Journal of Ubiquitous Systems & Pervasive Networks
Volume 8, No. 2 (2017) pp. 21-27

Complex system modeling and platform implementation for financial risk management in energy markets

Oscar Manco[a], Oscar Botero[b], Santiago Medina[c]

[a]*oscar.manco-lopez@u-pec.fr Université Paris - Est Creteil Paris, France*
[a]*oscar.botero@telecom-em.eu Institut Mines Telecom Paris, France*
[b]*smedina@unal.edu.co Universidad Nacional de Colombia, Colombia*

Abstract

Energy markets are in constant evolution and transformation. The dynamics have rapidly changed and both private companies and governments require appropriate tools and systems for management and monitoring. We propose a new approach to measure and manage energy trading financial risk. The approach is twofold: first we use complex modeling to represent the context and second, we implemented an information system to provide risk management tools anytime, anywhere. More in detail, we modeled trading agent's interactions and observe in advance scenarios that could jeopardize the system equilibrium. We then find the optimal balance for energy trading. From an academic point of view we contrasted techniques like Nash Equilibrium and Game theory and from a practical experience; we developed a software platform in partnership with the government regulator entity in Colombia XM.

Keywords: *Complex systems; risk management; service platform; optimization*

1. Introduction

Studies about electricity markets and their evolution have been directed towards two major currents. First, the tendency to estimate the market variables such as stock price, the price of contracts, demand level, supply level, generation capacity, among others; by using statistical tools either with mathematical models or simulations. Second, calculating exhibits in the functional systems, in order to establish with some certainty, the magnitude of the problems that happen within the operation. In the results found by Tushar [21] the equilibrium between supply and demand through the use of game theory, where consumers play an important role in creating price, was a very important advance. However, to maximize the profitability of the consumer is an ambiguous result, because despite being located at the end of the cycle of energy, what users seek is the reduction in cost without generating returns through speculation or arbitrage, and commonly is not the purpose of the business, it means the consumers used the energy as a necessary good not like a profitable one [16].

For his part some authors [1], [2], [15] performed decomposition of the variables involved in process of creating prices, including phenomena such as social affairs, climatic, economic indicators, regulatory requirements, using mathematical techniques, statistics or new technologies, such as artificial intelligence. That decomposition aims at a certain level of certainty, projecting price developments in the future. Quantify risk exposures related to the operation, and financial exposures linked to power generation have captured the focus of the different works developed so far [7], [15], [16]. While the ideal scenario is that the market remains in equilibrium, where agents maximizes their returns with minimal transaction costs, and where the energy supply is reached without incurring losses; there is another factor concerning the adequate capacity to meet contractual obligations. That is, if indeed the agent that has commitments, has the financial strength to honor them.

Energy markets determine the behavior of oligopoly and by the way induce various types of risks that compromise the operation in different markets and countries. Now, to establish what the consequences are, of exposure to different risks, sustainability becomes part of the discussions. All of the consequences they sought to be avoided, for example considering international agreements that establish "binding" commitments to reduce emissions. This leads many governments, trying to change their ways of generation in order to meet international requirements and sustainability.

[*] Corresponding author. Tel.: +33 640 29 78 20
E-mail: oscar.manco-lopez@u-pec.fr

DOI: 10.5383/JUSPN.08.02.004

Thus, the financial and economic problem has been addressed considering the interactions between agents from a purely functional or operational perspective. For Boreinstein and Bushnel [15],[16] it is evident that each agent, trader, generator or consumer should be at an established relationship level with other participants, looking for maximizing the results amid the laws of supply and demand. That said, there is a need to treat the physical phenomena from a financial point of view among the participants.

Historically, some unmet demand events have occurred since particular agents faced problems in its financial position to honor contractual obligations, even though the reaction is immediate by the regulator. One of the biggest complications is the exercise of predict the demand, which is a critical variable for generating prices. To this end there are plenty of models with the aim of establishing the best strategy in the energy auctions, which optimizes the profitability of generators but excludes income from traders whose main function is brokering with a different risk exposure.

In that way, the construction of an integrated model that determines the positions of financial risk of each agent, with their implications for the market is justified from the point of view of securing the energy supply. The rest of this paper is organized as follows: First we present a review of related research, followed by the methodology used, then we present the details of a proof-of-concept implementation of a forecast and risk management platform called RiskeR and we finally present our conclusions and future work paths.

2. Related Work

Energy markets are an oligopoly because participants often pursue strategies, and adapt those ones to changing market conditions [7][22]. Also performing replicating approaches that enable operation models in a complex frame given the large number of variables and situations to consider [11][22].

Game theory can represent strategic behavior, however, many of these models are very simplified and do not capture the complexity arising from the markets, but they bring partial signals of their behavior instead [17]. On the other hand, the agent-based simulation (ABS) overcomes some of the weaknesses of the model of market equilibrium centralized [9] where the main objective is the fulfillment of the demand but do not ensure the financial viability of service providers. ABS models can represent heterogeneous individual agents and their behavior, and the rules of the market and those agents act in a decentralized manner [6]. These models are increasingly used to analyze the decisions made by the generators, distributors, traders, regulators and consumers in a liberalized market [32].

The models often ignore market demand answers, the implied characteristics in the evolution of prices and restrictions intervals in the network [4]. The development of a ABS model, including the behavior of demand, price and availability, will allow progress in understanding how the energy markets operate and interact with new technologies and other factors underlying in the market.

The problem of energy market models has focused on the estimation of price developments, changes in demand, simulation of market strategies from producing agents, defining energy policies, technology selection, among others [32]. However, exploring the interrelationships of the agents with the operation of the electrical system in the short and medium terms from the point of view of its financial strength, it is something that should be explored.

The most important aspect that this paper addresses is to propose solutions that try to cover gaps in conceptual modeling of electricity markets related to a corporate risk approach [14]. Financial risk factors such as credit risk; counterparty, operational and market can affect the competitive position of the decisions of the agents. Thus it can impact its operation.

3.System Modeling

For many years the research question posed from different areas of science, focused on how to describe the characteristics of participants in a system and their relationships [12]. Agent-based modeling (ABM) has become a useful tool to approach the complexity of the interactions between the elements of the systems and the methodology has begun discussions about the degree of difficulty with which each system should be treated with their respective peculiarities [20], [24], [29].

However, describe phenomena that explain the relationship between the agents through equations is quite complex [31], i.e. it is not a simple process because the consideration of all characteristics through a single mathematical expression in a linear or polynomial way can be sometimes a simplistic explanation of physical phenomena.

According to complexity, a system is a combination of different logical or even physical entities that interact with each other to establish a specific purpose, namely to reach a target from the relationship between them. The systems can be dynamic, and it means that behavior changes over time or the systems can be stable, where the conditions, generally do not change and remains in equilibrium [8][25].

The integration of complexity and systems for their part, allows the composition of systems with many parts (or variables), with many degrees of freedom that are not equivalent between them meaning that each element is independent in making their decisions and governed by different parameters. That said we could define complexity as the study to determine how complex systems can generate simple behaviors but only if the origin of complex situations is understood, in other words if the physical phenomena are completely comprehended.

On the other hand, the risk measurement is an exercise in lifelong learning corresponding to all members involved in the organization, given that to ensure sustainability is necessary to keep under control most variables that threaten business viability [11]. This exercise consists of three elements that work on a scheduled basis and are as follows: First, the classification of risk given the impact they have with respect to the limitation in the scope of corporate objectives. Second one, the approximation to a measure of the likely impact on the results, if the materialization of risk occurs, in other words, evaluation. And finally, thirdly management and risk control, through the establishment of KRI [28], which are defined as tools to manage risk into an acceptable level for the strategy.

Our implementation is a risk tool that integrates the modeling using ABM and complexity. The model takes into account the expected return of agents that depends on the volume of transactions and ability to generate capital returns associated with the purchase and sale of energy in the electricity market. In that way, profitability, risk position, capital availability, adequacy of investments in time frames, liquidity, solvency and the management of the debt, specifically "outside capital" (financial liabilities with cost), are variables that must be in permanent evaluation. There are different variables considered in the decision process for buy or sell energy in the electricity market. Specifically, from the financial perspective, we defined the most important, like solvency, liquidity and risk position. However, in this paper's scope all of the variables related to the operational exposition will not be considered.

The proposed model is the description of the market model considering the financial exposure of individual and consolidated companies. We have parameters, constants, and variables subject of modeling. The energy is an active classified as a "utility - commodity" and does not distribute dividends during the analysis horizon, because in this case we do not evaluate the cash and equivalents, therefore the dividend is zero.

The goal of the agents is to do transactions in the market in order to reach the best profitability as they can, under the uncertainty conditions, specifically financial conditions from others.

The level of demand for each agent should be less (shortage) or higher (surplus) than the energy contracts that are signed. If the contracts are higher than demand level, the surplus will sell in stock exchange. And if the contracts are less than demand level, the shortage will be bought in stock exchange.

Each agent evaluates the decision process, considering variables involved in the physical phenomenon, in order to improve the performance in the market. The risk perception and the value generation depend on preferences, outcomes (decision for buy or sell energy to/from other agent after risk evaluation) and the penalties or awards inside of the framework of the decision

The model equation is defined as (1), where U t,i is the utility function:

$$U_{(t,i)} = (S_{(t,i)} * p_{(t,i)} - Q_{(t,i)} * p_{(t,i)}) + CC_{t,i} + (He - Ee) * pb_t - CG_{t,i} - OyM_t - D_{t,i} * Kd_{t,i} \tag{1}$$

The first part of the equation represents the quantity of energy through contracts, because there are differences between purchases (Q) and sold energy (S). The second part considers the quantity through stock market for reach the demand or obtains a profit using the surplus, and is possible discount the operative expenses. Finally, the last expression is the financial cost for the debt. The total expression defines the amount of money that determines the global operation for each agent (trader) and we can call it "profit and losses statement", using a financial perspective. Then, the energy will be obtained from the use of own resources (cash) and money that can be obtained through loans or even using the equity (capitalization).

In order to optimize the model, we use the simplex method in order to find a utility maximization through its linear behavior. The scenario simulation is performed for a month of operation programming, which requires the release of energy to final consumers through retailers, whose responsibility is the fulfillment of such dispatch of energy. To summarize, the model will maximize the following expressions (2)

$$\begin{gathered} Max\_U_{(t,i)} = (S_{(t,i)} * p_{(t,i)} - Q_{(t,i)} * p_{(t,i)}) \\ + CC_{t,i} + (He - Ee) * pb_t - CG_{t,i} - \\ OyM_t - D_{t,i} * Kd_{t,i} \end{gathered}$$

(2)

Profit and losses statement for trader and producer subject to,

$Ebit_{i,t}/(D_{t,i} \times Kd_{t,i}) \geq 2.5$ Financial Capacity

$D_{i,t}/Ebit_{t,i} \leq 4.0$ Maximum Leverage

$VaR1_{t,i} \leq 10\% * E_{t,i}$

$VaR2_{t,i} \leq 20\% * E_{t,i}$

$SCOS_{t,i} = [(E_{t,i} - VaR1_{t,i})/((pz_t - p_{t,i})*2)]$ Financial capacity of operations "Sell"

$SCOB_{t,i} = [(E_{t,i} - VaR2_{t,i})/((p_{t,i} - pmin_t)*2)]$ Financial capacity of operations "Buy"

$D_{t,i}/E_{t,i} \leq 80\%$ Financial leverage

$EBIT_{t,i}/(E_{t,i} + D_{t,i})$ = Expected $Return_{t,i}$

Where,

$p_{t,i}$ = The price at time t for contracts, considered by the agent i.

$Q_{t,i}$ = Quantity of energy purchased by agent i at time t, in contracts.

$S_{t,i}$ = Quantity of energy sold by agent i at time t using contracts

$Kd_{t,i}$ = Interest rate, financial cost for agent i, at time t.

$OyM_{t,i}$ = Operative and management expenses from agent i, at time t

$D_{t,i}$ = Total debt of agent i, at time t (outside capital).

$He_{t,i}$ = Quantity of surplus energy by agent i at time t.

$Ee_{t,i}$ = Quantity of shortages energy by agents i at time t.

pb_t = Price in stock exchange, spot price in the market.

$Ebit_{t,i}$ = Operating income after discount expenses and cost by agent i at time t

$VaR_{t,i}$ = Value at risk of financial operations form agent i, at time t

$E_{t,i}$ = Equity value composed by subscribed capital, reserves, accumulated profit, valorizations, and others.

$SCOB_{t,i}$ = Support capacity of operations, financial capacity for operations (buys)

$SCOS_{t,i}$ = Support capacity of operations, financial capacity for operations (sales).

$VaR1_{t,i}$ = Value at risk sales

$VaR2_{t,i}$ = Value at risk purchases

The method used for optimization of the proposed model is the simplex method in order to find a utility maximization through its linear behavior. In general, the expression is:

$$Max\_z = C^T * x$$

The Simplex method is a method using the interaction with the aim of gradually improving the final estimation at each next step. It is an analytical method for the solution of problems whose main characteristic is linear programming but is in the ability to solve much more complex problems, without initial restrictions on the number of variables.

4.Platform Implementation: Risker

We implemented an information system to provide risk management tools. The main objective is to provide financial risk management as a service for regulator entities as well as for energy agents. We used a typical client-server implementation relying on virtual cloud servers. There are two architecture models, test and production. The first test platform uses one virtual server using Nginx [33] as web server and in the same instance we use MySQL [35] as database provider. The backend is supported by Laravel [33][35], a PHP framework and front-end relies on html5, CCS3, JavaScript and Bootstrap for page-device adaptation. In

Fig. **1** we depict the test implementation architecture.

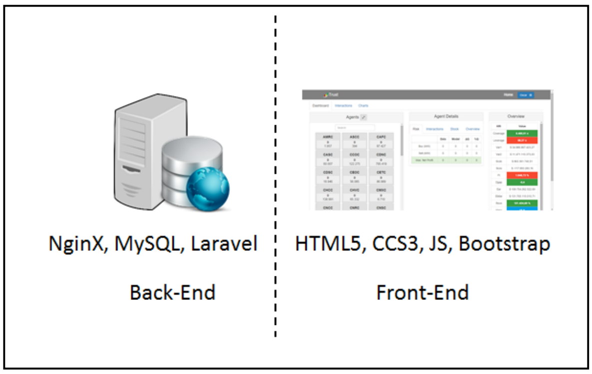

Fig. 1 Test Architecture

The production architecture consists into a web server (Nginx) with redundancy using an independent virtual server for each instance. There is one independent database server (MySQL), which is deployed with redundancy as well. An additional fileserver is used for data and configurations backup (Fig. 2).

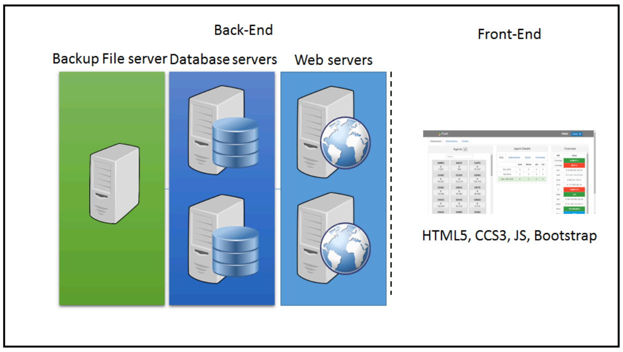

Fig. 2 Production Architecture

The platform welcomes the user with a landing page that leads, after successful authentication to the main dashboard (Fig. 3 and Fig.4)

Fig. 3 The Risker

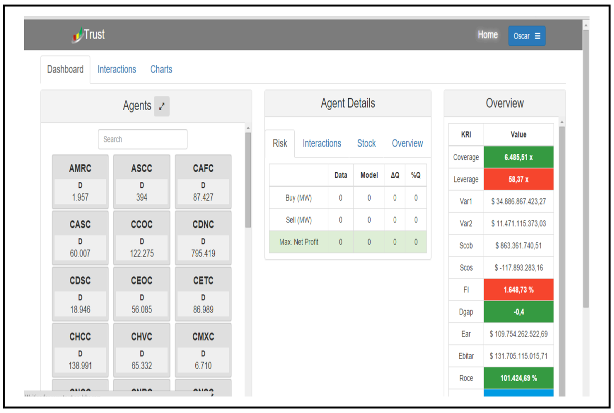

Fig. 4 The Risker Dashboard

The main dashboard page provides three tabs. The first one provides the list of energy company agents. A short name is display with a full name display while hovering. The agent display has two modes compact and expanded. The compact model displays the short name and the total energy demand assigned to that agent. The extended model displays the total energy for buy and sells as well as the current prices (Fig. 4)

The Agent Details section presents four tabs which display information about: Model forecast, buy and sell amounts, agent interactions with other agents, stock information and Key Risk Indicators (KRI) profile. The last panel displays a global overview of the whole system with corresponding KRIs. The metrics are colored regarding predefined thresholds. The thresholds are graded in four categories: red (critical), yellow (warning), blue (acceptable), green (good).

The second main tab depicts each agent interaction with rest of the system. We provide an interactive graph with proportional arrows showing buy/sell relationships as well as total traded energy amounts (Fig. 5).

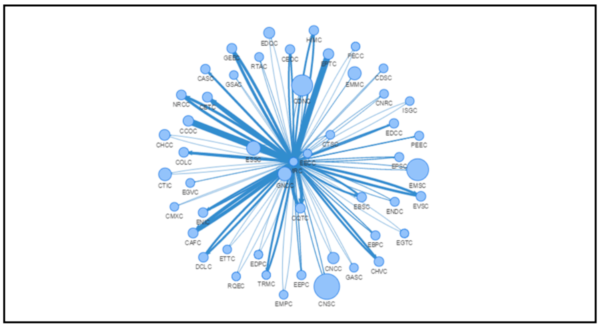

Fig. 5 Agents Interactions

The last tab provides charts with information regarding the individual percentage of agent participation in the market, comparison of the model forecast optimization in relationship with the current data per agent, as well as additional KRI charts (Fig. 6)

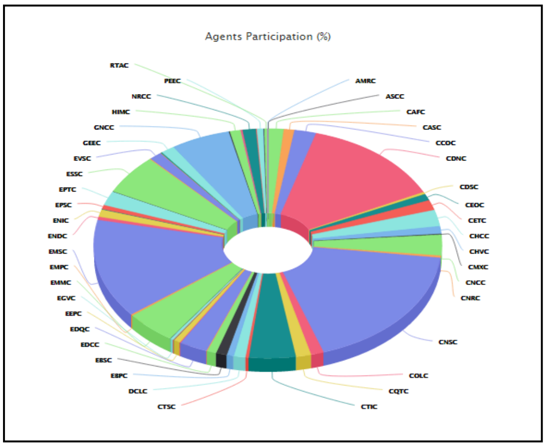

Fig. 6 Agent Participation and metrics charts

Finally the results are shown in the Fig. 7. Considering the initial demand level and the transactions between agents. It means the history of transactions can be changed in an optimal way.

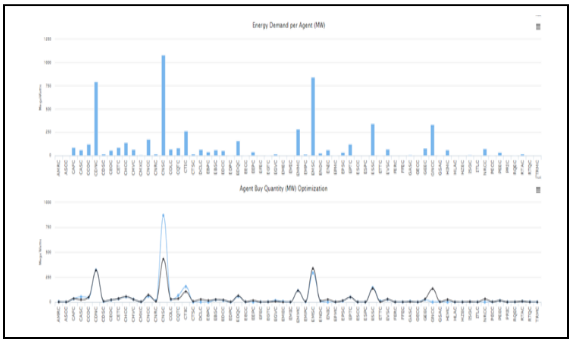

Fig. 7 Optimization of transactions.

5. Conclusion

We presented a complex model to represent energy trading agent interactions. We optimized a linear expression in order to find the system equilibrium. We went further and implemented a real web platform based on the core model. It provides financial risk indicators assessment as well as recommendations for market performance. As future work we will consider multiple optimization models to perform benchmarking. The platform will evolve towards an automated system to generate triggers and alarms regarding pre-defined risk scenarios. We consider that automatic data collection and data reporting are key elements to develop and reinforce. Data mining and open data can be also linked to provide useful information in order to increase model robustness and diversity.

Regarding the proposed model, we consider the inclusion of operational exposition variables like climatic variations, availability of energy generators, terrorism attacks, regulation reviews, financial hedges, and international economic perspectives. This can provide additional patterns and trends in order to provide more accurate and detailed risk management. The breakthrough that suggests this work, is the possibility of study directly the financial phenomenon implicit in the operations, and synchronizes with operational and macroeconomic developments that result in more robust models for analysis, i.e. comprehensive. Thus, with an identification of interactions and impacts, we can avoid affecting the system sustainability, managing a new branch of financial innovation, which is called systemic risk very different from conventionally known systematic risk.

6. References

[1] A.Sweeting,"Market power in England and wales wholesale electricity market 1995-2000", The Economic Journal, 117(520), pp. 654 – 685, 2007

https://doi.org/10.1111/j.1468-0297.2007.02045.x

[2] C.D.Wolfram,"Measuring duopoly power in the British electricity spot market", American Economic Review, Vol. 89, N°4, pp. 805 -826, 1999

https://doi.org/10.1257/aer.89.4.805

[3] C.J. Day, B.F. Hobbs, J-S. Pang, "Oligopolistic competition in power networks: A conjectured supply function approach", IEEE Transaction on Power systems, Vol. 17, N°3, pp. 597-607, 2002.

https://doi.org/10.1109/TPWRS.2002.800900

[4] E. Gnansounou, J Dong, S Pierre, A Quintero, "Market oriented planing of power generation expansion using Agent – based Model". Power Systems Conference and Exposition. IEEE PES. Vol. 3, pp 1306 – 1311, 2004.

[5] F. Costa, F. Rodrigues, G. Travieso & P. Villas Boas. "Characterization of complex networks: A survey of measurements". Advances in Physics. Vol 51, pp 167-242. 2007.

https://doi.org/10.1080/00018730601170527

[6] H. Kurdi. "Personal Mobile Grids: Ubiquitous Grid Environments For Personal Users." Journal of Ubiquitous Systems & Pervasive Networks 6.1 (2015): pp. 01-10.

[7] J Apt, L Lave, S Talukdar, M. Granger, Marija Ilic. “Electrical Blackouts: A Systemic Problem” Issues in science and technology. Vol. 20 Issue 4. 2004

[8] J. Buttler, N. Akchurina, “Nash Equilibria in Normal Games via Optimization Methods”, European Control Conference, pp. 724-729, 2013.

[9] J. Jackson. Improving energy effiency and smart grid program analysis with agent-based end-use forecasting models. Unknown Journal, 38:3771 - 3780, 2010.

[10] J. Kwapien, S. Drozdz. Physical approach to complex systems. Physics reports. 2012, 115 – 226

https://doi.org/10.1016/j.physrep.2012.01.007

[11] J. Yao, I. Adler, & S. S. Oren. Modeling and computing two-settlement oligopolistic equilibrium in a congested electricity network. Operations Research, 2008.

https://doi.org/10.1287/opre.1070.0416

[12] M. Čertický, J Michal, and P Radek. "Analyzing on-demand mobility services by agent-based simulation." Journal of Ubiquitous Systems & Pervasive Networks 6.1 (2015): pp. 17-26.

[13] M. J. Newman. “The Structure and Function of Complex Networks”. Society for Industrial and Applied Mathematics. Vol.45, No.2, pp.167–256. 2003.

[14] O Wyman, “Dinamic Financial planning” Global Risk and Trading, Marsh & McLennan Company. 2011.

[15] S Medina. “Risk evaluation in Colombian electricity market using fuzzy logic”. Energy Economics, Vol. 29, pp 999-1009. 2007

https://doi.org/10.1016/j.eneco.2006.02.008

[16] S. Boreinstein, J. Bushnell, & C.R. Knittel. Market power in electricity markets: Beyond concentration measures. The Energy Journal, Vol 0. Pp 65-88, 1999.

https://doi.org/10.5547/issn0195-6574-ej-vol20-no4-3

[17] S. Stoft. Power System Economics. Designing Markets for Electricity. IEEE/Wiley, February 2002.

[18] S. Yousefi, M. P. Moghaddam, and V. J Majd. Optimal real time pricing in an agent-based retail market using a comprehensive demand response model. Energy, doi:10.1016/j.energy.2011.06.045, 2011.

https://doi.org/10.1016/j.energy.2011.06.045

[19] T. Agarwal, S. Cui, “Noncooperative Games for Autonomous Consumer Load Balancing over Smart Grid”, Game Theory for Networks, third International ICST Conference, GameNets, 2012.

https://doi.org/10.1007/978-3-642-35582-0_13

[20] V. Nanduri and T. K. Das. A survey of critical research areas in the energy segment of restructured electric power markets. Electrical Power and Energy Systems, 31:181-191, 2009.

https://doi.org/10.1016/j.ijepes.2009.01.004

[21] W. Tushar, J.A. Zhang, D.B. Smith, S. Thiebaux, H.V. Poor, “Prioritizing Consumers in Smart Grid: Energy Management Using Game Theory”, International Conference on Communications, pp. 4239-4243, 2013

https://doi.org/10.1109/icc.2013.6655229

[22] X. Du, Y. Xi, & S. Li. Distributed model predictive control for large-scale systems. Proceedings of the 2001 American Control Conference, 4:3142-3143, 2001.

[23] X. Jiang, T. Chen, B. Zheng. Structure of local interactions in complex financial dynamics. Scientific reports. Vol 4, 5321 EP - 2014.

[24] Xiao, Mi et al. (2015). “A new methodology for multi-objective multidisciplinary design optimization problems based on game theory”. In: Expert Systems with Applications 42.3, pp. 1602–1612. https://doi.org/10.1016/j.eswa.2014.09.047

[25] Y. Nanpeng, S. Abhishek, & T. Leigh. Financial risk management in restructured power wholesale markets: Concepts and tools. IEEE trans.on pow. Sys. 2010.

[26] Yang, Yang, Jing Gu, and Zongfang Zhou (2015). “Complexity Study of the Credit Risk of a Business Group”. In: Discrete Dynamics in Nature and Society 2015. https://doi.org/10.1155/2015/527854

[27] Young, David, Stephen Poletti, and Oliver Browne (2014). “Can agent based models forecast spot prices in electricity markets? Evidence from the New Zealand electricity market”. In: Energy Economics 45, pp. 419–434. https://doi.org/10.1016/j.eneco.2014.08.007

[28] Yu, Nanpeng, Abhishek Somani, and Leigh Tesfatsion (2010). “Financial risk management in restructured wholesale power markets: Concepts and tools”. In: Power and Energy Society General Meeting, 2010 IEEE. IEEE, pp. 1–8.

[29] Z. Zhou, W. Kin Chan, & J. H. Chow. Agent-based simulation of electricity markets: a survey of tools. Artificial Intelligence Review, 28:305 -342, 2007.

https://doi.org/10.1007/s10462-009-9105-x

[30] Zhao, Jialin and Sang Baum Kang (2015). “Co-Simulation of Risk Factors in Power Markets”. In: Available at SSRN 2614664. https://doi.org/10.2139/ssrn.2614664

[31] Zhou, Zhi, Wai Kin Victor Chan, and Joe H Chow (2007). "Agent based simulation of electricity markets: a survey of tools". In: Artificial Intelligence Review 28.4, pp. 305–342. https://doi.org/10.1007/s10462-009-9105-x

[32] http://getbootstrap.com/

[33] http://nginx.org

[34] https://laravel.com/

[35] https://www.mysql.com/