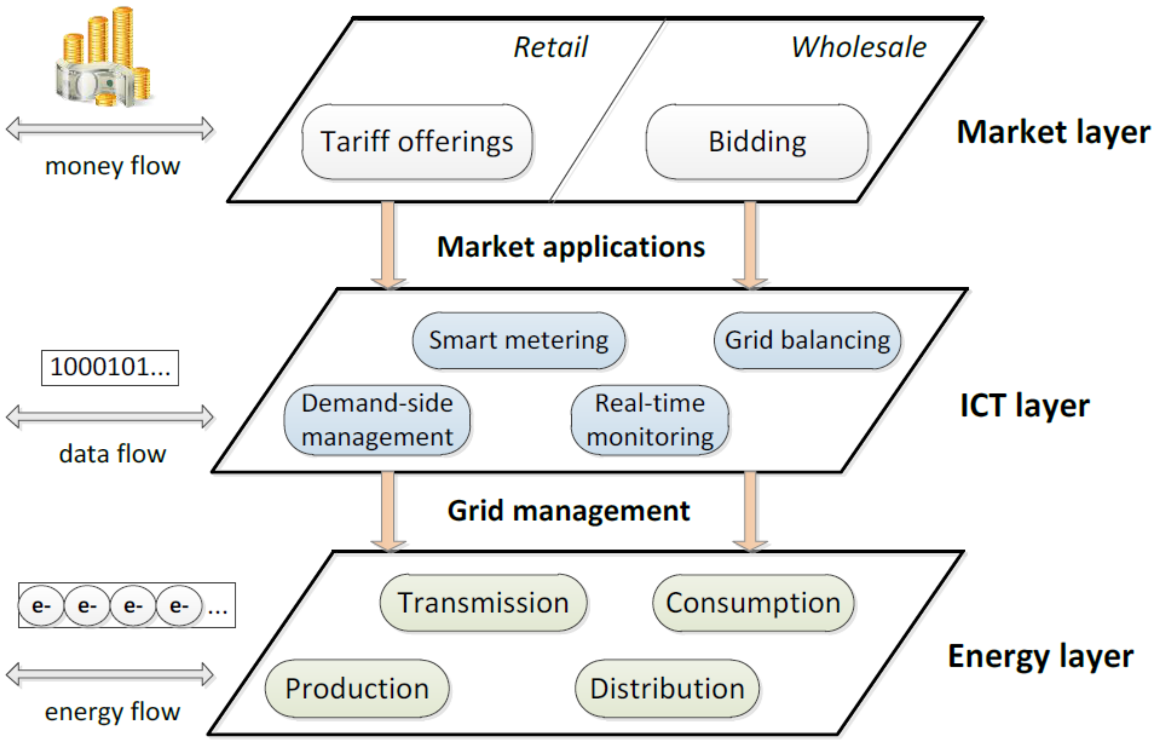

Figure 5: Multi-layered smart grid architecture [11]

The most important feature on the client-side is smart metering, implemented through an idea of advanced metering infrastructure (AMI, hereafter) with the aim to improve demand-side management and energy efficiency, and constructing self-healing reliable grid which can be able to recover after influence of malicious sabotage and natural disasters [10]. The AMI is the main factor in the smart grid which enables architecture for automated two-way communication between a utility company and a smart utility meter. A smart meter is advanced meter equipment which tracks detailed power consumption and communicates collected information to the utility company in order to monitor energy load and to bill consumers [12]. Consumers can be informed of amount of power they are using so they could control their power consumption, which can result in reduction of electricity bill and in reduction of greenhouse gas emission. By managing the peak load through consumer participation, the utility will likely provide electricity at lower and even rates for all.

ICT layer in general provides the base infrastructure for wholesale and retail electricity market and provides connection between energy and market layers of SG architecture. Energy layer acts similar to traditional power grid, but implementation is far more complex. As a result of electricity market decentralization and liberalization, instead of a few large power plants electric energy is fed into power grid from numerous distributed energy sources. As a response to decentralization of power sources, there are new limitations in transmission and distribution of electricity to end-customers in order to satisfy growing need for electricity supply. Wholesale and retail markets together create a market layer. ICT layer provides extensive set of information to retail customers which enables them to make better and more accurate decisions in choosing the appropriate tariff offered by energy companies. The wholesale market represents a deregulated market that is used by competitive energy companies buy desired amount of energy in order to ensure continuous supply for their customers.

2.1. Smart grid benefits

Evolution of traditional power grids into modern SG bring many benefits, which can be divided in five groups [7]:

- **Power reliability and power quality**: The SG provides more reliable power supply with fewer and briefer outages, power from renewable energy sources, and self-healing power systems. Additionally, ICT layer takes care of global load balancing which can be crucial in load peeks.
- **Safety and cyber security**: The SG continuously monitors itself to detect unsafe situations which could interrupt its normal operation. State-of-the-art cyber security is built into all systems and operations including physical power plant monitoring, and privacy protection of all end-customers.
- **Energy efficiency**: The SG provides reduced total energy usage. Some of the other benefits are: a reduced peak demand, reduced energy losses, and the ability to reduce end-customer demand by sending interruption signals instead of new generation in power system operations.

- **Environmental and conservation benefits**: The SG is “green”. It helps reduce greenhouse gases and other pollutants by reducing generation from inefficient energy sources. It also supports renewable energy sources, and enables the usage of the plug-in electric vehicles.
- **Direct financial benefits**: The SG offers direct economic benefits as a result of reduced energy losses and introduction of interruptible demand. Operations costs are reduced or avoided and customers have pricing choices and access to energy information.

2.2. Smart grid challenges

Although SG brings many advantages, there are also some challenges as traditional power grid evolves into modern SG with distributed power sources, two-way power flows and end-customer interaction [4]. Procedural challenges of the smart grid evolution are enormous, and need to be met as the SG evolves. Some of the most important procedural challenges are:

- **Complexity of the Smart Grid**: The SG is enormous complex system, with some parts sensitive to human interaction and response, and other parts that needs to react instantaneously and automatically. Speed and aspects of SG evolution will vary of environmental requirements and also, will be influenced by financial pressures.
- **Transition to Smart Grid**: Transition to the SG cannot be executed briefly. It takes a lot of time to prepare and adapt to various conditions that need to be met in order to complete transition. The SG supports gradual transition and long coexistence of diverse technologies, not only transition of legacy systems to modern today equipment, but also transition to equipment of tomorrow. Transition must be carefully executed in order to avoid unnecessary expenses and decreases in reliability and safety.
- **Research and Development**: The SG is an evolving goal and final stage of evolution cannot be exactly predicted. The smart grid will demand continuing R&D to assess the evolving benefits and costs, and to anticipate the evolving requirements.

- **Regulatory and Policy**: In order to maintain consistent regulatory and energy policy framework over a long transition period, there are many regulatory conditions which need to be met. Conditions vary of regulatory system which is different for every country.

Although the backbone of SG evolution is modern technology that supports ICT layer, there are still many challenges that need to be met:

- **Smart equipment**: Smart equipment refers to all equipment which is computer-based or microprocessor-based, including controllers, remote terminal units and intelligent electronic devices [12]. It also refers to the equipment inside homes, buildings and industrial facilities, mostly used for smart metering. Smart equipment also includes electromechanical switches, voltage controllers, and other older hardware that have been equipped with sensors and controls in order to monitor state, transmit that state for analysis, and execute control commands that are result from analysis. Some of these instruments have integrated units used for intelligent data processing, and they are used when remote analysis is unnecessary or not economical. This embedded computing equipment must be robust to handle future applications for many years without being replaced.
- **Communication systems:** Communication systems refer to the network infrastructure and communication protocols used to transmit collected data through SG using ICT layer [14]. These technologies are in various stages of maturity, hence SG must be robust enough to accommodate protocols and formats that emerge daily from the communications industries..
- **Data management:** Data management refers to all aspects of collecting, analyzing, storing, and providing data to users and applications, including issues of data identification, validation, accuracy, updating and consistency across databases. Data management methods which work well for small amounts of data usually do not work for large amounts of data generated in SG. In many cases entirely new data models and techniques such as data-warehousing and data-mining are being applied in order to handle the huge amount of data which additionally increases as a result of synchronization

between old and modern databases. Data management is among the most time-consuming and difficult task and must be addressed in a way that will be scalable.

- **Software applications**: Software applications refer to programs, algorithms, calculations, and data analysis used to process data collected in SG. Applications can range from low level control algorithms to massive software systems to support transaction processing. Application requirements are becoming more sophisticated in order to solve complex problems, and are demanding ever more accurate data in order to deliver results more quickly and accurately. Software solutions are also evolving and shifting to services oriented architecture built upon on a robust analysis, simulation and data management infrastructure. Software engineering is still emerging as a discipline and it is crucial in DG evolution because software solutions are at the core of every function and node of the SG [13].

2.3. Smart grid market modeling

Market layer is a very important part of the SG ecosystem. While the transition to the SG may unfold over many years, market layer is rapidly evolving. The main reason for progressive evolution of the market layer is potential possibility for electricity companies to make profit by trading energy on wholesale and retail market. Actors in the market layer exchanges price and balance supply and demand within the power system. The communication between the market layer and the domains supplying energy is crucial because efficient balancing between production and consumption is dependent on market domain. Energy supply domains include the Bulk Generation domain and Distributed Energy Resources (DER, hereafter) [15]. DER is represented in the transmission, distribution and customer domains, and it is typically served through aggregators. Communication for market interactions must be reliable and traceable. As the percentage of energy supplied by small DER increases, allowed latency in communications with other resources must be reduced. Table 1 shows different application categories in market layer.

Application category	Description
Market Management	Includes wholesale market exchanges for various regions, altogether with transmission and services and demand response markets.
Retailing	Retailers sell power to end-customers and may in the future aggregate or trade DER between customers or into the market. Most are connected to a various trading organizations to allow participation in the wholesale market.
DER aggregation	Aggregators combine smaller participants to enable distributed resources in order to participate in larger markets.
Trading	Traders participate in markets, which include aggregators and other qualified entities, in order to make profit only by buying and selling energy.
Market operations	Functions that make particular market function run smoothly. It includs financial and goods sold clearing, price quotation streams and balancing.

Table 1: Different application categories in market layer

The high-priority challenges in the market domain are extension of price and DER signals to customer domain, simplification of market rules, expanding the capabilities of aggregators and interoperability across all providers and consumers of market information. Also, there is a need to manage and regulate growth of energy trading on retail and wholesale market, and to further improve communication mechanisms for prices and energy information throughout market and consumer domains.

2.4. Multi-agent market models

Although there are many benefits from electricity market's decentralization and its evolution to SG, there are many challenges in designing such decentralized systems and predicting their impact on economy [16]. Recently there were some unsuccessful attempts to deploy such systems, i.e. California energy market and collapse of Enron, which showed that successful deploy of modern electricity market takes a lot of effort in market design and planning of demand response, capacity reserves and risk management [17]. Therefore, it is very important to thoroughly test system design proposals in a risk free simulated environment before deploying these ideas into the real world.

Agent-based modeling and simulation has emerged over the last few years as a powerful tool for testing end evaluating new solutions in energy sector [18]. There are few examples of such implementation. First, Electricity Market Complex Adaptive Systems Model (EMCAS) is an agent simulation that models an electric power system [19]. An EMCAS simulation includes both the customers who represent the end users of electricity and the demand companies from whom they purchase electricity. Agents inside simulation interact on several layers, including a physical layer, several business layers and a regulatory layer. Second solution is Multi Agent Intelligent Simulator (MAIS) and it serves as an agent-based support for analyzing dynamic price changes in the U.S. wholesale market. MAIS generates artificially numerous trading agents equipped with different learning capabilities and duplicates their bidding strategies in the California electricity markets during the crisis period [16].

Software agents are also used in the field of Agent-based Computational Economics (ACE) [19] that studies economic processes, including whole economies, as dynamic systems of interacting agents. ACE models can be exploited in many areas related to SG, such as understanding and evaluating market designs, evaluating the interactions of automated markets and trading agents, creating rich economic decision environments for human-subject experiments, and advising policy makers on the expected behaviors of markets or market interventions. ACE can be used to construct a rich simulated market environment in which agents face each other, representing trading entities in real-world market.

3. Wholesale market

There is an ongoing liberalization of energy market that is taking place in many countries over last two decades [25]. The main motivation for liberalization of power sectors worldwide is unbundling the vertically integrated monopoly structures that has traditionally managed generation, distribution and transport of energy. The introduction of competition on the market has been encouraged in order to introduce market forces in industry that was for many years constructed as a natural monopoly. The breach of natural monopoly has been enabled due to changes in generation technologies and modernization of energy transmission. Therefore the motivation behind electricity liberalization is, in the long run, to promote efficiency gains, to stimulate technical innovation and to lead to efficient investment.

3.1. History and structure of the wholesale market

Energy market liberalization was pioneered by Chile in 1982, by reform based on the idea of separate generation and distribution companies [21]. Formula used for calculating energy price was constructed as a function of the energy cost, cost of a dispatch system and a system of trading power between generators. Further implementation continued in 1986 and resulted with a partial vertical disintegration of the energy sector and formation of a wholesale energy trading mechanism. The Chilean reform was followed by the restructuring of the British and Welsh electricity sector in 1990s. Furthermore, the Nordic market opened in 1992 and Australian market began operating in 1994. There were a number of markets in northeast America opened in late the 1990s, followed by California in 1998 and Texas and Alberta three years later [26]. Number of liberalized electricity markets is growing worldwide, but the trend is most visible in Europe. Some of the pioneers in the electricity market reform have been successfully operating for over a decade, while others have made major changes in order to improve performance and survive. There are also some cases of failure in reformation of electricity market (e.g. California market crash in 2001 [17]), which are sometimes used to argue that electricity market liberalization is still not flawless.

3.1.1. Power exchanges and power pools

There is a need for organized markets at the wholesale level as a result of market liberalization. There are two types of market that emerged: *power pools* and *power exchanges*. They share many characteristics and it's not always trivial to distinguish them. The oldest and one of the most mature power exchanges in the world is called NASDAQ OMX[7]. Also, there are two types of power pools that can be identifies – technical and economic [22]. Technical power pools or generation pools have always existed. Vertically integrated utilities used a pool system to optimize generation with respect to cost minimization. In such a system the power plants were ranked based on costs of production. Hence, generation costs and network constraints were the determining factor for dispatch. Trading activities were limited to transactions between utilities from different areas and international trade activity was limited, due to a low level of interconnection capacity.

Economic pools or simply power pools have been established to facilitate competition between generators. They have been created as a result of public initiative by governments willing to introduce competition in generation of energy. Power pools have been used worldwide, for instance, in England and Wales [24]. Participation in an economic pool is mandatory, hence no trade is allowed outside the pool. Participants bid based on the prices at which they are willing to run their own power plants. The market clearing price (MCP, hereafter) is established through a one-sided auction as the intersection of the supply curve constructed from aggregated supply bids and the estimated demand, which automatically defines the market clearing volume (MCV, hereafter). One-sided auction is depicted in Figure 6.

[7] NASDAQ OMX is the single financial energy market for Norway, Denmark, Sweden and Finland. Before 1 November 2010, it was known by the name Nord Pool.

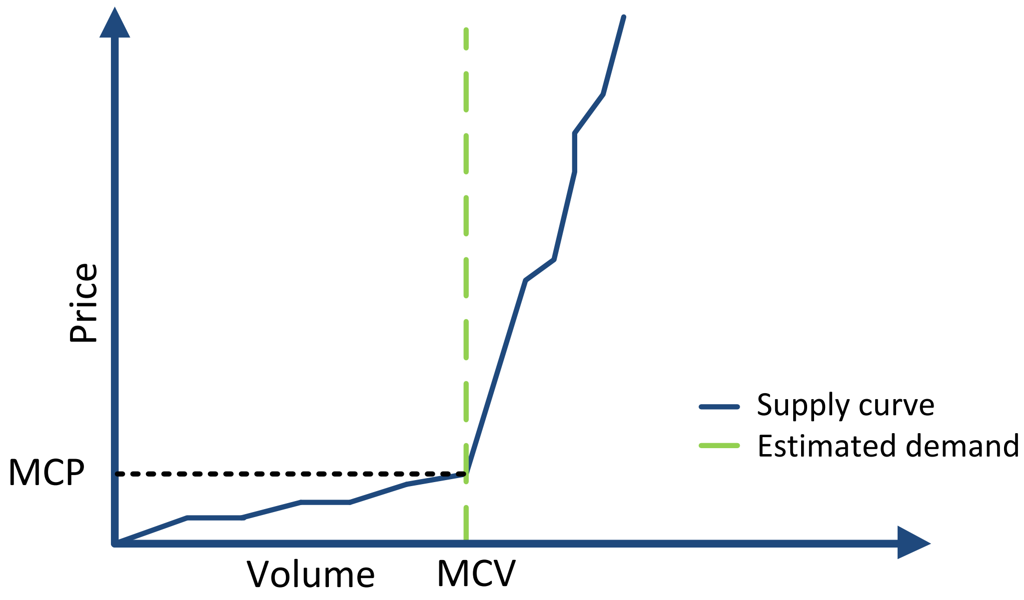

Figure 6: One-sided auction in power pool

Bids can be very complex, because of the technical aspects involved. Hence, the price determination mechanism requires complex optimizations which require computationally demanding operations.

On the other hand, power exchange is usually launched by a combination of generators, distributors and traders in order to create common marketplace for energy exchange. Many of European markets are based on power exchange model, and they are usually organized as a day-ahead electricity market [25]. The main role of a power exchange is to match the supply and demand in order to determine a publicly announced MCP. Generally, MCP is established as a result of two-sided auction that is conducted once a day. It is constructed as the intersection of the supply curve constructed from aggregated supply bids, and the demand curve constructed from aggregated demand bids, as depicted on Figure 7.

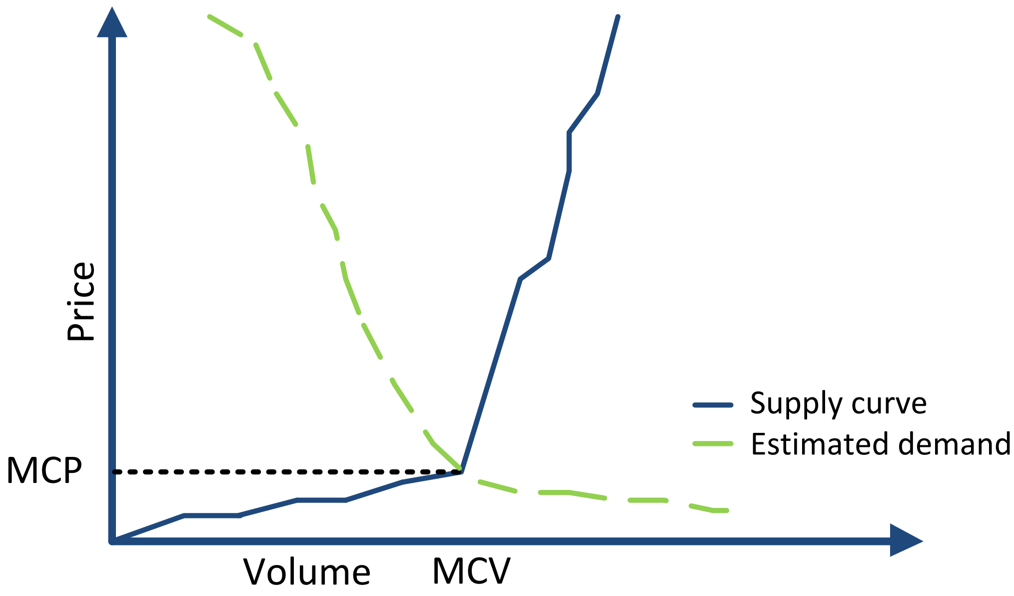

Figure 7: Two-sided auction in power exchange

Buyers and suppliers can submit their bids and offers for each hour of the next day, and MCP is calculated hourly as a result of balancing supply and demand. In uniform-price auction market buyer whose bids are higher or equal to the MCP pay that exact price (MCP), regardless of their actual bids. Respectively, suppliers whose bids are below or equal to the MCP also pays that same price. In contrast, in pay-as-bid auction market a supplier would be paid exactly for the amount he listed in his bid, which leads to a problem because as a result of transaction there is generated extra money paid by buyer but not paid to suppliers. There are many pros and cons for each of the models, but in practice, most markets have adopted the uniform-price auction design.

3.1.2. Nodal and zonal pricing

In cases when there is no transmission congestion[8], MCP is the only price in the market. When there is an occurrence of transmission congestion, there are two types of prices that can be introduced into market: locational marginal price (LMP, hereafter) and zonal market clearing price (ZMCP, hereafter).

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[8] Event that occurs when there is insufficient energy to meet the demands of all customers.

LMP can be expressed as a sum of generation marginal cost, transmission congestion cost and the cost of marginal losses, which can sometimes be ignored. Cost of marginal losses is usually area-dependent, and can be different for various nodes. Nodal prices are the ideal reference because the electricity value is function of place of generation and place of delivery. However, LMP usually comes with complexity of the pricing mechanisms, and could generate higher transaction costs.

In ZMCP concept, prices are the same within the zone, but they may vary depending of different zones and areas. The concept is mostly used in zones in which transmission congestion is expected to occur infrequently or has low cost of congestion management.

Locational pricing is widely used in meshed North American energy markets as a result of market's locational division caused by transmission lines. Zonal concept is more suitable for simpler electricity systems, such as in Australia. European market is very interesting because although it is quite complex, it is evolving into electricity market with zonal division, where zone is consisted of entire country [21] [26].

3.1.3. Market structure

In the energy market, the MCP is commonly known as the spot price. The spot electricity market is actually a day-ahead market in which the entities trade the energy for the next day, which differs from the actual definition of a spot market, characterized by immediate delivery and prolonged period of two days for financial settlement. Spot market is not suitable for energy market since transmission system operator (TSO, hereafter) requires advanced notice for energy distribution in order to ensure reliability of energy transmission. In short time periods before the delivery of energy, the TSO operates the balancing market in order to balance deviations in supply and demand contracts. The TSO needs to be able to call in extra production at very short notice, since the deviations needs to be corrected in short period measured in minutes or even seconds, in order to ensure energy delivery and to keep the system in balance. Spot and balancing markets are complimentary and although their functioning is quite different, they cannot function without each other. Balancing market is not the only technical market. In order to minimize reaction time in case of supply and demand deviation, TSO runs the assistant market which provides energy reserve and generating capacity market, which is used to temporarily invest in new generating capacity. Design and implementation of such a market requires a lot of work and knowledge due to its complexity and to responsibility to deliver energy to end-customers without disturbing the balance in the market.

3.2. Electricity loads and prices

In order to optimize and maintain balance on the day-ahead energy market, there is a strong need to determine and predict two essential values: *energy load* and *energy price*. Although there is a possibility for a manifestation of unpredicted load spikes whose effects can be minimized by using ancillary market mechanisms, price spikes are more common on the real day-ahead market. Another phenomenon frequently manifested on the market is seasonality and it is a result of pattern in energy consumption of end-users.

3.2.1. Price spikes

One of the features on the electricity markets are extreme changes in the spot prices known as jumps or spikes. In a short period of time, the price can increase temporarily and then drop back to the previous level. These temporary price escalations are responsible for a large part of the total price variation and the entities that are not prepared to manage the risk arising from price spikes can lose huge amount of money in a few hours. There is a measure that describes standard deviation of trading goods – volatility. As stated in [21], treasury bills have a volatility of less than 0.5%, stocks have a moderate volatility of about 1-15%, crude oil have volatility of 1.5-4%. Electricity has extreme volatility – up to 50%.

The spike intensity is non-homogeneous in time. The spikes are especially high during peak hours - around 09:00 and 18:00 on business days and during high-consumption period in areas with harsh weather conditions [27]. Figure 8 depicts an example of the price spikes manifestation at 6:00 and 18:00. It is not uncommon that prices can increase 10 times within few hours. As the time window increases and more data aggregates spikes manifestation is getting weaker.

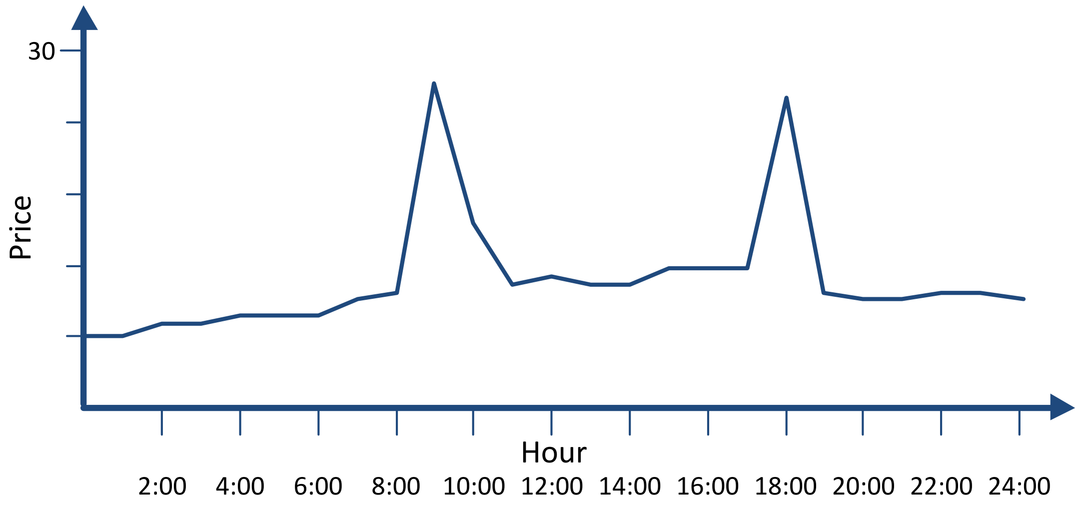

Figure 8: An example of the price spikes manifestation

Spikes on the energy market are the result of non-storability of electricity. Electricity cannot be substituted shortly after or before scheduled time of delivery. Currently there is no efficient technology for storing huge amounts of power, so it has to be consumed at the same time as it is produced. As a result, there are extreme load fluctuations caused by severe weather conditions often in combination with generation outages or transmission failures, which can lead to price spikes. The spikes are normally quite short-lived, and as soon as disturbance that caused the spikes is gone, prices fall back to a normal level. There are some markets where practically no spikes are present. The probable reason for absence of spikes is the low volume of energy traded on those markets. On the other hand, there are examples in the USA where the power companies had to file for bankruptcy because of the effects related to price spikes. Despite their rarity, price spikes are huge motive for designing mechanisms to protect from oscillations in energy prices.

3.2.2. Seasonality

Seasonality is a component of a time series which is defined as the repetitive and predictable movement around the trend line in definite time period. It is known that energy demand on the market exhibits seasonal fluctuations, which are usually, result of changing climate conditions, like temperature and number of climate hours. In some countries, there are also seasonal variations manifested in supply-side. Hydro units, for example, are heavily dependent on precipitation and snow melting, which varies from season to season. These seasonal fluctuations in demand and supply translate into seasonal behavior of electricity prices and spot prices in particular [28]. There are few levels of granulation when it comes to term of seasonality:

- Annual seasonality – it is mostly manifested because of change of seasons. It can be approximated by sinusoidal function – high prices in winter time and low prices during summer;
- Weekly seasonality – it is related to the business day – weekend structure. In the weekdays prices are higher than those during the weekends, when major businesses are closed.
- Daily seasonality – fluctuations that happen every day. Higher than average prices are observed during the morning and evening peaks, while midday and night prices tend to be lower than average. This corresponds to the time of day when people normally get up and go to work, and when they come home from work.

Different types of end-users were analyzed in [29]. Users were modeled as a part of PowerTAC[9] simulation, and as it is depicted in Figure 9, there has been an occurrence of weekly and daily seasonality. Top chart represents daily-seasonality in the energy usage of simple household. Bottom chart represents weekly-seasonality manifested in the energy usage of an office complex. Time axis depicted in the charts is measured in TAC hours – duration of one hour inside the PowerTAC simulation.

[9] Power TAC is an agent-based competitive simulation of future retail electric power markets.

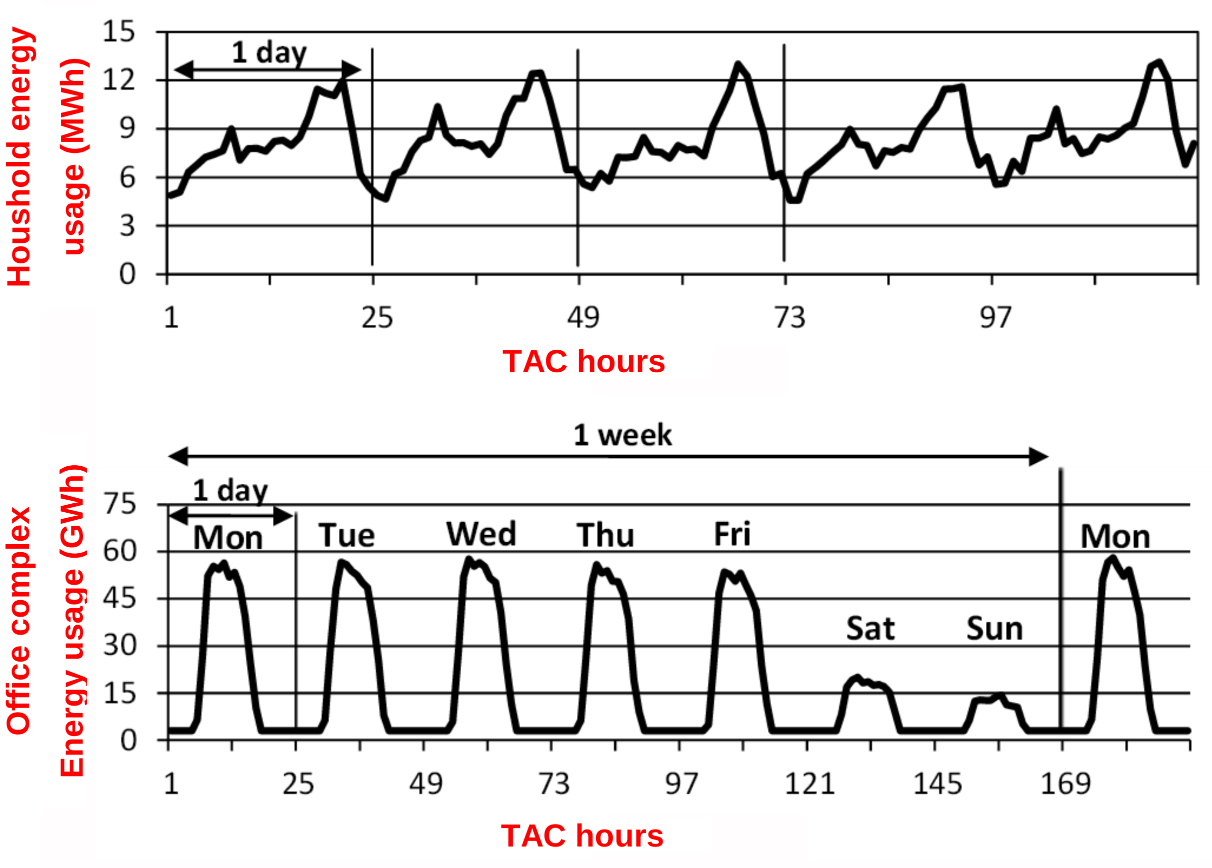

Figure 9: An example of daily (top chart) and weekly seasonality (bottom chart)

3.3. Modeling and forecasting electricity loads

In an evolved and competitive energy market the electricity is traded at market prices[10]. As a consequence, there is increased amount of risk borne by power producers, electric utilities and marketers. Management of a successful company on today's modern deregulated market requires a big amount of statistical analysis and educated guesswork. Energy demand may differ from expected amount stated in the contract and the actual volume available for trade may not be enough to cover produced costs. A deregulation of the market and introduction of competition has made forecasting a necessity for all market players. On today's deregulated market, over-contracting or under-contracting energy must be balanced on the balancing marker, which can lead to serious financial loss. As a result, load forecasting has become the central process in the planning and

[10] Market price is the economic price for which a good or service is offered in the marketplace.

operation of electric utilities, energy suppliers, system operators and other market participants. The basic quantity of interest is typically the hourly load demanded by end-customers. However, load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load and peak system load. The forecasts for different time horizons are important for different operations within a company. Error of the forecast depends on the time horizons and it is possible to predict energy load for the next day with error minimized down to few percent. Typically load forecasting is classified in terms of the time horizon’s duration, as *short-term* (STLF, hereafter), *medium-term* (MTLF, hereafter) and *long-term* load forecasting (LTLF, hereafter). STLF forecasting methods are used in operational phase of energy market in order to minimize energy imbalance. On the other hand, MTLF and LTLF forecasting methods are required for maintenance scheduling, fuel planning and planning of generation and transmission expansion.

Short-term load forecasting has become increasingly important since the rise of competitive energy markets. With fluctuations of supply and demand, there is a possibility of manifestation of price spikes which leads to huge financial loss. STLF can help to estimate energy demand in order to reduce effect of price spikes and to make decisions that can prevent energy overload. Hence, hourly and daily forecasts, which can be classified as STLF, are primary interest in everyday energy market operation. A large variety of methods and ideas have been tried for load forecasting, with varying degrees of success. They may be classified into two broad categories:

- *Statistical approach*; and
- *Artificial intelligence-based techniques*.

The statistical methods forecast the current load value by combining previous load information and previous or current values of exogenous factors, typically weather information and social variables. On the other hand, artificial intelligence-based methods are more flexible and can handle more complex situations on the market. Among these methods, neural networks have probably received the most attention. The employed algorithms automatically classify the input data and associate it with the respective output values, so there is no human supervision needed. This simplicity is at the same time their limitation.

The most suitable method for a particular company can be chosen only by testing various methods on real data. As in some cases there are no particular winners, many companies use several load forecasting methods combined or, often in cooperation with academics, create hybrid solutions that will suit to their particular needs.

3.3.1. Similar-day method

This simple approach is based on searching historical data for days with similar characteristics to the forecasted day. Similar characteristics may include day of the week, day of the year or even exogenous conditions, like weather information. The similar-day method can be also used for modeling energy load for some holiday. In that case, a search is conducted on the historical data in range on few years. The load of a similar day is considered as a forecast. Instead of a single similar-day load, the forecast can be a linear combination or a result of regression[11] that can combine several similar-days. The simplest, yet in some cases surprisingly powerful implementation of the similar-day method can be as follows: a Monday is similar to last Monday, and the same rule applies for Saturdays and Sundays; analogously, a Tuesday is similar to the previous Monday, and the same rule applies for Wednesdays, Thursdays and Fridays. This method can be used as a benchmark for more sophisticated models.

3.3.2. Exponential smoothing

Exponential smoothing is one of the statistic methods used to forecast energy load on the market. Using this method, prediction is constructed from an exponentially weighted average of past observations. The accuracy of exponential smoothing has led to its widespread use in a variety of applications. The idea is to aggregate historic data and to assign a weight to every value in order to achieve that the newer data have greater impact on predicting future values [30]. Simple exponential smoothing is based on weighting, where exponentially smaller weights are assigned to older observations:

---

[11] A statistical technique for estimating the relationships among the variables.

$$l_t = \alpha l_t + (1 - \alpha) l_{t-1} \tag{3.1}$$

When applied recursively to each successive value in the series, each new smoothed value is computed as the weighted average of the current value and the previous smoothed value. In effect, each smoothed value is the weighted average of the previous values, where the weights decrease exponentially depending on the value of parameter $\alpha \in (0,1)$.

Since energy load tends to show seasonal characteristic, there have been introduced more advanced exponential smoothing methods in order to provide more accurate forecast. As far as electricity load forecasting is concerned the implementation of following Holt-Winter's method has showed notable results [29] [31] [32]:

$$l_t = \alpha \frac{x_t}{S_{t-p}} + (1 - \propto)(l_{t-1} + T_{t-1}) \tag{3.2}$$

$$T_t = \beta \frac{l_t}{l_{t-1}} + (1 - \beta) T_{t-1} \tag{3.3}$$

$$S_t = \gamma \frac{x_t}{l_{t-1}} + (1 - \gamma) S_{t-p} \tag{3.4}$$

$$F_{t+h} = (l_t + hT_t) S_{t-p+h} \tag{3.5}$$

where listed variables are:

- F – forecasted value;
- h – time horizon;
- l – level of time series;
- T – trend of time series;
- S – seasonal adjustment;
- p – period of seasonal component; and
- α, β, γ – constants which must be chosen for the smallest sum of the squared forecast errors one of the following methods: MSE (*mean squared error*), NRMSE (*normalized root mean squared error*), MPE (*mean percentage error*) and MAPE (*mean absolute percentage error*).

Proposed Holt-Winter's method was tested in PowerTAC simulation, as described in [29]. Implementation showed notable results when tested on end-consumers with seasonal energy consumption.

3.3.3. Regression methods

Regression is one of the most widely used statistical techniques [31]. The general purpose of multiple regression is to learn more about the relationship between several independent variables and a dependent variable. Multiple regression is based on method of least squares. The model is fit in a way that the sum of squares of differences between observed and predicted values is minimal. For energy load forecasting regression methods are usually used to model the relationship of load and other factors such as weather, day type and customer type. The model expresses the load as a linear function of one or more explanatory variables and an error term:

$$L_t = a_0 + a_1 L_t^1 + \cdots + a_k L_t^k + \varepsilon_t \tag{3.6}$$

where L_t is the load, L_t^k describe independent variables correlated with load, a_k describes regression coefficients, and ε_t is noise. Independent variables can be simple, as weather conditions, but they can also be described as complex functions of simple variables.

In its classical form, multiple regression assumes that the relationship between variables is linear, but sometimes in the real-life implementation there are possible some deviations from the basic assumption [33]. Despite the large number of alternatives the linear regression models are still among the most popular load-forecasting approaches.

3.3.4. Autoregressive moving average model (ARMA)

Autoregressive moving average model is often used to predict energy load on the market. It is based on the moving average (MA, hereafter) model in which the time series is regarded as an unevenly weighted moving average of a random shock series[12] ε_t . The moving average model of order q is defined by:

$$L_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3.7}$$

MA models are not very useful in forecasting applications, but it its autoregressive form, it is a very powerful tool. In the ARMA model the current value of the time series L_t is expressed linearly in terms of its past values and in terms of previous values of the noise [34]. The autoregressive moving average model of order (p, q) can be written as:

$$L_t - \sum_{i=1}^{p} \omega_i L_{t-1} = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3.8}$$

Autoregressive moving average models have been extensively applied to energy load forecasting. There are also two modifications of this model: *autoregressive moving integrated average model* and *seasonal autoregressive moving integrated average model* and both of them are successfully implemented on various energy markets. Second one is used to forecast values on the set of date with expressed seasonality.

3.3.5. Reinforcement learning

Reinforcement learning is a type of a learning concerned with how an *agent* should take actions in an environment, in order to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead, the learner must discover which actions result with the highest reward [38]. In some cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards.

Reinforcement learning is different from supervised learning and artificial neural networks, which can be classified as a form of unsupervised learning. Supervised learning is learning from examples provided by an external supervisor.

[12] Random shock is noise that does not follow a predictable pattern.

Although this learning has many qualities, it is not adequate for learning from interaction. In interactive problems (i.e. wholesale trading in energy market simulation) it is often impractical to choose examples of desired behavior that are both correct for some scenario. Reinforcement learning enables agent to learn from its own experience and to determine which decision is the best in some particular situation.

Wholesale market also acts like environment in which all decisions are correct, but only some of them can yield maximum profit. Hence, entities competing in the wholesale market are able to use reinforcement learning to improve their bidding strategies. Paper by Weidlich and Veit [39] describes several adaptations of reinforcement learning methods suitable for the wholesale market:

- *Q-Learning*;
- *Learning Classifier Systems*;
- *Supply function optimizing agents*; and
- *Erev-Roth method*.

Weidlich and Veit describe in their paper detailed implementation and usage of Erev-Roth method, which can be defined as following:

$$Q_{t+1}(a) = \begin{cases} (1-\alpha)Q_t(a) + (1-\epsilon)R(r), & if\ action\ was\ chosen \\ (1-\alpha)Q_t(a) + \dfrac{\epsilon}{M-1}R(r), & else \end{cases} \tag{3.9}$$

$$\pi_{t+1}(a) = \frac{e^{Q_{t+1}(a)/\tau}}{\sum_{b=1}^{n} e^{Q_{t+1}(b)/\tau}} \tag{3.10}$$

where Q_{t+1} is calculated action value, M is number of actions, π_{t+1} is probability of choosing specific action and α, ϵ and τ are coefficients which need to be determined empirically. There are many variations and implementations of a base Erev-Roth method and one of them is explained in detail in chapter 6.2.2.3.

3.4. Modeling and forecasting electricity prices

With energy market deregulation and introduction of competition, new challenges have emerged on the market. One of them is caused by extreme price volatility and it has forced market players to cope with unstable price movements, along with energy load variations. Price forecasting has become a fundamental tool in creating a strategy development for trading on the energy market. This was a reason to increase number of researches in electricity price modeling and forecasting. The proposed solutions are classified based on the time horizon's duration. It is customary to talk about short-term (STPF, hereafter), medium-term (MTPF, hereafter) and long-term price forecasting (LTPF, hereafter).

The main objective of LTPF is planning of investment, such as determining the future sites or sources of fuel for power plants. MTPF or monthly time horizons are generally preferred for balance sheet calculations and risk management. It is mostly used to evaluate distribution of future prices over some longer period. But, when bidding on auction-type energy market, participants need to forecast spot price, because their orders will clear only if they are below/above MCP, depending whether it is ask or bid. Since the day-ahead market typically consists of 24 hourly auctions that take place simultaneously one day in advance, STPF with time horizons from a few hours to a few days is of great importance in daily market operations.

As far as the modeling and forecasting techniques are concerned, generally they can be traced back to models that originate either in electrical engineering or in general market models. On today energy market, price modeling and forecasting have an essential role and they have also been at the center of intense studies in other markets, including financial. Depending on the objectives of the analysis, a number of methods for modeling price dynamics have been proposed, ranging from stochastic models to game theoretic approaches. Some of the methods will be described in the next chapters.

3.4.1. Spike preprocessing

One of the big problems in price prediction on the energy market can be connected to anomalies in price trends, manifested through price spikes. Leaving spikes untreated in the data will later result in more anomalies in forecasted data. There are some solutions to eliminate spikes inside the dataset:

- First solution is to substitute price spike with the average of the neighbor values, or with the similar-day prices. But total removal of price spikes can result in getting the wrong price trend as forecast output.
- Better solution would be not to remove spikes completely, but to limit their severity by using threshold filter. After executing chosen treatment of the price spikes, dataset is ready for executing price forecast.

3.4.2. Quality assessment of a price forecast

There is a need to assess the quality of price forecasting, in order to achieve better results on the market. The most widely used measures of forecasting accuracy are those based on absolute errors, i.e; absolute values of difference between actual value (P_h) and predicted value ($\widehat{P_h}$) for a given hour [21]. One of the most popular measures for quality assessment of the forecasting is Mean Absolute Error (MAE, hereafter), defined as:

$$MAE_{daily} = \frac{1}{24}\sum_{h=1}^{24}\left|P_h - \widehat{P_h}\right| \tag{3.11}$$

In some cases when two distinct data sets are compared, better performance is shown by using one of the methods for determining relative percentage error. One of them is Mean absolute percentage error (MAPE, hereafter). For hourly prices the daily MAPE is defined as:

$$MAPE_{daily} = \frac{1}{24}\sum_{h=1}^{24}\frac{\left|P_h - \widehat{P_h}\right|}{P_h} \tag{3.12}$$

The MAPE measure works well in load forecasting, since actual load values are rather large, but when applied to electricity prices, MAPE values could be misleading. In particular, when electricity prices drop to zero, MAPE values become very large regardless of the actual absolute differences $|P_h - \widehat{P_h}|$. There is a way to adapt this method for using in price forecasting - absolute error $|P_h - \widehat{P_h}|$ needs to be normalized by the average price of that day. The modified measure, also known as the Mean daily error (MDE), is given by:

$$MAPE_{daily} = \frac{1}{24}\sum_{h=1}^{24}\frac{\left|P_h - \widehat{P_h}\right|}{\bar{P}_{24}} = \frac{1}{\bar{P}_{24}} MAE_{daily} \quad (3.13)$$

One of the measures mostly used in prediction evaluation and data training for some learning methods is Root-mean-square deviation (RMSE). It is defined as:

$$RMSE_{daily} = \sqrt{\frac{\sum_{h=1}^{24}(P_{h,t} - \widehat{P_{h,t}})^2}{24}} \quad (3.14)$$

The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power and it measures accuracy for continuous variables. The MAE and the RMSE can be used together to measure the variation in the errors forecasted set.

In general, MDE compared to other measures puts more weight to errors in the high-price range, so it is more suitable to use to evaluate price forecasting on the energy market.

3.4.3. Time series models with exogenous variables

As explained in chapter 3.3.4, variations of the autoregressive moving average model are widely used on a day-ahead market for both price and load prediction. One of them – ARIMA, has shown notable performances especially in spot price forecast [35]. ARIMA-type models relate the studied signal to its own past, and additionally, they correlate the signal with influence of various exogenous factors, like weather conditions, load profiles, etc. In order to accurately capture the relationship between price and load or weather conditions, time series models with exogenous or input variables can be used. Proposed models can usually be viewed as a generalization of existing autoregressive models. The autoregressive moving average model with exogenous variables – ARMAX$(p, q, r_1, \ldots, r_k)$ can be defined as:

$$\varphi(B)P_t = \vartheta(B)\varepsilon_t + \sum_{i=1}^{k} \psi^i(B)v_t^i \tag{3.15}$$

where set of r_k's models multiple exogenous variables, and $\psi^i(B)v_t^i$ is a shorthand notation with ψ^i being the corresponding coefficients of exogenous variables. In order to adapt to specific conditions on the market, different transformations can be applied to mimic characteristics of ARIMAX and seasonal ARIMAX models.

3.4.4. Interval forecasts

There are some forecast models which can predict price intervals on the market [35]. Such forecasts may be especially relevant for risk management purposes where companies are more interested in predicting intervals for future price movements than simply estimates for the exact time point. However, while there is a variety of studies on evaluating point forecasts in electricity markets, forecasting of price intervals is not so evolved. In their paper, Misioerk et al. [35] described a model for interval forecasting of electricity prices. For every processed time series intervals are calculated by taking the quintiles of a standard normal random variable rescaled by the standard deviation of the residuals in the calibration period. Afterwards, the quality of the interval forecasts is evaluated by comparing the nominal coverage of the models to the true coverage. Alternative solution consists of computing the quintiles of the empirical distribution of the one-step-ahead prediction errors. The drawback of this approach is that it needs more data for initialization. This approach can be used not only in combination with time series models, but also with any forecasting techniques (including AI-based methods).

4. Power Trading Agent Competition

Power trading agent competition (PowerTAC, hereafter) was first introduced in 2011 and it was developed by John Collins, Wolfgang Ketter, Prashant P. Reddy i Christoph M. Flath [36]. PowerTAC represents a model of modern energy market on which multiple brokers compete in order to make profit to their owners, usually energy companies. Brokers are represented by intelligent software agents, and their main role is to buy energy on the wholesale market in order to satisfy energy demand on the retail market. Another important part of PowerTAC is the model of distribution utility, whose general role is to maintain the global balance of supply and demand on the market.

Trades on the wholesale market are executed thorough contracts with energy producers, other brokers and distribution utility. On the other hand, one of the biggest factors on the retail market is customer share, which can be increased by publishing multiple tariffs suitable for various end-customers. Tariffs can vary depending on sign-up bonuses, periodic payments, and fixed or variable payments proposed in tariff specification. Fixed tariffs are specified for certain part of the day, and variable tariffs target smart-appliances which can be controlled by signals sent through the power grid.

In competitive environment modeled by PowerTAC game every broker needs to adapt to variable conditions on the market either by forecasting future energy price and demand, or some other strategy. By forecasting conditions on the market, brokers can buy energy on the wholesale market for lower price and then sell it to their end-customers on the retail market, which results in making profit. Forecasted values are sometimes crucial to avoid creating imbalance of energy supply and demand, which in usually results in penalties that broker must pay to distribution utility. During the game brokers maintain their portfolios in which contains information like executed contracts, published tariffs, number and type of end-customers, etc. By maintaining portfolio broker is able to review information on executed trades and customer usage, which can be crucial in forecasting some of the key values on the market, like energy price and energy demand.

In PowerTAC simulation time proceeds in “time slots”, each one representing one hour in simulation time. In the real-time, duration of one TAC-hour is five seconds. Average duration of one simulation is 60 TAC-day, which is approximately 2 hours in real-time. During the simulation broker has an account in central bank and every TAC-hour he gets information regarding his account’s balance. At the beginning of each timeslot broker also receives information regarding his current market position and his published tariffs. Weather forecast and current weather conditions are broadcasted to the all brokers in each timeslot and they represent valuable factors in process of forecasting energy load and price, energy usage and production of some end-customers is closely related to current weather conditions. Broker’s interactions in the PowerTAC simulation are depicted in Figure 10.

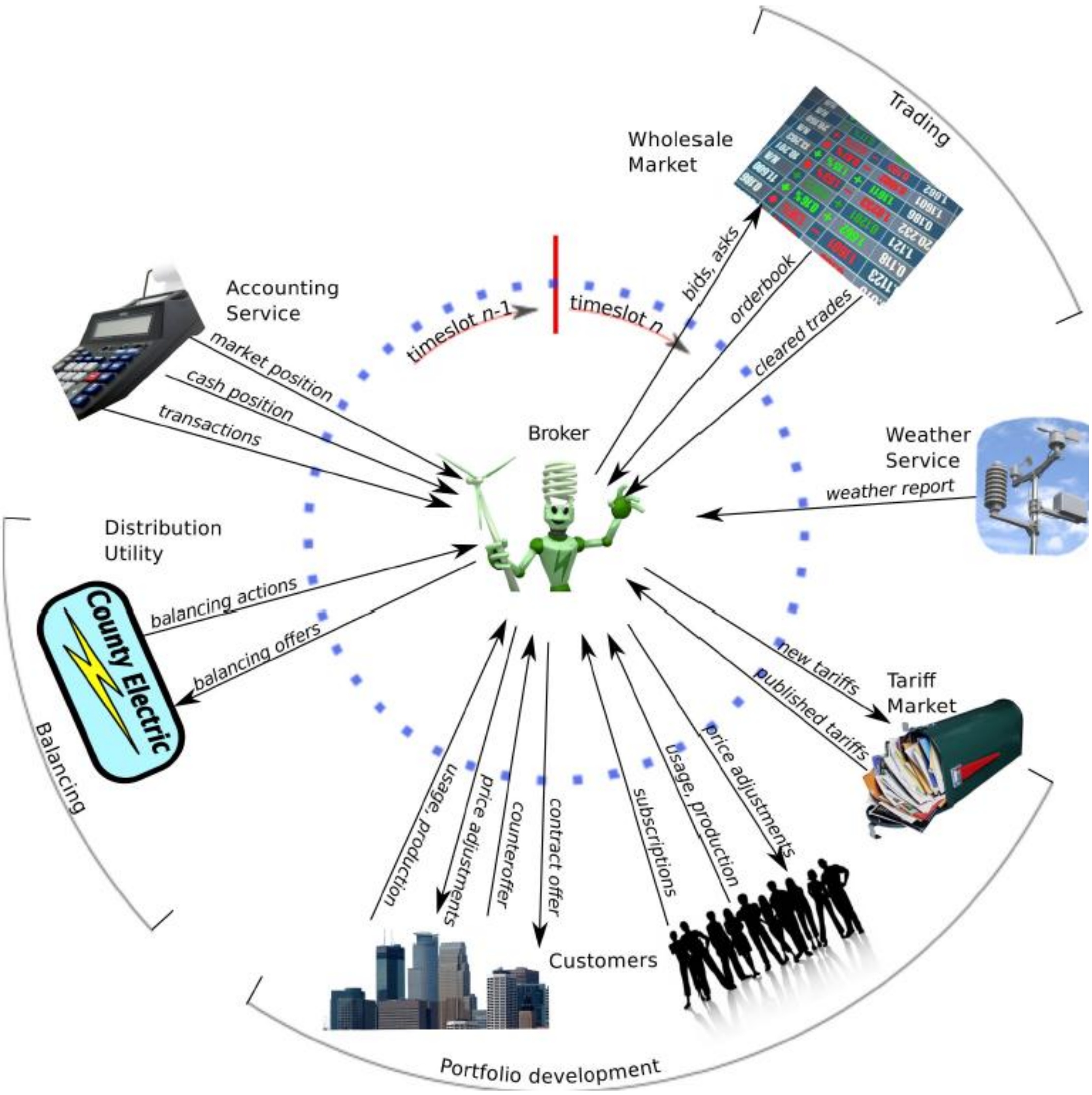

Figure 10: Broker’s interaction in PowerTAC simulation [36]

4.1. Retail market

Main interaction with end-customers takes place in the retail market, where broker publish their tariffs in order to increase their customer share. Brokers need to develop a set of tariffs suitable for various types of customers, and carefully plan the payment for delivered energy, in order to make profit. Tariffs are published every 6 TAC-hours, and they need to contain all the necessary information that describe the conditions offered by tariff. Tariff specification must contain:

- Specific time intervals in which tariff is defined. It determines tariff's duration;
- Amount of consumed or produced energy included in tariff. Some tariffs can also declare amount of energy that can be revoked by sending interrupt signals to smart-appliances;
- Payment details for the energy specified in the tariff specification. Payment can be defined in relation to time units, or to energy units; and
- Communication channels used to publish tariff revocation or change in tariff specification.

4.2. Distribution utility

One of the integrated parts of PowerTAC simulation is distribution utility. In general, its role is to maintain balance of energy demand and supply on the market, and to provide competitive environment. Distribution utility operates on three different levels:

- It distributes power through the transmission grid to the customers and brokers must pay distribution fees for the use of the distribution grid;
- It operates the balancing market in order to maintain balance between demand and supply on the market; and
- It offers default tariffs for energy consumption and production, and in that way it creates a limit for broker's profitability.

4.3. Wholesale market

The wholesale market in Power TAC represents energy exchange where brokers can trade energy with large producers and other brokers in order to satisfy energy demand on the retail market. Wholesale market operates as a periodic double auction and represents a traditional energy exchange like NordPool, FERC[13], or EEX6[14] [36]. Since the wholesale market is modeled by following principles of day-ahead market, brokers can buy and sell energy for the future 24 hour (in PowerTAC represented as timeslots) and optimize their portfolios. Broker participates in the trade by placing the bid for one of the next 24 timeslots. Every bid must contain:

- Broker's name;
- Timeslot for which the order is placed;
- Amount of energy in MWh; and
- Price for energy unit (€/MWh).

Orders placed for timeslot which are already disabled are being discarded. When the simulation clock is advanced to a new time slot, the wholesale market clears the orders for each of the enabled time slots. Orders with positive amount of energy are considered as bids, and those with negative amount of energy are considered as asks. Clearing process begins with sorting the orders – highest to lowest price for bid orders, and lowest to highest price for ask orders. After that begins the construction of demand and supply curves from orders placed for enabled timeslots. Clearing price is determined on the crossing of supply and demand curves. If curves do not cross then the clearing price is set at the mean of the lowest bid and the highest ask price. Bids are executed if specified price is higher than the last cleared bid. Following the same principle, asks are executed if specified price is below the last cleared ask. Figure 11 depicts an example of clearing process on the wholesale market.

[13] http://www.ferc.gov

[14] http://www.eex.com/en

All orders are sorted in two groups: *bids* and *ask*. Bids are sorted by decreasing price and asks are sorted by increasing price. Orders without specified price (bid 1 and ask 1) are called *market orders*, and they are placed in the first place of the sorted series. In the clearing process described in Figure 11 bids 1-8 are matched by lower-priced asks, as well as asks 1-6 are matched with higher-priced bids. Bid 8 and ask 6 represent the clearing limit. Hence, orders represented by bids 8-10 and ask 7 cannot be executed. Cleared amount is 27 MWh and the cleared price is 16, calculated as a mean value of prices on the clearing limit (16 and 18).

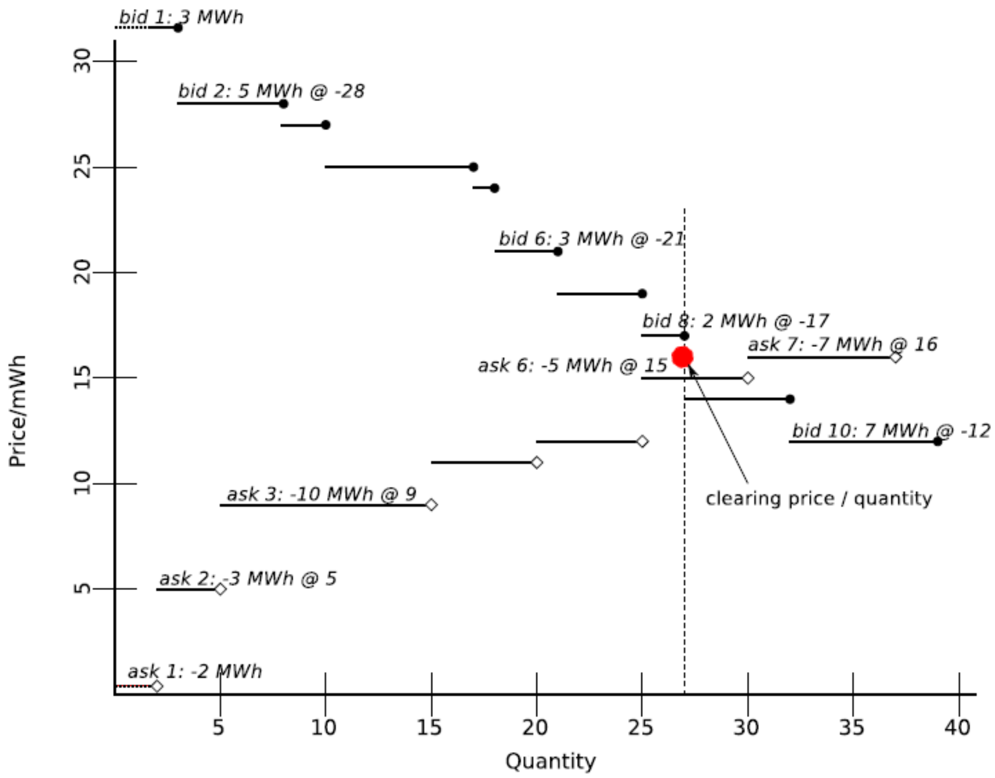

Figure 11: Example of wholesale market clearing process

After the clearing process is finished, following actions are executed:

- Broadcasting of cleared price and total amount of cleared energy to all brokers;
- Publishing of not cleared orders;
- Publishing of broker-specific information regarding cleared trades;
- Publishing broker-specific information regarding broker’s current market position and cash balance; and
- Order list clearing.

5. Intelligent trading agent for power trading through wholesale market - CrocodileAgent 2013

CrocodileAgent 2013 is an intelligent agent developed in University in Zagreb in order to participate in PowerTAC 2013 competition. Last year, University in Zagreb participated in PowerTAC 2012 competition with CrocodileAgent 2012 which was the base for this year's improvements. CrocodileAgent 2013 has modular architecture, depicted in Figure 12, which enables him to successfully participate in retail, wholesale and balancing markets, which are integrated parts of energy market modeled in PowerTAC simulation.

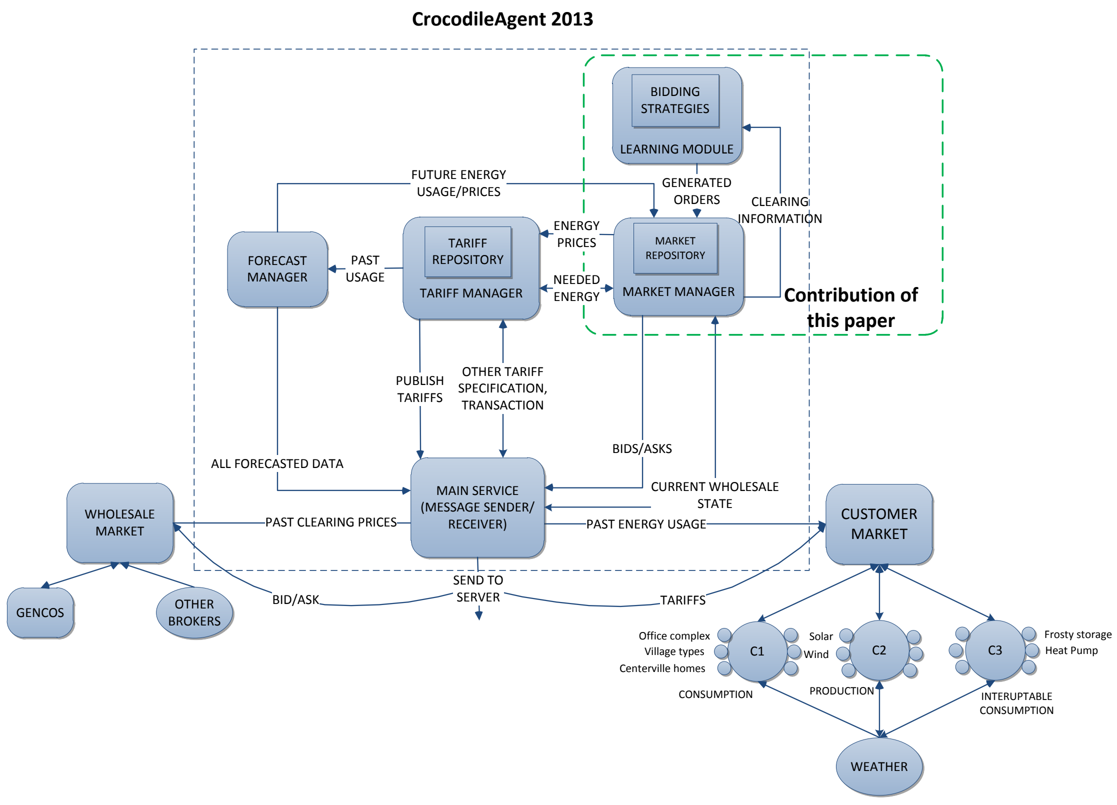

Figure 12: Modular architecture of CrocodileAgent2013

There are significant improvements in comparison to last year's agent. One of them is learning module, which enables broker to adapt to current conditions on the market, and to be more reactive while trading on the wholesale market. This master thesis will cover implementation of smart bidding strategies on the wholesale market, with ultimate goal to increase broker's profit.

CrocodileAgent's activity on the customer market is described in [37]. In his master thesis, Matetic describes broker's reactivity on the customer market and the principle of the tariff design. CrocodileAgent also tracks the number of subscribers on the customer market, in order to enable prediction energy amount that needs to be bought on the wholesale market.

5.1. Competing in PowerTAC competition

Broker's actions in PowerTAC simulation can be simply described with following:

- Attract customers with publishing suitable tariffs;
- Predict energy usage on customer market;
- Buy needed amount of energy on the wholesale market; and
- Minimize imbalance of energy supply and demand in order to avoid negative effects on the balancing market.

Since the PowerTAC wholesale market is modeled as a day-ahead market, energy can be traded for the next 24 hours. Thus, energy load and price prediction can be crucial in developing broker's strategy. Broker's total profit in the simulation is generally calculated as sum of total revenues on wholesale, customer, and balancing market, minus distribution costs. Balancing transactions can have huge impact on the broker's revenue – broker must deliver energy to the end-customer, so in case of energy shortage, distribution utility balances energy shortage, which will result in broker's profit loss on the balancing market. Also, in case of energy surplus balancing mechanisms are executed and energy is sold for much lower price than in the wholesale market.

Figure 13 depicts negative effect of imbalance on the market. It is expressed through balancing cost that needs to be paid on the balancing market in order to compensate for energy shortage.

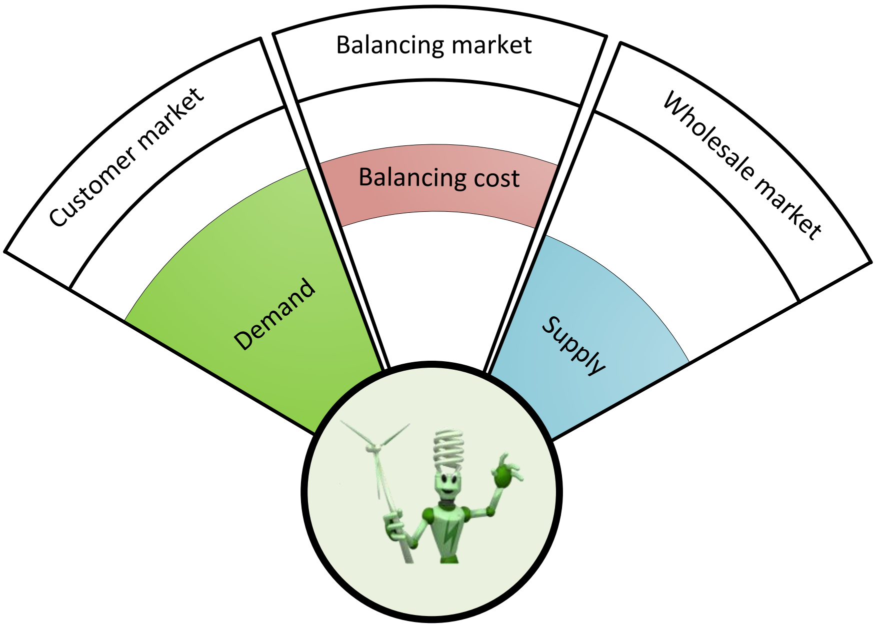

Figure 13: Negative effect of imbalance on the market

Although CrocodileAgent 2012 has achieved some notable results in last year's competition [29], it is noticed that there was a negative impact on broker's revenue produced by balancing market. It was a motivation for implementation of smart bidding strategies on the wholesale market in order to increase broker's robustness[15] and to provide adequate support to trading on the customer market. Some of the features from CrocodileAgent 2013 were tested in PowerTAC trial competitions[16] and results achieved in those games will be evaluated later.

5.2. Design of CrocodileAgent 2013

As depicted in Figure 12, CrocodileAgent has a quite modular architecture, in order to easily generate separated strategies for wholesale and customer market. Agent is implemented in Java[17] programming language and using Spring[18] framework. Spring framework is used in order to enable broker to communicate with PowerTAC game simulator, and to enable communication between broker's

---

[15] The ability to resist change without adapting its initial stable configuration.

[16] Warm-up competitions held to test some new functionalities in brokers publised by participants.

[17] http://www.java.com/en/

[18] http://www.springsource.org/

modules. CrocodileAgent is implemented on top of agentware[19] provided by Power TAC organizers in form of the Maven[20] project called sample-broker project.

CrocodileAgent's modular architecture is represented by several Java classes with `@Service` annotation which originates from Spring framework. On start of broker's lifecycle Spring framework scans entire project, and creates bean of every class with `@Service` annotation, providing one instance of those classes in broker's lifecycle. Those instances are called singletons, and enables memory persistence and easy communication between modules in broker's lifecycle. Most of the services in brokers' architecture implements interfaces that provide method for receiving custom messages from simulator. There are three main services which enable broker's interaction on customer and wholesale market:

- `MarketManagerService` – represents *market manager* module responsible for trading on the wholesale market. It enables broker to generate orders for wholesale market, and to track various information regarding trading on the wholesale market. It implements several methods which enable broker to exchange messages with simulator:
    - `activate(timeslotIndex)` – incoming message, marks the beginning of timeslot and signals broker to prepare order for enabled timeslots; and
    - `handleMessage(template)` – incoming message, enables broker to receive cleared trade, balancing transaction, distribution transaction, market position , weather report and orderbook information.
- `TariffManagerService` – represents *tariff manager* module responsible for trading on the customer market. This module enables broker reactive response triggered by multiple events on the customer market. Complex implementation of tariff module is thoroughly described in [37].
- `PortfolioManagerService` – *portfolio manager* module which enables exchange of common information between `MarketManagerService` and

[19] Template software used by broker developers as a starting point in broker development process.

[20] http://maven.apache.org/

`TarifManagerService`. It implements several methods which enable broker to communicate with simulator. It also implements tracking of subscribers on the customer market, which serves as a useful source for forecasting future energy load.

Market manager module communicates with *learning module* which enables broker to adapt his basic strategy to specific conditions in day-ahead wholesale market. Implementation of order generation and learning module is explained in the next chapters.

5.2.1. Basic order generation

Market manager module in CrocodileAgent's implementation represents module responsible for bidding on the wholesale market. In the beginning of each timeslot broker needs to prepare orders for enabled timeslots. First step is to retrieve amount of needed energy from portfolio manager, which is calculated based on customers' information sent by tariff manager.

Next step is preprocessing of needed amount in which amount of already cleared energy needs to be subtracted from retrieved amount. In order to minimize negative effects on the balancing market, broker always tries to buy slightly larger amount than retrieved from portfolio manager, leaving that extra amount to be processed by learning module.

After preprocessing of needed amount market manager calculates basic unit price. Basic unit price calculation is a function of remaining timeslots in which broker is able to place order for target timeslot. In last step, broker sends needed amount of energy and calculated unit price to learning module, which returns final order after choosing the appropriate strategy. Order that is returned from learning module is ready to be sent to simulator. Process that describes generation of basic order is show in Figure 14.

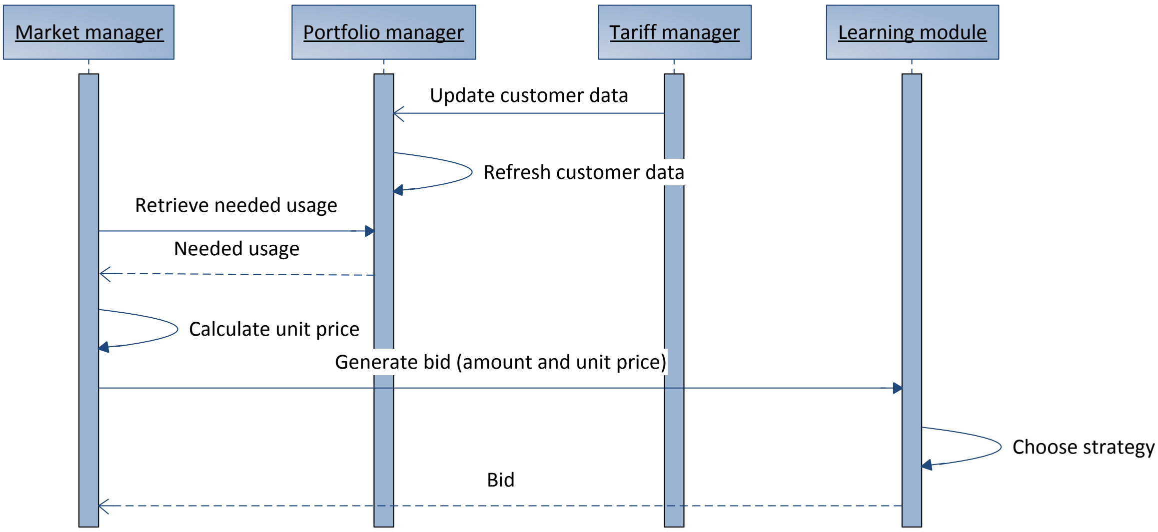

Figure 14: Sequence diagram of order generation

5.2.2. Learning module

One of the key features in wholesale module implementation is learning module. It is designed to enable broker to adapt to various conditions on the market. Main functionalities of the learning module can be expressed through optimization of basic wholesale bidding in a way which will minimize negative effects of the balancing market. Architecture of the learning module along with its interaction with market manager module is depicted in Figure 15.

Implementation of the learning module is based on Erev-Roth method adapted to match mechanisms on the PowerTAC wholesale market. There are three integrated parts of the module:

- **Bidding strategies**: set of 5 strategies used to modify basic order from market manager. Strategies are designed to balance energy demand and response on the wholesale market and they enable broker to adapt to different conditions on day-ahead market.
- **Reward module**: module designed to evaluate each strategy based on its efficiency on the wholesale market. It uses market transactions information as input, provided by PowerTAC simulator in the end of each timeslot. It also calculates value of each strategy which is used to choose appropriate strategy.

- **Weighted randomizer**: module designed to choose bidding strategy based on action value. Choosing function is designed as a simple random function used in many statistical methods, but it is impacted by probability for choosing each strategy. Module is invoked in the beginning of each timeslot in order to choose appropriate strategy for modeling of basic order.

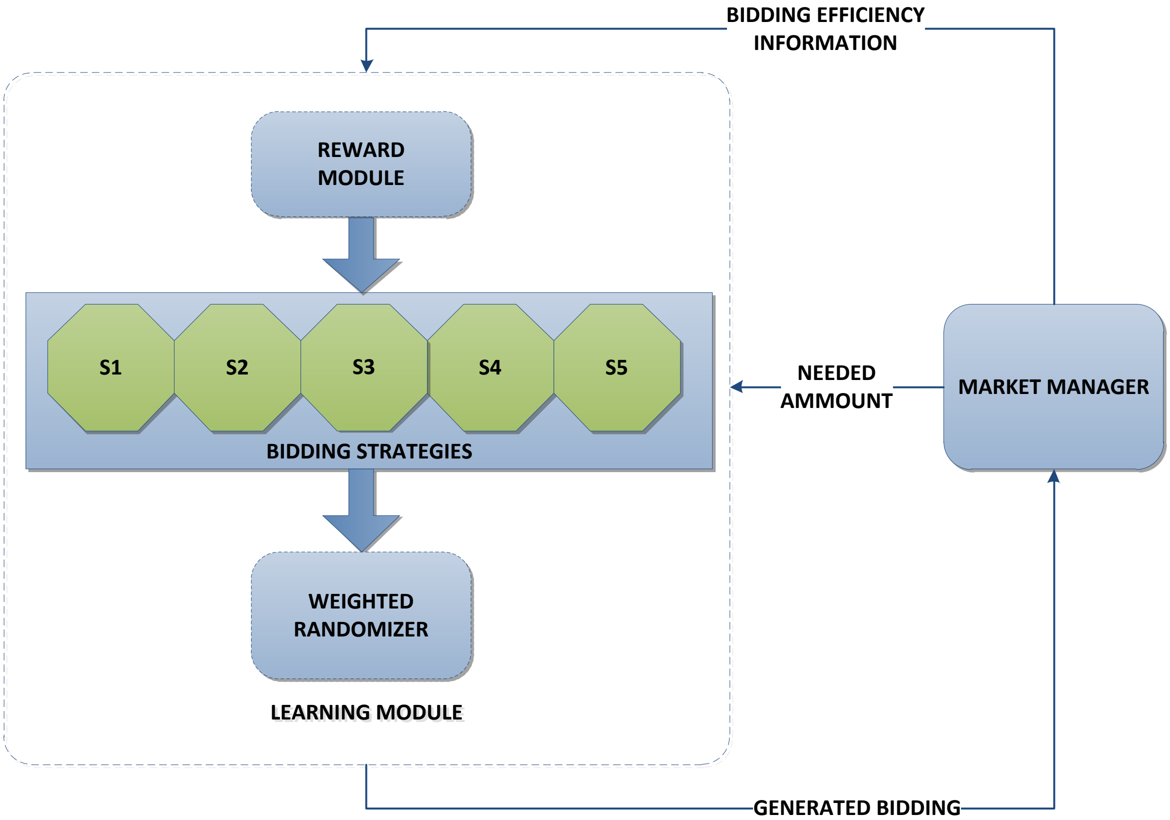

Figure 15: Architecture of the learning module

5.2.2.1 Strategies

In order to optimize bidding on the wholesale market, CrocodileAgent has several strategies suitable for various conditions on the market. CrocodileAgent's general strategy on the wholesale market is based on buying an amount of energy needed to satisfy demand on the retail market. Market manager sends to the learning module a needed amount and unit price specified in basic order. Those values are used as an input values for strategy modeling inside the learning module. Role of each strategy is to simply adjust inputted amount of energy and unit price based on rules implemented inside the strategy. Strategies inside the learning module are designed are described in Table 2.

Strategy number	Buy	Sell
1	amount = input amount * 1.2 price = input price	amount = input amount * 0.1 price = input price * 0.9
2	amount = input amount * 1.1 price = input price	amount = input amount * 0.2 price = input price
3	amount = input amount * 1.2 price = input price	amount = input amount * 0.3 price = input price
4	amount = input amount * 0.9 price = input price * 0.9	amount = input amount * 0.2 price = input price
5	amount = input amount * 1.2 price = input price * 0.9	amount = input amount * 0.2 price = input price * 1.1

Table 2: Strategies inside CrocodileAgent's learning module

Each strategy is designed to slightly adjust input energy amount and input unit price. Multiplying coefficients for each strategy are determined empirically. Since CrocodileAgent 2013 is trying to avoid negative energy imbalance, in case of selling energy, coefficients are set to prohibit selling amount of energy larger than 30% of input amount. On the other hand, in case of buying energy, coefficients are set to enable slightly over-buying or under-buying of energy.

Initial strategy design is quite simple in order to enable easy validation of learning module. There is also a possibility to implement smart strategies using neural networks and autoregressive models.

5.2.2.2 Adaptation of Erev-Roth method

Wholesale energy markets are perfect candidates for implementation of reinforcements learning, as it is explained in chapter 4.3.5. PowerTAC simulation has limited duration, and participating brokers can model the game environment, which makes it a suitable environment for implementation of reinforcement learning.

There are some modifications of method proposed in order to adapt to PowerTAC wholesale market, which is modeled as a day-ahead market. In the PowerTAC wholesale market, broker can trade energy up to 24 times (24 different timeframes) for chosen timeslot. Figure 16 depicts an example where broker places 24 different trades for timeslot 25.

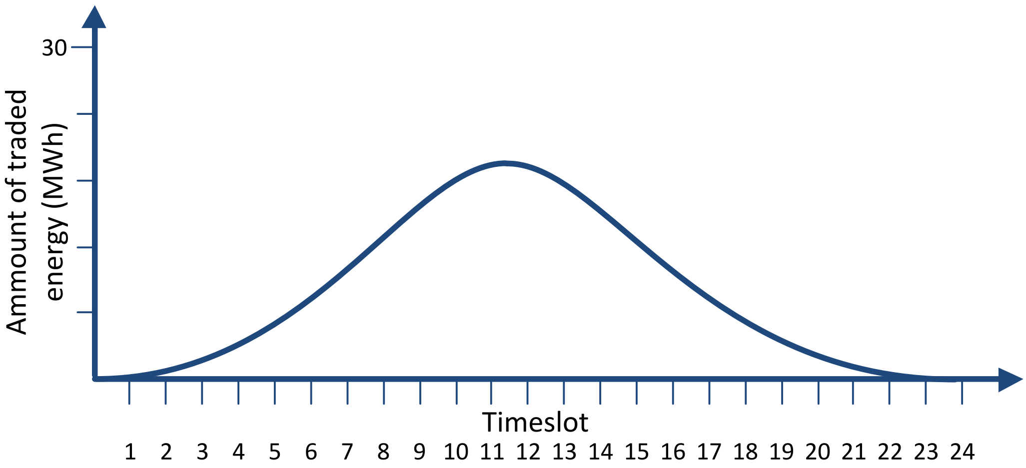

Figure 16: Example that shows multiple trades for desired timeslot

Since there are multiple chances to trade for desired timeslot which enables broker to choose different strategies, there is a need to modify Erev-Roth algorithm. Proposed solution is described below:

$$Q_{t+1}^{c}(a) = \begin{cases} (1-\alpha)Q_{t+1}^{c}(a) + (1-\epsilon)r_{t}^{c}, & if\ action\ was\ chosen \\ (1-\alpha)Q_{t+1}^{c}(a) + \dfrac{\epsilon}{M-1}r_{t}^{c}, & else \end{cases} \tag{5.1}$$

$$\pi_{t+1}{}^{c}(a) = \frac{e^{Q_{t+1}^{c}(a)/\tau}}{\sum_{b=1}^{n} e^{Q_{t+1}^{c}(b)/\tau}} \tag{5.2}$$

where Q_{t+1}^{c} and $\pi_{t+1}{}^{c}$ represent calculated action value and action probability for trade in timeframe $c, c \in [1,24]$. Timeframe represents ordinal number of trade for desired timeslot. In basic Erev-Roth method action values are calculated as function of total trade impact for desired timeslot. Hence, broker can use only single strategy while trading for desired timeslot.

This modification of basic Erev-Roth method enables broker to trade up to 24 times for desired timeslot with support of reinforcement learning. Proper use of this method should progressively result with optimal strategies for each of 24 possible timeframes in which broker can trade for desired timeslot. Example showing strategy convergence for 24 timeframes is depicted in Figure 17.

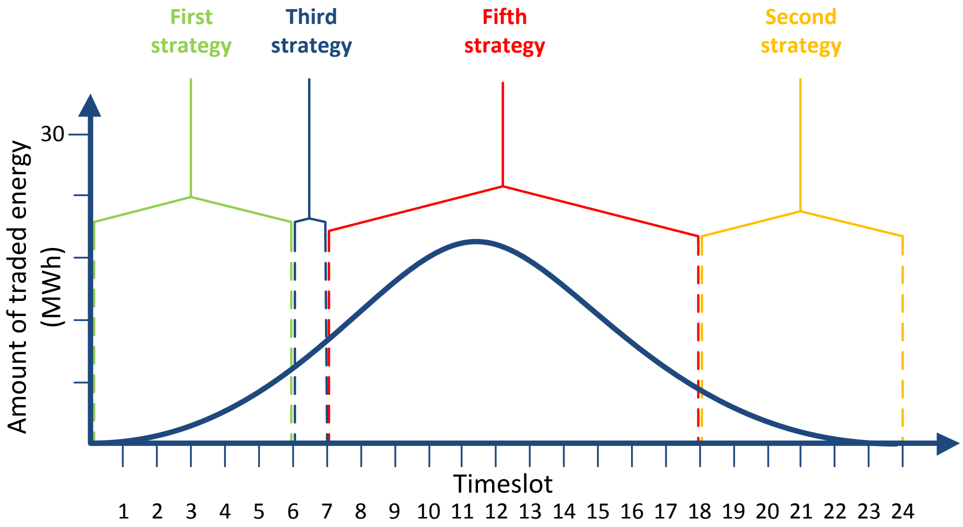

Figure 17: Example result of modified Erev-Roth method – convergence of best strategies for each timeframe

5.2.2.3 Reward function

Reward function is used to evaluate efficiency of each strategy. In modified Erev-Roth implementation each timeframe has own reward in order to enable differentiation of best strategies for each timeslot. In implementation of CrocodileAgent 2013 reward is calculated as a function of wholesale trading efficiency in observed timeframe compared to broker's total revenue for desired timeslot. Reward function is defined below:

$$r_t = profit_{customer\_m} + profit_{t,wholesale\_m} - cost_{balancing\_m} \tag{5.3}$$

where $profit_{customer\_m}$ is calculated as a total profit on the customer market in the timeslot m, $profit_{t,wholesale\_m}$ is calculated as a total profit on the wholesale market in the timeslot m and $cost_{balancing\_m}$ represents a total cost of balancing transactions in the timeslot m.

In this adaptation of Erev-Roth method reward function is defined on interval [0,1]. Hence, calculated reward needs to be normalized by following expression:

$$r_{t,normalized} = \frac{r_t - r_{t,MIN}}{r_{t,MAX} - r_{t,MIN}} \tag{5.4}$$

Normalized reward is used in action value calculation, which has a great impact in choosing appropriate strategy in the future.

5.2.2.4 Weighted randomizer

Weighted randomizer is a module used for choosing a best suitable strategy in specific timeframe for desired timeslot. Module connects probability of each strategy with random function. Choosing of strategy is described by Algorithm 1:

```
random = generateRandom(0,1);
for(i = 0; i< actions.length; i++){
  for(j = 0; j < i; j++){
      sum += action[j].getProbabilityForTimeframe()}
  if(random <= sum){
     return action[i];} }
}
```

Algorithm 1: Strategy choosing

5.3. Implementation of learning module

Learning module is implemented following the principles of object-oriented programming, in order to provide easy integration into wholesale module and to enable future improvements. Implementation of the learning module is descriped with class diagram depicted in Figure 18. Core of the learning module is `ErevRothImplementation` singleton class, which needs to be instanced in broker's initialization process. Initialization proccess of learning module consits of setting list of strategies, initialization of α, ϵ and τ variables and calculation of initial reward, value and probability for each strategy. List of strategies is fed into instance of `WeightedRandom` class created in initialization process of `ErevRothImplementation`.

Abstract class `Action` defines `valueMap` and `probabilityMap`, needed for proper functioning of each action in learning module. Using of Map structure is necessary in order to use adapted Erev-Roth method and it is used to track value and probability for each of 24 timeframes.

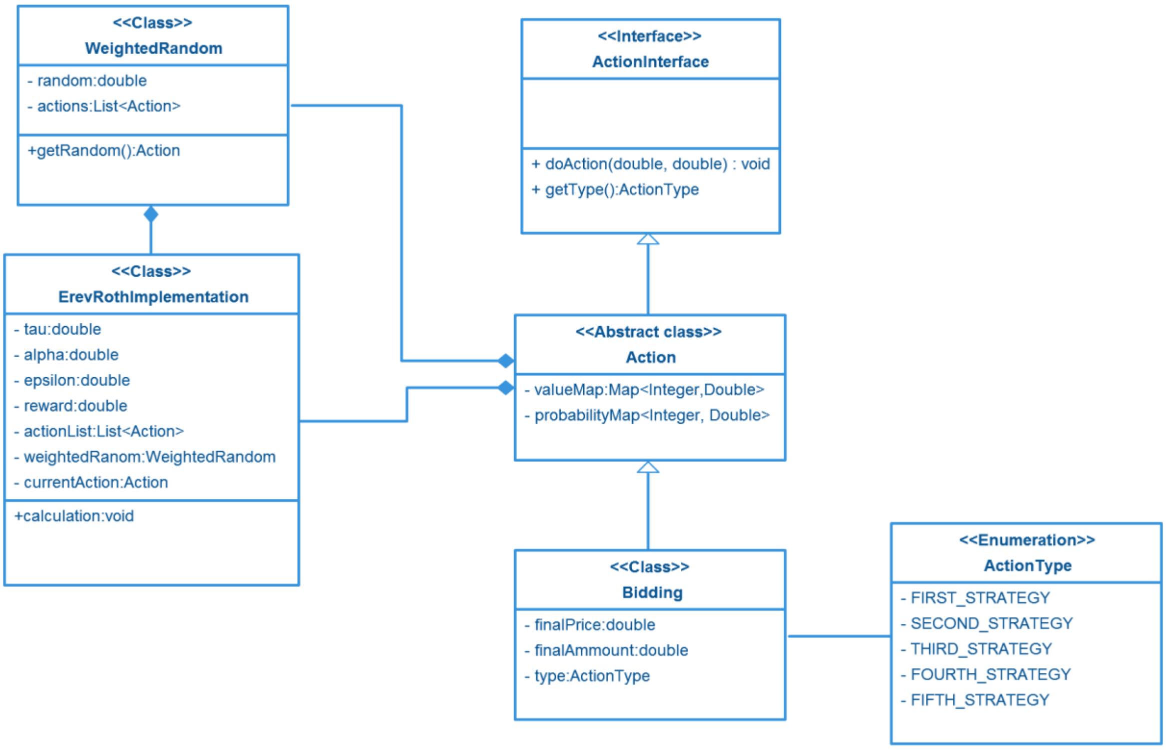

Figure 18: Implementation of learning module

All strategies in learning module are instances of class `Bidding` which extends abstract class `Action` and implements interface `ActionInterface`. Action interface has declared method `doAction()` which needs to be overridden in class that implements `ActionInterface`. Overridden method in class `Bidding` is used to define behavior of each strategy.

Figure 19 depicts interaction between market manager, learning module and PowerTAC simulator during simulation lifecycle. After module is initialized and initial values and probabilities for each action are calculated, learning module is ready to model received basic order depending on chosen strategy. After receiving modeled order market manager can send order to simulator. After receiving market clearing information market manager sends request for evaluation of previously chosen strategy, which triggers calculation of reward inside learning module. This procedure will be invoked every time when broker receives activation message from simulator and energy amount received from portfolio manager is a non-zero value.

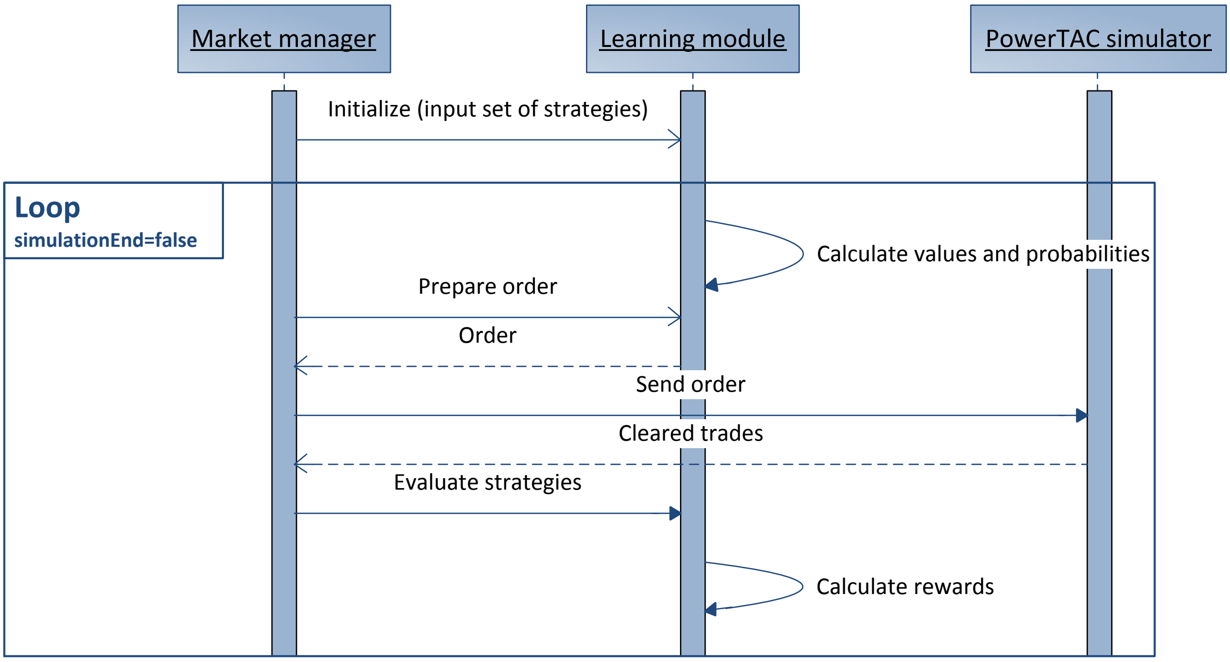

Figure 19: Sequence diagram describing one iteration of learning module

6. CrocodileAgent 2013 performance evaluation

In order to enhance CrocodileAgent's performance in competitive wholesale market, there are several improvements in this year's implementation of the agent. One of the integrated parts in CrocodileAgent 2013 is learning module based on Erev-Roth reinforcement learning method, adapted for PowerTAC wholesale market. The main objective of implemented improvements was to enable broker efficient trading on the wholesale market in a way that minimizes negative effects on the balancing market. In order to test efficiency of newly implemented learning module, there is a need to evaluate broker's performance in a competitive environment.

6.1.1. Evaluation environment

CrocodileAgent 2013 is an intelligent software agent designed and implemented for competing in PowerTAC 2013 competition. In order to test robustness and to ensure proper interaction of newly implemented modules within broker, there was a need to run some local simulations. Latest version of the game simulator, altogether with game-related modules and dependencies are provided on official GitHub page[21] of PowerTAC competition.

PowerTAC server distribution provides testbed environment which can be easily configured and adapted to various features of development version of the broker. Another important module available on PowerTAC GitHub page is sample broker, which is usually used as a base for developing PowerTAC agent. Sample broker can be useful to create local competitive environment by adding multiple instances of sample broker, each with slightly changed parameter in basic setup

The best way to test broker's performance and to evaluate results of implementation is to participate in PowerTAC competition. This year's competition consists of 4 trial competitions, held in March, April, May and June and a final

[21] https://github.com/powertac/

competition which is scheduled from July 8 until July 16. Each broker which participates in competition has its own set of strategies, which globally provides perfect competitive environment to test and evaluate broker's performance. Crocodile Agent's improvements described in this master thesis were deployed and tested in this year's PowerTAC May trial competition. Along with CrocodileAgent 2013 developed at the University in Zagreb, there were six other participants:

- AstonTAC - Aston University, England;
- INAOEBroker01 - National Institute of Astrophysics, Optics and Electronics, Spain;
- cwiBroker - Centrum Wiskunde & Informatica, Netherlands;
- MLLBroker - University of Freiburg, Germany;
- UTest - The University of Texas at Austin, United States; and
- LARGEpower - Rotterdam School of Management, Netherlands.

Each PowerTAC competition consists of multiple games with different game sizes (number of participating brokers), providing different conditions on the market in each game. Also, each participating broker has developed its unique strategy which models competition environment through the broker's interaction.

Variable number of participating brokers and market conditions which change progressively make PowerTAC 2013 the perfect environment to test new improvements implemented in CrocodileAgent 2013.

6.1.2. Key Performance Indicators

In order to test and evaluate new improvements implemented in wholesale module of CrocodileAgent 2013, there is a need to define Key Performance Indicators (KPIs, hereafter) to be measured in the evaluation process. An analysis of PowerTAC 2013 March trial [40] defines important performance indicator for wholesale, customer and balancing market and some of them are used to evaluate the efficiency of CrocodileAgent's 2013 wholesale trading.

Since CrocodileAgent's wholesale strategy is aimed at minimizing negative effects of the balancing market, there are several important KPIs defined to measure broker's performance, defined in Table 3.

KPI	Description	Measurement
$RMS_{imbalance\_amount}$	Root mean square imbalance for the balancing transactions. Since balancing mechanisms are executed to balance energy shortage or surplus, RMS is used to track absolute deviation.	Value is measured as a root mean square value of energy amount of all balancing transactions during the competition.
$\mu_{imbalance\_amount}$	Amount of energy traded on the balancing market expressed in kilowatt-hours. Positive value indicates balancing of energy shortage and negative value indicates balancing of energy surplus.	Value is measured as an arithmetic mean value of energy amount of all balancing transactions during the competition.
$\mu_{imbalance\_price}$	Mean balancing price per energy unit. Positive values indicate cost of balancing energy surplus and negative ones indicate cost of balancing energy shortage.	Value is measured as an arithmetic mean value of energy price of all balancing transactions during the competition.
WCR	Wholesale clearing rate. Zero-value indicates that none of placed orders were cleared and high number indicates that placed orders were not well designed.	Value is defined as a as the ratio between the number of successful trades and the number of submitted orders

Table 3: KPIs used to evaluate performance of CrocodileAgent 2013

In order to enable evaluation of results from PowerTAC trials, there are detailed logs from each game available on the PowerTAC competition webpage. There is also a tool called PowerTAC *logtool* which enables the extraction of raw data from downloaded log files. Logtool converts log files with *.state* extension into serialized objects and enables manipulation of instanced objects in order to enable thorough evaluation.

Another tool used for result evaluation is a *visualizer* web-application developed at University of Zagreb as a part of PowerTAC project [11] [41]. Visualizer provides user-friendly interface to track details and status of each game in the competition. It provides interfaces for tracking aggregate and per-timeslot activities on customer, wholesale, and balancing market, which can be very useful in evaluation of broker's performance.

6.1.3. Results and discussion

During the PowerTAC trial competition there were some problems in communication between some brokers and PowerTAC game simulator, as a result of different time synchronization. Since PowerTAC simulator broadcasts activation messages to brokers in the beginning of each timeslot, it is necessary that each broker is synchronized to the Internet time standard (NTP). As a result of communication problems, many of games were irregular, so only a few games were included in evaluation process, in order to provide reliable data. Games with following IDs were included in the evaluation: 23, 49, 54, 57, 59, 64, 69 and 101.

As it is previously explained, there are several KPIs measured in order to evaluate CrocodileAgent's wholesale bidding mechanisms. Table 4 contains values of performance indicators which were calculated based on data extracted from PowerTAC 2013 May trial log files.

Broker/KPI	$RMS_{imbalance\_amount}$	$\mu_{imbalance\_amount}$	$\mu_{imbalance\_price}$	WCR
AstonTAC	2624,64	3664,25	81,29	0,83
cwiBroker	8089,81	869,07	81,34	0,51
INAOEBroker	2664,31	-940,35	-50,16	0,23
CrocodileAgent	5340,98	19075,23	84,89	1,40
MLLBroker	15896,79	-10145,83	-736,66	0,12
UTest	9412,37	-25827,20	-1856,97	0,41
LARGEpower	1543,16	-368,78	-16,24	1,73

Table 4: Calculated performance indicators for PowerTAC May trial

Calculated $RMS_{imbalance\_amount}$ values indicate that CrocodileAgent wholesale bidding needs to be improved in order to decrease energy imbalance. Some brokers like MLLBroker, cwiBroker and UTest have even larger value of $RMS_{imbalance\_amount}$, which suggests that they have different strategy on the wholesale.

The other value used as indicator of imbalance amount, $\mu_{imbalance\_amount}$ shows that amount of energy that CrocodileAgent buys on the wholesale market is too large. When compared to value of $RMS_{imbalance\_amount}$ it indicates that in some games Crocodile agents has placed a few orders which resulted in huge energy surplus. Since high values (spikes) have a great impact on calculation of a mean value, CrocodileAgent's $\mu_{imbalance\_amount}$ value is the highest among the other brokers.

If broker has energy surplus, it needs to sell it on the balancing market in order to maintain balance of energy supply and demand. $\mu_{imbalance\_price}$ shows that although CrocodileAgent buys excessive amount of energy, he still manages to make profit by selling energy surplus in the balancing market. Most of the agents (INAOEBroker, MLLBroker, UTest and LARGEPower) pay the balancing cost in order to balance their energy shortage. Figure 20 depicts charts from balancing market in the game 23. It shows that CrocodileAgent has an energy surplus, but it manages to sell it on the balancing market. This particular game shows CrocodileAgent's quite balance wholesale trading. Peaks depicted in Figure 20 are a result of fast changes in number of subscribers on the customer market which has an impact on forecasting basic demand.

If only trading on the balancing market is observed, CrocodileAgent's orders in the wholesale market are well constructed and balanced, as it is shown by WCR indicator. But still, better performance can be achieved by offering slightly lower unit price. MLLBroker and UTest have very low WCR values, which suggests that their orders do not clear very often. That is confirmed by value of their $\mu_{imbalance\_amount}$ and $\mu_{imbalance\_price}$, which indicate substantial energy shortage.

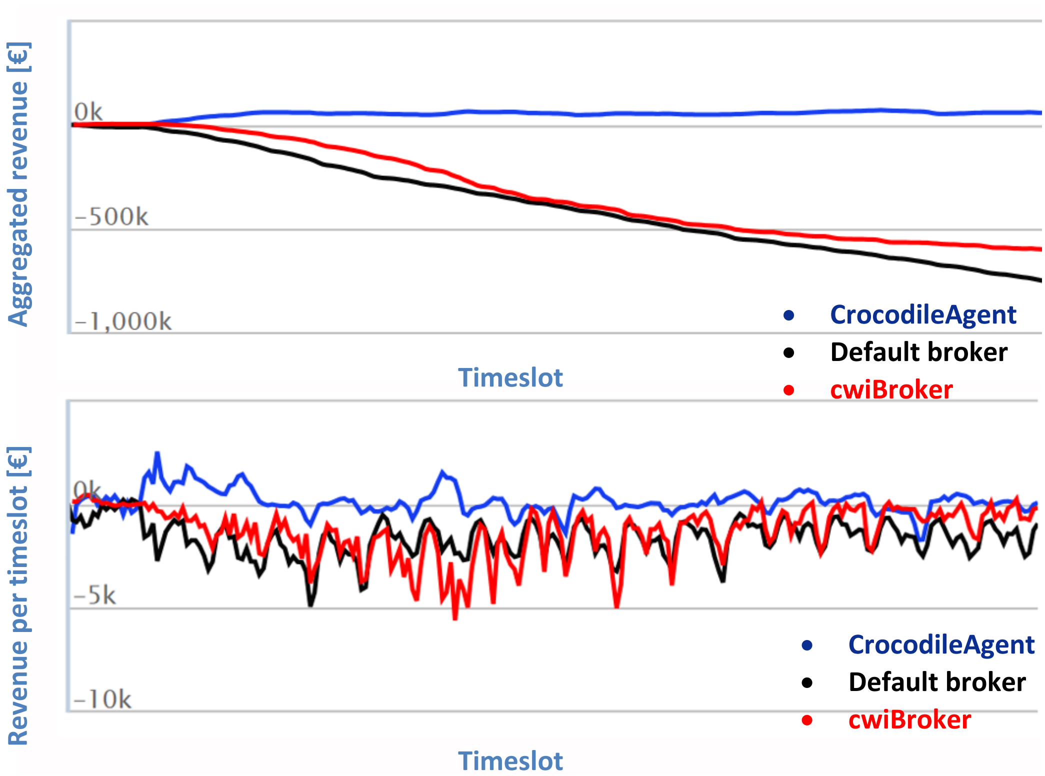

Figure 20: CrocodileAgent's revenue on the balancing market

In order to further evaluate CrocodileAgent's total performance in PowerTAC 2013 May trial, logtool is used to calculate amount of energy traded on customer, wholesale and balancing market. Values are presented in Table 5. As it is already assumed, CrocodileAgent buys 125% of needed energy, which indicates that there is a strong need to adapt generation of basic order for the wholesale market.

Broker/traded amount[GWh]	Customer market	Wholesale market	Balancing market
CrocodileAgent	-574,489,539	775,918,723	-192,373,719

Table 5: Amount of energy traded by CrocodileAgent on customer, wholesale and balancing market

To make the final conclusion for observed games of PowerTAC 2013 May trial, there is a need to correlate measured KPIs with total revenue of participating brokers. Figure 21 shows *total revenue*[22] of each broker which participated in

[22] It is calculated as a sum of profit on the wholesale, customer and balancing market, minust the cost of distrubution fees.

observed games. Although KPIs show that CrocodileAgent needs to improve load forecasting for generation of basic orders, CrocodileAgent manages to make substantial profit on the customer and balancing markets, which in most cases results with top results in total revenue. It is a result of good communication between his modules. In observed games of PowerTAC 2013 May trial CrocodileAgent managed to earn total of nearly 5.000.000 € which puts him in the first place.

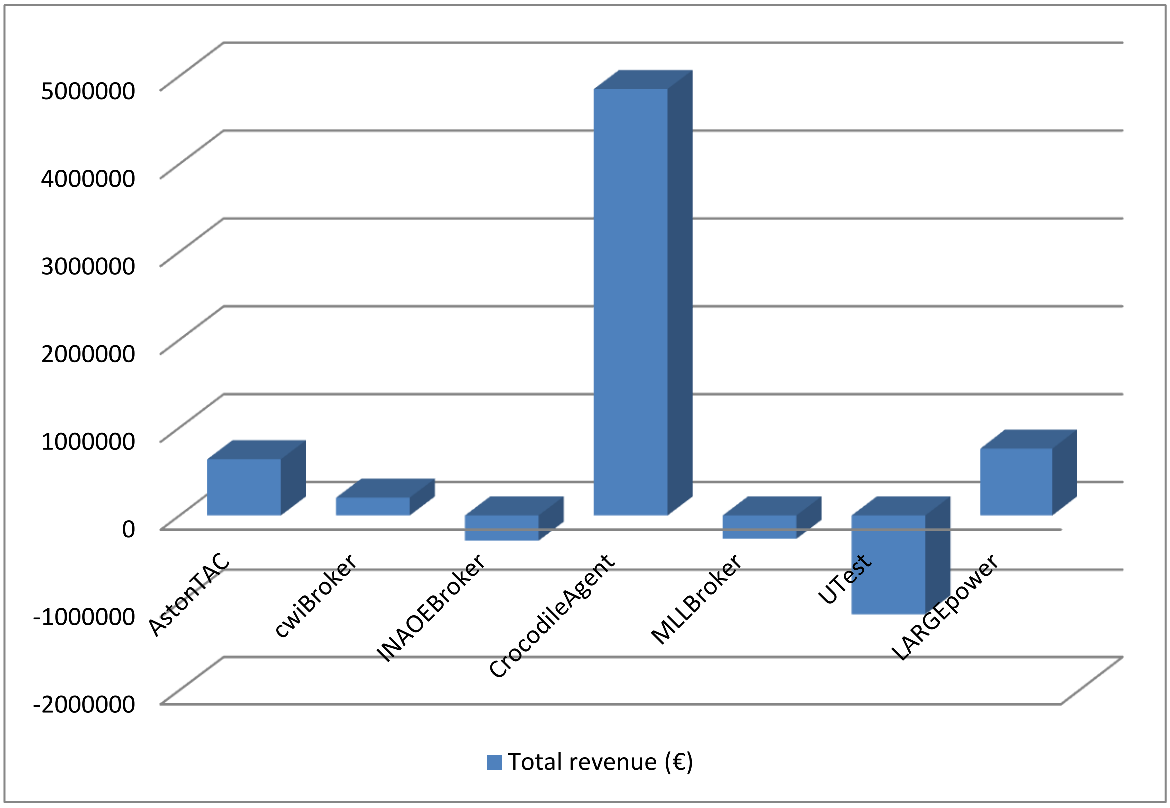

Figure 21: Total revenue in observed games

Many games in PowerTAC May trial were irregular due to manifestation of *infinite orders* and problems with broker – simulator synchronization. Hence, the real performance of participating brokers could not be shown. In June, 2013 another PowerTAC trial was organized. All of the games in the competition were regular and there is a notable difference in broker's results. Since there were no manifested irregularities, PowerTAC 2013 June trial has provided a perfect environment for testing CrocodileAgent's learning module. It is noticed that while trading on the wholesale market, CrocodileAgent has a *learning period* – period in which broker's orders result in large imbalance, which triggers a negative reinforcement. As a result, broker progressively learns to choose the most suitable strategy for the particular timeframe. Figure 22 depicts charts from balancing market in the game 11 from PowerTAC 2013 June trial. As it is previously described, after the learning period CrocodileAgent's wholesale trading results in minimized energy imbalance on the balancing market. On the other hand, LARGEpower's imbalance increases progressively, which indicates a need to optimize its wholesale strategy.

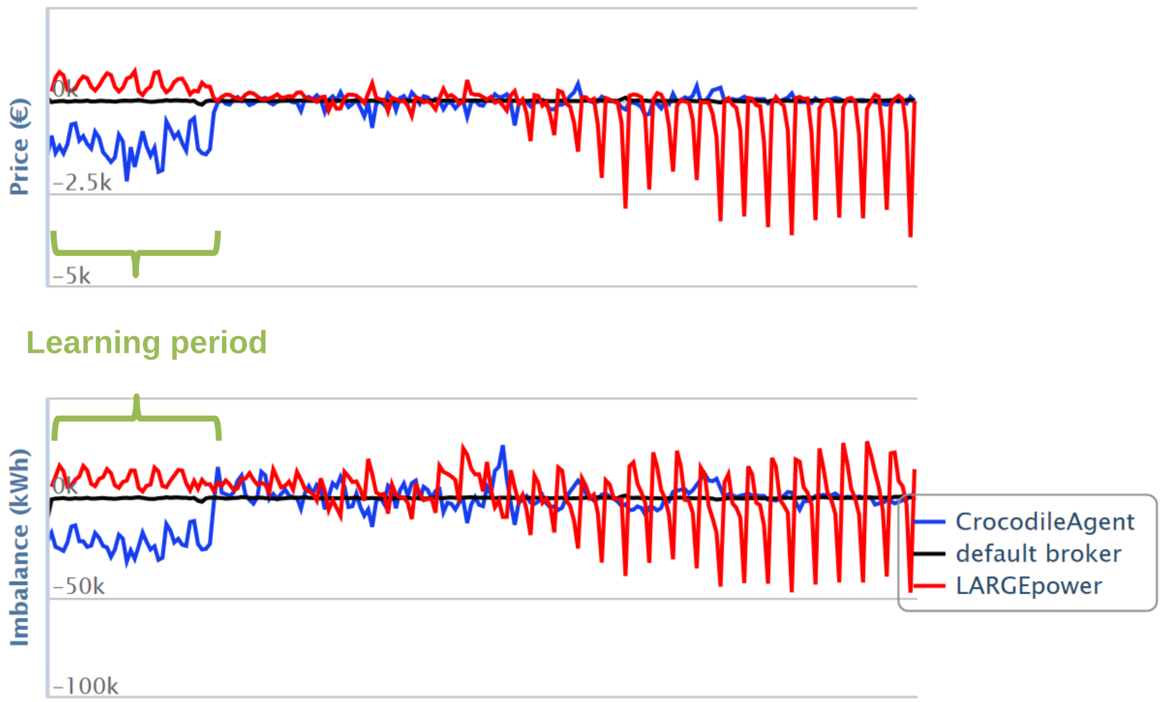

Figure 22: Progressive decrease of negative effects on the balancing market

Conclusion

The structure of energy market is going through major changes as a result of progressive liberalization and decentralization. The introduction of a smart grid concept has resulted in modernization of a traditional power grid, enabling usage of intelligent software agents as representatives of trading entities on such modernized energy market.

PowerTAC competition models the modern energy market and provides a competitive environment suitable for experimentation. Main entities in the competition are brokers whose goal is to maximize their profit while trading on the customer, wholesale and balancing market. One of the brokers designed for competing in PowerTAC 2013 competition is CrocodileAgent 2013, developed at University in Zagreb. This paper presents key features of CrocodileAgent's wholesale module, designed to improve trading on the wholesale market, while minimizing negative effects on the balancing market. One of the most important features described in the paper is the learning module which enables broker to adapt to various market conditions.

Newly implemented modules were evaluated in PowerTAC 2013 May trial, providing insight in performance of CrocodileAgent 2013. Evaluation results proved the efficiency of CrocodileAgent's wholesale module and pointed out some weaknesses in generating basic orders. Hence, future work includes improvement of energy load forecasting in order to avoid energy surplus.

PowerTAC final competition is scheduled to be held in July 2013, collocated with the Twenty-Seventh AAAI Conference on Artificial Intelligence (AAAI-13) in Bellevue, Washington. Final competition will provide another chance to test implemented features described in this paper.

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Summary

Intelligent trading agent for power trading through wholesale market

This master thesis describes an implementation of intelligent software agent for efficient trading in the modern energy market, with special emphasis on wholesale trading. Main motivation for this work arises from the evolution of energy market, which provides a possibility for implementation of complex software solutions in order to improve market trading mechanisms. The emphasis of this master thesis was placed on the design and implementation of adaptive wholesale module which is an integrated part of the CrocodileAgent 2013, developed at University in Zagreb. The solutions described in this thesis were evaluated on the Power TAC 2013 May trial competition.

Keywords: smart grids, software agents, energy market modeling, Power Trading Agent Competition, energy wholesale market

Sažetak

Inteligentni programski agent za trgovanje električnom energijom posredstvom veleprodajnog tržišta

U ovom diplomskom radu opisan je razvoj inteligentnog programskog agenta za trgovanje na tržištu električne energije, s posebnim naglaskom na trgovanje na veleprodajnom tržištu. Motivacija za izradu ovog rada proizlazi iz razvoja tržišta električne energije, što omogućava implementaciju složenih programskih rješenja u cilju poboljšavanja mehanizama za trgovanje elektičnom energijom. Naglasak rada je na dizajnu i implementaciji modula za trgovanje na veleprodajnom tržištu električne energije, koji je ujedno sastavni dio programskog agenta CrocodileAgent 2013, razvijenog na Sveučilištu u Zagrebu. Rješena opisana u radu testirana su i evaluirana u sklopu probnog natjecanja PowerTAC 2013 održanog u svibnju 2013. godine.

Ključne riječi: napredne energetske mreže, programski agenti, modeliranje tržišta električne energije, Power Trading Agent Competition, veleprodajno tržište električne energije