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Multi-Energy Retail Market Simulation with Autonomous Intelligent Agents

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Abstract

Electricity, natural gas, and heat are essential energy sources to our urban societies, and the industries that supply these energies have a strong influence on the progress of our societies. Recent developments in these industries, restructuring process and technological advance in the energy conversion sector, force the industries being studied to converge into a large multiple-energy industry in which profit-oriented market players from the industries vie to sell their products to residential, commercial, and industrial consumers. Understanding the behavior of the competitive multiple-energy market is vital for both policy makers who shape the structure of the market and market players who actively participate in the daily operation of the market.

This dissertation offers a methodology that utilizes agent-based simulation to study the behavior of a multi-energy retail market. The characteristics of agent-based simulation – simplicity, flexibility and decomposability – have allowed the market to transform into a simulation platform that is formed by loosely interconnected autonomous market actors and to develop the emerging behaviors from simple interaction among the market actors. Machine learning ability of the complex adaptive market actors has been processed by evolutionary particle swarm optimization after a comparison analysis was successfully performed among several competing algorithms, namely genetic algorithms, particle swarm optimization, and evolutionary particle swarm optimization. An artificial neural network with back propagation method has been used for improving forecasting ability of some complex market actors.

Using the multi-energy retail market simulation platform, three test studies has been performed to determine the followings: the competency of the simulation platform, the value of using a suitable programming approach to a specific problem, the optimization quality of several selected algorithms, and the role of a particular market actor in the market. The results from these studies clearly indicate that the multi-energy retail market simulation platform has enough potential to be used as a test bed in learning the behavior of a multiple-energy retail market.

Resumo

Electricidade, gás natural e calor são fontes de energias essenciais às nossas sociedades urbanas, e as indústrias que utilizam essas energias têm uma forte influência no progresso das nossas sociedades. Os desenvolvimentos mais recentes, nomeadamente o processo de reestruturação e o avanço tecnológico no sector da conversão energética, estão a compelir as indústrias a convergir para organização de empresas multi-energia de grande dimensão, as quais, sendo orientadas ao lucro, procurar ganhar vantagens concorrenciais no mercado energético, competindo pela venda dos seus produtos aos consumidores residenciais, comerciais e industriais. A compreensão do funcionamento deste mercado multi-energético é vital tanto para o estabelecimento de legislação específica para o sector que molda a estrutura do mercado, como para os próprios actores deste mercado.

Esta dissertação propõe uma metodologia que utiliza simulação baseada em agentes autónomos para estudar o mercado de retalho multi-energético. As características dos agentes – simplicidade, flexibilidade e compartimentação – permitiram obter uma representação do mercado através duma plataforma formada por actores de mercado autónomos interconectados, e inferir os comportamentos emergentes a partir das interacções simples entre os diversos actores. As capacidades de aprendizagem automática adaptativa foram processadas através de algoritmos de optimização evolucionária baseada em enxames de partículas. Também são utilizadas redes neuronais para previsão do comportamento complexo de alguns actores de mercado.

Com base na plataforma implementada para simulação do mercado multi-energético, foram desenvolvidos três estudos para determinação do seguinte: proficiência da plataforma de simulação utilizada, competência da abordagem de programação para um problema específico, qualidade dos resultados de diferentes algoritmos de optimização, e análise do papel do regulador no mercado. Os resultados obtidos nesta dissertação indicam claramente que a plataforma de simulação desenvolvida tem potencial para ser usada como base de estudo do comportamento do mercado multi-energético de retalho.

Résumé

L'électricité, gaz naturel, et chaleur sont des sources de l'énergie essentielles à nos sociétés urbaines, et les industries qui fournissent ces énergies ont une influence forte sur le progrès de nos sociétés. Développements récents dans ces industries, processus de restructuration et avance technologique dans le secteur de la conversion d'énergie, forcez les industries qui sont étudiées pour converger dans une grande industrie d'énergie multiple dans laquelle les joueurs de marché à but lucratif des industries rivalisent pour vendre leurs produits à résidentiel, commercial, et consommateurs industriels. Comprendre le comportement du marché d'énergie multiple compétitif est vital pour les deux faiseurs de la politique qui façonnent la structure du marché et joueurs de marché qui activement participent à l'opération journalière du marché.

Cette dissertation offre une méthodologie qui utilise la simulation agent-basée pour étudier le comportement d'un marché de la vente au détail multi-d'énergie. Les caractéristiques de simulation agent-basée simplicité, flexibilité et decomposability - a permis au marché de transformer dans une plateforme de simulation qui est formée par les acteurs de marché autonomes vaguement interconnectés et développer les nouveaux comportements d'interaction simple parmi les acteurs de marché. La capacité de l'apprentissage automatique des acteurs de marché adaptatifs complexes a été traitée par l'optimisation de l'essaim de la particule évolutionnaire après qu'une analyse de la comparaison ait été exécutée avec succès parmi plusieurs algorithmes en concurrence, à savoir algorithmes génétiques, optimisation de la particule swarm, et optimisation de la particule évolutionnaire swarm. Un réseau artificiel neuronal avec en arrière méthode de la propagation a été utilisé pour capacité de la prévision en amélioration de quelques acteurs de marché complexes.

Utiliser la plateforme de la simulation du marché de la vente au détail multi-d'énergie, trois études de l'épreuve ont été exécutées pour déterminer le followings: la compétence de la plate-forme de la simulation, la valeur d'utiliser une approche de la programmation convenable à un problème spécifique, la qualité de l'optimisation de plusieurs algorithmes sélectionnés, et le rôle d'un acteur de marché particulier dans le marché. Les résultats de ces études indiquent clairement que la plateforme de la simulation du marché de la vente au détail multi-d'énergie a assez potentiel pour être utilisé comme un banc de test dans apprendre le comportement d'un marché de la vente au détail multiple d'énergie.

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1. Introduction

1.1 Background

During recent decades, utilities in electricity, natural gas, and district heating industries have experienced a series of organizational changes due to the application of restructuring process in these industries. The main objective of restructuring process in these energy industries has been to improve the efficiency of these economies. Competition, a major driving force behind every competitive market, has been introduced to every area in the industries except the areas where their monopolistic nature is unbreakable, such as in energy transportation networks.

As a result of introducing competition into the industries, every market player in non-monopolistic areas has been given more freedom in order to promote healthy competition. Energy suppliers are now able to market their products freely, and energy consumers are no longer tied to local energy distributors. Since consumers have been given more freedom in choosing energy providers, the main reason of an energy consumer attaching to an energy provider has dramatically shifted from “having no other option” to “economically motivated choice”.

Recent technological advances in energy conversion area have also increased the options available to consumers regarding energy providers. With the progress of technology in energy conversion equipments such as micro-turbine, heat pump, and fuel cell, producing one type of energy from another has been more economical and easier than ever. The consumers’ consumption of one energy type now highly depends on the economical attractiveness of that energy as the consumers have alternative measures to fulfill their energy consumption with other competing energy types.

These dramatic changes in the characteristics of the consumers lead to the conclusion that market structures designed for trading one type of energy is no longer appropriate to be applied in energy markets, especially in the retail area where retail consumers generally have simultaneous access to several energy providers and possess in-house energy conversion equipments. With the help of ever-improving energy conversion devices and higher levels of freedom resulting from the restructuring process, retail consumers can now minimize their energy consumption cost by consuming optimally from different energy types according to the economical hierarchy of competing sources. The preferences of consumers now determine the demand for a particular energy type in this new market structure.

Taking the above information into consideration, it is obvious that one is witnessing the birth of an enlarged competitive energy market, with several energy forms competing one another, and a flexible composite demand served by conversion technologies. The distinctive characteristic of this enlarged multi-energy market is the possibility of having competing parallel infrastructures in the territory, as opposed to the isolated version of one energy market.

Understanding the behavior of the open multi-energy market is vital for both policy makers who shape the structure of the market and market players who are actively involved in daily operation of the market. In order to design the market to be efficient, fair, and stable, the policy makers need to study the consequences of every market rule applying to the market in advance. Similarly, capturing the nature of the market is the basic requirement for the market players to effectively develop competitive marketing strategies and to survive in this fittest survival contest market structure. Studying the behavior of the market through a computerized market simulation is one of the best ways to capture the nature of the rapidly evolving competitive energy market in its early stage.

Since marketing concepts have been shifting in energy industries, traditional computerized tools used in analyzing, optimizing and controlling an energy system would no longer be as effective as before. These traditional approaches, which generally adopt an over-simplified structure to obtain a manageable and controllable mathematical system and usually follow monopolistic rules, could not provide sufficient ability to study the complexity and dynamic nature of the competitive multiple-energy market and micro interactions among its market players.

Developing a tool that can capture the full complexity of a multi-energy market is a very challenging task. Fortunately, agent-based simulation, which is widely seen as the bottom-up study of a decentralized system whose global behavior arises from the local interaction of autonomous adaptive agents, has great potential to be an effective approach for this particular problem since competitive energy markets has been considered as complex adaptive systems consisting of numbers of adaptive actors involved in parallel and distributed local interactions. This dissertation proposes an agent-based simulation methodology for studying the behavior of a retail market that trades multiple types of energies, namely electricity, natural gas and heat.

1.2 The Objectives and Contributions of the Dissertation

The main objective of this dissertation is to develop a simulation platform that can effectively represent the level of complexity seen in a real-life competitive market for a multi-energy retail market using distributed computing architecture and to study the complex and dynamic behavior of the market from the platform. In order to attain this objective, the following sectional objectives were stated and fulfilled progressively:

- Develop main principles for the market participants of the simulation platform. The aim of this section is to assign distinct objectives to each market player according to the behavior of the market player observed in real-life energy markets.
- Model the market participants mathematically depending on their principles and objectives. After the main objectives of the market participants have been clearly defined, this section intends to develop internal models for the market participants, which is intentionally designed to pursue the goals of the market participants, using analytical approaches.
- Introduce an agent-based simulation approach to the market participants. When the internal models of the market participants have been properly developed, the next step is to introduce the agent-based simulation approach to these goal-oriented market participants. The agent-based simulation transforms the market participants into complex adaptive systems and introduces local interactions among these systems.
- Determine an effective distributed computing approach for the platform. Since the structural design of local interactions among the market participants has a distinct effect on the computational performance of the platform, this section determines a suitable design for the interactions required by this particular problem.
- Evolve designated market participants. Market participants having complex objectives and surrounded by a complex environment require a higher level of computational intelligence. Evolving them along with the evolution of the platform is essential for the survival of these market participants. This section explores the possibility of evolving complex market participants using evolutionary computation and neural networks. It is suggested that evolutionary computation approach can be used for formulating effective strategies while neural networks can be applied for foreseeing the actions of competitors.

- Study the emerging behavior that arises from the platform. This section analyzes the results from the platform and specifies the nature of behavior. Based on the analysis, it can be stated that the suggested simulation platform develops the emerging behavior, similar to the behavior shown in a real-life competitive market.

There are not many similar approaches, to author knowledge, attempting to study the behavior of a multi-energy retail market. Therefore, the need of research in this field is urgent. This dissertation proposes an innovative simulation platform to study the behavior of a multi-energy retail market in advance, and use the knowledge obtained from those studies in real-world problems. Although this simulation platform introduces pioneering approaches in the study of the multi-energy retail market, it does not present itself as a market simulation platform for industrial use. The main idea of this dissertation is simply to state that developing a fully comprehensive methodology for studying complex multi-energy retail markets is now possible and to show one such implementation.

1.3 The Organization of the Dissertation

Electricity, natural gas, and district heating industries are considered in this study due to their essential status in urban societies as well as current phenomenon in these industries such as industry boundary shifting with technological developments, company boundary shifting as cross-sector mergers become possible with deregulation, and regulatory boundaries shifting. The dissertation is organized as following:

- **Chapter 2** provides a broad theoretical background of the suggested energy industries. In this chapter, the organization and market structure of each suggested energy industry is broadly discussed. This chapter also firmly establishes the facts that contribute the birth of an enlarged multi-energy market. Moreover, computational mechanisms applied to utilities as well as markets in the suggested energy industries are thoroughly reviewed in this chapter.
- **Chapter 3** presents the background knowledge of computational mainstream technologies applied in this dissertation: agent-based simulation, evolutionary computation, and other supporting approaches. This chapter also provides the

critical review of application of agent-based simulation to competitive markets and evolutionary computation to agent learning.

- **Chapter 4** provides the detailed description of suggested simulation platform. The analytical formulation of the internal model of each agent is extensively explained in this chapter. The chapter also introduces new, innovative concepts for the behaviors of consumers and energy retailers.
- **Chapter 5** offers a glance on the relationship between programming designs and computation efficiency. Several programming approaches, namely sequential programming, concurrent programming, and parallel programming, are considered in this design-efficiency relationship study, and the advantages and limitations of each approach are discussed. The results from the sample scenarios used in the programming design comparison study are further discussed in this chapter to highlight the behaviors of the internal models of the market participants.
- **Chapter 6** concentrates on the evolution of complex market participants. This chapter proposes a methodology for evolving a complex market participant with evolutionary computation, neural networks, and computer simulation approach. Detailed comparison of the performance of selected algorithms, namely genetic algorithms, particle swarm optimization, and evolutionary particle swarm optimization, is also presented in this chapter.
- **Chapter 7** discusses a case study that establishes the role of a regulator in a competitive multi-energy retail market. The results from the scenarios representing an immature open energy market, a mature open energy market, and a transitional energy market are thoroughly analyzed in this study, and the final findings support the participation of the regulators in competitive energy markets.
- **Chapter 8** provides all the relevant conclusions from the dissertation and suggestions for future work.

1.4 References and Curriculums

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2. The Emergence of Multiple-Energy Industries

Abstract

Electricity, natural gas, and heat are essential energy sources to our urban societies, and the industries supplying those energies have strong influence on the progressive development of our societies. Better understanding of these industries is necessary in order to manage them properly for the benefit of the societies. Therefore, the overviews of the suggested industries are broadly discussed in this chapter first. Afterward, how external influences – restructuring process, and technological advance in energy conversion sector – force the considered industries to converge into a larger multi-energy industry in which market players from the industries vie to sell their products to residential, commercial, and industrial energy users are explained thoroughly. The emergence of wholesale and retail markets in the multi-energy industry is established, and the broad definitions and functions are assigned to market players involved in the multiple-energy market based on their characteristics seen in the single-energy industries. How computer-based programs may have helped the understanding of the behavior of energy markets and the functions of the market players in the single-energy industries are also reviewed.

2.1 Introduction

Energy is a resource that improves the quality of our lives immensely. Using the right machines and tools, energy can easily send us from one place to another. It can also provide us heat, cooling, and light to shield ourselves from nature's extreme conditions. Moreover, energy consuming machines used in labor-intensive jobs increase our productivity, and energy consuming entertainment devices bring joy to our daily lives.

At least ten distinct types of primary energy sources exist on earth: coal, oil, natural gas, nuclear, geothermal, biological/chemical, hydroelectric, wind, wave/tidal and solar energy [1]. Among these primary energy sources, fossil and nuclear fuels are not renewable and have fundamentally limited availability. Many energy types that accompany our daily life such as electricity and heat are further produced from these primary energy sources

The development of energy industries began in the middle of the eighteenth century with the Industrial Revolution. A steadily increasing usage of energy in industry, commerce, agriculture, transportation, and residential area were noticed since then, and this trend had contributed to a steady increase in productivity. Two and a half centuries later, human beings are now prodigious users of energy compared to other species, using ten to a hundred times as much as is needed for biological survival [2].

Among many energies needed in a modern society, electricity, natural gas, and heat are essential energy sources to modern day stationary environments such as residential housing, business buildings and industrial zones [3],[4]. These essential energy sources play an important role in further development of human race, and the efficiency and organizational structure of the industries supplying them will surely shape the well-being of our societies.

This chapter provides a broad theoretical background of the energy industries being considered in this study and highlights the possibility of a multiple-energy market emerging from these industries. The functions and market structure of electricity, natural gas, and district heating industries are presented in section 2.2, section 2.3, and section 2.4 respectively. Driving forces behind the emergence of a multiple-energy market is further discussed in section 2.5 along with the market structure of the multiple energy market and its market actors. Finally, section 2.6 provides several conclusions regarding the energy industries being studied.

2.2 The Overview of an Electricity Industry

Electricity is a unique commodity. It is produced by converting some other form of energy, mainly heat or mechanical motion, into electric power. Electricity has two advantages over all other forms of energy: flexibility and controllability [5]. It can be transformed into heat, mechanical motion, electrical activity for electronic equipments, or light easily and economically. It can also be turned on and off in a millionth of a second, and can be easily tracked from a small amount to the quantities that can power entire city. Nevertheless, unique physical properties of electricity – traveling at the speed of light and being unable to store economically – limit the usability of electricity to a level in which every quantity produced must be consumed by all customers within a tenth of a second.

Electricity industries are the largest and the most complex systems ever constructed on earth. Countless component parts are involved in building a power system, which takes responsibility to produce, transport and distribute electricity to end-users spreading over an area of the size of a country or more. The capital involvement in an electricity industry is staggering; an average of 250 billion dollars of yearly revenue is collected in United States alone [6].

2.2.1 The Organization of an Electricity Industry

The organization of an electricity industry is related to its market structure. For the electricity industry with vertically integrated structure, all sectors in the industry are treated as an integrated system. Centralized approach on planning, operation, and control are norm in the system, and consumers are generally charged with a price that is the summation of all the costs occurred during generation, transmission and distribution of electricity.

With the progress of restructuring process in the electricity industry, certain sectors of the electricity industry are inevitably separated in order to promote the competition in the industry. Although functions in natural monopolistic entities, namely transmission and distribution networks, do not deviate much from the traditional approach, the generation sector is separated into small generation utilities so that higher competition will emerge in the sector [7]. Retailing is separated from the distribution networks to accommodate the competition in retail level, and power exchange or power pool is introduced at wholesale level to further intensify the competition.

Regardless of the market structure, a typical electricity industry can be represented with following four sectors:

Generation Sector: Electricity can be commercially produced in numerous power generation plants using different technologies with different resources; however, they all share the same fundamental producing electricity with a magnetic field developed by turning wires with the motive force acting against a fan or turbine. Wide variety of energy sources are utilized in producing electricity; however, coal, oil, natural gas, water (hydro power) and uranium (nuclear power) are main energy sources. The cost incurred in the generation sector accounts for about 35% to 50% of the final cost of electricity delivered to end-users [8]. The generation cost is related to the efficiency of generating plants and their fuel mix since generating plants with different efficiency produce different levels of output, and various fuels have different prices. The efficiency of generating plants with traditional technology typically varies from about 18 percent to 36 percent depending on the size and technology of the plants; however, the efficiency of the plants can be dramatically increased to 60 percent with combined cycle gas turbines.

Transmission Sector: The transmission system is a large interconnected network of three-phase lines, transporting electricity in bulk from generation plants to various locations where it can be sold to local distribution companies and other utilities. Most part of the transmission system is generally laid out in a meshed network for reasons of reliability and stability of system operation. Consequently, much of the cost in the transmission system comes from maintaining the system in stable conditions, instead of moving electricity. The cost of transmission represents about 5% to 15% of the final cost of electricity [8]. The voltage level in the transmission system is essentially high, in the range of 34.5 KV to 765 KV or more, in order to effectively reduce the losses occurred during the transmission of electricity.

Distribution Sector: The main function of a distribution network is to transfer electricity from the transmission system to individual business and homeowners. Lines and transformers are the backbones of the distribution network. The distribution cost accounts for about 30% to 50% of the final cost of the electricity [8]. Unlike transmission networks, distribution networks have lower voltage level, and are generally designed to be in radial shape with only one downstream path, built to be as reliable as possible, to each consumer or a group of consumers in order to lower the construction cost of the network.

System Operation Sector: The system operation in an electricity industry is a coordinated effort that continuously matches the production of generation plants with the consumption of end-users to maintain a healthy transmission system [8]. Unique properties of electricity – traveling in speed of light and being unable to store economically – force the electricity industry to be operated with very little margin in timing and quantity matching between production and consumption. Whenever consumption has changed, the system operator must make sure that there are some changing in the generation side to compensate it. The system operator's job includes real-time dispatching, which is to run generators in economically optimal order as well as controlling the system in a reliable way that no transmission lines are overloaded.

2.2.2 The Characteristics of Electricity Markets

Under traditional monopolistic market structure, electric utilities directly offered electricity to end-users with regulated price. As restructuring process has transformed the structure of the electricity industry be more competitive, wholesale and retail markets have been created as a way to intensify the competition at every level in the industry.

Bilateral Transactions: The bilateral transactions are long-term financial agreements between sellers and buyers to trade electricity at certain price. Under the traditional structure, the transitions are usually bilateral between individual generators and the utility as well as between the utility and individual consumers. However, the individual generators can make direct transitions with consumers, trading entities, or a pool under competitive market structure. A typical bilateral transaction can be classified according to its characteristics as firm or non-firm, short or long-term.

Wholesale Market: Wholesale is defined as a sale made by a producer to parties other than end-users [8]. In an electricity wholesale market, electricity generators and buyers – retailers, load aggregators and consumers whose consumption is large enough to participate in the wholesale market – bid to buy and sell electricity through a central clearing institution. A power exchange or power pool is usually associated with the electricity wholesale market, and it is often associated with an independent system operator. Regarding trading electricity, there are two auction methods widely used in electricity wholesale markets; locational-marginal-price and pay-as-bid approach. In an electricity wholesale market using the pay-as-bid method, electricity selling generators receive exactly what they bid if the bids have been accepted. Generators in a market with a locational-marginal-price scheme are paid by a specific market-clearing price instead of their bidding prices [9].

Retail Market: Retail refers to the sale to end-users. In an electricity retail market, retailers buy electricity from an electricity wholesale market and sell it through bilateral contracts directly to end-use consumers whose consumption is too small to take part in wholesale business. Generators, distribution companies and load aggregators usually compete for the role of the retailers. The functions of the retailers generally consist of a series of commercial functions, procuring, pricing, and selling electricity, and also metering its use, billing for it and collecting payment [8].

2.3 The Overview of a Natural Gas Industry

Natural gas is regarded as a premium fuel. Being a non-toxic fuel with a remarkably clean and controllable flame while burning, natural gas offers considerable economical and environmental benefits to industrial, commercial and residential consumers [10]. Raw natural gas produced by digging gas wells consists of methane, natural gas liquid, water, carbon dioxide, nitrogen, and hydrocarbons. The quality of raw natural gas is then standardized by a process that decreases the share of hydrocarbons and other unwanted components before delivery to end-use consumers.

2.3.1 The Organization of a Natural Gas Industry

Like electricity industries, natural gas industries began with a monopolistic market structure due to natural monopoly in pipeline transportation and distribution networks, and the scale of economy in production sector. However, many natural gas industries have recently been liberalized in order to improve the efficiency of the industries and to reduce the overall cost of natural gas.

Whatever the market structure, the process of delivering natural gas from gas wellheads to end-users in a typical natural gas industry can be divided into five segments: natural gas production, pipeline transportation, storage, distribution, and system operation.

Natural Gas Production Sector: Natural gas production consists of a set of functions – exploration, drilling, and gathering – in order to produce and deliver the natural gas to the storages or pipeline transportation hubs [11]. It is a multiple-product economy with substantially high start-up fixed cost. In general, heavily investing in the acquisition of drilling rights and technology is the beginning step of the natural gas production, and exploration and actual drilling follow. Then, the gathering process collects natural gas produced by individual wellheads and delivers it to a location where it can be injected into a pipeline or storage facility.

Pipeline Transportation Sector: The natural gas transportation network delivers natural gas from wellheads to local distribution companies or directly to large consumers using high-pressure pipeline network. It offers several services including delivering natural gas with different levels of calorific value, and providing different input and output pressures at different times and locations in the pipeline. The movement of natural gas is usually driven by pressure difference between a gas reservoir and a pipeline entrance. It can travel with average speed of 40 km/h and can be arranged by using high-pressure compressors. Although constructing a natural gas transportation segment is expensive due to high fixed costs in building the pipeline, operating costs are relatively low as little cost is incurred during moving natural gas around the pipeline. In general, natural gas transportation charges make up more than 40% of residential gas bill and accounts for between a third and one-quarter of industrial and commercial bills [12].

Distribution Sector: Natural gas distribution networks provide the final link in natural gas transportation chain, delivering natural gas from city gate stations, storage facilities, and other natural gas supply sources to local industrial, commercial, and residential consumers. The distribution networks generally operate at lower pressure than pipeline transportation network and offer different pressure services to different customers by adjusting associated pressure regulators.

Storage Sector: Storage facilities are usually established near load centers. They are utilized for maintaining a steady flow through pipelines when contingencies has occurred and for storing natural gas during off-peak periods and supplying it back to consumers in peak hours to mitigate the effect of peak demand. The availability of natural gas from the storage facilities pushes peak prices toward competitive level and relieves congestion in pipelines. As competitive market concept is now applicable to natural gas industries, the natural gas storage facilities can be commercially used for storing natural gas when the price is low in off-peak periods, and then resell this natural gas in the local market with higher price during peak hours.

Pipeline Operation Sector: The natural gas pipeline operation involves a complex decision making process. It is performed by dispatchers who make operating decisions to balance supply and demand at all times and to operate the network reliably and cost effectively. The dispatchers' critical decisions are generally associated with when to turn on/off which compressor. It is considered to turn on compressors in order to increase the pressure in the pipeline system if the consumption of natural gas increases and vice versa [13]. These decisions have significant impact on the operation of the natural gas pipeline system.

2.3.2 The Characteristics of Natural Gas Markets

Open access and unbundling of pipeline transportation in natural gas industries have led to the creation of two main business areas where natural gas and transportation are traded separately [11]. Market players in a natural gas industry trade transportation services to ship natural gas through pipelines in transportation markets in addition to wholesale and retail markets facilitating the trading of the natural gas as a commodity.

Transportation Market: In a transportation market, natural gas transportation services such as pipeline capacity and natural gas shipments for delivery of natural gas to a desired location are sold by pipeline transportation companies to other market players in the form of transportation contracts. The transportation contracts can be either firm or interruptible, depending on the reliability of the services. A firm transportation contract gives its holder the right to transport a specific amount of natural gas between injection and withdrawal point over the whole life of the contract; however, an interruptible transportation contract offers the contract holder the limited right to ship a specified volume of natural gas within a certain period under the arrangement of the pipeline company according to the availability of pipeline capacity.

Wholesale Market: Purchase of natural gas for further resale takes place in a natural gas wholesale market. Market actors involved in the natural gas wholesale market include producers, pipeline transportations, local distribution companies and traders.

Retail Market: The natural gas retail market is a place where retail transactions occurred among natural gas suppliers and end-users. Retail competition takes place among natural gas providers who compete against one another by offering attractive natural gas supply contracts to end users. It is desired to have high competition among the natural gas suppliers in the natural gas retail market since it may push lower the retail natural gas price to the sum of the wholesale natural gas price plus distribution charge.

2.4 The Overview of an District Heating Industry

A district heating system is a centralized heat production and distribution system for an urban area. In the district heating system, heat is centrally produced in precise locations and distributed in the form of hot water or steam to consumers located in different buildings. Heat is primarily used for heating buildings and domestic hot water, and for industrial purposes such as process heat. Many types of consumers require heat. Residential consumers are the main user of heat with consuming about 60% of total heat consumption while consumption share of commercial and industrial consumers stands at about 15% each [14].

Development of the industrial-scale heating business started in the early of 20^{th} century with the provision of heat to a number of buildings from one boiler through a suitable distribution medium, which was steam in the United States and hot water in Europe. Today, the number of district heating users in Europe is over 100 million of which more than 50% is in Russia. A further 26% is concentrated in the neighboring Eastern European countries while consumers from Western Europe account for 20% [15]. About 250 urban steam district heating systems are in operation in the United States serving a broad base of residential, commercial and industrial consumers. District heating systems have also been installed more recently in Japan, China, and South Korea.

2.4.1 The Organization of a District Heating Industry

District heating systems are said to be more integrated than other energy networks in order to provide optimal efficiency and performance [16]. Typical sectors of a district heating systems include production, transmission and distribution. The distributed heating systems generally own heat-producing plants and deliver heat to end-users at a price, which includes all the costs associated with delivering heat.

Production Sector: Heat having the form of hot water or steam is first produced in heat production plants. Then, it is transferred to end-users at the speed of approximately 1-3 m/s through transportation pipes for being used in production of hot tap water or household heating [17]. Energy resources used in production of heat include natural gas, coal, oil, wood, waste incineration, geothermal and many more; however, natural gas and coal are commonly used, covering more than 50% of total market share [18].

Transmission Sector: The heat transmission pipelines connect distributed local distribution networks altogether, forming large interconnected networks in large urban areas. A transmission network in a heat industry performs the task of transporting heat from production plants to local distribution networks. The economically viable distance for transporting heat in most district heating systems is limited to 10 to 15 km; however, a few systems are able to cost-effectively transport heat to 50 km due to their very efficient transmission and distribution pipelines [3].

Distribution Sector: In general, heat distribution companies are either municipal utilities or consumer co-operatives. These local heat distributors receive heat from production plants or the transmission network and deliver it to end-use consumers.

System Operation Sector: District heating management is generally a centralized process. The system operation in a district heating system basically has two variables to balance, supply temperature and flow, in order to manage sufficient supply for the demand of heat consumers. Since higher supply temperature causes increased heat lost during distribution as well as reduced production capacity in heat production facilities, it is a delicate task for a district heating dispatcher to operate a district heating system economically.

2.4.2 The Characteristics of District Heating Markets

The district heating systems in some large urban regions are vertically separated. An urban district heating grid with third party access competition among many suppliers is rarely seen; however, there are examples of competition among heat producers using a variety of primary fuels and technologies.

Wholesale Market: In a disintegrated district heating industry, many heat producers and local heat distribution companies participate in a wholesale heat market for trading heat. In general, transmission companies owned by the municipalities purchase heat from heat producers according to their bidding prices through heat exchange market and sell the heat back to local heat distribution utilities [3]. The heat price, which is paid to all heat producers, is calculated on the basis of supply and demand.

Retail Market: Heat distribution companies usually resell heat that they have bought from a wholesale heat market to end-use consumers in a retail market.

2.5 The Emerging Multi-Energy Industry

The providers of essential energy sources for modern urban societies – electricity, natural gas, and district heating industries – generally share similarities in the following traits:

- Organizational structure
- Complexity in the operation of networks
- Effect of the scale of economies
- End users

Each energy industry in these three industries is generally organized as a system that is formed with the following three distinct sectors:

- Generation – the sector that produces energy
- Transmission – the sector that transports a particular energy from generation sectors to local distribution sectors
- Distribution – the sector that delivers a particular energy from generation or transmission sectors to end-users

Moreover, the operations and controls of these industries are extremely complex due to the fact that transmission sectors in these systems are usually built as networks of wires or pipelines. Furthermore, the scale of economies plays crucial role in the economical performance of these industries as each system usually covers a whole city or even an entire country. More importantly, all of three industries supply respective energies to the same end-users – residential, commercial, and industrial consumers.

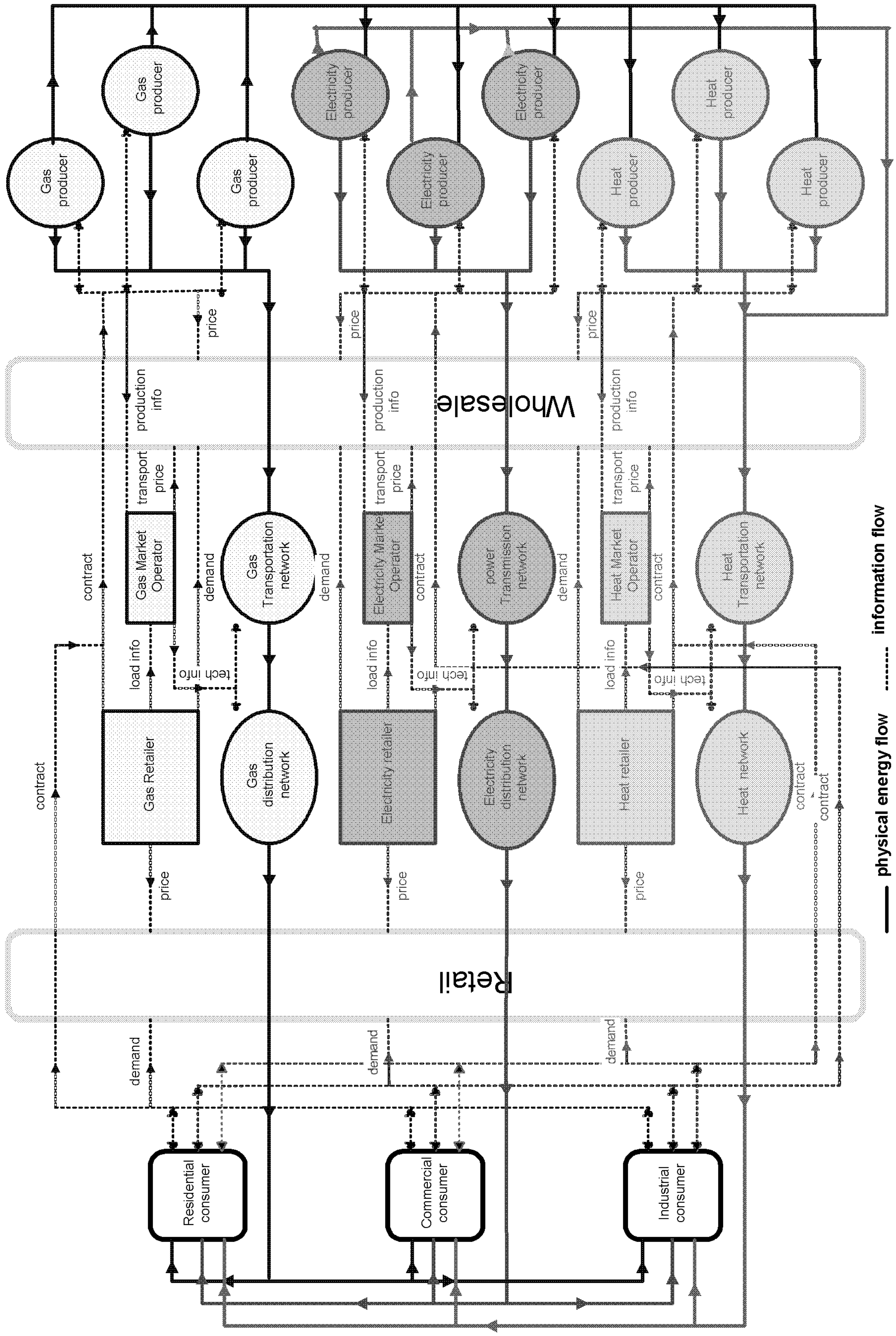

Fig. 2.1. Simplified structure of electricity, natural gas and district heating industries

The simplified organization of electricity, natural gas and district heating industries operating in the same territory is shown in Fig. 2.1. Thick lines indicate the physical energy flowing from supply sides to end-users through transportation networks in these industries while thin dotted lines provide the information and business transactions flow among market participants in the industries. The resemblance of these industries is clearly noticeable in this figure.

Until recently, utilities in these industries have been operating either as public utilities or regulated investor-owned utilities. These utilities were monopolistic and organized as vertically integrated systems. They offered respective energies to end-users with the prices set by government-appointed independent regulators and took the responsibility to ensure adequate supply for the demand of all users in exchange for receiving reasonable rate of return on their services.

Why were these industries originally organized as vertically integrated systems? One strong candidate answer for this question lies in the monopolistic nature in their distribution and transmission networks since building overlapping networks are undesirable due to cost, space and appearance constraints [3]. The nature of the scale of economies in the industries and the possibility of lowering unit production cost with bigger production plants may also be included in the list of the answers [8]. Improving efficiency of these industries and reducing technical difficulties by operating the industries with central coordination are other possible answers.

The structure of these industries was generally evolved along with the assumption that each industry was a closed system where production, transmission, distribution, and consumption were internally intertwined together. The consumption changing in the industry was considered to be directly connected to the physical and economic conditions of the region that the industry existed, and the development of the production, transmission, and distribution sectors was totally evolved around the condition of the consumption. Even if the energy industries being considered in this study hypothetically existed together in the same region, these industries might well be considered as unrelated systems to one another due to the closed system assumption. The effect of the behavior of consumers was also largely discounted in these industries; however, neglecting the behavior of the consumers did not prove wrong as the consumers had no other option than to accept the offer from monopolistic utilities in order to consume energy. Although the consumption sectors of these industries have been integrated in real-world, little or no attention was paid on this fact.

In recent years, unreasonable rate structures and growing public concern about current practices failing to develop proper cost-minimizing incentives for improving the efficiency of energy industries have led to the reviewing of regulated structure in these industries. One of the widely used regulations in these industries, the cost-of-service regulation, has also done more damage than good for the industries lately since the idea that the benefit from any innovation would go directly to consumers has indirectly discouraged utilities to adopt innovative approaches [19]. As a result, the effort to restructure energy industries into more efficient industries in which energy prices are connected to true marginal costs has been seen in these industries throughout the world. The main objectives of the restructuring process in these industries are to reduce energy prices and to provide strong cost-minimization incentives for transforming these industries to be efficient as possible. The best way to achieve above objectives together is to establish a common energy market with perfect competition among and within these industries.

The transformation of an energy industry from monopoly to competition has several names. One popular name is “deregulation”. It receives this name as the energy industry quits using practice where rules and regulations have been heavily used in order to make the industry work and switches to the practice where competition and its invisible hand do the work of what a regulatory body has done in vertically regulated structure, effectively ending the era of regulation [20]. However, others argue that the word “restructuring” is more compactable with the situation as the rules and regulations still exist in different form in the industry with competitive structure [21].

Regardless of names, the suggested industries have been recently reformed by opening energy markets, by introducing competition in supply and consumption sectors, by unbundling once integrated energy services, and by providing open access to transportation networks for the same reason; to reduce energy prices closed enough to marginal costs and to send strong signals for cost-minimizing innovation. Retail competition resulted from reformed in these industries also allows consumers to vote with their wallets about how they want their energy demand to be fulfilled. The consumers are finally given the right to change energy suppliers as they see fit, and they do so whenever they see economical advantage. Thus, consumer preference now has direct influence on the ratio of their energy consumption mix for the first time.

Recent technological advance in energy conversion sector has led the invention of efficient energy conversion devices, and widespread introduction of these devices has a profound effect on electricity, natural gas, and district heating industries. The introduction of new gas-fired combine heat and power (CHP) units not only have had impact on the electricity trade but also have affected on natural gas and heating business [22]. More importantly, economically efficient in-house energy conversion devices such as micro gas turbines, fuel cells, and heat pumps have provided end-users of these industries greater flexibility in selecting energy suppliers. With the help of the efficient in-house energy conversion devices, the consumers in these industries are no longer needed to attach to a specific supplier for their energy needs. They can simply buy one type of energy and fulfill the demand of other energy types with in-house energy conversion devices if they see it as beneficial for them.

Although physical properties and operational procedures in these industries are different, resemblance in their organizational structure, similarity in their functions, and operation in close proximity make them compete with one another somehow. The appearance of cross-industry competition between natural gas and district heating industry has been noticed when the license to supply energy to a region is given only to suppliers from one type of energy [3]. Technological revolution in energy conversion sector has also intensified the cross-industry competition further in supply and consumption sectors.

Taking the above information into consideration, electricity, natural gas, and district heating industries are now converging into one large competitive energy industry in which companies having the same function in different energy industries now directly compete against one another for better profit and market share. With no doubt, the recent converging forces of restructuring, technological revolution, and similarity in organizational structure has contributed the birth of a multi-energy market where market players from electricity, natural gas, and district heating industries vie to sell their products to residential, commercial, and industrial energy users.

2.5.1 The Emergence of Multiple-energy Markets

In the multi-energy industry, individual energy markets from the suggested industries may converge into a larger energy market where energy companies from different industries trade multiple commodities together. Recent cross-industry mergers between companies from these industries support the collision of wholesale and retail markets from these industries. The development of wholesale and retail markets in the multi-energy industry and how computational tools have been used in energy markets are further described in following sections.

2.5.1.1 The Development of Wholesale Markets in the Multi-energy Industry

In a wholesale market under a single-energy industry, energy suppliers and wholesale buyers from the same industry trade the same type of commodity; however, a wholesale market in the multi-energy industry may have market players making transactions on trading multiple commodities simultaneously.

The energy suppliers who own combined heat and power plants are the perfect examples of cross-industry trading and the emergence of wholesale multi-energy markets. They have tendency to participate in natural gas markets for their resource requirement, and in electricity and district heating markets for marketing their products [3]. Moreover, greater interest on expanding business to rival industries has been expressed by utilities from the supply sector of natural gas and electricity industries after successful attempts on restructuring in these industries [23]. The recent trends on mergers between natural gas and electricity utilities, which are relatively new to energy business, have also redefined the position of these energy utilities into multi-energy utilities [24]. Therefore, it can be concluded that technology revolution and restructuring process in these industries effectively encourages the energy utilities to expand to new areas, and these new expansion will inevitably result to form multi-energy firms, which own multiple energy production plants. Shifting in the behavior of these energy utilities leads to the emergence of multi-energy wholesale markets.

2.5.1.2 Available Computational Tools for Wholesale Energy Markets

Studying the behavior of a wholesale energy market from a computerized model receives much attention nowadays. There are two main approaches used in studying the behavior of a wholesale energy market; a top-down equilibrium-oriented approach and a bottom-up agent-based simulation approach. Although computational methods used in studying the behavior of a single-energy wholesale market may not be directly applicable to the multi-energy wholesale market, it is worthwhile to follow their evolution, and to use that knowledge as a starting point in developing a methodology for studying the behavior of a multi-energy market.

Market equilibrium models have been widely used in developing generator competition behavior in wholesale electricity markets. These models have heavily relied on the approach of defining market equilibrium as a set of variables that simultaneously satisfy each market participant's net benefit maximization – prices, producer input and output decisions, transmission flows, and consumption – while clearing the market. Several types of strategic interactions, most of them being familiar concepts of game theory and only differ in the anticipation of each generating firm on the reaction of rival firms on its decisions, have been applied in modeling energy markets, and these models can be roughly divided into following sections:

- Bertrand game
- Cournot Strategy
- Supply Function Equilibrium
- Conjectured Supply Function
- Collusion, arbitrage and Stackelberg game

In a market model with Bertrand gaming approach, an electricity supplier takes a general assumption that other competing market players will not change their prices in response to his pricing [25]. The competition in the market with Bertrand game is extremely high, and the energy price can even fall to the marginal cost if no constraints on capacity or transmission costs are applied. However, when such constraints or costs exist, the energy price can rise above the marginal cost and even fluctuate without end [26].

A less intense form of competition is found in market models with Cournot competition, where an electricity supplier instead determines the quantity to generate or sell based on the assumption that its opponents will not alter their production quantities [27]. Cournot conjecture game concept is widely applied in modeling electricity markets due to its simplicity and the possibility that an electricity market involving long-term commitment to capacity may develop Cournot-type behavior in the long run even if its electricity suppliers compete on the price in short run [28, 29]. However, Cournot models' high sensitivity to demand elasticity sometimes leads to produce very high and unreliable prices in electricity markets with low demand elasticity.

The inability to represent power pool type auctions, in which power producers bid supply functions for their output, with the models of Cournot and Bertrand has led to consider supply function equilibrium (SEF) as an alternative approach in electricity market modeling [30]. The equilibriums from SEF models indicate the intermediate level of competition, lying between the Bertrand and Cournot results. However, the major drawbacks of SFE models, limited applicability to large networks and uncertainty in obtaining equilibrium, negate the potential of SEF in electricity market modeling [31]. When larger networks are considered, supply functions have to be degraded into linear functions with either fixed slope or intercept, and the model's ability to find the optimal strategy is dramatically decreased [32].

The market model with conjecture supply function (CSF) introduces the belief of generation firms concerning how total supply from rival firms will affect electricity price. The model can be viewed as the generalization of the Cournot model in which each generating company is allowed to conjecture that rival firms will adjust their supplies in response to price changes. It is also an approximation of a SEF model; however, unlike SFE models, the assumed and actual responses may differ in CSF model [33].

New marketing concepts are further introduced in order to understand the unique behavior of electricity markets. Electricity suppliers that follow the concepts of cooperative Nash bargaining game are used in studying the development of collusion behavior in wholesale electricity markets [34]. The impact of arbitraging on an imperfect bilateral electricity market in which electricity suppliers purchase scarce transmission services is determined by developing a model that employs arbitragers who eliminate the price difference between locations. The results from the model indicate that the price difference between different locations is effectively reduced with the arbitraging approach [35]. Meanwhile, the behavior of a unique electricity market formed with a group of different size of power producers developing a relationship of leaders and followers between large and small producers are studied by using Stackelberg model [36].

Another field intensely involved in modeling energy markets is agent-based computation. Scientists from the agent field argue that complex interactions and interdependencies among market participants from energy industries are much like those studied in game theory [37]; however, the strategies of these participants are often too complex to be conveniently modeled by standard game theoretic techniques [38]. Therefore, using agent-based computation to study complex systems is the good choice for modeling complex energy markets. A recent surge in the development of energy markets with agents has strongly supported the argument of agent scientists, and these agent-based market models have produced many interesting results.

One of the pioneering methodologies using agent-based technology to model wholesale electricity markets was developed by Dunn and Brown for comparing market prices and bidding strategies of individual generators under the different trading arrangements in England and Wales electricity market [39]. Using bottom-up modeling approach, they developed the electricity market with generating firms represented by computer generated autonomous adaptive agents and performed the detailed comparison study between the Pool's day-ahead market versus the bilateral short-term market.

North [40] later developed SMART II+ model to explore the infrastructure interdependencies between natural gas and electricity industry. The model included an integrated set of agents representing producers, consumers, transmission infrastructures of natural gas and electricity, and interconnections between the two infrastructures in the form of natural-gas fired electric generators. His investigation indicated that the rapid expansion of highly competitive natural-gas fired electrical generators contributed to the increase in market interdependency between natural gas and electricity markets. Moreover, this increase in market interdependence pits the electricity and natural gas markets against each other during simultaneous disruptions and drive up the prices for both commodities.

Veselka et al. [38] modeled the electric market complex adaptive system (EMCAS), a system-wide agent-based simulation platform, for studying the behavior of electric power markets. The EMCAS model was developed as an electronic laboratory that probes the possible effects of market rules and conditions by simulating the strategic behavior of market participants. The market participants, including generation companies, demand aggregators, consumers, and independent system operators, were transformed to autonomous agents in the EMCAS, and the success of these agents relied on its own decisions and actions as well as on the decisions and actions of other market participants. As the simulation progressed, the agents evolved their strategies on the basis of the success or failure of their previous actions.

Ragupathi and Das [41] presented a methodology for analyzing the gaming behavior of power suppliers in a wholesale electricity market using a novel simulation based multi-agent system with reinforcement learning algorithm. Their approach included two key elements: a stochastic game model for competitive bidding process among suppliers, and the system operator equipped with a unit commitment and optimal-power-flow program. The model was applied to study the behavior of a wholesale electricity market under perfect or imperfect competition with or without transmission congestion.

One noticeable outcome from the study was that market clearing prices were higher in the market with imperfect competition than perfect competition, indicating the existence of market power.

Xiong et al. [42] invented a market model using a multi-agent approach, in which each adaptive agent represents a generator who participates in a day-ahead auction market and develops bidding price based on Q-Learning algorithm, to compare two distinct market pricing rules; uniform pricing and pay-as-bid. The experimental results showed that the pay-as-bid auction indeed result in lower market prices and price volatility as expected.

2.5.1.3 The Development of Multi-energy Retail Markets

Generally, consumers from retail area have simultaneous access to multiple types of energy including electricity, natural gas and district heating in urban area. With the help of technological revolution and restructuring process in energy industries, the retail consumers are getting more and more control over their energy consumption mix. The consumers' preference for different energy sources now have influence on the energy consumption mix of the consumers, and their preference will eventually weigh on the convergence of single-energy retail markets from these industries into a large multi-energy retail market where load aggregators, retailers, and local distribution systems from different single-energy industries may vie to sell their commodities to end-use household, commercial, and industrial consumers. Along with the improvement in the level of freedom and conversion technology, the difference in physical properties of different energy sources turn out to be less of a hindrance for the retail consumers, and energy retailers from different energy industries may now have to battle one another for selling their commodities. The energy providers who can offer economically attractive package to the consumers will be the successful players regardless of what type of energy they offer in this multi-energy retail market.

To date, the studies on energy markets have primarily focused on wholesale market. Many methodologies have been developed in order to understand the behavior of a wholesale energy market; however, only a little attention has been paid on understanding the behavior of a retail energy market. To the author's knowledge, only one incomplete approach has been made to study the behavior of a retail electricity market recently [43].

2.5.2 Available Computational Tools for Market Actors

The emergence of the multi-energy markets from once highly regulated electricity, natural gas, and district heating industries is now fully established. The next step is to define participants most likely to be involved in trading multiple commodities in the multi-energy markets. Since the multi-energy markets are the outcome of the convergence of three single-energy markets, which have similar functions and organization, market participants defined for an electricity market [44] – energy producers, transmission companies, independent system operator (ISO), energy retailers, local distribution companies, consumers, and regulatory body – can be used for representing the market players of the multi-energy market. Although physical properties of these industries are different, similarity in the organization of these industries helps the market players sharing the similar function from these industries to be grouped together and assigned with a common market participant title associated with their overall function. The broader representation of the market participant titles is further discussed in following sections. Furthermore, the computer-based methods that help the functions of a particular market participant under a single-energy market scheme are reviewed under the respective market participant title.

Energy Producer: Market participants with this title are involved in producing particular types of energy and in making profit with selling those energies to wholesale buyers through a wholesale multi-energy market. Energy producers usually own one or more energy producing plants, and perform typical functions such as developing profit-maximizing marketing strategies and long-term planning on production expansion in order to maximize their profitability.

Many computational tools have been developed for solving problems that arise from routine functions of energy producers such as production expansion planning, which determines what type of production facility should be built and when its production will be available. In a power system, it is called generation expansion planning (GEP), which is generally defined as the planning process to determine what type of generation units should be constructed and when these generation units come on line over the long-term planning horizon while minimizing the total cost and maximizing the reliability over different types of constraints. Among many computation methods applied to solve GEP problems, linear programming (LP) method was the pioneer method [45]. Later, dynamic programming (DP) method outperformed earlier methods, including LP in solving GEP problems [46]. David and Zhao [47] later offered an improved method that integrates an expert system into a DP based GEP program. The long term GEP problem was effectively handled by Bender's decomposition method mixing with stochastic linear programming and dynamic programming [48]. Lately, Jia et al. [49] proposed an advance dynamic programming for solving GEP in deregulated market situation.

The artificial intelligent approaches have also been widely applied to GEP problems. Sasaki et al. [50] formulated the GEP problem as a 0-1 integer-programming problem and mapped it onto the modified Hopfield neural networks. Kannan et al. [51] offered evolutionary computation approaches to solve the GEP problem and proposed that evolutionary approach could find the best planning plan for the long term.

Transmission Company: This type of market participant performs the advanced expansion planning for expanding its network in a timely manner to accommodate new energy production facilities, to provide more secure and stable transmission services, and to increase revenue. This kind of network expansion planning is considered as a transmission planning in power systems. It can be defined as a planning process that takes some input information as a starting point and combines the information with different predefined transmission expansion options in order to provide one or more quasi-optimal transmission plans [52]. Several methods that have claimed to find the optimum solution for the transmission expansion problem include classical optimization techniques, heuristic methods, and artificial intelligence related approaches. As in other power system optimization problems, classical optimization techniques such as linear programming [53], dynamic programming [54], mixed-integer programming [55], and Benders decomposition [56] have been initially used in solving the transmission expansion problem.

One of the first heuristic approaches that tried to solve the transmission expansion problem was later proposed by Bennon et al. [57]. They developed a model that uses a common heuristic procedure to allocate the additional circuits using sensitivity analysis to remove overloads. Recently, Latorre et al. [58] invented a heuristic method that took advantage of the natural decomposition of the transmission expansion problem in operation and investment sub-problems. As expected, the artificial intelligence approaches have also been heavily involved in the transmission expansion problem. The list of the approaches includes expert systems [59], fuzzy set theory [60], simulated annealing [61], and genetic algorithms [62].

Independent System Operator: Independent system operator (ISO) is the entity that oversees the operation of a particular energy system, may provides system-wide information for the benefits of other parties, and possibly acts as a market clearing institution in a Pool type energy market. Running all energy production facilities in their optimal production levels, determining market clearing price for the energy market, and maintaining the energy system in secure, stable, and reliable state are a few functions that the ISO is required to perform. In order to do these functions in a timely manner, the ISO usually receives help from optimization programs such as economic load dispatching (ELD) and optimal power flow (OPF). The ISO may also perform load forecasting on the behalf of the system for the benefit of other market participants.

In order to operate an electric power system most economically while operating the system within its security limits, ELD programs help the ISO to determine optimal settings of generator units for predicted load demand over a certain period of time. An early ELD program applied linear programming [63]; however, the attention was later paid more to the Dantzig-Wolfe decomposition method, which resolved the problem into a master problem and several smaller linear programming sub problems [64]. Dynamic programming approach overtook the duty to solve the ELD problem from linear programming and Dantzig-Wolfe decomposition methods [65]. Since the time that the superiority of the artificial intelligent approaches over classical mathematical approaches in complex optimization problems has been noticed, a number of artificial intelligence techniques including evolutionary programming [66], genetic algorithms [67], and neural networks [68] have been widely used in solving the ELD problems.

Similarly, classical mathematical approaches were the first dominant methods in solving OPF problems in power system. Romano et al. [69] applied the Dantzig-Wolfe decomposition principle to the OPF problems. In a series of papers, Burchett et al. [70, 71] reported the formulation and implementation of a quasi-Newton approach and sequential quadratic programming for solving the OPF problems. Evolutionary algorithms later took the leading role in solving OPF problem [72]. An et al. [73] further extended the development of the OPF approach into natural gas system and proposed an interior-point based OPF program for operating an integrated electricity and natural gas network efficiently.

Computer-based methods have also been applied for the optimal operation of natural gas networks. Sun et al. [74] developed a fuzzy expert model for optimizing natural gas pipeline operation. Moreover, Nimmanonda et al. [75] proposed a simulation approach to study the behavior of a natural gas system. It employed both a consumer demand model developed from historical data and an expert system to operate the natural gas system efficiently.

Another possible function of the ISO is forecasting energy demand of its territory. The load forecasting in an electric power industry can be performed using four principal computer-based forecasting methods: Statistical methods, intelligent systems, neural networks, and fuzzy logic. The statistic methods, which include Box and Jenkins algorithms [76], regression [77], least-square estimation [78], and spatial load forecasting [79], were the dominant methodologies in the early era of electric power load forecasting. The intelligent systems [80] later appeared in the electric power forecasting area with very satisfactory performance. Then, artificial neural networks [81, 82], fuzzy logic [83], and their integrated approach [84] have taken control the task of performing load forecasting in the electric power system due to their advantages.

Load forecasting for natural gas has also been extensively studied. A neural networks approach [85] has been seen as an influential technique for the natural gas load forecasting while statistic learning theory based support vector machine approach [86] has offered itself as an alternative method in forecasting natural gas demand**.**

Energy Retailer: The load aggregator, energy broker, and local energy consumer co-op fit the profile of an energy retailer. It provides business link between energy producers and end-users, and may cooperate with local energy distribution companies for delivering energy to consumers. The energy retailer is financially motivated and may actively participate in both wholesale and retail energy markets in order to maximize its profitability. The success of the energy retailer may lie on its marketing strategies as well as its ability on getting energy supply from the wholesale energy markets with competitive price and successfully marketing the energy in the retail energy markets.

Although developing marketing strategies with computational tools is relatively new for recently emerged energy retailers, the computer models have been widely used in developing successful marketing strategies for business firms from other areas. Shiraz et al. [87] developed a genetic algorithm based approach to improve decision making ability of brand managers in an oligopolistic retail market for coffee. Moreover, Naitoh and

Terano [88] proposed an agent-based simulation model for analyzing corporate behaviors of competing business firms. Their simulator employed evolutionary computation to evolve decision-making characteristic of the firms. Furthermore, Dawid [89] performed a systematic study of multi-agent economic models in which the strategies of individuals were evolved using genetic algorithms. Vriend [90] developed an agent-based market in which seller firms compete with one another by setting production quantity individually, which in turn jointly determines market price of the goods produced. Genetic algorithm based strategic decision-making was separately applied at the individual level as well as at the population level in the model.

Local Distribution Company: A market participant from this group may perform the advanced planning to expand its distribution network in a timely manner to provide reliable services to end-use consumers with ever-increasing energy demand and to increase its revenue. Distribution network planning in electric power system is a complex task in which planners must ensure that there is adequate substation capacity (transformer capacity) and feeder capacity (distribution capacity) to meet the load demands. Among numerous approaches used for power distribution planning, mathematical programming approaches, including mixed- integer programming [91], branch and bound [92], Bender decomposition [93], and dynamic programming [94], were predominantly used in the early stage of computerized distribution planning. However, these methods did not have ability to overcome the complexity and dimension of a large real-world problem within a reasonable time. Therefore, a number of approaches based on heuristic [95] and the artificial intelligent approaches, which include expert systems [96] and genetic algorithms [97], were developed to tackle the complex distribution planning problems.

Recently, Boulaxis and Papadopoulos [98] have proposed a new algorithm for the optimal feeder routing problem using dynamic programming technique and geographical information system. Furthermore, Espie et al. [99] have offered a methodology that utilizes a number of discrete evaluation criteria within a multiple criteria decision-making environment to examine an electricity distribution system planning with consideration on issues such as load growth, distributed generation, asset management, quality of supply, and environmental issues.

Consumer: This type of market participant purchases a mix of energies from retail markets to satisfy its demand. As in-house energy conversion technology has progressed, the physical property gap among different energies is no longer a constraint for consumers. Their preference may now determine their energy consumption mix. The energy prices now become some of the important parameters to be considered by the consumers, and they may try to find the optimal energy mix for their energy requirement in order to minimize their energy consumption cost.

Imitating the decision-making process of consumers was considered before. Nimura et al. [100] introduced a fuzzy method that helps consumers determine the best choice in making bilateral transactions in an electricity retail market. In their approach, electricity spot prices and related consumer's preferences were first represented as a band of fuzzy numbers. Then, the differences in the offered price for a bilateral contract and the spot prices were compared with the preference index, and the overall grade of matching the price differential and the consumer's preference indicates the degree of consumer satisfaction regarding the offered price for the bilateral transaction. Dyner and Franco [101] offered a consumer decision-making process incorporating the concept of bounded rationality for an electricity market, providing an alternative ground to the traditional fully-rational decision making approaches. Giulietti et al. [102] considered residential consumers' choice in changing suppliers in U.K. natural gas market as a consumer investment decision and studied how the consumers exercised choice and the implication of their decisions on industrial and regulatory policy. Their finding illustrated the importance of consumer choice in the formation of market power and in the benefits of opening monopoly markets to competitors.

Regulators: Regulators are entities that facilitate the operation of market mechanisms. The regulators in the multi-energy market may issue directives or regulations to guide the market into a transparent and fair battleground for all participants. In order to issue the appropriate directives in a timely manner, the regulators may study the possible effect of the directives that they would issue in advance.

The effect of market rules on electricity markets has been observed using computer-based methods. The model of Dunn and Brown highlighted the possible consequences of adopting the Pool type day-ahead market and the bilateral short-term market in electricity industries [39]. Moreover, Xiong et al. [42] offered a model to compare the effect of two distinct market pricing rules; uniform pricing and pay-as-bid. The existence of market power [41], collusion [35], and arbitrage [36] in energy markets has also been confirmed and, the attempts to eradicate these unwanted behaviors have been proposed with computer-based approaches.

2.6 Conclusions

Electricity, natural gas, and heat are essential energy sources to our urban societies, and the industries supplying them have strong influence on the progressive development of our societies. A closer view on these industries indicates the existence of similarities in the organization and functions of these industries. These similarities and their overlapping operating area provide a basic ground for the emergence of cross-industry competition and mergers among companies having the same functions and interests from the suggested industries. The competition is no longer restricted to exist within a particular energy industry, and the section-wide cross-industry competition will eventually replace the existing competition practice.

The liberalization process in these industries also further supports the system-wide cross-industry competition. With the new level of freedom resulting from the market liberalization process, consumers can now exercise the right to choose energy suppliers for particular energies according to their individual preference. This consumer choice is further extended into multiple energies when economically efficient energy conversion devices are currently available to the consumers.

When we consider these influences together, we can clearly see that the emergence of the multiple-energy markets in which market players from the suggested industries vie to sell their products to residential, commercial, and industrial energy users is imminent. The review of computer-based methods applied to energy markets in the suggested energy industries provides the history of the evolution of computer-based approaches in understanding the behavior of energy markets, and it can be used as the foundation in studying the behavior of the multi-energy markets.

Since the multi-energy markets are emerged from the convergence of several single-energy industries, it is reasonable to assume that typical market participants involved in these single-energy industries may still participate in the multiple-energy markets. The transformation of market participants from the single-energy industries to the multiple-energy market and how the market participants utilize computer-based methods for better functioning is further reviewed.

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3. Computer Modeling Tools for Complex Markets

Abstract

Computer modeling tools are widely used in solving complex problems in energy markets. This chapter explores the possibility of using particular computational methods in modeling a simulation platform for multi-energy markets. Being able to analyze complex systems by just providing theoretical assumptions makes computer simulation a likely candidate for the simulation platform. Agent-based modeling adequately fulfills the basic requirements in overcoming the complexity associated with energy markets; decomposition, abstraction, and organization. Furthermore, evolutionary computation is considered for developing computational intelligence in complex adaptive agents of the market model. Finally, the characteristics of artificial neural networks, being able to learn from past experiences and accurately forecast the outcome, offers itself as a useful tool in the prediction area.

3.1 Introduction

The emergence of multi-energy markets introduces new market mechanisms and provides unfamiliar territories for market participants. In these unfamiliar battlegrounds, it is crucial for energy utilities, more than ever, to adapt to their new environment and explore appropriate strategies as quickly as possible in order to be competitive in this fittest survival contest market structure. In the process of renewing strategies to follow the market pace, market participants must abandon the outdated objectives rooted in single-industry, regulation-based, and coordinated-effort and progress with new objectives, which are compactable to the nature of profit-oriented multi-energy markets.

Taking the problems mentioned above into consideration, the urgent need for a methodology that have enough potential to adequately analyze the extremely complex nature of real-world multi-energy markets becomes apparent. However, the complexity of interactions is of high level in this multi-energy open market, and it is a daunting task to try to develop any mathematical model to describe the behavior in detail of such a type of market.

Decentralized market economies such as energy markets are considered as complex adaptive systems, consisting of large numbers of autonomous market players involved in parallel local interactions [1]. Many attempts have been made to uncover the secrets of real-world energy markets but only little understanding has been achieved due to the dimension and complexity associated with the energy markets. However, recent progress in the advanced computer-based modeling and analysis tools has led to rapid expansion of interest in using computerized approaches to study real-world energy markets.

In the energy market modeling history, many well-established methods seeking an equilibrium solution were first developed using a set of equations derived from theories [2- 4]. These classical equation-based models were generally based on empirically implausible assumptions regarding static market equilibrium. They often required simplifying assumptions to achieve analytical or computational tractability and had obligation to obtain a numerical or analytical solution. Therefore, these methods had limited ability in solving complex adaptive systems. Another main failure of the classical equation-based models was their dominant form of modeling based upon the rational choice paradigm. The rational choice assumption is unrealistic and may not offer valuable advice to a decision maker; however, allowing deduction is the main reason for the dominance of the rational choice approach in the classical models [5].

The alternative approach to the comprehensive math model with rational choice is agent-based simulation, which addresses the weakness of the equation-based models, and it is often the only viable way to study a population of agents who are adaptive rather than fully rational. Agent-based simulation is characterized by the intersection of two scientific fields, namely computer simulation and agent-based modeling. Computer simulation concerns techniques for simulating phenomena on a computer, such as discrete event, object-oriented, and equation-based simulation [6]. On the other hand, agent-based modeling is characterized by the existence of many agents who interact with one another with little or no central direction. The emergent properties of an agent-based model are then the result of "bottom-up" processes, rather than "top-down" direction [7].

Scientists find agent-based simulation useful when addressing changes that cannot be easily forecast, but the causes can be identified retrospectively. Agent-based simulation can also be more flexible and responsive than alternative modeling methods. Therefore, agent-based simulation approach seems to have enough potential to represent the extremely complex nature of multi-energy markets and their complex adaptive market participants.

This chapter explores the possibility of using agent-based simulation to develop a simulation platform for studying the behavior of multi-energy markets. The pros and cons of the traditional computer modeling methods are discussed in the next section. The overview of computer simulation, which is one of the basic foundation methods of agent-based simulation, is presented in section 3.3. Section 3.4 discusses agent-based modeling and its ability in representing complex adaptive systems. Then the overview of particle swarm optimization is discussed in section 3.5. Evolutionary computation applied for developing learning ability in sophisticated market players is presented in section 3.6, and the overview of artificial neural networks are explained in section 3.7. Finally, section 3.8 presents the overall conclusions regarding this chapter.

3.2 The Overview of Traditional Computer Modeling

The traditional modeling techniques can be broadly categorized into four groups:

- Equation-based models – these are usually developed from a set of equations, which is derived from theories and seek a static or equilibrium solution. The weakness of these methods is that they are often based on empirically implausible assumptions regarding static market equilibrium, generally require simplifying assumptions to achieve analytical or computational tractability, and have obligation to obtain a numerical or analytical solution.
- System models – they represent the flow of information and material as a set of differential equations linked through intermediary functions and data structure. Although they are equipped with the ability to represent feedback and dynamic process, which are the shortcoming of the equation-based models, they have limited power in explaining about local heterogeneity and interactions.
- Statistical models – they transform information into the estimation of parameters that represent average effects over available data and are widely accepted due to their ease of use. Their major drawback is only applicable to the process of stationary and uniform over space and time in order to represent dynamics and interactions.
- Cellular models – cellular automata and Markov models, which operate over a lattice of congruent cells, are included in this type of models. Although the

cellular models offer greater flexibility in representing dynamics and interactions, they have limitation in presenting the global changes in the system into the cellular level.

3.3 The Overview of Computer Simulation

Computer simulation involves representing a model as a computer program, which can be used to model either quantitative theories or qualitative ones. Bratley et al. [8] define the computer simulation as driving a model of a system with suitable inputs and observing the corresponding outputs. Although this definition is useful, it does not suggest the diverse purposes with which the application of computer simulation is usually associated [5]. These purposes include:

- *Performance* – Computer simulation can be used to perform tasks that mimic human intelligence such as medical diagnosis, speech recognition, and function optimization. The artificial intelligence methods, which exploit the special strengths of digital computers, can be thought of as computer simulation of human perception, decision making, or social interaction.
- *Training, Entertainment, and Education* – Many successful computer simulation systems are designed to provide knowledge or to entertain people by providing reasonably accurate and dynamic interactive representation of a given environment.
- *Proof, Prediction, and Discovery* – As a scientific methodology, computer simulation's value lies principally in proof, prediction, and discovery. The proof of extremely complex behavior resulting from very simple rules has been demonstrated using computer simulation [9]. Computer simulation is also able to take complicated inputs, process them by taking hypothesized mechanisms into account, and then generate their consequences as predictions. But the use of the computer simulation for the discovery of new relationships and principles is at least as important as proof or prediction. Social scientists have been quite successful in using computer simulation to discover important relationships and principles from very simple models.

Computer simulation is a third way of conducting scientific research. Its approach deviates from two standard methods; induction, which intends to find the patterns in empirical data, and deduction, which involves in setting assumptions and determining consequences that arise from those assumptions. A computer simulation generally starts with a set of explicit assumptions; however, it does not try to prove theorems. Instead, the computer simulation generates data that can be analyzed inductively. While induction can be used to find the patterns in data and deduction can be used to find the consequences of assumptions, simulation modeling can be used as an aid in intuition [5].

3.4 Agent-based Modeling for Complex Systems

The new development in computer based modeling has opened up the window of opportunity to use computer models in the study of real-world complex systems. In order to tackle the complexity associated with real-world systems, these new computer models are fundamentally based on foundation tools that keep the complexity under control: decomposition, abstraction, and organization. Decomposition, the most basic technique and yet most useful for tackling complex system, is to slice the system being studied into smaller but more manageable pieces, each of which can be dealt with in relative isolation. Abstraction is the process of defining a simplified model of the system that emphasizes some of the details or properties while suppressing others. Organization is the process of defining and managing the interrelationships between the various problem-solving components [10]. One of the emerging methods in computer-based modeling that effectively employ above techniques and handles complex systems well is agent-based modeling.

3.4.1 The Characteristics of Agent-based Modeling

Agent-based modeling systematically separates a complex system into autonomous subsystems that interact with one another in flexible ways. Then, it employs multiple agents to represent the disintegrated components of the system and introduces interactions among them; either to achieve their individual objectives or to manage the dependencies that ensue from being situated in a common environment [11]. This type of modeling is rapidly becoming popular in the area of economy due to its potential for predicting individual and group behaviors and exposing emergent properties, which refers to the observed behavior of the model that is not explicitly programmed and is therefore unanticipated in the sense that the theory did not predict it.

One type of the vital elements of agent-based modeling is agents. One of the well-developed definitions indicates that an agent is an identifiable problem-solving entity with well-defined boundaries and interfaces and usually situated in a particular environment over which it has partial control. The agent receives inputs related to the state of its act on the environment through sensors and acts on the environment through effectors. Furthermore, it has control both over its internal state and over its own behavior and is capable of exhibiting flexible problem-solving behavior in pursuit of its design objectives, being both reactive and proactive [12].

When agents are properly defined, running an agent-based model is just down to instantiating these agents, letting them interact, and monitoring what happens. Spinning the model forward in time is executing the model and is all that is necessary in order to solve the model. Thus, agent-based modeling has great potential to overcome many of limitations. Flexibility is its greatest strength, and the small details critical to the system being studied can be easily incorporated since obtaining a closed-form analytical equilibrium solution is not a requirement. Once the mechanism of the model is established, researchers have greater flexibility to design and execute experiments to explore alternative causal mechanisms.

Agent-based modeling generally employs simulation; however, it does not necessarily aim to provide an accurate representation of a particular empirical application. Instead, the goal of agent-based modeling is to enrich our understanding of fundamental processes that may appear in a variety of applications. Most of the reason for using agent-based modeling is to simulate the system as a last resort simply because the target environment is inaccessible or too complex to be solved by other existing approaches.

When determining whether agent-based modeling is appropriate for a particular system, a number of factors need to be considered. First, it is highly suitable for a process where the environment is highly dynamic, uncertain, or complex due to its capability in flexible autonomous actions. Second, it is also appropriate to the system where environments are naturally modeled as societies of agents, either cooperating with one another to solve complex problems or else competing with one another, since the idea of agent is seen as natural metaphor. Third, it is a good choice to use in the environment with distribution of data, control, or expertise in which a centralized solution is almost impossible.

There are several advantages and disadvantages of using agent-based modeling over conventional mathematical theorizing. Relatively easy to adjustment of the rationality of agents in agent-based models is the most visible advantages of all. Flexibility in modeling and obtaining an entire dynamic history of the system being studied by merely executing it are other main advantages. However, one significant disadvantage of agent-based modeling is being unable to provide any information on the robustness of the system. The only way to treat this problem is through multiple runs, systematically varying initial conditions or parameters in order to assess the robustness of results.

3.4.2 Application of Agent-based Modeling

The application of agent-based modeling to complex systems can be roughly divided into three distinct sections [13]:

- Using agent-based modeling as a classical computer simulation approach
- Using agent-based modeling as the substitute for analysis
- Using agent-based modeling as the complementary to mathematical theorizing

As a replacement of classical computer simulation, an agent-based model can be used in the process of verifying numerical results obtained from a model fully described with mathematical equations since both the mathematical model and agent-based model should produce the same solution. Moreover, it can be used as a novel kind of Monte Carlo simulation for stochastic models in which the solutions will be some distribution of outcomes and often can not be computed analytically.

The second usage of agent-based modeling is applied when a model is completely intractable either apparently or provably. For example, there is no closed form solution to certain relatively simple differential equations, and purely analytical approaches may only offer a little hope of progress for this type of problems. In such circumstances, agent-based modeling may be the last resort to explore such processes systematically.

The last and most popular usage of agent based modeling occurs when the problem is impossible to be completely solved by conventional mathematical-oriented methods that do not use distributed representation. Agent-based modeling may act as an addition to a numerical model in order to gather some additional understanding. Several models that can be put under this category have been developed, and the study on the self-organizing capabilities of specific types of market process has received a lot of attention from agent-based researchers.

Among pioneers who applied agent-based modeling to complex market models, Mark [14] first developed an agent-based oligopolistic market in which genetic algorithms based seller firms behaving bounded rationally competed for financial success. He reported the emergence of globally optimal joint pricing across the seller firms without any explicit price collusion. Young [15] proposed another evolutionary model in which agents with finite memory played a best reply strategy based on its idiosyncratic memory in the context of the bargaining game. According to his model, the stochastically stable equilibria were only obtained in some Nash games. Moreover, Axtell [16] developed a model in which agents from a heterogeneous population were paired at random and involved in Pareto bilateral goods exchange [16]. The model demonstrated that the number of interactions among agents to establish the equilibrium in the economy was linearly related to the number of agents and had quadratic relationship with commodities.

The stock markets were also playgrounds for agent-based researchers. Arthur et al. [17] invented the Senta Fe artificial stock market with agent-based modeling in which heterogeneous agents formulated their expectations adaptively based on past market performance and made decisions on whether to invest in a risky stock or a risk-free bond. The model demonstrated that beliefs among the agents co-evolved with time and produced a regime similar to rational expectation equilibria when available alternative expectations were limited. However, the market evolved to more complex structure with the success of the agents involved in exploring new expectations. Tay and Lin [18] later modified the Senta Fe artificial stock market by introducing the inductive reasoning process, which employed genetic, fuzzy, and classifier system, to traders in order to formulate their expectations inductively. The findings from their model exhibited characteristics that were very similar to actual data.

LeBaron later proposed an agent-based stock market to study the growth and dividend payments in financial markets [19]. In his model, trading rules available to investors were co-evolved using genetic algorithms, and the investors who have different memory lengths evaluated their trading rules based on their past performances. The return, volume, and volatility produced from the model were remarkably similar to the actual financial time series data. Recently, Chen and Yeh [20] constructed an artificial stock market that included an additional social learning mechanism to prove that social learning in the form of imitation of strategies was important in stock markets along with individual learning. The traders attended schools, which were simply the groups of agents developing superior models for forecasting stock returns, to get additional social learning support. The model demonstrated that successful forecasting methods quickly turned to obsolete along with the increase of their success, as a result of being adopted by increasing number of traders.

Izumi and Ueda [21] developed a new agent-based foreign exchange model in which agents controlled by behavioral rules developed from field data competed with one another to develop methods for predicting changes in future exchange rates. Their model provided a possible explanation for the emergence of following empirical features: peaked and fat-tailed rate change distribution and a negative correlation between trading volume and exchange rate volatility.

The complexity associated with restructured energy markets also demanded the use of agent-based modeling. Many successful agent-based approaches have been applied to energy wholesale [22-26] and retail markets [27].

3.4.3 Java Agent Development Framework (JADE)

In order to simplify the development of agent-based system for focusing more on the logic of the application rather than on middleware issues such as communication and collaboration of the entities of the system, several special toolkit and libraries have been developed. A software framework that helps in hiding all complexity of the distributed architecture is JADE, which is a middleware developed by TILAB for the development of distributed multi-agent applications based on a peer-to-peer communication architecture.

JADE simplifies the development of applications that require negotiation and coordination among a set of agents in the environment where the resources and the control logics are distributed [28]. JADE is a middleware that complies with the standard of Foundation for Intelligent Physical Agents (FIPA). The FIPA is an international non-profit association of companies and organizations with the goal of producing software standards to enable inter-working between heterogeneous inter-acting agents and agent-based systems [29]. JADE is fully developed in Java programming language and it is based on the following principles [30]:

- Interoperability – JADE's agents can interoperate with other agents that also comply with the FIPA standard.
- Uniformity and portability – JADE is independent of underlying network and Java version.

- Easy to use – The complexity of the middleware is hidden behind a simple and intuitive set of application program interfaces.
- Pay-as-you-go philosophy – Programmers have luxury to use only the features that they need for their application.

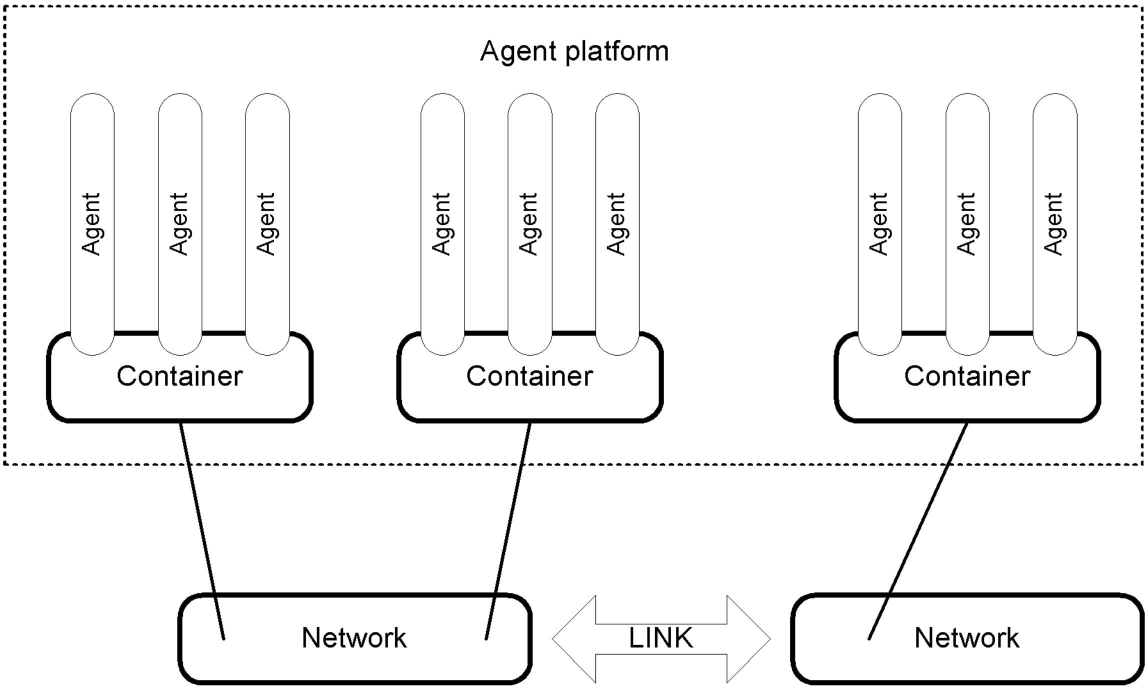

Fig. 3.1. JADE agent platform being distributed over several networks

The libraries required to develop application agents as well as run time environment are included in JADE. The run-time environment of JADE provides basic services, and it must be activated on the device before agents can be executed. Each instance of the JADE run-time is called a container and a set of all containers is called a platform. The platform provides a homogeneous layer that hides the complexity and diversity of the underlying networks.

JADE provides the basic services necessary to distributed peer-to-peer applications in both fixed and mobile environments. Its first service is to allow each agent to dynamically discover other agents and to communicate with them according to the peer-to-peer paradigm. Agent communication is generally performed by exchanging asynchronous messages among the agents, a common model for distributed and loosely-coupled type communications. The structure of the asynchronous messages complies with the ACL language defined by FIPA. To further support the implementation of complex conversations, JADE offers a set of typical interaction patterns to perform specific tasks, such as negotiations, auctions, and task delegation. To facilitate the creation and handling of message contents, JADE provides the support for automatically converting back and forth between the format suitable for content exchange and the format suitable for content manipulation. To increase scalability or also to meet the constraints of environments with limited resources, JADE supports the opportunity to execute multiple parallel tasks within the same Java thread. Furthermore, JADE promotes mobility of code and of execution state, meaning an agent can stop running on a host, migrate to a different remote host, and restart its execution from the point it was interrupted. A naming service and yellow page service that can be distributed across multiple hosts are also included in the platform.

3.5 The Overview of Particle Swarm Optimization

Particle swarm optimization (PSO) is an advance optimization technique developed by Kennedy and Eberhart in 1995 [31]. Since then, it has been widely researched and successfully applied in various problem domains. The original intention was to graphically simulate the graceful, but unpredictable choreography of a bird flock, and to use it as a simulation of a simplified social system.

The implementation of PSO for this study is as follow: Random initialization of a population of individuals with positions and velocities on *d* dimensions in the problem space is performed as the first step. Afterward, the fitness is evaluated from the desired optimization fitness function in *d* variables for each individual. Then the best fitness available to the population as well as each individual is updated. This is done by comparing the current fitness of a particle with its best ever fitness, *pbest*. If the current fitness is better than *pbest*, then the current value is set as the *pbest* and its location set equal to the current location in *d*-dimensional space. Furthermore, the particle's fitness is compared with the best overall fitness of the previous population, *gbest*. If the current value is better than *gbest*, then *gbest* is reset to the current particle's value. Then, changing the velocity and position of the particles is made according to the movement rule. These steps are repeated until a stopping criterion is met.

The movement rule of the particles can be stated as:

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \tag{3.1}$$

where V_i is called the velocity of particle i and is defined by

$$V_i^{(k+1)} = wV_i^{(k)} + Rnd_1 c_1 (b_i - X_i) + Rnd_2 c_2 (b_g - X_i) \tag{3.2}$$

where

$\mathbf{x}_i^{(k)}$ = location of particle i at generation k

$\mathbf{V}_i^{(k)}$ = velocity of particle i at generation k

And, the parameters, w and c, are weights fixed in the beginning of the process. Rnd_i is random number sampled from a uniform distribution in [0,1].

3.6 Evolutionary Computation for Agent Learning

Real-world problems are getting more and more complex. As a result, traditional analytical tools can not cope with the complexity associated with the real-world problems, and the new attempts to solve the real-world problems by imitating the mechanism observed in natural evolution gave birth to evolutionary computation. Several scientists individually developed algorithms that employed the common concepts of evolutionary computation, and these algorithms received the name of evolutionary algorithms (EAs).

EAs can be broadly defined as interactive algorithms, which improve the performance of a population of potential solutions, with respect to a particular search problem, through the application of operators inspired in natural evolution; natural selection, recombination and mutation. The primary task of EAs is to efficiently sample a very large search space, and to find solutions that conform to the objective of the problem.

Interest in EAs-related research has increased rapidly in recent years. The increase in interest in EAs was due to the benefits offered by these methodologies, which can be summarized as follows:

- EAs are based on probabilistic transition rules and perform searches from a population of points. Therefore, EAs have less chance of becoming trapped in a local optimum and can explore a complex and uncertain area to find a globally optimal point.
- EAs use fitness and objective functions, which are information directly related to the search direction. Therefore, EAs can deal with non-smooth, non-continuous, and non-differentiable functions, and this makes EAs to be more flexible and robust algorithms than conventional methods.

3.6.1 The Characteristics of Evolutionary Algorithms

In general, EAs perform following steps, not necessarily all of them, in order to solve a problem: A suitable data structure is first chosen to represent potential solutions of a particular search problem. After the data representation is selected, a population of potential solutions or individuals is randomly generated. Then those randomly generated individuals undergo an evaluation process to receive appropriate fitness values, which indicate the level of suitability of the individuals to the particular problem specification. When the evaluation process has finished, genetic operators are applied to the individuals to produce new individuals. Selection, recombination, and mutation are typical genetic operators of EAs; however, combination sequence of the genetic operators may differ for different EAs implementation. Afterward, replacement process is performed in order to produce a new population, constituting the next generation. The process of application of evaluation and genetic operators into the population and producing the next generation is repeated until a stopping criterion, which is a maximum number of generations or the achievement of a compliant solution to the problem, is met.

Regarding data representation, EAs usually employ one of the following data structures to represent solutions or individuals [32]:

- Binary strings
- Integer or real-valued vectors
- Finite state representations
- Parse trees

Choosing a suitable data structure for the solution to a given problem is important since it has major impact on the performance of EAs. Another aspect to consider in the data representation is the status of the length of the data structure. Both fixed length and variable length data structure are used in EAs. The fixed length data structure is more commonly used due to its simplicity; however, the variable length representation provides more flexibility, allowing mapping structure of different sizes and forms.

The evaluation process is required to assign a fitness value to each solution or individual sampled by EAs. The fitness of an individual is an indication of its adaptivity to a particular environment in nature; however, it is considered as the performance of the individual to a particular problem in case of EAs.

Among many genetic operators, the selection operator is characterized by the selection pressure or selection intensity they offer to EAs. There are six common implementations for this operator [32]:

- Proportional selection
- Tournament selection
- Truncation selection
- Linear rank selection
- Exponential rank selection

In case of proportional selection, the probability of selecting a particular individual is simply proportional to its fitness. Tournament selection is accomplished by selecting the fittest element among a group of randomly chosen individuals. In truncation selection, individuals are first sorted from the highest to lowest according to their fitness, and the individuals who have higher ranking than the predefined arbitrary threshold value are later selected with the same probability while the remaining are excluded from the selection process. In linear rank method, individuals whose values have been altered based on the relative position of each individual are initially sorted according to their fitness. Two arbitrarily determined values are then assigned to the best and worst individuals, and other individuals receive new fitness values linearly distributed between the best and the worst. The exponential rank selection method only differs from linear rank in the selection probability, in this case applying the exponential function.

Another genetic operator, recombination, is utilized by some EAs that employ the recombination process. Crossover and intermediary recombination are the methods mainly used for recombination. In case of crossover, the process is as follow: Two individuals from a population are first chosen by a predefined selection process, and the genetic cut and paste process takes place in their genetic materials only if they pass the probabilistic test. The chance on recombination of two individuals depends on a crossover rate. If recombination occurs, two new individuals having genetic materials from both parents are produced by a predefined crossover method; otherwise, the original two individuals are passed on to the next step of the reproduction process.

There are three common crossover methods to combine the genetic materials of two individuals: one point, two point, and uniform crossover. In case of one point crossover, one cutting point is randomly selected within the boundaries of individuals as the crossover point, and the segments between the crossover point and the end of the individuals are swapped to generate two new individuals. Two points crossover employ two randomly chosen cutting points, and the segments between these two points exchange to produce new individuals. Uniform crossover utilizes a randomly produced binary pattern to determine the contribution of each parent to its offspring.

Intermediary recombination produces the offspring using a contribution from all parents. Two distinct intermediary recombination methods are global intermediary recombination, which is resulted from averaging the value of all parents, and local intermediary recombination, which is based on averaging the values of a randomly chosen subset of the parents

Mutation process is the final step of the reproduction process. The mutation operator typically forces EAs to sample new points of the search space; therefore, it is essential in maintaining diversity, and in renewing genetic material in EAs. The mutation process is applied to each locus of all individuals with certain probability, which is typically low.

Another important aspect of EAs is the replacement policy, which determines how to replace current population with new generation. The policy to replace all the individuals of the current population with the new generation has been used in early generation of EAs; however, the approach of replacing only certain number of individuals having the lowest fitness in the population is more common in later generation of EAs. The latter approach proves to be performing better in most applications since it prevents good individuals from being eliminated from the population in the selection process.

3.6.2 The Major Evolutionary Algorithms

EAs are artificial intelligent methods based on the mechanics of natural selection. The process of evolution generally leads to the optimization of behavior within the context of a given criterion. It has been indicated that artificially simulating evolutionary process provides a general problem-solving technique. A variety of EAs have been developed, and the most popular EAs developed so far are the followings:

- Evolutionary strategies/Evolutionary programming
- Genetic Algorithm
- Genetic Programming

Evolutionary Programming/Evolutionary Strategy: These algorithms are a stochastic optimization process, which emphasizes on behavioral linkage between parents and their offspring rather than their genetic link [33]. Therefore, there is no restriction on the representation of the solutions in these algorithms. Apart from keeping the behavioral link between offspring and parents, they also employ real value vectors for representing a population of potential solutions, maintain the mutation as the dominant operator, and use a selection mechanism for choosing the best individuals from the population. Mutation changes the solutions according to a statistical distribution in which the probability of minor changes occurring in the solutions is high, while that of major changes occurring in the solution is low [34].

Randomly creating an initial population of the solutions is the first step of these algorithms. Then they proceed with the following two other steps until termination criteria, reaching an iteration limit or obtaining an acceptable solution, are satisfied:

- Offsprings are created by directly duplicating parent solutions. Afterward, each offspring is mutated according to the statistical distribution obtained from a chosen mutation method.
- Then, fitness values are assigned according to the performance of the off-springs regarding the problem. Finally, based on their fitness values, these offsprings are deterministically selected to form a new population.

Although evolutionary programming totally relies on the mutation, some evolutionary strategies employ the self-adaptation of mutation variances and application of recombination process as additional search operators [35].

Genetic Algorithms: Genetic algorithms (GAs) share the basic feature of EAs; the notion of sampling a population of the solutions, the use of mutation and recombination operators, and the probabilistic nature of these operators. However, it has one new features comparing with other algorithms; the application of the probabilistic selection process.

The standard GAs operate on a population of individuals, each individual representing a solution coding of all decision parameters. These individuals are further selected according to their fitness values, which reflect the quality of the solutions, for the reproduction process. Then the reproduction of selected individuals is taken place through the high probability crossover and very low probability mutation. Finally, the replacement process is performed to replace the current population of individuals with newly reproduced individuals. The whole process continues until a pre-specified termination criterion holds [36].

A number of GAs with features deviating from the standard GAs have been successfully applied in various problems. These new features include using integers for solution representation, and employing different kinds of selection, crossover, mutation, and replacement schemes [37]. The success in optimization problems, particularly in those problems in which the size or complexity of the search space renders infeasible the use of other optimization methods, makes GAs the most popular evolutionary algorithm.

Genetic Programming: The main intention of genetic programming (GP) is to evolve computer program; therefore, tree representation is applied as chromosomes in GP. Two distinct natures are noticeable in the nodes of GP trees; function nodes and terminal nodes. Function nodes are external vertices of the trees and usually correspond to mathematical functions and conditional operators. On the other hand, terminal nodes are external nodes, corresponding either to a variable relevant to the problem domain or to a constant [38].

Apart from the new kind of representations, the basic flow of GP is very much like the one of GAs. The initial trees and their terminal and function nodes are randomly generated from respective sets. Then, a scalar fitness value is assigned to each tree according to its performance to the problem. Later, selection process is taken place to select the fittest individuals. Afterward, recombination is performed with crossover, which is the most important operator in GP. This process is repeated until the termination criterion is satisfied.

3.6.3 Evolutionary Particle Swarm Optimization

Evolutionary particle swarm optimization (EPSO) can be seen as a hybrid method of the evolution strategies and particle swarm optimization technique. It has been described as a combination of above two methods in sequence; each one is capable of producing not only better individuals but also an average better group [39].

The general scheme of EPSO is the followings: A population of individuals with positions and velocities on d dimensions in the problem space is randomly initialized as in PSO. Then, replication process is taken place with the individuals being duplicated r

times. Afterward, mutation is performed on the strategic parameters of each individual. Furthermore, offsprings are produced from the individuals according to the movement rule. Utilizing the desired optimization fitness function in *d* variables, the fitness value of each individual is later evaluated. Afterward, the process of comparing the fitness of individuals for determining their *pbest and gbest* is performed as in PSO. Finally, the selection process is performed by stochastic tournament and the best individuals survive to form a new generation.

The reproduction is performed by utilizing EPSO's movement rule as follows. Given a particle $\mathbf{X}_i$, a new particle $\mathbf{X}_i^{new}$ results from

$$\mathbf{X}_i^{(k+1)} = \mathbf{X}_i^{(k)} + \mathbf{V}_i^{(k+1)} \tag{3.4}$$

$$\mathbf{V}_i^{(k+1)} = w_{i0}^{*}\mathbf{V}_i^{(k)} + w_{i1}^{*}(\mathbf{b}_i - \mathbf{X}_i) + w_{i2}^{*}(\mathbf{b}_g^{*} - \mathbf{X}_i) \tag{3.5}$$

where

$\mathbf{b}_i$ = best point found by particle i in its past life up to the current generation

$\mathbf{b}_g$ =best overall point found by the swarm of particles in their past life up to the current generation

$\mathbf{X}_i^{(k)}$ = location of particle i at generation k

$\mathbf{V}_i^{(k)}$ = velocity of particle i at generation k

w_{i0} = weight conditioning the *inertia* term (the particle tends to move in the same direction as the previous movement)

w_{i1} = weight conditioning the *memory* term (the particle is attracted to its previous best position)

w_{i2} = weight conditioning the *cooperation* or *information exchange* term (the particle is attracted to the overall best-so-far found by the swarm).

The symbol * indicates that these parameters are considered strategic parameters and will undergo evolution under a mutation process to be explained.

In fact, the movement rule is an intermediary recombination process in which parents contribute every variable of the offspring. The special features of EPSO include a provision of elitism and an adaptive recombination operator. The development of movement rule is illustrated in Fig. 3. 2.

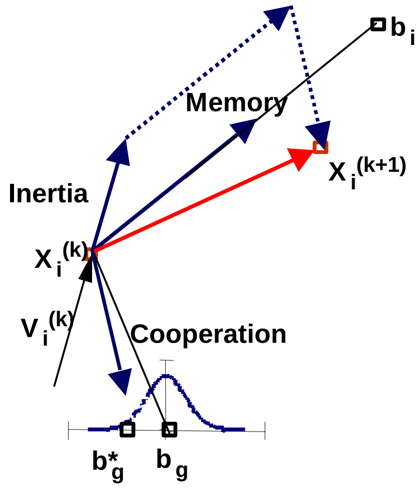

Fig. 3.2. Illustration of EPSO particle reproduction: a particle $\boldsymbol{X}_i$ generates an offspring at a location commanded by the movement rule.

As in a σSA-Evolution Strategy, object parameters and strategic parameters in each individual are defined differently. Object parameters can be stated as those giving the phenotypic description of a solution. And, strategic parameters are those that condition the evolution of a given solution.

The basic mutation rule for the strategic parameters is the following:

$$w_{ik}^{*} = w_{ik}\left[\log N(0,1)\right]^{\tau} \tag{3.6}$$

where logN(0,1) is a random variable with lognormal distribution derived from the Gaussian distribution N(0,1) of 0 mean and variance 1. τ is a learning parameter, fixed externally, controlling the amplitude of the mutations, and smaller values of τ generally lead to higher probability values close to 1.

As for the global best $\mathbf{b}_g$, it is randomly disturbed to give

$$\mathbf{b}_g^{*} = \mathbf{b}_g + w_{i4}^{*} N(0,1) \tag{3.7}$$

where w_{i4} is the forth strategic parameter associated with particle i. It controls the "size" of the neighborhood of $\mathbf{b}_g$ where it is more likely to find the real global best solution or, at least, a solution better than the current $\mathbf{b}_g$. This weight w_{i4} is mutated according to the general mutation rule of strategic parameters, allowing the search to focus on a given point.

EAs have been widely applied in problems from every corner of energy systems, especially in power system. Since the application of EAs in energy systems has been broadly mentioned in the section-wise discussion about market actors in the previous chapter, the review of this section only pays attention to using EAs for agent learning.

Along with the development of agent-based modeling, a broad range of algorithms have been tested to represent machine learning process of adaptive agents. Evolutionary computation has been seen as an influential approach in developing computational intelligence in agents [1]. Dawid [40] performed a systematic study of multi-agent economic models in which the strategies of individuals were evolved using genetic algorithms. His model demonstrated that particular aspects of implementation such as configuration of parameter settings can change the outcomes of the model in the long run. Vriend [41] developed an agent-based market in which seller firms compete with one another by setting production quantity individually, which in turn jointly determines the market price of the goods produced. A genetic algorithm based learning algorithm was separately applied to the individual level as well as population level. The results from the model indicated that the spite effects – which can be defined as choosing actions that hurt one but hurt others even more – emerged in the population learning, driving the aggregate behavior toward the competitive level. Lane et al. [42] used a genetic algorithm to evolve adaptive agents in their put options electricity market model. The result from their model indicated that it is possible to develop profitable valuations for use with buying and selling options using genetic algorithms.

3.7 The Overview of Artificial Neural Networks

An artificial neural network (ANN) is defined as a parallel architecture in which interconnected elementary processing units perform some basic operations over its inputs, and present the consequent result as its output, which may be used by other similar units. The implementation of ANN were originated from the need of developing parallel processing systems, somehow inspired by the brain model, in order to perform better than conventional programs in computation intensive problems. Nowadays, ANN claims to solve a lot of real-world problems, from the function prediction and system modeling to the pattern recognition with the ability to generalize imperfect input data.

Many types of ANNs have been developed so far. Some of the most popular ANNs include multilayer perceptron (MLP), learning vector quantization, radial basis function (RBF), Hopfield sets and Kohonen maps. Depending on the data processing character of the network, ANN can be classified into either feed forward or recurrent.

Moreover, a learning method is also used in specifying the ANN as some ANNs employ supervised training, while others choose unsupervised or self-organizing [43].

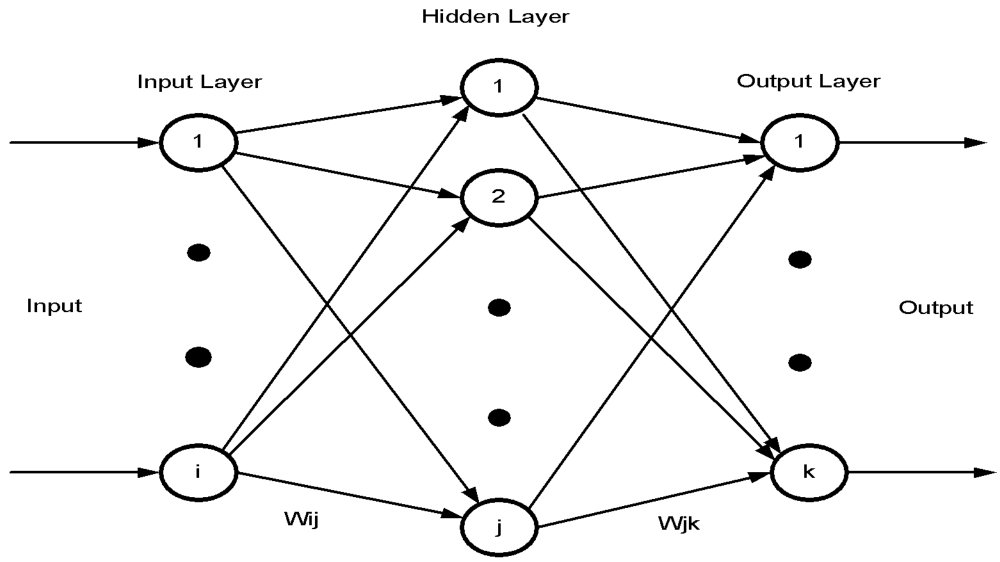

Fig. 3.3 Topology of ANN with 3 layers perceptron model

Above figure shows one of the most popular models of ANN, the multi-layer perceptron (MLP) model. The ANN with MLP model works as follows: The input layer first receives a vector x that stimulates the network. The contribution of the i^{th} element of this vector into the j^{th} unit of the hidden layer is given by the product $x_i w_{ij}$, where w_{ij} is the weight of the link between the units i and j. The total excitation net_j at the j^{th} unit input is given by the sum of all the products $x_i w_{ij}$ of every link between this unit and the units of the previous layer. The value net_j is changed by a non-linear function that establishes the output state O_j of the j^{th} unit. Output values of all hidden units are added at the units of the last layer to decide its output state.

Using above idea, the training algorithm can be summarized as follows:

- Randomly initialize the weights and the biases.
- Introduce inputs and target outputs to the neural networks.
- Determine actual outputs and calculate the error. If the error is smaller than the predefined value, then stop the process.
- Otherwise, adjust weights and biases using a specific algorithm and go back to step 2.

Among many advantages ANNs brought to our society, computational speed is the most visible one. Because of its massively parallel nature, ANN can perform calculations at much more higher rates than traditional methods. Being able to learn the characteristics of input signs and to adapt to changes in data are seen as other advantages of ANN. Its non-linearity also offers better performance in function simulation and signal filtering operations than classical linear techniques. The ability of ANN to learn and approximate relationships between input and output decoupled from the size and complexity of the problem is a big bonus. On the other hand, the non-linear transference function associated with each unit induces the emergence of multiple local minimums, and uncertainty to reach them all during training are in the down side of ANN. Another disadvantage of ANN is that training may be very slow for large dimension problems.

3.8 Conclusions

Computational tools have been used in solving complex problems of energy systems. In the history of using computer-aided tools in energy systems, several math-oriented approaches such as linear programming and dynamic programming first dominated the area. However, their limited ability in solving large and complex problems dramatically reduced their domination in the area and eventually led to the development of artificial intelligence approaches.

Traditional modeling approaches utilize the systems developed from a set of powerful mathematical equations or information to solve complex problems. The clarity and validity of the solutions are their greatest strength; however, these methods tend to lose their strength with increasing size and complexity of the problem as well as inability to address the problem in micro and macro levels simultaneously.

Computer simulation, which starts with a set of explicit assumptions and produces data that can be analyzed inductively, is a suitable tool for solving large and complex problems from energy systems. There are a variety of purposes for using computer simulation tools, including testing performance, training, entertainment, education, proof, discovery, and prediction.

Agent-based modeling offers the ability to bring computer simulation to a new level. Agent-based modeling is a powerful modeling tool that follows the basic rules for keeping complexity in guard, decomposition, abstraction, and organization, and employs agents that are complex adaptive systems. This type of modeling is rapidly becoming popular in the area of energy market modeling due to its potential for predicting individual and flock behavior, and exposing emergent property.

Evolutionary computation, whose algorithms improve the performance of a population of potential solutions with respect to a particular search problem through the application of natural selection, recombination, and mutation, provides much needed adaptation in intelligent agents. Evolutionary particle swarm optimization, which borrows the successful ideas from evolutionary strategies and particle swarm optimization, provides itself as a powerful method for complex optimization problems.

The overviews of particle swarm optimization, which was originated in a simplified simulation of a graceful but unpredictable choreography of a bird flock, and artificial neural networks, which were originated from the need of developing parallel processing systems and somehow inspired by the brain model, inform the readers the general knowledge of those methods.

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4. Modeling Multiple-Energy Retail Markets with Agents

Abstract

As a result of market efficiency improvement and recent technological break-throughs in the energy conversion area, electricity, natural gas and district heating industries previously accustomed to operate in parallel with some degree of independence have been forced to compete in the enlarged multi-energy market. Understanding the behavior of this relatively unknown multi-energy market is crucial for many parties involved in these industries; however, to the author's knowledge, very few attempts has ever been made on studying the behavior of this enormously complex market with a large number of market actors. This chapter proposes a pioneer computer simulation approach that employs agent-based modeling for the process of understanding the behavior of the emerging multi-energy market. With agent-based simulation, the development of a complex market model, which is an almost impossible task using an analytical approach that requires simplification and distortion of market rules, becomes a manageable task. Market actors of the multi-energy market are modeled as complex adaptive agents, and the behavior of the market is basically emerged as a consequence of local interactions among the market actors. Another contribution of this chapter is the development of an appropriate methodology for the simulation of consumers' adaptability to the changes of the market. Without the adaptive behavior of the consumers, direct competition among rival energy industries might not be able to establish properly as required in an actual market. Furthermore, the role of a retailer is properly defined and an appropriate methodology is developed in order to represent this profit-oriented self-adapting market actor.

4.1 Introduction

Many attempts have been made to study the structure, efficiency and evolution of a complex energy market for several decades [1-3]. Most of those attempts have modeled the complex energy market with fixed decision rules, common knowledge assumptions, and imposed market equilibrium constraints. Requiring to simplify the market to a manageable and controllable mathematical system has been the norm in these approaches due to the limitation on computational capability. Being unable to represent the complexity and dynamic of actual energy markets has been their common weakness. Contrary to these modeling approaches, the market must be modeled with minimal simplifications and market equilibrium constraints over market rules in order to effectively represent the behavior of real-world energy markets in depth.

Energy markets around the world are adjusting themselves from the regulated and centralized monopoly economies to the decentralized open markets with the intent of promoting competition among suppliers, and providing choices for consumers. As the structure of energy markets has been changed, there is an urgent need for new modeling approaches that are suited to new environment. Many of modeling tools that have been developed over the last two decades are generally based on the implicit assumption of a centralized decision-making process. Although these tools are very detailed, complex, and useful in studying the regulated energy industries, their ability is questionable to adequately analyze the market forces prevalent in the open energy markets.

Although developing a market model compliant with an open market paradigm is challenging enough for research, it becomes more complicated when one realizes that the competitive market is extended to competition among several forms of energy and not only restricted to one. In fact, the development of cost-efficient conversion technologies has introduced competition among energies such as gas and electricity while steam from district heating is competing with the distribution of gas or electricity in some countries [4].

Taking the problems mentioned above into consideration, an urgent need of a methodology that has enough potential to analyze the complex nature of a real-world multi-energy market becomes apparent. Although possible emergence of multi-energy industry has been addressed [5], very few attempts, to the author's knowledge, have ever been made to study the behavior of multiple-energy markets. The attempt on developing a model for the rapidly evolving multi-energy market is an enormous and overwhelming task. Many obstacles must be overcome to make the attempt successful.

One of the methods perfectly suited in this delicate situation is computer simulation. It has been widely adopted in social science and engineering as a methodology [6]. Computer simulation involves representing a model of either quantitative or qualitative theories as a computer program, and executing the model with suitable inputs and observing the corresponding outputs. With computer simulation, in contrasts to other methods, it is possible to formalize complex theories, to carry out experiments, and to observe the occurrence of emergence. Because of its distinct ability, computer simulation has been chosen for postulating the behavior of the multi-energy market in this study.

Furthermore, agent-based modeling is incorporated in the computer simulation of the multi-energy market to tackle the complexity problem. Several paradigms have attempted to tackle the complexity of systems, and the similarity in the successful attempts indicates that three fundamental foundations – decomposition, abstraction and organization – are vital in keeping the complexity under control. Therefore, agent-based modeling, which manages to decompose complex problems into multiple autonomous components that can act and interact in flexible ways to achieve their set objectives, is the perfect candidate to overcome the complexity problem associated with the multi-energy market. One of the crucial components of agent-based modeling is autonomous agents.

Like other decentralized market economies, energy markets are complex adaptive systems, consisting of large numbers of autonomous agents involved in parallel local interactions [7]. A number of market actors are organized in a hierarchical, working together to achieve the functionality of a particular energy market at any given time. Since these market participants have their own supporting role in the market and the behavior of the market generally emerges from interactions among individual market actors, the behavior of highly complex energy markets can not be adequately studied without assigning appropriate functions to the market actors.

In order to reduce the dimension of the problem, directly address the shortage of research on retail competition, and introduce the concept of consumer choice, this study only pays attention on the retail sector of the multi-energy market. Three energy industries - electricity, natural gas, and district heating industries – are considered in this study due to the similarity of their organization as well as the existence of cross-industry competition among them.

The market actors also perform similar functions in these energy industries. In each industry, energy producers supply a particular form of energy to end-use consumers through energy transportation and/or energy delivery networks under the guidance of a regulatory body while market operators and retailers make business transactions with both the energy suppliers and the consumers. The role and functionality of some of the market actors have been well established; however, these market actors need to be redesigned in order to comply with the new market structure. There are new market actors who need to be developed from the scratch since no similar functions have ever existed in old paradigm. After intensive research has been made on the literature of energy markets, the functions of every market actor are individually established with theoretically motivated process of abstraction.

This chapter is dedicated to defining the role of each and every market actor in the emerging multi-energy retail market and their specific functionalities, and to model these market actors as autonomous intelligent agents. The definition, functionality and mathematical formulation of 19 agents are thoroughly explained in next section. Afterward, the detailed interactions of the agents are further discussed in section 4.3, and overall conclusion is reported in section 4.4.

4.2 Mathematical Formulation of the Agents

Being able to represent the complexity of the multi-energy retail market and its dynamic nature in depth, a system-wide agent-based simulation platform has been modeled with 19 vital agents. These agents include Economy, Information Environment, Consumer classes, and groups of market actors involved in single-energy markets. Consumer is further divided into three classes: Residential, Commercial, and Industrial. A group of market actors involved in electricity business include Power Regulator, Power Market Operator, Power Deliverer, and two electricity Retailers: Retailer One, and Retailer Two. Similarly, a group of market actors participating in gas market are Gas Regulator, Gas Market Operator, Gas Deliverer, Retailer Three, and Retailer Four. And, Heat Regulator, Heat Market Operator, Heat Deliverer, and Retailer Five constitute a group of market actors from heating sector.

Above agents can be reorganized into seven categories according to their similar role and function. The broad explanation of these categories is summarized as follow:

A – Information Environment – This type of agent assumes the role of a scheduler that controls the operation of the market model, and the information processor.

B – Economy – This agent produces basic data such as economic drive, season of the year, and weather conditions for further use in developing energy demand.

C – Regulator – In the simulation to be reported, the regulatory agent imposes simple restrictions such as limiting duration between successive product price movements and imposing price-cap over price of energy products.

D – Consumer – Agents of this type represent not individual consumers, but rather classes of consumers such as residential, commercial, or industrial. Each agent purchases a mix of energies and changes market shares of these energies according to prices, needs, elasticity of demand, and adjustment delays to price changes.

E – Delivery – Such agents perform duties such as extending networks over the territory to supply new consumers, under request from the Retailers. Network expansion is performed using functions that optimize paths and profits, which are also available in GIS platforms. An agent of this type has logic of its own and also seeks to maximize profit while guaranteeing contracts of supply.

F – Market Operator – This agent simulates the wholesale market to generate the day-ahead wholesale energy price.

G – Energy Retailer – Every agent of this type has following internal functions: monitoring its performance in terms of profitability as well as market share movement, finding optimal decision combinations for performance improvement, and improving management efficiency. Among various duties, achieving maximum profit while providing reliable service to consumer is the ultimate goal for a profit-oriented energy retail supplier. One important function inside a Retailer is strategic planning. Therefore, these agents are equipped with an inner capacity for simulating the market and guessing other actor moves. This is a “simulation inside the simulation” process, based on the best knowledge an agent has of the behavior of others. An agent of this type may use neural networks to predict prices and uses evolutionary computing simulation to plan ahead and to derive an optimal strategy both for expansion of the business and for price determination.

In order to address the complexity problem efficiently, the multi-energy retail market platform has been modeled in two layers; an entity layer and a sub-entity layer. Entities on the entity layer are given higher ranking order while the market actors inside the entities, which form the sub-entity layer, are set to perform their duties in lower hierarchy order.

It is undeniable that the functions associated with each entity account for at least one research field of energy industries. Therefore, developing a simulation platform consisting of seven entities is beyond a reasonable workload for a dissertation. In order to reduce the workload to a manageable level, the analytical formulations of some entities are stripped down to minimal. However, these stripped entities can still develop the behavior similar to the one seen in real-world. Definition and mathematical formulations of fundamental entities of the multi-energy retail market platform is further explained in following sections.

4.2.1 Information Environment Entity

Information environment entity represents the role of the information exchange center of the platform. All information available to public passes through this entity. It also plays the role as a library in which market participants can freely publish their significant findings or announcements and periodically collect useful information for further assessment. Another specialty of this entity is information processing. Since the interest of information receiving parties may not be the same as information announcing ones, the information processing is performed for smoothing information flows among market participants. Furthermore, this entity works as a scheduler that oversees the timing of the agents' participation in the market platform to ensure that information exchange among market actors are performed in a timely manner as well as an optimal way. There are six entities – Economy, Consumer, Market Operator, Regulator, Energy Deliverer and Retailer – evolving around the Information Environment as shown in Fig. 4.1.

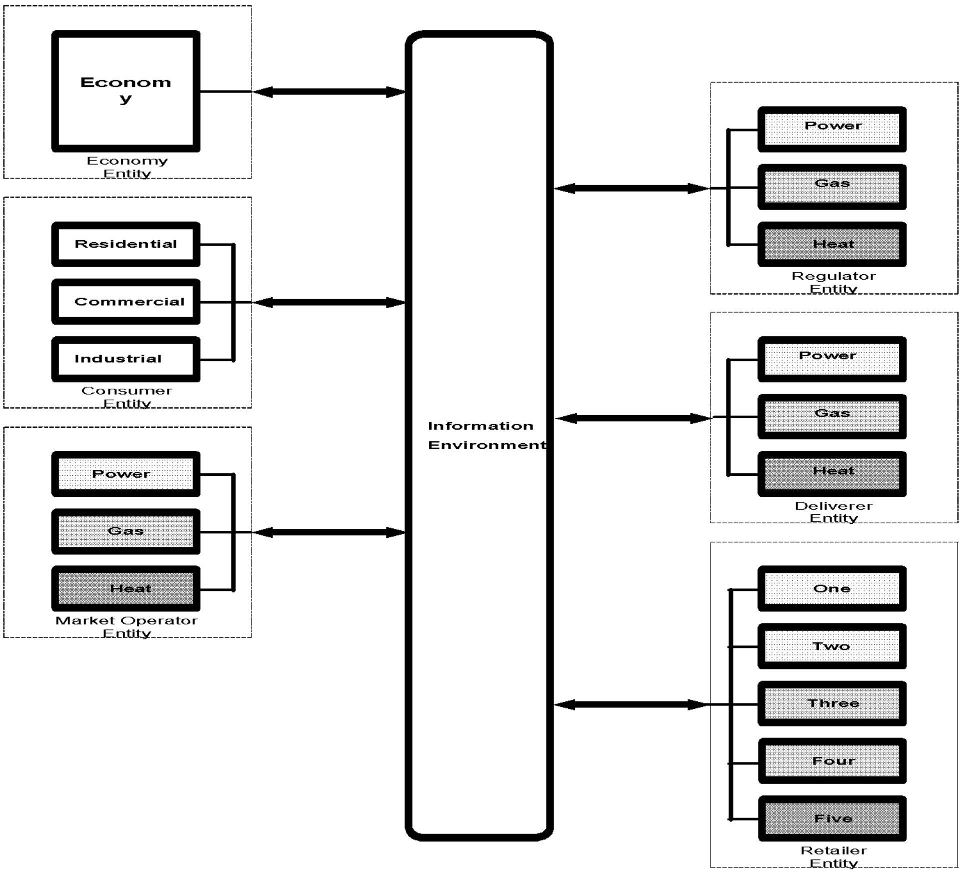


Fig. 4.1. Operation of market players evolving around Information Environment

The formation of the market actors' participation in the market platform is set as a daily pre-arranged sequence in which each market actor performs its functions once. Scheduling the market actors is a two-step process. It is done sequentially at the entity level; however, switches to a parallel processing at the sub-entity level. The entity level scheduling starts with Economy entity acting first. Its functions include requesting information from Information Environment, performing internal tasks, and returning publicly available updated information back to where it came from. Afterward, the Information Environment processes the information and transforms it into the type of information compliant with other market actors. This process is repeated for other remaining entities with the order of Regulator, Consumer, Energy Deliverer, Market Operator, and Retailer respectively. In case of the entities that contain a sub-entity level, agents in those sub-entities work in parallel. With this combination of sequential and parallel approaches, the Information Environment manages to operate the market platform more efficiently.

Regarding the information processing, several data manipulations are done in this entity. One of the data transformations, deviation of energy prices, is derived for the Economy with the data received from Retailers, current and reference energy prices, using following equation.

$$DEP_i = \sum_{j=1}^{n} \frac{{}_jEP_i - {}_jREP_i}{{}_jREP_i} \tag{4.1}$$

where

DEP_i = Deviation of energy prices related to Consumer class i

${}_jEP_i$ = Energy price set by Retailer j for Consumer class i

${}_jREP_i$ = Reference energy price set by Retailer j for Consumer class i

n = Number of Retailers

Another similar information manipulation is performed for Consumers classes to produce the public education mood, which is an indicator of public awareness, from public education indexes evaluated by Regulators as follow:

$$PEM_i = \sum_{j=1}^{n} PEI_j \tag{4.2}$$

where

PEM_i = Public education mood applied by Consumer class i

PEI_j = Public education index evaluated by Regulator j

In case of Energy Deliverers, energy-wise consumption, actual share, and market share are produced from consumer-wise data received from Consumer classes using following equations.

$$DC_i = \sum_{j=1}^{n} \sum_{k=1}^{m} {}_kC_j \tag{4.3}$$

where

DC_i = Consumption related to energy type i

${}_kC_j$ = Consumption related to Retailer j utilized by Consumer class k

n = Number of Retailers competing under energy type i

m = Number of Consumer classes

$$DAS_i = \sum_{j=1}^{n} \sum_{k=1}^{m} {}_kS_j \tag{4.4}$$

where

DAS_i = Actual share of energy type i

${}_kS_j$ = Actual share of Retailer j utilized by Consumer class k

n = Number of Retailers competing under energy type i

m = Number of Consumer classes

$$DMS_i = \frac{DAS_i}{\sum_{j=1}^{n} \sum_{k=1}^{m} {}_kS_j} \tag{4.5}$$

where

DMS_i = Market share of energy type i

DAS_i = Actual share of energy type i

${}_kS_j$ = Actual share of Retailer j utilized by Consumer class k

n = Total number of Retailers

m = Number of Consumer classes

Similar approach is also applied for Retailers. The energy consumption, actual share, and market share of a particular Retailer is calculated by using following equations.

$$RC_i = \sum_{j=1}^{n} {}_iC_j \tag{4.6}$$

where

RC_i = Consumption related to Retailer i

${}_iC_j$ = Consumption related to Retailer i utilized by Consumer class j

n = Number of Consumer classes

$$RAS_i = \sum_{j=1}^{n} {}_iS_j \tag{4.7}$$

where

RAS_i = Actual share of Retailer i

${}_iS_j$ = Actual share of Retailer i utilized by Consumer class j

n = Number of Consumer classes

$$RMS_i = \frac{RAS_i}{\sum_{j=1}^{n}\sum_{k=1}^{m} {}_kS_j} \tag{4.8}$$

where

RMS_i = Market share of Retailer i

RAS_i = Actual share of Retailer i

${}_kS_j$ = Actual share of Retailer j utilized by Consumer class k

n = Total number of Retailers

m = Number of Consumer classes

4.2.2 Economy Entity

Energy demand, in reality, appears to be the instantaneous outcome of simultaneous actions of many parties involved with complex motives. This entity acts as the counterpart of an energy demand developing component in real-world. It performs the process of developing energy demand of the understudy territory using a mathematical-oriented approach. As we know that the pattern of economic development and weather conditions are parameters that have influence on the need for energy in real-world, demand influential parameters such as regional economic information and weather status has been mathematically produced. The econometric modeling process, which postulates explicit casual relationships between the dependent variables and other economic, technological or demographical variables [8], later utilizes above data for the development of daily energy demand of the territory. The type and arrangement of information exchanged between Economy and Information Environment is implicitly displayed in following figure.

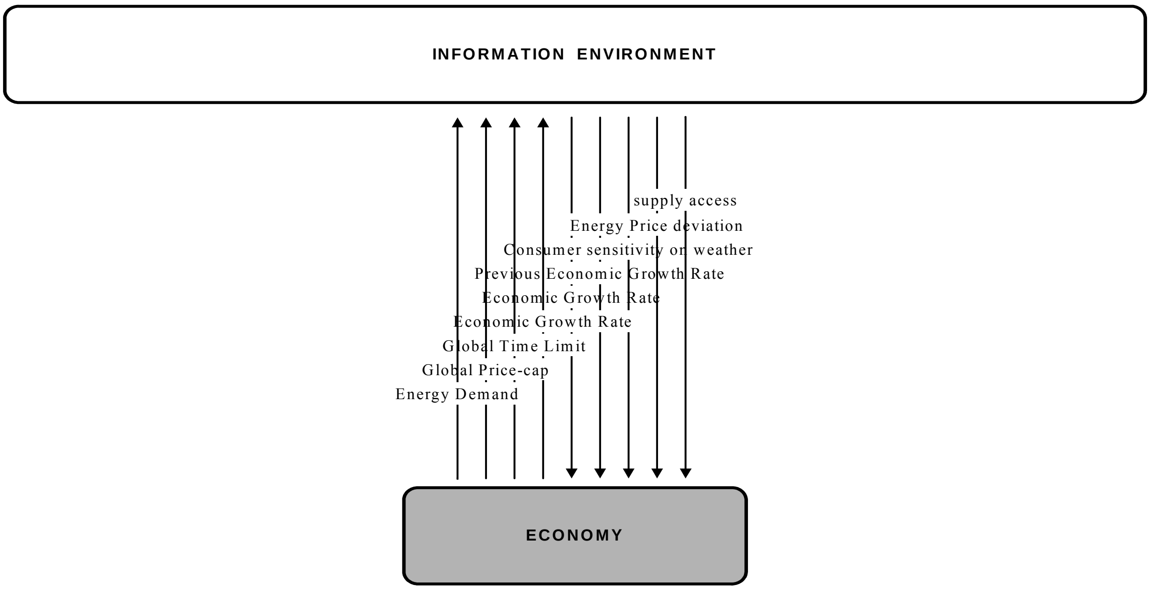


Fig. 4.2. Information flow between Economy and Information Environment

In the process of forecasting daily energy demand, five major parameters known to be shaping the pattern of energy demand is placed under consideration. These factors include economic growth, daily weather status, seasonal effect, weekly effect, and demand elasticity. The definition of each parameter and its mathematical formulation are further discussed in following sections.

4.2.2.1 Economic Growth

Economic development is considered to be the major driving force behind the growth of energy demand. In general, economic performance is measured with economic growth rate, which is the rate of growth in gross domestic product (GDP). In this study, it is produced by the iterative updating approach, which produces a new economic growth rate of the territory based on historical data, at the beginning of a particular year. The economic growth rate of the present year is considered as the combination of the previous year growth rate and a restricted random variation. The random variance is set to be within the positive and negative half of the growth rate of the previous year, effectively limiting the variation of the new economic growth rate. The following equation is applied for formulating the economic growth rate of the region.

$$\mathrm{EGR}_{y} = \mathrm{EGR}_{y-1} + \mathrm{RAM}_{y} \tag{4.9}$$

subject to:

$$-\frac{EGR_{y-1}}{2} \le RAM_y \le +\frac{EGR_{y-1}}{2}$$

where

EGR_y = Economic growth rate of year y

EGR_{y-1} = Economic growth rate of year y-1

RAM_y = Random variance generated for year y

4.2.2.2 Seasonal Effect

It is well-established knowledge that the pattern of energy demand changes seasonally. Significant variation in humidity and temperature at different seasons leads the curve of energy demand having different shape. In this study, temperature is considered to be taking the leading role in the seasonal effect, and the development of seasonal effect is entirely based on temperature. As historical data suggests that average temperature pattern of a particular territory may have the shape of a cosine curve – representing a curve of the lowest temperature for winter, a curve of the peak temperature for summer, and having the conjunction curves of temperature between the lowest and highest curve for spring and autumn – the following mathematical formulation is used in calculating the nominal temperature of a particular day, which indirectly represents the seasonal effect.

$$SNT_d = AT + \left| -\mathrm{Cos}\left(\frac{|D - LD| \times \Pi}{180}\right) \times R \right| \qquad (4.10)$$

where

SNT_d = Seasonal nominal temperature occurred at day d

D = Number of days between the beginning of a year and a particular day d

LD = Number of days between the start of winter season and the end of a year

AT = Yearly average temperature

R = Maximum temperature range with respect to yearly average temperature

4.2.2.3 Daily Weather Effect

The consideration of energy demand changing due to the effect of weather usually involves several parameters such as temperature, humidity or solar condition. Although humidity or solar condition plays some role in the changing of energy demand, the major influence generally comes from daily temperature variation. Therefore, the temperature of a particular day is formulated by a method that adds random variance, which is generated with Gaussian probability and is set to vary within the range between the predefined upper limit and lower limit values, to the seasonal nominal temperature. The temperature of a particular day can be generated using following equation.

$$\mathrm{TEMP_d} = \mathrm{SNT_d} + \mathrm{RAM_d} \tag{4.11}$$

subject to:

$$\text{Lower limit} \leq \mathrm{RAM_d} \leq \text{Upper limit}$$

where

$\mathrm{TEMP_d}$ = Temperature occurred at day d

$\mathrm{SNT_d}$ = Seasonal nominal temperature occurred at day d

$\mathrm{RAM_d}$ = Random number generated for day d

The temperature is then transformed into a weather index, a coefficient factor that loosely represents the level of energy consumption. Based on the assumption that energy consumption can significantly increase with respect to the increase in the variation of the temperature from the comfort value, which is a generalized temperature value of an environment in which general population is able to rest comfortably, the index of weather condition can be formulated as:

$$\mathrm{WEATHER_d} = \left(\frac{\left| \mathrm{TEMP_d} - \mathrm{COM} \right| \times \mathrm{IDX}}{\mathrm{DIST}} \right)^2 \tag{4.12}$$

where

$\mathrm{WEATHER_d}$ = Weather index value

IDX = Maximum value of coefficient factor

DIST = Range between comfort temperature and extreme temperature at one edge

$\mathrm{TEMP_d}$ = Temperature occurred at day d

COM = Pre-defined comfort temperature

4.2.2.4 Weekend Day Effect

Another well-known fact, weekend days having significant lower energy demand than weekdays, is also considered in this study. The lost of demand is resulted from the closure of a number of offices and factories in weekend break. In order to represent this situation effectively, a weekly index, which is a unit ratio between energy demand factor of weekend and weekday, is generated by a Gaussian probability approach, and can be represented by:

$$\mathrm{WEEK}_d = \begin{bmatrix} 1 & \text{....if d is weekday} \\ \mathrm{WR} & \text{....if d is weekend} \end{bmatrix} \tag{4.13}$$

subject to:

$$\mathrm{MIN} \le \mathrm{WR} \le 1$$

where

WEEK_d = Weekly demand index at day d

WR = Demand ratio at weekend with respect to weekday

MIN = Predefined minimum demand ratio developed from historical demand data

4.2.2.5 Demand Elasticity

According to conventional economic theory, energy demand would rise with increased in income of consumers. This assumption emphasizes the coupling effect between the energy demand and purchasing power of consumers. Therefore, for the consumer with stable income, it is reasonable to assume that they may cut their energy demand when the energy price increases. The possibility of demand decreasing due to the rising of energy price is indicated by Stoft [9], and this effect is considered as demand elasticity and mathematically formulated in the following way.

$$\mathrm{DE}_d = \sum_{i=1}^{n} \frac{1}{\mathrm{DEP}_i} \tag{4.14}$$

where

DE_d = Demand elasticity occurred at day d

DEP_i = Deviation of energy prices related to Consumer class i

n = Number of Consumer classes

In order to represent consumers geographically and compliant with a GIS platform, the land is divided into squares or blocks, each block having a number of consumers of different classes (typically, residential, commercial and industrial). After the parameters that influence energy demand have been defined and evaluated, the energy demand of a particular consumer block is calculated by using an econometric method. The econometric method connects the energy demand of the block with the controlling parameters through a non-linear equation expressed in (4.15).

$$ {}_{n}ED_{d} = \left[WEEK_{d} + (1 + TIME_{d}) \frac{EGR_{y}}{2} + (wf_{i} \times WEATHER_{d}) \right] \frac{{}_{n}BASE_{y}}{DE_{d}} \tag{4.15} $$

where

${}_{n}ED_{d}$ = Energy demand of block n at day d

EGR_{y} = Regional economic growth rate of year y

$TIME_{d}$ = Normalized duration

wf_{i} = Weather dependency of Consumer class i

$WEATHER_{d}$ = Weather index at day d

${}_{n}BASE_{y}$ = Yearly reference energy demand of block n

$WEEK_{d}$ = Weekly index at day d

DE_{d} = Demand elasticity occurred at day d

Furthermore, the energy demand of a particular consumer class and the understudy region are calculated using following equations.

$$ {}_{i}CED_{d} = \sum_{j=1}^{n} {}_{j}ED_{d} \tag{4.16} $$

where

${}_{i}CED_{d}$ = Energy demand of Consumer class i at day d

${}_{j}ED_{d}$ = Energy demand of block j at day d

n = Number of blocks belonging to Consumer class i

$$ RED_{d} = \sum_{j=1}^{n} {}_{j}CED_{d} \tag{4.17} $$

where

RED_{d} = Regional energy demand at day d

${}_{j}CED_{d}$ = Energy demand of Consumer class j at day d

n = Number of consumer classes

Much of the data required in developing energy demand has been produced with mathematical functions. However, replacing mathematically produced data with historical time-series data or another similar data type can be easily done if one wishes to farther increase the complexity of the model.

4.2.3 Regulatory Body Entity

The responsibilities of a regulator include protecting consumers from profit-oriented entities and their economical exploitation, establishing an environment in which all market participants compete with one another fairly, and directing the market to operate in an efficient and reliable way. In order to fulfill these responsibilities, the regulator periodically issues directives and takes initiatives. In this study, the regulator assumes the role of a policy-setting entity who intends to improve market efficiency as well as to protect consumers. To do that, the regulator imposes directives such as setting time limits for the minimum time required to wait between two consecutive marketing decisions and imposing price-limit on the energy prices. It also takes initiatives such as educating the market actors by providing useful information.

Under this entity, there are three individual regulators – Power Regulator, Gas Regulator and Heat Regulator – operating separately in respective industries. These regulators simultaneously communicate with Information Environment for exchanging data. The data type and arrangement of information exchanged between these agents are implicitly displayed in the following figure.

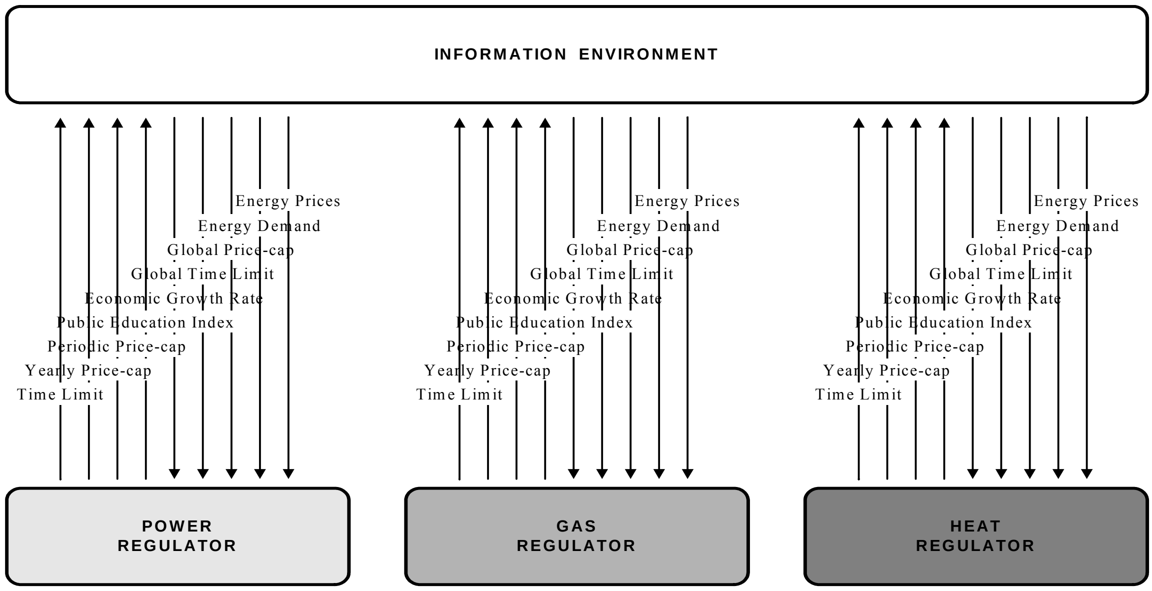


Fig. 4.3. Information flow between market actors under regulator entity and Information Environment

Due to the sheer size of the multi-energy market and the number of consumers participating in it, delivering marketing decisions of retailers in real time seems to be more damage than beneficial to the consumers if the information is not easily accessible. Small retail consumers, lacking resources to receive the information on time, are particularly vulnerable to rapid changes in the market. In order to mitigate this problem, time limits are imposed by the Regulators to allow enough time for spreading the information among consumers.

First, a universal time limit is loosely set at entity level, replicating the actual situation where energy policy makers at national level may set one limit while lower hierarchy actors such as electricity, natural gas and heating regulators may adjust this limit according to their individual preferences. This approach is mathematically formulated as:

$$\mathrm{MTL_i} = \mathrm{GTL} \times \mathrm{CT_i} \tag{4.18}$$

where

$\mathrm{MTL_i}$ = Minimum time limit set by Regulator of energy type i

GTL = Global time limit set by national policy maker

$\mathrm{CT_i}$ = Preference coefficient of Regulator of energy type i regarding time limit

In case of price-limit, it is a two-step process. First, a price-limit is set for the year, considering stability and consistency as the highest priority. In order to promote flexibility, another periodic price-limit is introduced beneath the boundary of the yearly price-limit. These two price-limit methods can be mathematically formulated as:

$$YPL_s = AEP \times \left[1 \pm \frac{EGR \times TF \times CP_i}{100}\right] \qquad \begin{vmatrix} \text{if s is maximum, } \pm \text{ turn } + \\ \text{if s is minimum, } \pm \text{ turn } - \end{vmatrix} \tag{4.19}$$

where

YPL_s = Yearly energy price limit

AEP = Average energy price

EGR = Economic growth rate

TF = Transferring factor

CP_i = Preference coefficient of the Regulator of energy type i regarding energy price

And,

$$PPL_s = EP \times \left[1 \pm \frac{PC \times CPC_i}{100}\right] \qquad \begin{vmatrix} \text{if s is maximum, } \pm \text{ turn } + \\ \text{if s is minimum, } \pm \text{ turn } - \end{vmatrix} \tag{4.20}$$

subject to:

$YPL_{min} \le PPL_s \le YPL_{max}$

where

YPL_s = Yearly energy price limit

PPL_s = Periodic energy price limit

PC = Predefine percentage limit

CPC_i = Preference coefficient of regulator of energy type i regarding price-limit

EP = Current energy price

Public awareness indicates the level of interest or attention general public paid to a particular issue. The level of public awareness defines the state of public understanding on the issue and its advantages and disadvantages. Improving public awareness can be done by initiating campaigns that spread useful information or by promoting the information through educational programs. In this study, the regulator is designed to be able to participate in public awareness improvement campaigns and to spend sufficient time and money on promoting information that it wishes to spread among market participants. The deviation of energy prices and energy demand level are considered as influential factors that control the timing and intensity of these campaigns. One of the triggering factors of the campaigns, deviation of energy prices, is calculated using following equation.

$$PD = \sum_{i=1}^{n} \frac{{}_{i}EP_{d} - {}_{i}REF}{{}_{i}REF} \tag{4.21}$$

where

${}_{i}EP_{d}$ = Energy price related to Consumer class i at day d

${}_{i}REF$ = Reference energy price related to Consumer class i

PD = Energy price deviation index

n = Number of Consumer classes

Public education index, which indicates the degree of public awareness, is then developed as:

$$PEI = PEM \times PD \tag{4.22}$$

subject to:

$$PD \geq 0$$

where

PEI = Index of public education

PEM = Maximum limit of public education index

PD = Price deviation index

4.2.4 Consumer Entity

Fundamental functions of a consumer include setting personal preference about the products offered by retailers, paying attention on the marketing evolution of different energy products and reacting properly by adjusting energy consumption accordingly. In this study, a particular Consumer class is equipped with functions such as evaluating its attitude toward the products offered by competing retailers, closely following the actions of retailers and developing appropriate reactions in its consumption pattern, and evaluating the economic feasibility of these reactions if the consumption tends to be higher than the installed capacity. Consumer attitude development, energy consumption adjustment, and economical feasibility investigation are explained more detail in following sections.

Each Consumer class is considered as a container that unites individual consumers having similar consumption pattern. In the process of Consumer class development, individual consumers have been classified into typical consumer types – residential, commercial and industrial – according to their energy consumption pattern. Afterward, the classified consumers are placed under the name of the class they belong to. Then, the behavior of that particular Consumer class is adopted as the common behavior of the individual consumers involved in that class. With this approach, a large number of consumers can be deducted to three typical Consumer classes. This approach gives the opportunity to shrink the number of consumers without compromising their individuality. As mentioned before, there are three Consumer classes – Residential, Commercial and Industrial – under this entity. The details of the information exchanged between these market actors and Information Entity is shown in following figure.

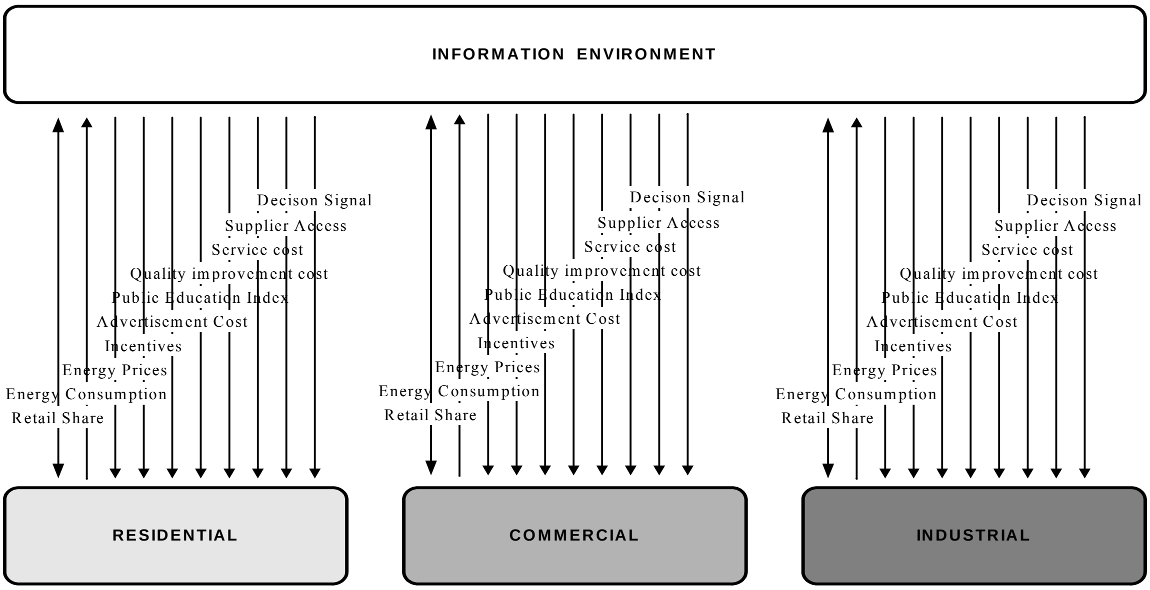


Fig. 4.4. Information flow between market actors under Consumer entity and Information Environment

4.2.4.1 Consumer Attitude

The attitude of consumers toward the products from competing retailers has influence on decision-making habit of consumers. Since Consumer classes in this study are designed to be adaptive agents that are irrational, emotional, and having incomplete knowledge, the decisions of a particular Consumer class are strongly influenced by its preference or perception.

It is widely believed that consumers use cues to infer the extent of superiority or excellence of the products [10]. These cues typically are classified as intrinsic or extrinsic [11]. Intrinsic cues are related to physical condition of the products while extrinsic cues include general aspects such as price and brand name. Most of the research works on consumer cues has concentrated on price, brand name, and the level of advertising [12-

14]. In this study, public awareness, publicity of the products from competing Regulators, amount of incentives received from purchasing the products, support provided after sale, and quality of the products are considered as the parameters influencing the perception of the consumers.

These influential parameters are first defined quantitatively and afterward translated to the attitude of the consumers, which influences on its decision-making habit. The values of the parameters that affect the attitude of the consumers fluctuate with the variation of the spending on them; however, these parameters become fixed values if there is consistence spending on them for certain period. The process of quantitatively defining the consumers' perception is better explained in following mathematical equations.

An attachment perception, which is strongly related to incentives, is calculated as

$$ {}_{i}RM_{j} = RI \times \tan^{-1}\left(\frac{{}_{i}I_{j}}{{}_{i}EP_{j} \times CRM} \right) \tag{4.23} $$

where

${}_{i}RM_{j}$ = Attachment perception of Consumer class j to energy from Retailer i

RI = Maximum attachment index value

${}_{i}I_{j}$ = Incentive given to Consumer class j by Retailer i

${}_{i}EP_{j}$ = Energy price related to Consumer class j set by Retailer i

CRM= Coefficient factor regarding attachment perception

For publicity perception, the formulation becomes:

$$ {}_{i}AM_{j} = AI \times \tan^{-1}\left(\frac{AD_{i}}{MAD} \right) \tag{4.24} $$

where

${}_{i}AM_{j}$ = Publicity perception of Consumer class j to energy from Retailer i

AI = Maximum advertisement index value

AD_i = Amount spent on advertisement by Retailer i

MAD = Maximum spending on advertisement

For customer service perception,

$$ {}_{i}SM_{j} = SI \times \tan^{-1}\left(\frac{SS_{i}}{MSS \times MS_{i}} \right) \tag{4.25} $$

where

$_iSM_j$ =Customer service perception of Consumer class j to energy from Retailer i

SI = Maximum service index value

SS_i = Amount spent on service improvement by Retailer i

MS_i = Market share of Retailer i

MSS = Maximum spending on service improvement

For product quality perception,

$$_iQM_j = QI \times \tan^{-1}\left(\frac{QS_i}{MQS \times MS_i}\right) \tag{4.26}$$

where

$_iQM_j$ = Product quality perception of Consumer type j to energy from Retailer i

QI = Maximum quality index value

QS_i = Amount spending on quality improvement by Retailer i

MS_i = Market share of Retailer i

MQS = Maximum spending on quality improvement

Finally, public awareness perception is formulated as

$$PA_i = BS + (AE_i \times PEI) \tag{4.27}$$

where

PA_i = Public awareness perception of Consumer class i

BS = Base sensitivity index

PEI = Public educational index achieved from improvement programs

AE_i = Effect of advertisement on Consumer class i

After above influential consumer perceptions have been developed, the attitude of a particular Consumer class toward a particular product is defined using following equation.

$$_iAT_j = PA_j + (RE_j \times {}_iRM_{ji}) + (AE_j \times {}_iAM_j) + (SE_j \times {}_iSM_j) + (QE_j \times {}_iQM_j) \tag{4.28}$$

where

$_iAT_j$ = Attitude index of Consumer class j toward energy of Retailer i

PA_j = Public awareness perception of Consumer class j

RE_j = Effect of public relation on Consumer class j

$_iRM_j$ = Attachment perception of Consumer class j toward energy of Retailer i

AE_j = Effect of advertisement on Consumer class j

$_iAM_j$ = Publicity perception of Consumer class j toward energy of Retailer i

SE_j = Effect of customer service on Consumer class j

$_iSM_j$ = Customer service mood of Consumer class j toward energy of Retailer i

QE_j = Effect of product quality on Consumer class j

$_iQM_j$ = Product quality perception of Consumer class j toward energy of Retailer i

4.2.4.2 Consumption Adjustment

Microeconomic theory suggests that consumers will increase their demand to the point where the marginal benefit they derive is equal to the price they have to pay [15]. Following the above idea, it is reasonable to conclude that the demand should decrease when the price is above the marginal benefit and vice versa. Additionally, the movement of market share of an energy product can be inversely related to the changing of its price in general. Using those ideas as the foundations, the following mathematical formulation is defined as a way that consumers adjust their share of consumption in response to changing of energy prices.

$$ {}_i NS_j = \frac{\left({}_i CP_j\right)^{-{}_iAT_j}}{\sum_{k=1}^{n}\left({}_i CP_k\right)^{-{}_iAT_j}} \tag{4.29} $$

where

${}_i NS_j$ = Nominal share of Retailer j under Consumer class i

${}_i CP_j$ = Normalized price of energy from Retailer j related to Consumer class i

${}_i AT_j$ = Attitude index of Consumer type i to energy of Retailer j

n = Number of Retailers

Energy prices used in above equation are normalized prices in order to standardize the prices of products from different industries. The normalization process is performed according to the following equation.

$$ {}_i CP_j = \left({}_i P_j - {}_i CI \times {}_i I_j\right) Eff_j \tag{4.30} $$

where,

${}_i CP_j$ = Normalized price of energy from Retailer j related to Consumer class i

${}_i P_j$ = Price of energy from Retailer j related to Consumer class i

${}_{i}I_{j}$ = Incentive received by Consumer class i from Retailer j

Eff_{j} = Efficiency of energy from Retailer j

${}_{i}CI$ = Coefficient index regarding incentives related to Consumer class i

4.2.4.3 Consumer Grouping

This market simulation is developed using a territory-oriented approach, representable in a GIS platform (Geographic Information System). The area is divided into squares or blocks, each block having a number of consumers of different classes (typically, residential, commercial and industrial). Crossing the territory there are networks serving the clients that buy different types of energy: electricity, gas or heat. Grids develop in the same territory, competing for clients. There are areas already developed and areas under development, not yet served by one or all the networks. Consequently, consumers have different arrangements of access to the energies supplied by different networks.

In order to represent this situation properly, individual consumers under a particular Consumer class are reclassified into eight groups; each group represents one of the combinations that can be developed using three sources. These consumer groups can be further regrouped into four supply access categories; the consumer group having access to no energy at all, the consumer group having access to one type of energy, the consumer group having access to two types of energy, and the consumer group having access to all three types of energy.

To represent the consumers in more sophisticated and realistic way, energy consumption of a particular consumer is divided into two parts: fixed and variable. The fixed component represents energy consumption from unique applications (i.e. lighting in electricity) that can only be supplied by a particular energy supplier. The variable part of consumption is acknowledged as the consumption from applications that can easily be supplied by any of the competing energies with affordable energy conversion devices. This approach allows the consumers to be properly represented as sophisticated individuals having both consumption components that they intend to maintain the existing state at all cost and that they are willingly to adjust if there is economical advantage for doing so.

The fixed and variable component of a consumer is treated as a share or percentage distribution of the total consumption of the consumer. The fixed share of the consumer is assigned by a predefined value that is differently set for different consumers according to their respective consumption pattern and energy access. The variable share is a fraction of the consumer's demand in which the utilization of competing energies can fluctuate without restriction. After the fixed and variable shares of the consumer have been identified, the consumption share of the consumer can be evaluated by using following equations. For consumers who have access to all three energies, the formulation becomes:

$$ {}_{i}GS_{j} = {}_{i}FS_{j} + \left({}_{i}VS \times \frac{{}_{i}NS_{j}}{\sum_{k=1}^{n} {}_{i}NS_{k}} \right) \tag{4.31} $$

where

${}_{i}GS_{j}$ = Group share regarding energy type j under Consumer class i

${}_{i}FS_{j}$ = Fixed share regarding energy type j under Consumer class i

${}_{i}NS_{j}$ = Variable share regarding energy type j under Consumer class i

${}_{i}VS$ = Variable share of Consumer class i

${}_{i}NS_{k}$ = Variable share regarding energy type k under Consumer class i

n = Number of available energies to the group

The same equation can be used for consumers having access to two energies. The number of available energies is reduced to two in this situation.

The equation for consumers connected to only one type of energy is defined as:

$$ {}_{i}GS_{j} = 1 + {}_{i}FS_{j} - \sum_{k=1}^{m} {}_{i}FS_{k} \tag{4.32} $$

where

${}_{i}GS_{j}$ = Group share regarding energy type j under Consumer class i

${}_{i}FS_{k}$ = Fixed share regarding energy type k under Consumer class i

${}_{i}FS_{j}$ = Fixed share regarding energy type j under Consumer class i

m = Number of energies available in the territory

Obviously, the consumption share of consumers who do not have access to any energy type is set to zero.

4.2.4.4 Economic Feasibility

The decision of a consumer on changing consumption of competing energies due to the marketing decisions applied by retailers must be checked for economical feasibility as the consumer intends to justify his own action. It is reasonable to assume that consumers may have willingness to make adjustment in their energy consumption if and only if they sense an economic advantage. Therefore, an economic feasibility evaluation is performed when the consumption is expected to exceed the existing installed capacity, and the outcome plays important role in making a decision for installing new equipments or energy conversion devices. Both the benefits and the losses that result from changing energy consumption are put together on the balance in this evaluation process. Technically, the evaluation starts with calculating potential demand of a group under a particular Consumer class with following equation.

$$_{i}GD = \sum_{j=1}^{n} {}_{i}BD_{j} \tag{4.33}$$

where

n = Number of blocks belonging to the group

$_{i}GD$ = Energy demand of the group under Consumer class i

$_{i}BD_{j}$ = Energy demand of block j belonging to the group under Consumer class i

Afterward, the potential energy demand of the group is used in the following equation to evaluate the possible consumption of the group for a particular energy.

$$_{i}GP_{j} = \frac{_{i}GD \times {}_{i}GS_{j} \times Eff_{j}}{BN} \tag{4.34}$$

where

$_{i}GP_{j}$ = Consumption of energy type j in the group under Consumer class i

$_{i}GD$ = Energy demand of the group under Consumer class i

$_{i}GS_{j}$ = Group share of energy type j under Consumer class i

Eff_{i} = Conversion efficiency of energy type j

BN = Number of blocks belonging to the group

After the consumption of the energy under the group is established, the capacity needed for accommodating present consumption is determined by the following equation:

$$ {}_{i}IC_{j} = \frac{{}_{i}GP_{j}}{{}_{i}CZ_{j}} \tag{4.35} $$

where

${}_{i}IC_{j}$ = Capacity of equipment needed by the group to house the present consumption of energy type j under Consumer class i

${}_{i}GP_{j}$ = Consumption of energy type j of the group under Consumer class i

${}_{i}CZ_{j}$ = Discrete size of the equipment available for energy type j under Consumer class i

Then, the cost of installing new equipment for accommodating new consumption is defined as follows:

$$ CDC = \left({}_{i}IC_{j}^{after} - {}_{i}IC_{j}^{before} \right) \times EQ \tag{4.36} $$

where

${}_{i}IC_{j}$ = Capacity of equipment needed by the group to house the consumption of energy type j under Consumer class i

EQ = Price of energy conversion device in discrete size

CDC = Cost of extra energy conversion device needed

The cost of the equipment is then discounted with respect to its lifetime to determine the daily-levelized cost. First, a discount rate is calculated using the following equation.

$$ D = (1 + i)^{Y} \tag{4.37} $$

where

i = Interest rate

D = Discount rate

Y = Number of years

Using the discount rate received from the above equation, the daily-levelized cost is then defined with following equation.

$$ DLC = CDC \times \frac{i \times D}{(D - 1) \times 365} \tag{4.38} $$

where,

i = Interest rate

D = Discount rate

DLC = Daily-levelized cost

CDC = Cost of extra conversion device

After the cost section of the economic feasibility evaluation has been identified, the benefit part is determined by calculating the potential daily profit using the following equation.

$$DP = {}_{i}GD \times \left({}_{i}GS_{j}^{after} - {}_{i}GS_{j}^{before} \right) \times Eff_{j} \times AP_{j} \tag{4.39}$$

where

DP = Potential daily profit achieved by adjusting consumption

${}_{i}GS_{j}$ = Group share of energy type j under Consumer class i

${}_{i}GD$ = Energy demand of group under Consumer class i

Eff_{j} = Conversion efficiency of energy type j

AP_{j} = Average price of energy type j

The decision to adjust consumption is made according to the outcome from the comparison between the profit and cost. The adjusting consumption is favorable for the consumer when the profit is higher than the cost and vice versa.

4.3.4.5 Incorporating Time Delay

Although the Consumer class has been broadly defined as an entity that represents a set of individual consumers, it would be more realistic if the consumption adjusting reaction of this entity were developed as a joint reaction of many individual consumers. Therefore, the consumption adjusting is designed to occur gradually during certain time span to reflect the behavior of individual consumers with different preferences. The following equation guides the consumption share to smooth changes along an S-shaped curve in which slow and steady changes occur at both beginning and ending parts of the time span while steep changing occurs in the middle. It is the combination of two equations in which each equation produces half of the S- shape curve respectively.

$${}_{i}S_{j} = {}_{i}GS_{s} \pm \left[\frac{{}_{i}GS_{end} - {}_{i}GS_{begin}}{\pi} \times Tan^{-1}\left(\frac{T \times C}{T_{m}^{2} - T^{2}} \right) \right] \quad \text{if} \begin{bmatrix} s = \text{begin}, \pm \text{ become} + \\ s = \text{end}, \pm \text{ become} - \end{bmatrix} \tag{4.40}$$

where

$_iS_j$ = Actual share changing occurred for energy type i at day j

$_iGS_s$ = Group share of energy type i at state s

T_m = Half of delay time span

T = Duration between the time that decision first taken affect and present day

C = Coefficient factor of share changing

The consumer's accessibility to competing energies, its actual consumption share of competing energies, and the result from the economical feasibility evaluation play important role in the process of transforming the consumer's potential energy demand into actual consumption. Actual consumption of a particular energy type under a particular Consumer class is calculated using following formula.

$$EP_i = \sum_{j=1}^{N} {}_jED \times Eff_i \times S_i \tag{4.41}$$

where

EP_i = Consumption of energy type i under the Consumer class

$_jED$ = Energy demand of block j

Eff_i = Conversion efficiency of energy type i

S_i = Actual share of energy type i under the Consumer class

N = Number of blocks belonging to the Consumer class

Total consumption of the energy in the understudy territory is then defined as:

$$TEP = \sum_{i=1}^{N} {}_iEP \tag{4.42}$$

where

$_iEP$ = Consumption of the energy under Consumer class i

TEP = Total consumption of the energy

N = Number of Consumer classes

4.2.5 Energy Deliverer Entity

Energy delivering utilities provide energy transportation services to consumers under the request of retailers or other parties with similar function. Maximizing profitability and providing reliable services are the main objectives of the energy distributors. They view typical functions such as exploring the territory to locate profitable consumers and expanding the existing network as key factors in achieving their objectives. Therefore, Energy Deliverers are designed to engage in network expansion functions; exploring the territory for finding a potential consumer with highest profitability, connecting it to the existing network with minimal cost, and increasing profit with transporting more energy to consumers existing along the new connection. There are three individual Energy Deliverers under Energy Deliverer entity. The following figure displays the information flow and scheduling arrangement between Information Environment and these Energy Deliverers.

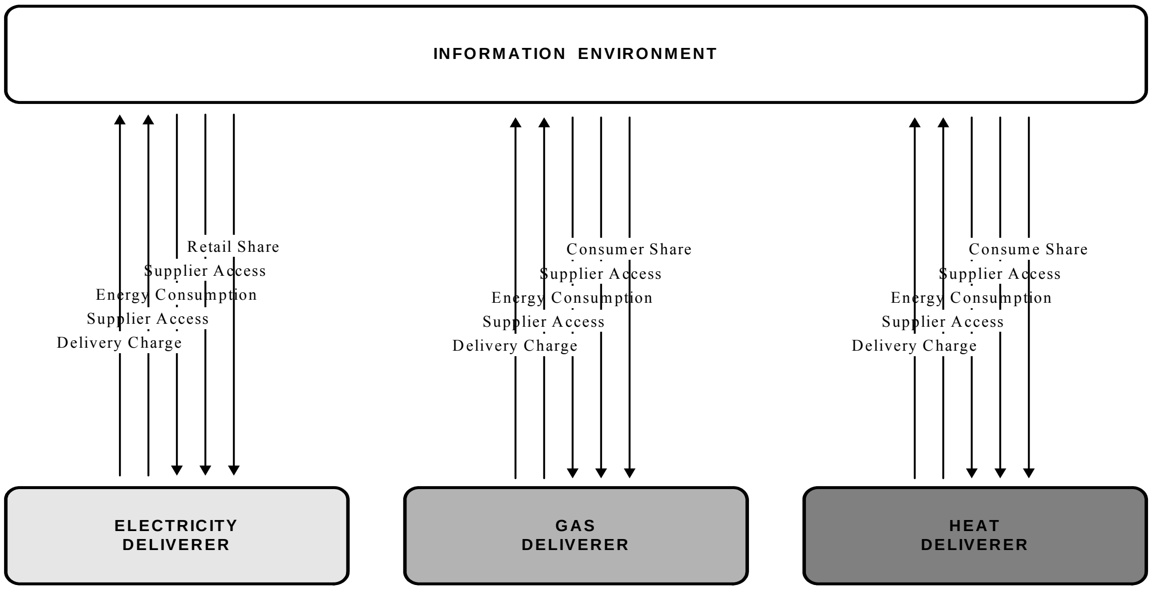


Fig. 4.5. Information flow between market actors under Energy Deliverer entity and Information Environment

Locating potential consumers is the first step in the network expansion of a particular Energy Deliverer. It can be performed by a process that first calculates potential daily revenue and installation cost resulting from connecting blocks and then develops profitability ratios from them. The profitability ratios of the blocks are then sorted according to their merit, and the block having the highest ratio above the predefined lower limit is chosen as a potential consumer. The calculation of the daily revenue of a particular block is performed using following formulation.

$$ {}_{i}REV_{j} = RED_{j} \times Eff \times DC \times {}_{i}MSC \tag{4.43} $$

where

Eff = Conversion efficiency of the energy belonging to the Energy Deliverer

${}_iREV_j$ = Generalized revenue received from block i at day j

RED_j = Regional energy demand at day j

DC = Delivery charge

${}_iMSC$ = Coefficient of market share regarding different connection; 1.5 times of the share of a particular energy type in the blocks connected to 2 types of energy, the same share of a particular energy in the blocks connected to all types of energy, and set 1 in blocks connected to only one type of energy.

The investment cost incurred from connecting a block to a neighboring block includes the costs associated with equipment, transportation, and much more. This one-time investment cost is then transformed into the daily cost for the lifetime of the equipment using a depreciation method. It is a method that uses the interest rate and the lifetime of the equipment to calculate the daily-levelized cost, which occurs along the life span of the equipment. The daily-levelized cost can be calculated using a similar approach to that applied in section 4.3.4.4, employing (4.37) and (4.38).

After having finished evaluating the revenues and the installation costs of the blocks, the profitability ratios are then calculated using following equation. If the profitability ratio of a particular block is higher than the predefined limit set by Energy Deliverer and the highest among rival potential blocks, it is then chosen as a candidate block to be connected to the existing network.

$$PR = \frac{REV_j}{DLC} \tag{4.44}$$

where

PR = Profitability ratio of a particular block

REV_j = Generalized revenue received from the block at day j

DLC = Daily-levelized cost

After the candidate block has been selected, the most profitable route between the candidate block and one of the blocks from the existing network is determined using a modified path analysis. The method used is similar to the Euclidean distance function that calculates the actual distance from one point to another, but instead of finding the shortest or least-cost route between two locations, a modified version has been developed to find the most profitable route between two points. Since the least-cost route can not be interpreted as the most-profitable route in the situation where blocks have different revenues, the most profitable path analysis is an appropriate choice for this study. Both the revenue yielded from a particular block and the costs associated with the network installation are considered equally important parameters in the most profitable path analysis.

Finding the most profitable path starts with modeling a cost grid. It is developed by calculating potential installation costs of equipments occurred to blocks and assigning those costs to all the blocks in the territory respectively. Although the cost of equipment is the same for every block, the installation costs of the blocks tend to be different due to the hidden costs associated with the equipment transportation cost, the level of difficulty to install, and so on. Using the installation costs of the blocks, a unit cost grid, which is a set of uniform costs involved in connecting blocks in the territory, is developed using following formula.

$$UC_b = Coef \times \left[\frac{EC_a + EC_b}{2} \right] \qquad \begin{bmatrix} Coef = 1.0 \ \text{ if blocks are not in diagonal} \\ Coef = 1.414 \ \text{ if blocks are in diagonal} \end{bmatrix} \tag{4.45}$$

where

UC_b = Unit cost for connecting adjacent blocks, block b to block a

EC_b = Equipment installation cost at block b

EC_a = Equipment installation cost at block a

After the unit cost grid has been developed, a profit grid is defined by calculating the expected profits of the blocks in the territory using following equation.

$$EP_b = PP_b - UC_b \tag{4.46}$$

where

EP_b = Expected profit at block b

PP_b = Potential profit at block b

UC_b = Unit cost value for connecting block b

Then, a weighted-distance mapping, which finds the most accumulative profit from each block to a source block, is formulated by using the profit grid and the candidate block. The source blocks include both the blocks connected to the existing network and the candidate block. The procedure for creating the most accumulated profit grid consists of using a weighted-distance function that searches for adjacent blocks (horizontal, vertical, and diagonal neighboring cells), which have highest values, from a source block. Afterward, the searched blocks are included into source blocks so that their adjacent neighboring blocks can also be checked for the highest value. This process is iterative and continued by searching for the next adjacent blocks with the highest value until every block is assigned with a cumulative cost value.

Using the profit grid, the weighted-distance function produces an accumulative profit grid in which the blocks are assigned with the most accumulative profit to the source blocks. Once the weighted-distance function has been applied, the most profitable path from the candidate block to the existing network can be determined by using the most profitable path analysis. Aside from a candidate block, the most profit analysis needs two additional grids, the accumulative profit grid and a back-link, which assigns a specific code number to each block according to its direction to a source block. The most profitable path analysis produces a path travels from the candidate block to the existing network and is guaranteed to be the most profitable route.

After the most profitable path has been established between the candidate block and a source block from the existing network, the actual network installation for that path is started with iteratively connecting the blocks nearest to the source block one after another. When the installation is finished for a particular block, that block is set to immediately consume the energy. And the revenue of a particular Energy Delivery increases with the growing number of consumers due to its network expansion. The equation used in calculating the revenue of the Energy Deliverer is:

$$\mathrm{DR}_i = \mathrm{TEC}_i \times \mathrm{DC} \tag{4.47}$$

where

DR_i = Revenue of the Energy Deliverer at day i

TEC_i = Energy consumption at day i

DC = Delivery charge

In case of the cost, the daily-levelized cost occurred in present time is considered as the summation of the existing daily-levelized cost occurred from the installation made before and the new daily-levelized cost occurred from the current installation. This approach can be mathematically formulated as:

$$\mathrm{TDLC}_i = \mathrm{DLC}_i^{\mathrm{existing}} + \mathrm{DLC}_i^{\mathrm{current}} \tag{4.48}$$

where

TDLC_i = Total daily-levelized cost occurred by installation at day i

DLC_i = Daily-levelized cost occurred by a particular installation status at day i

Finally, the profit of the Energy Deliverer is calculated using the following equation.

$$DP_i = DR_i - TDLC_i \tag{4.49}$$

where

DP_i = Profit of the Energy Deliverer at day i

DR_i = Revenue of the Energy Deliverer at day i

$TDLC_i$ = Total daily-levelized cost occurred by installation at day i

4.2.6 Market Operator Entity

In a real-world energy market, a market operator (or independent system operator in some market structures) accepts bids from energy producers, may operate the energy system in optimal way, and makes decision about final spot prices. Since the behavior of the wholesale market is out of the scope of this study, the Market Operator is simply represented as a day-ahead energy price simulator, which produces day-ahead spot prices from the record of contract prices from the contracts made between energy producers and energy retailers. The data flow between Market Operators and Information Environment can be seen in following figure.

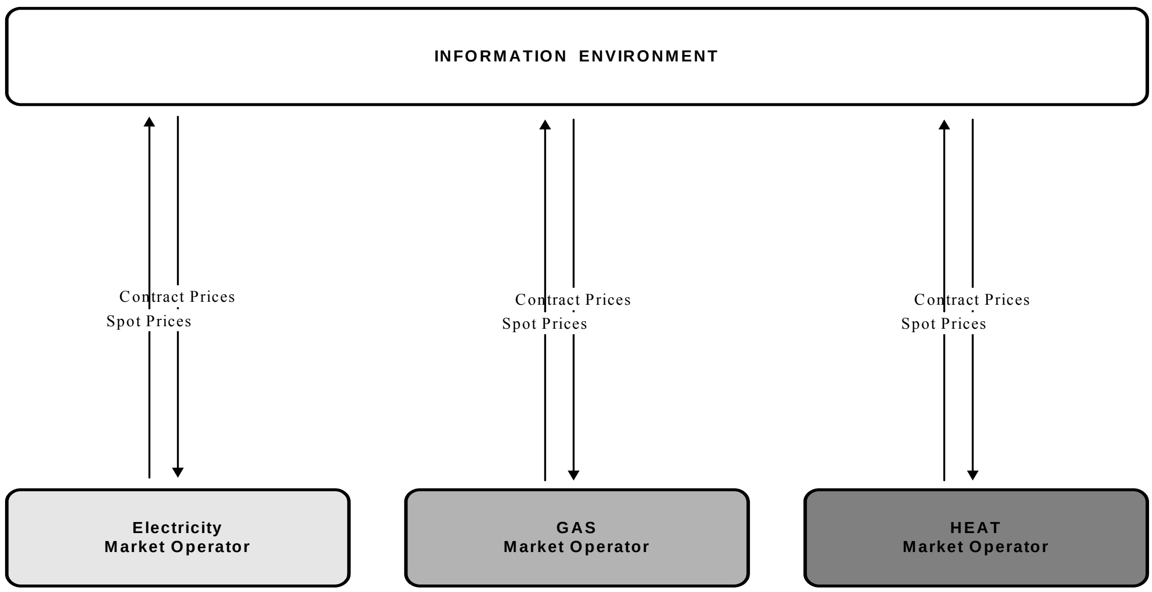


Fig. 4.6. Information flow between market actors under Market Operator entity and Information Environment

The day-ahead spot price of a particular energy type is defined as:

$$SP_i = \sum_{j=1}^{N} \frac{ACP_j \times R}{N} \qquad (4.50)$$

subject to:

$$\frac{1}{2} \le R \le \frac{3}{2}$$

where

SP_i = Spot price at day i

ACP_j = Average contract price made by Retailer j

R = Randomly generated number

N = Number of Retailers supplying a particular energy type

4.2.7 Energy Retailer Entity

Among various duties, achieving maximum profit while providing reliable service to consumers is the ultimate goal for a profit-oriented energy retail supplier. The profit of a retailer is generally defined as the difference between the revenue and cost. In this study, the mathematical formulation for calculating the profit of a particular Retailer is seen as:

$$PF_i = \sum_{j=1}^{n} UEP_i^j \times P_i^j - \left|FC + UC_i \times UEP_i\right| \qquad (4.51)$$

where

PF_i = Profit received by the Retailer at day i

UEP_i^j = Consumption of the energy by the Consumer class j at day i

UEP_i = Total consumption of the energy at day i

FC = Fixed cost of the Retailer

UC_i = Production cost of the commodity at day i

P_i^j = Price of the energy related to the Consumer class j at day i

n = Number of Consumer classes

The functions assigned to the Retailer includes monitoring its economical performance in terms of profitability as well as market share, finding a optimal set of marketing decisions to improve its performance, and improving efficiency in management area. The decision makers of the Retailer closely monitor its economical performance and the behavior of market and develop a basic marketing strategy, which has influence on its marketing decisions, for using as a guideline. The basic marketing strategy of the Retailer in this study can be one of three: profit-oriented, share-oriented, and neutral.

This basic marketing strategy of the Retailer is formulated based on the general behaviors of the Retailer such as their approach to profitability, market share gaining, and aggressive marketing. As an example, a Retailer may opt to play safely and feel pleased with less profit but stable market share if it is a conservative player. However, an aggressive player may pursue higher profit without paying much attention to the condition of its market share. Predefined limits on the profitability and movement of market shares, which are tied to the behaviors of the Retailer as mention above, are set with the values quantitatively translated from the behavior of the Retailer. Percentage limits on the profit and market share decreases are assigned to the Retailer differently according to its aggressiveness, profitability awareness and view on market share.

There are a series of steps in formulating the basic marketing strategy of the Retailer. First of all, the average value of the daily profit and share is calculated at the end of a particular month using a series of equations. The average daily profit of particular month is calculated using the following equation.

$$MP = \frac{\sum_{i=1}^{n} DP_i}{N} \tag{4.52}$$

where

MP = Average daily profit of the month

DP_i = Daily profit at day i

n = Number of days in the month

The average daily share of the month can also be calculated using similar type of equation as:

$$MS = \frac{\sum_{i=1}^{n} DS_i}{N} \tag{4.53}$$

where

MS = Average daily share of the month

DS_i = Daily share at day i

n = Number of days in the month

Similarly, the historical average daily profit and share can be determined by using above equations, setting the time span to entire number of days simulated so far.

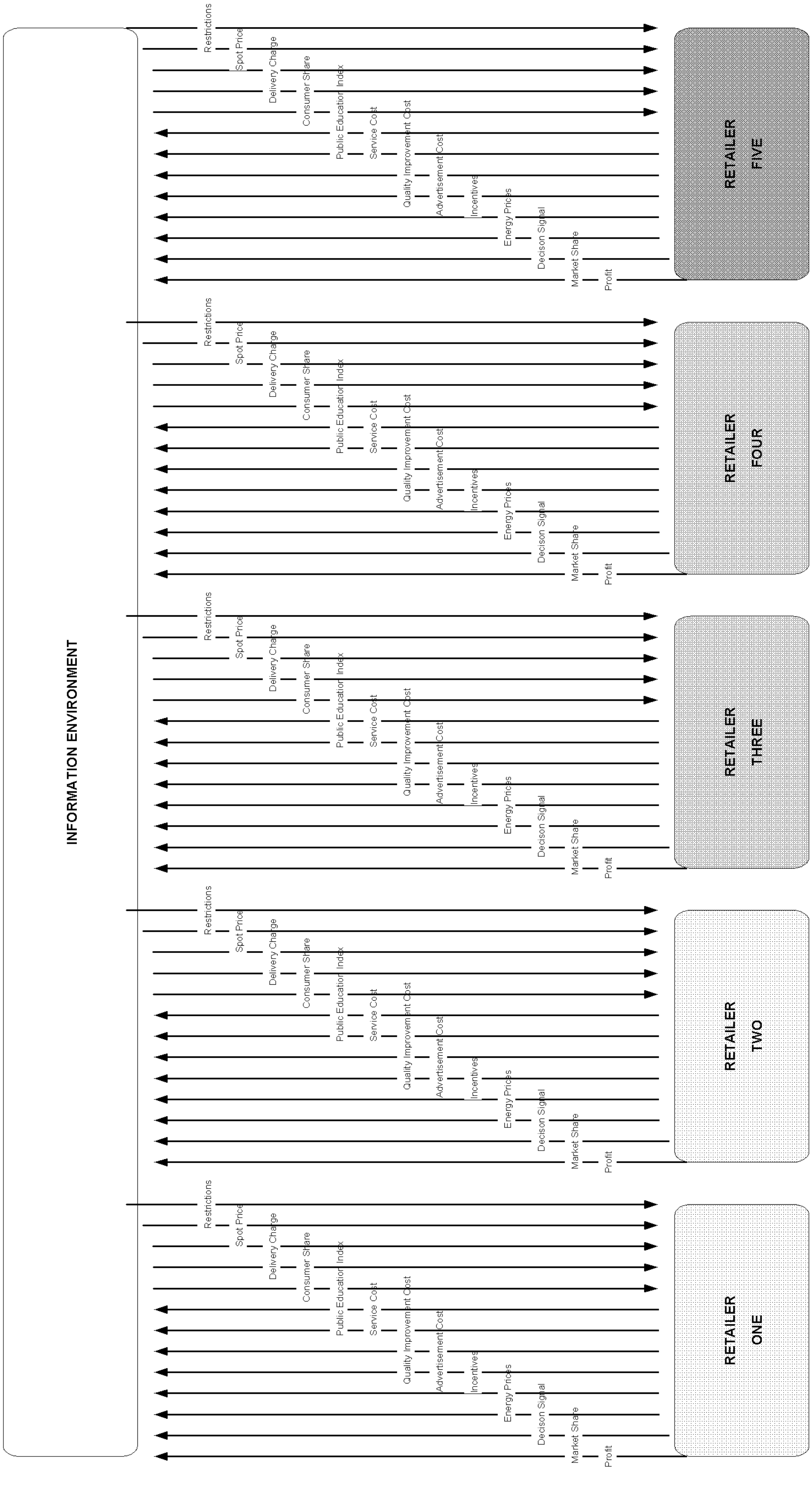
Then the comparisons are made between the historical average daily profit and the average daily profit of the month as well as between the historical average daily share and the average daily share of the month. Priority is given to profitability, and the basic marketing strategy of the Retailer is a profit-oriented agenda when the average daily profit of the month is lower than the acceptable level, which is the summation of the percentage limit of the profit decrease and the historical average daily profit. When the average daily profit is above the acceptable level and the average daily share of the month is less than the summation of the percentage limit of share decrease and the historical average daily share, the strategy becomes a share-oriented approach. However, the strategy is set to be neutral when the condition is between above two strategies.

After the basic marketing strategy of the Retailer has been established, it is the beginning of the process of evolving several important marketing decisions into one joint optimal decision. The marketing decisions considered in this study for manipulating the profitability and the market share management include:

- Incentives and energy prices related to residential, commercial, and industrial consumer
- Spending on management efficiency improvement and advertisement
- Investment on improving service and quality of products

Marketing decision changing of the Retailer is restricted by regulations such as certain time limit between two successive changes. In order to be compliant with above time separation limit, the Retailer only evaluates the market situation and makes marketing decisions after the time limit requirement has been fulfilled. When the time is right, the Retailer determines the optimal marketing decision with evolutionary computation based algorithms, which evaluate the problem and finds the best option using a Darwinian approach. Evolutionary algorithms, which possess attractive features such as capability of finding global optimum or quasi-optimum solutions when dealing with discrete type problems and ability in handling different kinds of constraints quite easily, are well suited to use in multi-objective and constrained problems [16].

There are five retail agents under this entity. The name of these agents and the data flow between them and Information Environment are shown in the following figure.


INFORMATION ENVIRONMENT
Restrictions
Spot Price
Delivery Charge
Consumer Share
Public Education Index
Service Cost
Quality Improvement Cost
Advertisement Cost
Incentives
Energy Prices
Decison Signal
Market Share
Profit
RETAILER ONE
RETAILER TWO
RETAILER THREE
RETAILER FOUR
RETAILER FIVE

The Retailer applies an evolutional-based method to manipulate the parameters that have influence on its profitability in a timely manner. An individual or solution, which is a set of influential parameters on the profitability, acts as a possible decision of the given problem. Then, the fitness function is established by using the objective function of the problem. Since the Retailer may hold the main interest on both profit and market share, they are considered as the main economic performance indicators and included in the objective function. The objective function that determines the performance of a particular solution or individual is defined as:

$$\text{Maximize } OBJ = \sum_{d=1}^{n} \left[Eco_d - Pen_d\right] \qquad (4.54)$$

subject to:

$$Price_a^{min} < Price_a < Price_a^{max}$$

$$DevPrice_a < Limit$$

$$Incentive_a^{min} < Incentive_a < Incentive_a^{max}$$

$$Advertise_a^{min} < Advertise_a < Advertise_a^{max}$$

$$Service_a^{min} < Service_a < Service_a^{max}$$

$$Quality_a^{min} < Quality_a < Quality_a^{max}$$

$$Management_a^{min} < Management_a < Management_a^{max}$$

where

n – number of days of an internal simulation

Eco_d = Economic performance at day d

Pen_d = Penalty assigned at day d

$Price_d$ = Energy prices charged to residential, commercial and industrial consumers

$Incentive_d$ = Incentives given to residential, commercial and industrial consumers

$Advertise_d$ = Spending on advertisement

$Service_d$ = Spending on customer service improvement

$Quality_d$ = Spending on quality improvement of the product

$Management_d$ = Spending on management efficiency improvement

The objective function can be broken down into two parts: economic performance and penalty for violating constraints. The economic performance of the Retailer can be evaluated using the following generalized formula.

$$Eco_d = P_d \times UP_d + S_d \times US_d \tag{4.55}$$

where

UP_d = Unit profit of the Retailer at day d

US_d = Unit market share of the Retailer at day d

P_d = Profit weight factor at day d

S_d = Share weight factor at day d

The Retailer is designed to use different evaluation methods in different marketing strategies. When the basic marketing strategy is profit-oriented, the economical performance is evaluated as follow:

$$Eco_d = \begin{Bmatrix} P_d^1 \times UP_d + S_d^0 \times US_d \quad \text{if } \delta P_d \geq 0 \\ P_d^2 \times UP_d + S_d^0 \times US_d \quad \text{if } 0 > \delta P_d \geq \delta P_{\lim it}^{lower} \\ P_d^3 \times UP_d + S_d^0 \times US_d \quad \text{if } \delta P_d < \delta P_{\lim it}^{lower} \end{Bmatrix} \tag{4.56}$$

subject to:

$$S_d^0 < P_d^1 < P_d^2 < P_d^3 < 1$$

where δP_d represents the derivative of the current profit with respect to the reference profit. The value of profit weight factor changes with respect to the condition of δP_d. The predetermine value, $\delta P_{\lim it}^{lower}$, is set as the lower limit of the profit derivation.

When the basic marketing strategy is share-oriented type, the economical performance is evaluated as:

$$Eco_d = \begin{Bmatrix} P_d^0 \times UP_d + S_d^1 \times US_d \quad \text{if } \delta S_d \geq 0 \\ P_d^0 \times UP_d + S_d^2 \times US_d \quad \text{if } 0 > \delta S_d \geq \delta S_{\lim it}^{lower} \\ P_d^0 \times UP_d + S_d^3 \times US_d \quad \text{if } \delta S_d < \delta S_{\lim it}^{lower} \end{Bmatrix} \tag{4.57}$$

subject to:

$$P_d^0 < S_d^1 < S_d^2 < S_d^3 < 1$$

where δS_d is the derivative of the current share with respect to the reference share. The value of share weight factor changes with respect to the condition of δS_d. The predetermined value, δS_{limit}^{lower}, is also set as the lower limit of the share derivation.

In the case of the neutral strategy, the formulation for the economical performance of the Retailer becomes:

$$Eco_d = \begin{Bmatrix} P_d^1 \times UP_d + S_d^1 \times US_d \quad \text{if } \delta P_d \geq 0 \\ P_d^2 \times UP_d + S_d^2 \times US_d \quad \text{if } 0 > \delta P_d \geq \delta P_{limit}^{lower} \\ P_d^3 \times UP_d + S_d^3 \times US_d \quad \text{if } \delta P_d < \delta P_{limit}^{lower} \end{Bmatrix} \tag{4.58}$$

subject to:

$$P_d^1 < P_d^2 < P_d^3 < 1$$

$$S_d^1 < S_d^2 < S_d^3 < 1$$

where δP_p is the derivative of the current profit with respect to the reference profit. The value of profit and share weight factor changes with respect to the condition of δP_p. The predetermined value, δP_{limit}^{lower}, is also set as the lower limit of the profit derivation.

Basically, the basic marketing strategy of the Retailer is a set of predefined limits upon profitability and market share movement, quantitatively translated from the behaviors of the Retailer. Penalty is considered as the internal punishment for violating those predefined limits set according to the basic marketing strategy of the Retailer. At the beginning of each episode of the evolution, the profit and market shares of the Retailer are taken as the reference values. Then, the evolution process is taken place, and the internal simulation is executed. During the internal simulation, predicted daily profit and market share obtained with a particular set of marketing decisions are compared with the references, and the penalty is assigned according to the status of the profit, market shares, and the predefined limits on profitability and market share of the Retailer. When a profit-oriented move is foreseen, the formulation for calculating the penalty becomes:

$$Pen_d = C + \delta S^2 \times F \tag{4.59}$$

It is evaluated as follows when action prepared is share-oriented.

$$Pen_d = C + \delta P^2 \times F \tag{4.60}$$

Furthermore, it is calculated as follows when the action is decided by a neutral strategy.

$$Pen_d = C + (\delta P^2 + \delta S^2) \times F \tag{4.61}$$

where

C	= Constant
F	= Penalty factor
δS	= Deviation of market share with respect to a reference share
δP	= Deviation of profit with respect to a reference profit

This section represents a brief description about the Retailer entity and its functions. However, Chapter 6 is devoted to explaining the Retailer entity and its evolution.

4.3 Implementation of the Simulation Platform

For a better understanding of complex market behaviors that arise from interactions among market actors, agent-based simulation method was selected for modeling the emerging multi-energy retail market. The market players were modeled as complex adaptive agents that has ability to interact one another in a common environment. The market actors detected the existing status of the common environment, analyzed the situation, formulated the scenarios for maximizing the profit, and altered the common environment with turning their scenarios into actions. During a cycle of simulation, each market actor performed the tasks mentioned above rotationally, and the simulation cycle was ended when every market actor finished performing their duties for one time.

The multi-energy retail market simulation platform was developed based on JADE (Java Agent Development Framework), which is a distributed multi-agent software framework based on a peer-to-peer communication architecture, fully implemented in the Java language [17]. It simplifies the implementation of multi-agent systems through a middle-ware that claims to be compliant with the FIPA specifications and through a set of tools that supports the debugging and deployment phase.

The simulation platform was designed to schedule the agents in a hybrid of sequential and parallel ways. The sequential scheduling was performed for entity level where the entities were generally required to wait for receiving updated information. The parallel scheduling approach was then applied for the agents under a particular entity in order to utilize the benefits of parallel processing.

The general implementation of the simulation platform presented in this chapter is as follow:

The multi-energy market simulation began with the Economy agent producing regional economic growth rate and meteorological information such as weather index. Using economic growth rate and weather index, potential energy demand of a particular block was calculated using (4.15). Potential energy demand of a particular type of Consumer class was attained by summing the energy demand of all blocks with similar load patterns.

Then, the Regulatory body made enforcements to direct the market into a more efficient and reliable situation. The minimum requirement for global time duration between successive decision-making was set at one month, and the ceiling and floor were assigned to the changing of energy prices and incentives.

Using (4.29), nominal market shares of competing energies were calculated. Classification of consumers was done by categorizing the consumers according to their access to energy suppliers, and their demand availability factor was determined with access position. With the nominal market share of the competing energies and demand availability due to accessibility, expected market shares of the competing energies under a particular Consumer class were determined, and the effect of reaction-delay in market shares were inserted using equation (4.40). The demand for each energy type was then calculated from the potential energy demand of a particular consumer block and the expected market share of an energy commodity. An economic feasibility check was later performed when the demand was greater than the existing capacity of the equipment, and energy consumption of the block was determined using recommendation from economic feasibility check for new equipment installation.

Afterward, the Energy Delivery entity began its process by locating the most potentially profitable consumer at present. A search to find the most profitable route to that consumer was performed utilizing the most profitable path analysis. After having finished planning expansion, construction process was started with connecting the blocks in the plan, nearest to the existing network, one by one until the final block in the expansion plan has been connected. The generalized duration of two months is taken as construction time for connecting two adjacent blocks.

Later, the Market Operator entity acted as the wholesale energy market and produced wholesale energy prices daily. Any Energy Retailers who consumed more energy than they had bought with contracts would be directly buying energy from the wholesale market for their consumers.

Moreover, the Retailer entity monitored movements of market shares and profitability, evaluated its economical performance, and defined its operational state, in which profit-taking or share-taking state was assigned when the decrease in profit or share was beyond the allowable limit, and neutral state otherwise. Then the process of manipulating influential variables such as energy prices, incentives, publicity, service, quality, and management efficiency was performed using evolutionary techniques. Number of solutions in the population was set at 20 and each solution possessed ten individual decisions. Each solution is assigned with random numbers at initial stage and gradual improvement is sought afterward.

The fitness function, which measures the quality of each solution, was created based on the objective function as in (4.54) and was used as the criterion for the selection of solutions to the next stage. Another simulation was set up inside the objective function to foresee the quality of given solutions. Two months duration was taken as the length of the simulation inside the objective function. The selected solution was then modified with a mutation that caused changes to each decision inside the solution due to the probabilistic procedure. After the mutation process finished, solutions were evaluated and selected according to their fitness value and the process was complete for one generation. This process was repeated until predefined stopping criteria were satisfied.

The best solution was taken as the optimal decision for the current situation and its individual decisions were assigned as the candidate value to replace the existing one. The decision-making duration, which was the delay time in decision-making process, was set at 14 days and the candidate variables came into affect after that duration. The next optimization step is started when consecutive price setting time limit is passed, and a new population is created with the upper half of the solutions inherited from the previous optimization and randomly generated decisions, otherwise.

The Information Environment entity oversaw the overall operation of the platform and accepted the information from market actors who wished to display it and released it when requested. Market information was gradually updated with incoming and outgoing information from the market players. Finally, one cycle of simulation ended when every market participant finished performing their duty.

4.4 Conclusions

This chapter proposes a pioneer simulation approach with agent-based modeling in the process of reproducing and understanding the behavior of the emerging multi-energy retail market. Several innovative approaches were developed and employed in this model in order to create the platform that has enough potential for studying the complex nature of a real-world energy market.

In order to tackle the complexity problem associated with energy markets, agent-based simulation was introduced. Market actors of the multi-energy market were modeled as autonomous intelligent agents focusing on their objectives individually. Using the JADE open source platform, local interactions were introduced among the market actors. Since complex markets could be broken down into autonomous market actors with the methodology proposed in this study, developing the multi-energy retail market, which is an extremely difficult problem for an analytical method, became a manageable work.

Several agents were developed to represent the vital organs of the multi-energy retail market. First, the Economy agent assumed the role of data developer. Many data required in this simulation were produced using complex mathematical functions in the Economy agent. Replacing the mathematically produced data with historical time-series data or similar type of data can be easily done if one wishes to further increase the complexity of the model.

Second, the method proposed for a consumer agent in this study filled the void left behind when market transition transformed regulated energy markets to open energy markets. Much-needed sophistication and complexity to formulate the idea of consumer choice were extensively employed in this methodology. Without complex consumer agents, there is no effective way to introduce competition to the multi-energy retail market.

Third, the Energy Deliverers were equipped with an efficient network expansion method based on graph theory. This method offers the advantage of being able to expand networks geographically without consuming too much computational power.

Finally, the role of a Retailer was defined, and an appropriate model was developed to represent this profit-oriented self-adapting market actor. In order to introduce intense competition in the multi-energy retail market, Retailers were equipped with self-adapting methods that utilizes evolutionary approaches. Without the existence of sophisticated self-adaptation in the Retailers, the idea of improving the efficiency of the market through competition seems to be a distant dream.

The approach presented in this chapter proposes a methodology to study the complex behavior of an open multi-energy retail market. An effective way of studying complex systems has been found. The role of market actors in the market has been clearly defined. Innovative approaches have been created for modeling these market actors.

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5. Test Market Simulations with the Simulation Platform

Abstract

Previously, how market actors behave in the emerging multi-energy retail market have been defined, and how emerging behaviors occur in the market from local interactions among its market participants have been discussed. The development of the market simulation platform is complete, and the working market simulator is in place. However, clear understanding of the behavior of the market and its market actors are yet to be achieved. This chapter concentrates on the behaviors of the market actors that emerge from the simulation of a hypothetical multi-energy retail market. Furthermore, a study that explores the efficiency of different programming approaches reveals that applying a suitable programming approach to the problem provides significant saving in program execution time.

5.1 Introduction

The development of the multi-energy retail market simulation platform has been extensively discussed in the previous chapter. Each market actor involved in the multi-energy retail market has been properly defined, and local interactions among those market actors have been firmly established. Now, it is the time to test the potential of the simulation platform and to see how the multi-energy retail market will evolve along the simulation time span.

This chapter concentrates on a study that has been created for highlighting the capability of the simulation platform. The study discusses the history of the development of the platform and the attempts on computational efficiency improvement. Several programming approaches – sequential programming, concurrent programming, and parallel programming – have been tried along the development of the market simulation platform, and the computational efficiency of each approach is later tested by running the same test simulation on the platforms that employ these programming approaches. Then, the important results obtained from the test simulation with parallel programming platform are further discussed in order to clarify the behavior of market actors.

The development of this chapter is arranged as follow: The following section thoroughly discusses the characteristics and parameters of the hypothetical test case. Section 5.3 provides a broad programming history of the market simulation platform and discusses the benefits obtained from switching from one approach to another. Then, the behaviors of the market actors are discussed based on the results obtained from the test simulation in section 5.4. The summary of the findings of the studies are further discussed and reported in section 5.5.

5.2 The Description of a Hypothetical Test System

In order to test the actual potential of the multi-energy retail market simulation platform, a test system is established in a hypothetical region. The region has the shape of a square and is further sliced into 100 small blocks. According to the characteristics of consumers dwelling on the blocks, these blocks are individually labeled with the name of typical consumer types; residential, commercial and industrial. The placement of consumers in the region is shown in the following figure.

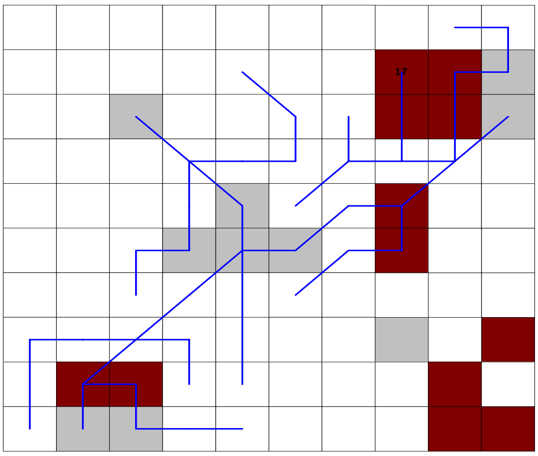


Fig. 5.1. The allocation of consumers in the hypothetical region

The shade of a particular block indicates the characteristics of the consumers dwelling on the block. White blocks represent residential consumers. Light gray blocks are for commercial consumers, and dark grey blocks stand for industrial consumers. There is the possibility that several different consumers may coexist in a particular block; however, the characteristics of the dominant consumer determine the label of the block. Moreover, the center of the block is assumed as the load center of consumers existing in the block.

Table 5.1. The number of consumers allocated in the region

Consumer Type	Number of Consumers
Residential	78
Commercial	10
Industrial	12
Total	100

Then, lines from energy transportation networks connect individual consumers to supply sectors of electricity, natural gas, and district heating industries. In order to begin the test case with relatively similar initial condition, all three networks have a completely overlapping network structure, sharing the same consumers in the same territory.

The sample energy market simulation is run on a computer network, which has 5 computers connected in parallel or on a single computer according the nature of the simulation platform. When it runs on a computer network, agents are arranged on the network computers in the way that there are no two parallel scheduling agents under each entity exist on the same computer. The Consumer agents are designed to act in a low public awareness approach.

Moreover, an approach that tolerates more on losing profit than market share is used as the marketing behavior of the Retailers. The test simulation is fixed at 24 months for market simulation and at 2 months for internal simulations inside evolutionary process. During market simulation, all five Retailers are equipped with evolutionary particle swarm optimization (EPSO), and their evolution process is designed to take place in every month. A population of 20 individuals is applied in each EPSO. The stopping criterion is the same: in the first episode, when performing the first internal simulation, the evolutionary process will be stopped if after 50 consecutive generations there is no improvement in the fitness function; in all the following internal simulations, during the market simulation of 24 months, the threshold of 10 generations is used instead of 50.

5.3 Analysis on Computational performance of the platform

This section discusses the computation performance improvement findings during the development of the multi-energy retail market simulation platform. Several programming languages and approaches have been tested for improving the computation efficiency of the platform along the track of the development of the simulation platform.

Although the findings have enough merit to be discussed in here, it is not the outcome of an intentionally designed study to compare the programming languages and associated programming approaches.

Along the history of the development of the simulation platform, several programming approaches have been tried. First, C++ programming language was chosen in developing the simulation platform due to its popularity and proven efficiency. Since most of market actors involved in energy markets generally act sequentially, waiting for the response of other related parties before making their own decisions, sequential programming approach using the C++ language was considered as a viable option for the moment. As a result, the simulation platform was initiated using sequential programming approach. Each market actor in the simulation platform was developed as an object written in C++ language. Then, an object that acted as a central scheduler introduced the interaction among the market actors, and a working market simulator was finally obtained. The market simulation platform with sequential programming approach can be graphically expressed in the following figure.

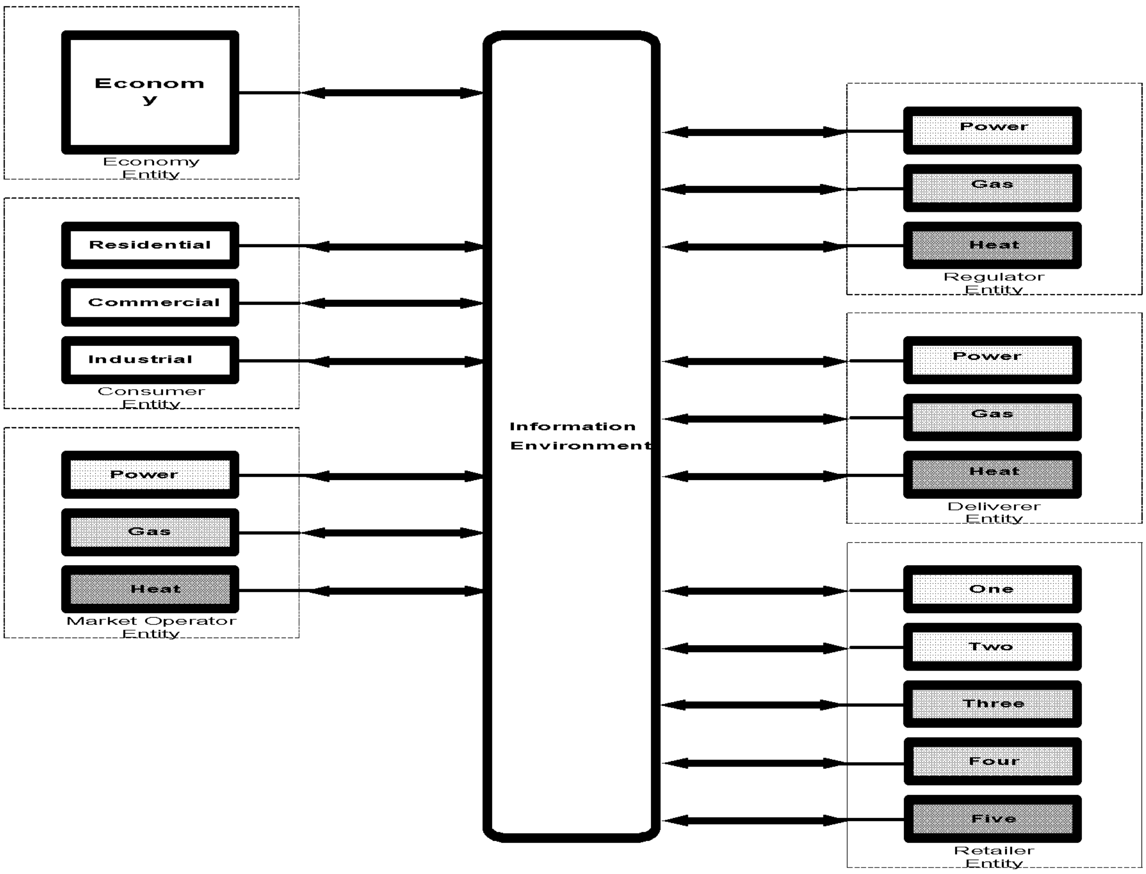


Fig. 5.2. Scheduling sequence of the market simulation platform with sequential programming approach

In the sequential platform, the market actors were positioned as a client/sever network and interconnect one another through the central scheduler, Information Management agent, in sequential order. During the simulation, each market actor was required to wait for its turn to perform its own duty. While one was performing its task, other actors were set to be idle. The deficiency of the sequential platform was not noticeable at the moment since most of the market actors involved in the multi-energy market simulator were natural sequential players, needing to wait for the information from other actors to perform their work.

As the development of the platform progressed, scheduling sequence of the market actors in the platform has evolved from sequential to semi-parallel scheduling. Instead of developing the platform with all market actors working in a single hierarchy layer, two layers processing have been introduced. The market actors having similar activities and functions have been placed under respective entities in this new approach. The entity level has been given higher hierarchy status in processing and arranged to work in the sequential way as in the sequential platform. However, the market actors involved under the control of each entity have been considered for parallel processing since there has been no significant connection among the similar type of market actors. As a result, the programming approach on the market platform has been shifted from the sequential approach to the semi-parallel approach in order to accommodate the new development.

Due to the C++'s restricted ability in handling parallel processing, the platform has been entirely reprogrammed with Java programming language, and the market actors have been redeveloped as Java coded agents. Multi-threading function of Java has allowed me to utilize concurrent and parallel programming approaches easily. In the process of developing interactions among the market actors, a middleware, Java Agent Development Framework (JADE), has been brought in to simplify the coordination and communication process of the platform. JADE is an open source platform aimed for agent-based modeling and entirely developed with Java. With the help of Java and JADE, the market platform has been able to operate in concurrent processing. The structure of the market simulator processed under the concurrent approach can be shown as follows:

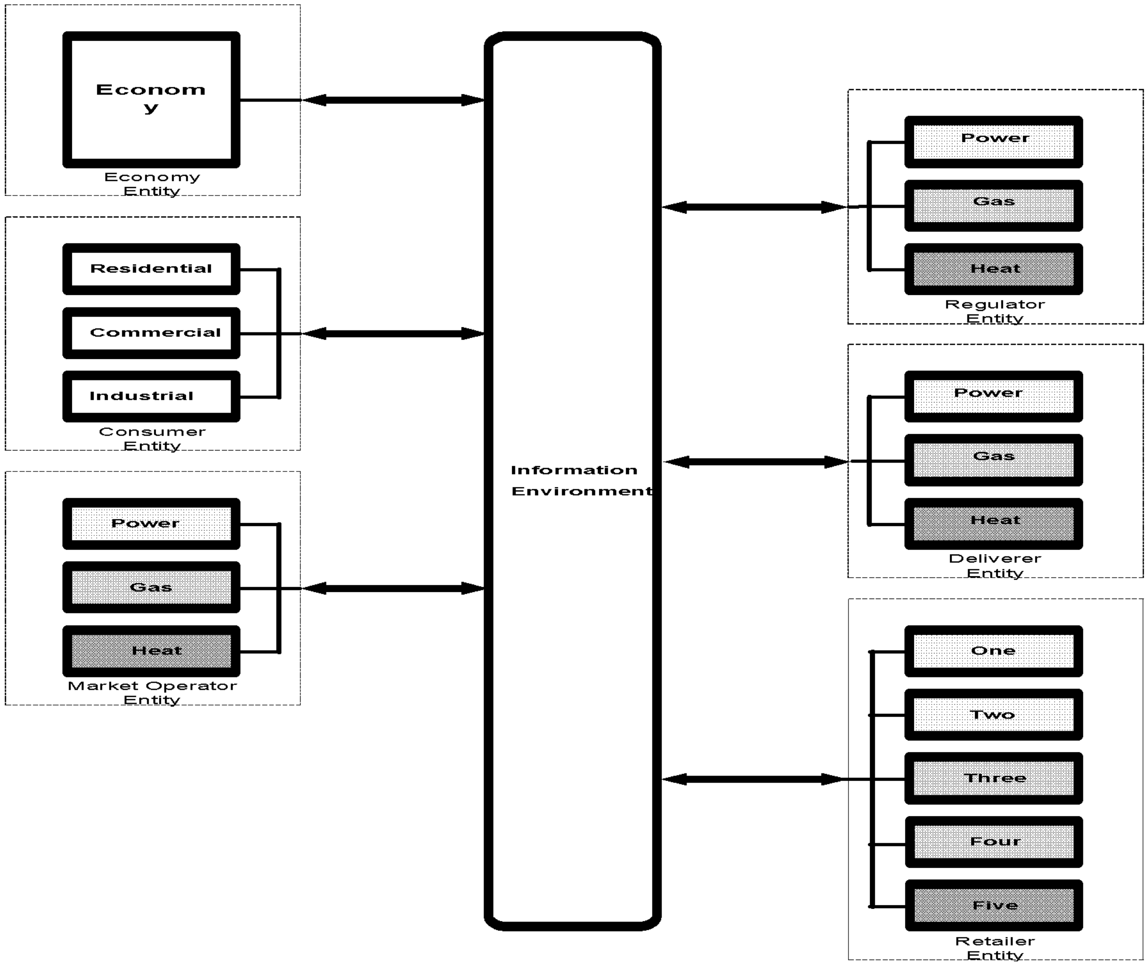


Fig. 5.3. Scheduling sequence of the market platform with concurrent programming approach

In the concurrent platform, the entities have functioned in sequential way. When market actors belonging to one entity has individually performed their task, market actors from other entities has been required to wait as in the sequential platform. However, the market actors under control of the entity have been able to work in parallel.

The development of the platform has been concentrating only on single computer so far. Since the idea of parallel processing has been successfully included in the platform, the next step is to develop the platform fully compliant with parallel processing and to deploy the platform on multiple computers. The final development of the simulator has been to shift the market simulator from the concurrent approach to the parallel processing running on a multiple computer network. After finishing careful adjustment on the simulation platform, it is turned into the parallel processing oriented simulator that runs on a computer network formed by five computers. The market actors are carefully arranged on five computers, placing the market actors under the control of each entity on different computers to maximize the computational efficiency of the simulator. The detailed arrangement of the market actors on the five-computer network can be seen in the following figure.

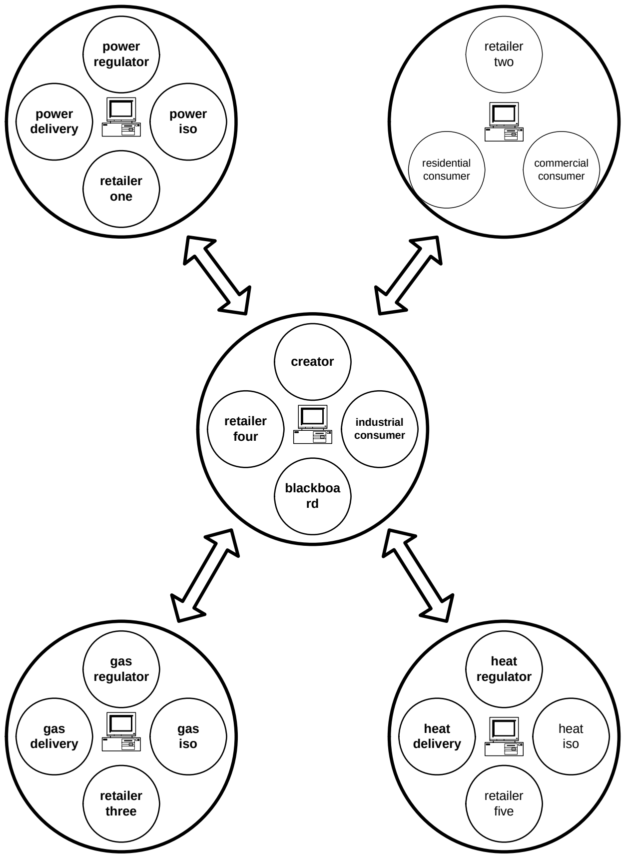


Fig. 5.4. The structure of the market simulator with parallel processing approach

In the parallel processing platform, the entities are still required to operate sequentially. However, the ability to replace the market actors under each entity on different computers provides a chance to explore the full potential of parallel processing. By carefully balancing the workloads of the market actors on parallel computers, the computational efficiency of the platform can be further maximized.

After the multi-energy retail market simulation platform has been successfully developed, a test that can determine the computational performance of different programming approaches has been performed. The idea of the test has been to highlight the level of the benefit achievable by applying the most suitable approach to the problem.

The test simulation that uses the same condition mentioned above has been run on the simulation platforms that employ three different programming approaches – C++ sequential platform, Java concurrent platform, and Java parallel platform. Since the computational performance has been our main interest in this comparison, only running time of each simulation on different programming platforms has been taken as the index values to be compared. The time consumption for running the test simulation on different platforms can be seen in the following figure.

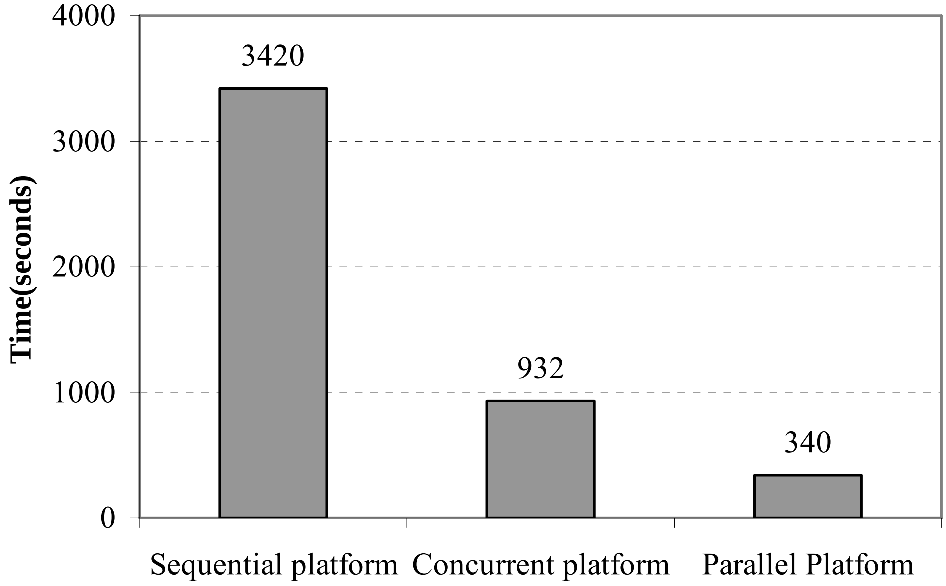


Fig. 5.5. Computational efficiency comparison of three programming approaches

According to the results, a vast amount of time can be saved by switching the platform from sequential to concurrent processing. It is true that much of the code written in C++ has been modified, upgraded, and cleaned during the process of transforming the market simulator from the sequential platform to the concurrent platform. However, both platforms share the same structure, and the staggering time-saving received by switching to the concurrent platform is beyond the benefit possibly achieved by just improving computer codes. Although it is difficult to directly compare the results of these two platforms as they have some differences in coding, the superiority of the concurrent programming over sequential approach is clearly visible. And the benefit obtained with the concurrent approach highlights the effect of applying a suitable programming approach to the problem being studied.

When the market simulator has been switched from the concurrent processing to the parallel processing approach, further time-saving is achieved. However, the time-saving achievement with the parallel processing running on five-computer network is only half of the time-saving that could have been achieved in theory. The reason behind this setback is the nature of the problem in which the market actors are designed to perform their duty in the semi-parallel approach. As a result, the advantage provided by parallel processing is not fully accessible in this market simulation problem.

5.4 Significant Results from the Simulation

In order to clarify the behavior of the platform and its market actors, the results from the test simulation running on the parallel processing platform are analyzed and discussed in this section. The results obtained from each market actor are placed under the name of the associated market actor.

5.4.1 Economy Entity

The significant results that can explain the behavior of Economy – economical growth rate (EGR), daily temperature and daily energy demand – are reported in this section. Two important factors shaping energy demand pattern, the economical growth rate and the daily temperatures, are displayed in Fig. 5.6 and 5.7. It is noticed that randomly generated EGR at second year being lower than the EGR at first year, indicating the drop in economic expansion of the region. And the time-series of daily temperatures have the shape of a deteriorated cosine curve with the highest temperature values appearing in summer time while the lowest one in winter season. Although these data have been artificially generated, the structure of data produced by the mathematical model is consistence with the nature of actual time-series data.

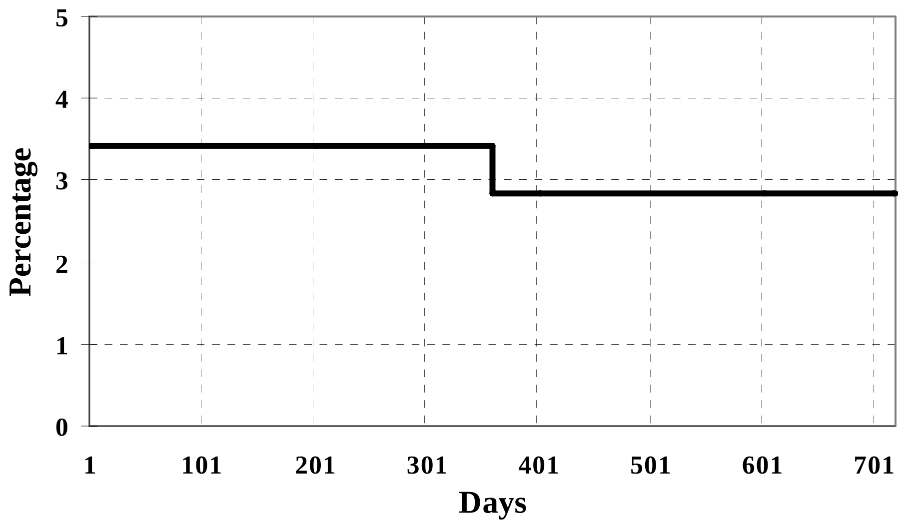


Fig. 5.6. Economic growth rate of the territory during simulation

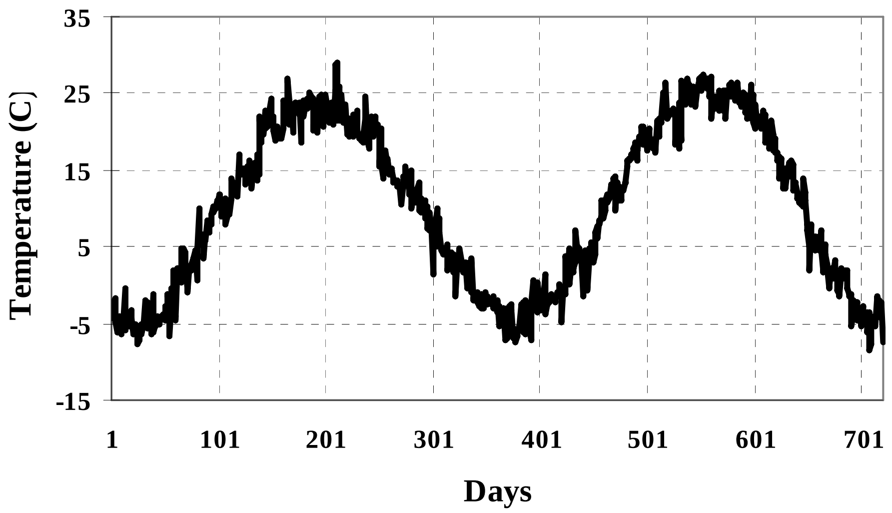


Fig. 5.7. Temperature of the region during simulation

Potential energy demand of the territory, simulated by using demand-influencing parameters such as temperature and EGR, is shown in Fig. 5.8. According to the figure, the energy demand of the region is higher in the second-half of winter at the beginning of the year, falling down in spring, then moving up in summer, coming down again in autumn and moving up again in the first-half of winter at the end of the year. This W-shape appearance in the time-series energy demand of one-year period perfectly duplicates the behavior of seasonal energy demand variation seen in actual time-series data. The spikes and sags that appear in the energy demand curve are good examples of the effect of weekly factor on the demand as it usually drops during the weekend. The effect of another major influential parameter on energy demand, economical growth rate, is noticed with the daily energy demand dropping due to the lower economical expansion of the region in the second year of the simulation. The gradual drop of demand in the second year period also explains the effect of demand elasticity occurred from ever-increasing energy prices during the simulation.

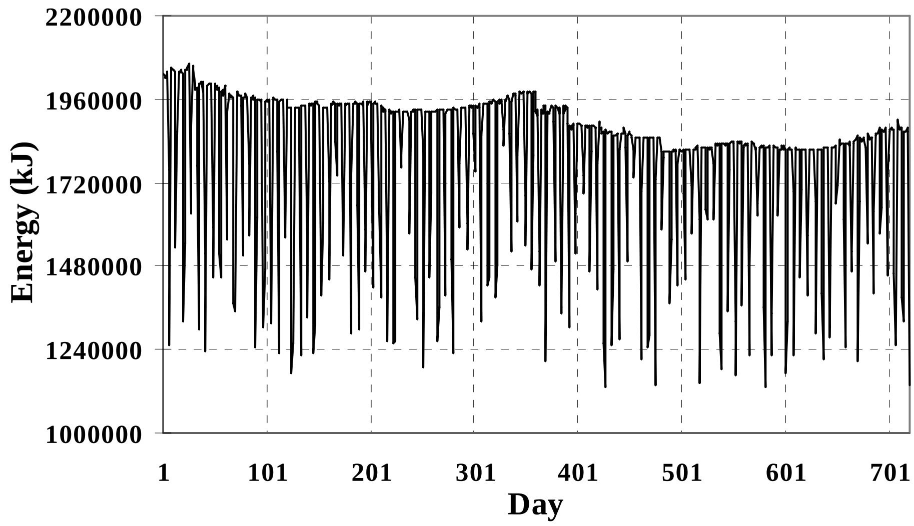


Fig. 5.8. Energy demand of the region during simulation

5.4.2 Consumer Entity

As this entity represents three Consumer classes - Residential, Commercial and Industrial – the results obtained from these classes are separately presented in this section. The market share fluctuation of competing Retailers under a particular Consumer class is chosen to display as an example behavior of this entity. These results indicate the effect of consumer choice on the competing Retailers.

The market share fluctuation of the Retailers in Residential class is shown in Fig. 5.9. The shape of the fluctuation appeared in the figure indicates the level of struggle or competition that appeared in this Consumer class. Constant and dramatic shifting between the shares of electricity marketing Retailers, Retailer One and Two, display the level of internal competition between Retailers supplying the same energy type. The fact that the big spike in the share of Retailer Four at the beginning of the simulation being compensated by the visible drops in the shares of other competing Retailers indicates the cross-industry competition and the effect of the decision-making of one party on other competing parties in the market. Another fact noticeable on the graph is the sudden vertical increase of the market shares of Retailers related to electricity and heating. It is the result of network expansion approach in which the sudden surge in demand occurred when new consumers are occasionally commissioned into the system.

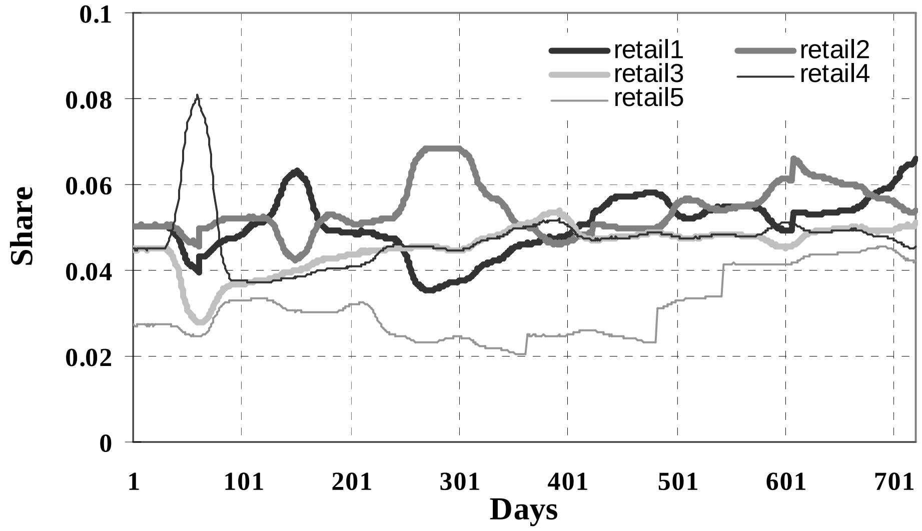


Fig. 5.9. Fluctuation of market shares of Retailers in residential area during simulation

Similar behaviors are seen in Fig. 5.10, which displays the market share movements that occurred in Commercial class. In this Consumer class, the oscillation of market shares is less severe compared to the Residential class. One plausible conclusion that can be made from less competitive condition in this Consumer class is the development of unsupervised coordination among Retailers. Another interesting result is the nature of demand surge due to the participation of new consumers. The market shares of the electricity offering Retailers are dramatically increased when a new consumer is commissioned for the first time to electricity network. However, the market shares of the electricity Retailers later decrease when heating network enters into competition to supply heat to that consumer, effectively lowering the demand of the electricity by the consumer.

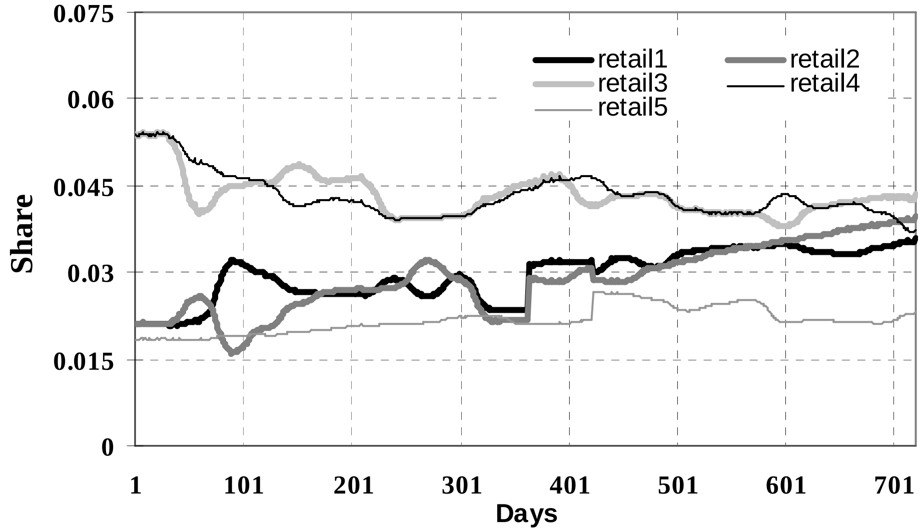


Fig. 5.10. Fluctuation of market shares of Retailers in commercial area during simulation

The market shares gained and lost in Industrial class are more dramatic according to the result shown in Fig. 5.11. The market shares of Retailers marketing electricity and heat are gradually on the rise, robbing the market shares of gas related Retailers, Retailer Three and Four. As the Industrial class is designed to be more aware of market situation and profit oriented, the effect of marketing decisions of the Retailers on this actor is higher comparing with other actors under the same entity.

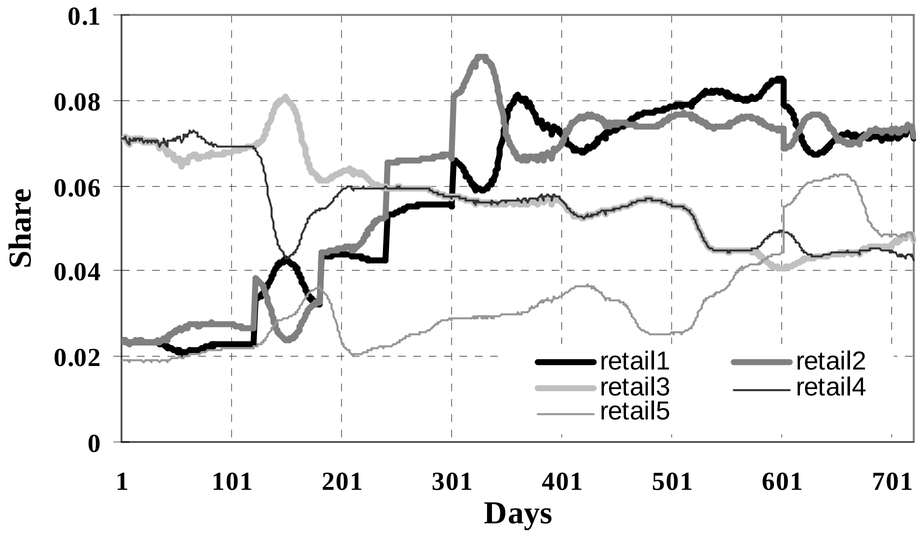


Fig. 5.11. Fluctuation of market shares of Retailers in industrial area during simulation

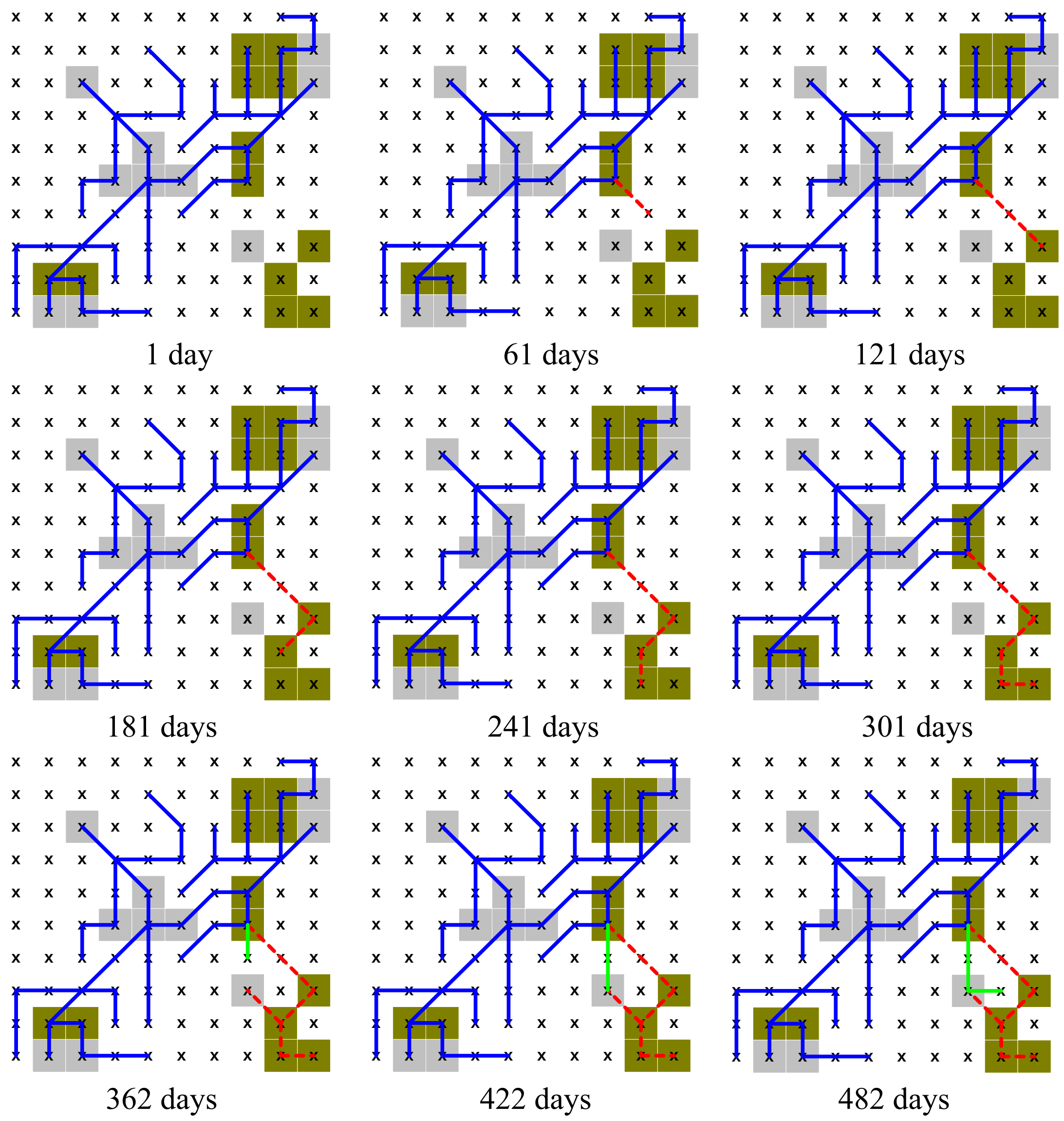
5.4.3 Energy Deliverer Entity

Under the Energy Deliverer entity, three networks – electricity, natural gas and district heating networks – are designed to have similar operating structure supplying the respective energy to the same consumers in the same territory at the initial stage of the simulation. However, different network expansion schemes applied by each network later stretch their network to new consumers in different way.

Since different strategies have been applied for finding new consumers, network expansion of each system occurs in different time and places. In case of Electricity Deliverer, its strategy on finding new consumers has allowed him to start the network expansion at the early stage of the simulation. Consequently, it has had the advantage of connecting potential consumers who never had access to any energy supply before. As a result, the expansion of electricity network has resulted in recruiting high energy consuming customers such as industrial and commercial consumers at first. The electricity network expansion displayed in Fig. 5.12 enforces the above idea with its network extension mostly passes through high energy consuming areas.

According to the consumer finding strategy of Heat Deliverer, its network expansion has started at the late stage of the simulation. Consequently, the high energy users who had already been occupied by other competing Energy Deliverers have been posted as unattractive consumers for the Heat Deliverer. Therefore, the Heat Deliverer has chosen to extend its network to new residential consumers instead of connecting to the high energy consumers with high competition. The network expansion of the Heat Deliverer is seen in the later section of Fig. 5.12.

The new consumer finding strategy of Gas Deliverer has found no attractive consumers throughout the simulation. As a result, there has been no network expansion in the gas network.



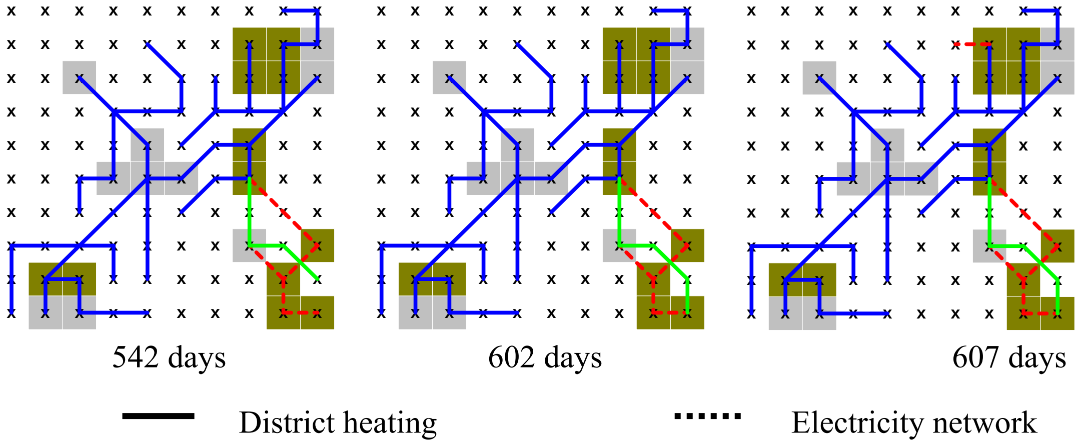


Fig. 5.12. Expansion of the networks along the simulation

5.4.4 Market Operator Entity

The day-ahead spot energy prices from agents belonging to the Market Operator entity – Power Market Operator, Gas Market Operator and Heating Market Operator – are represented in this section. The day-ahead spot prices of electricity are shown in Fig. 5.13. The simulator from the Power Market Operator produces the daily spot price of electricity, oscillating around the average contract price of 0.04 euro/kWh. This simulated spot energy prices, ranging between 0.03 euro/kWh and 0.05 euro/kWh, offer electricity marketing Retailers the choice of whether to buy electricity through contracts or from the wholesale market. Buying electricity from the wholesale market is more beneficial for the day the spot price is lower than contract price and vice versa.

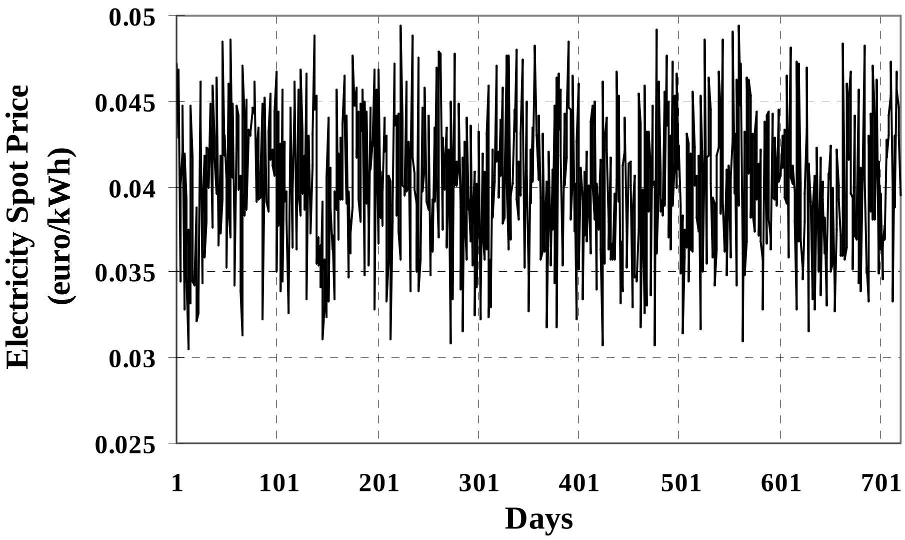


Fig. 5.13. Time-series day-ahead spot price of electricity during simulation

A similar situation is noticed in the result obtained from the Gas Market Operator. As shown in Fig. 5.14, the daily spot price of natural gas oscillates around the contract price, 0.43 euro/m^3, ranging between 0.34 and 0.52 euro/m^3. This simulated behavior of the Natural Gas Market Operator is in line with the objective of this agent, providing reasonable day-ahead spot gas price to the market platform and opening the another front line to be considered in decision-making of gas marketing Retailers.

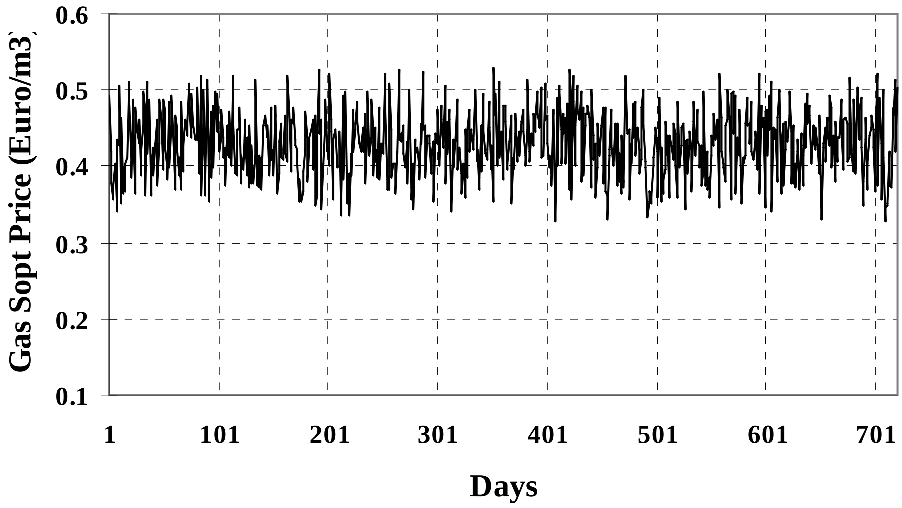


Fig. 5.14. Time-series day-ahead spot price of natural gas during simulation

And the result received from the Heat Market Operator as shown in Fig. 5.15 indicates that the daily spot price of heat from district heating oscillates around the contract price, 0.04 euro/kWh, ranging between 0.03 and 0.05 euro/kWh.

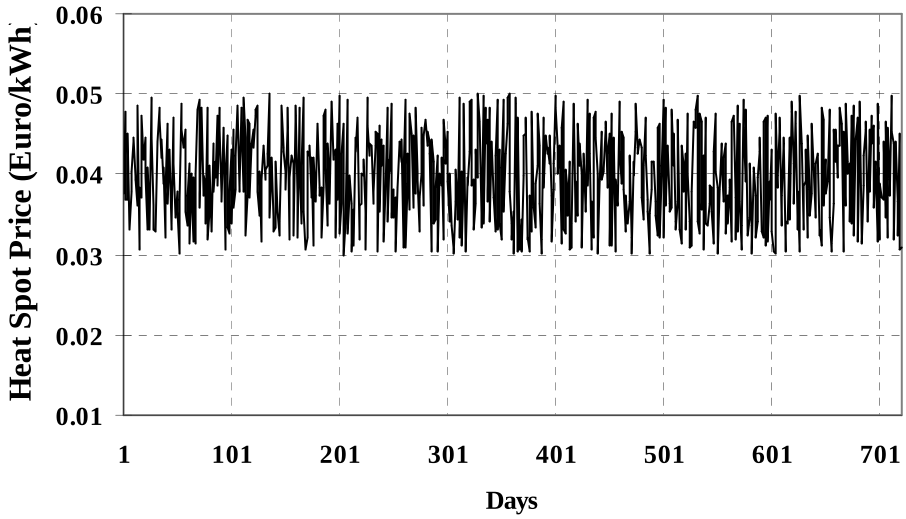


Fig. 5.15. Time-series day-ahead spot price of heat during simulation

5.4.5 Energy Retailer Entity

The actions of Retailers, the evolution of their marketing decisions, and the effects of those actions are presented in this section. The results include energy prices, incentives offered to the Consumer classes, spending on advertisement, and investment in improvement of service and quality of the commodity. These results are divided into five parts; each part explains about a particular Retailer.

The results discussed in this section are from Retailer One, one of the two electricity marketing Retailers. In order to achieve maximum profit, the Retailer One employs an approach that increases the prices of electricity and decreases the incentives given to Consumer classes as shown in Fig. 5.16. Furthermore, the Retailer One proposes an attractive product marketing package to lure consumers and increase market share accordingly. The evolution of the product marketing package, which includes spending on advertisement, service and quality, from the Retailer One is seen in Fig. 5.17.

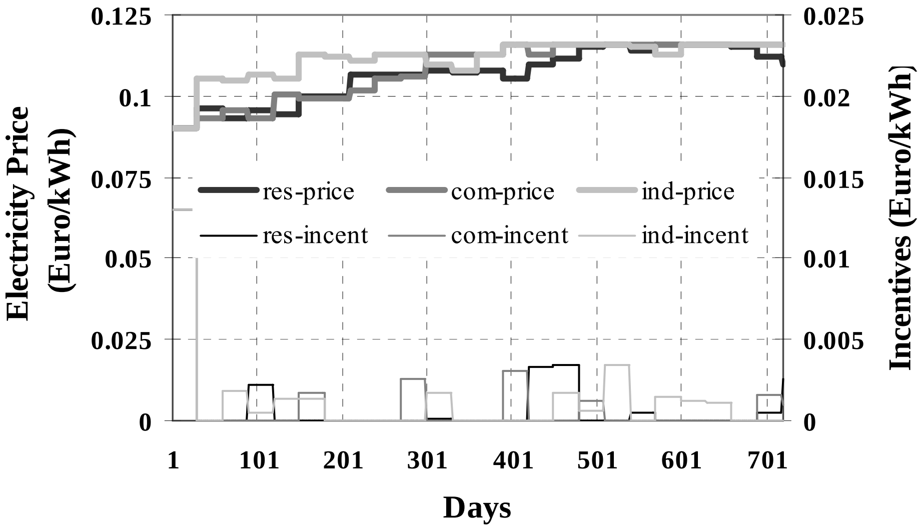


Fig. 5.16. Retailer One's marketing decisions regarding prices and incentives during simulation

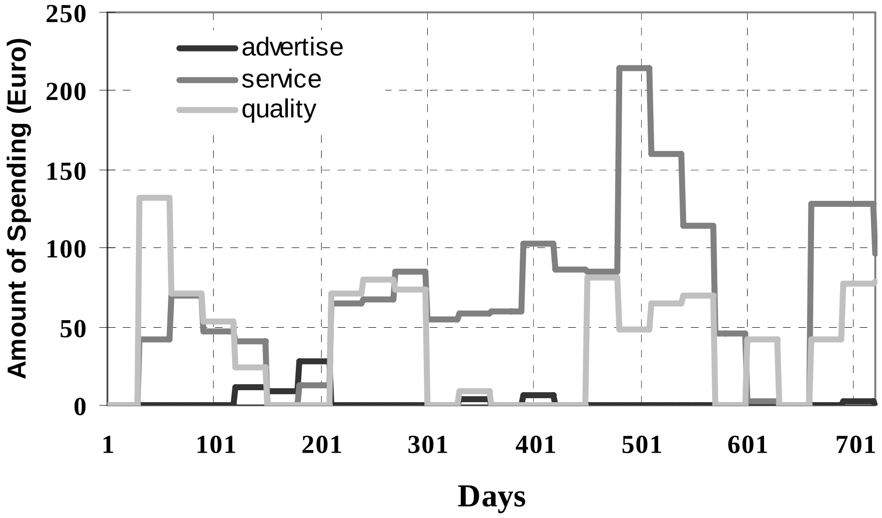


Fig. 5.17. Retailer One's marketing decisions regarding product marketing during simulation

The effect of these marketing decisions changing is seen in Fig. 5.18 and Fig. 5.19. With support from other Retailers altogether deciding to make profit from increasing energy prices, the Retailer One gains more market share even if it has increased the prices of electricity. In here, market share indicates the share regarding consumption while current share stands for the share associated with demand. The effect of price changing in electricity coupling with offering attractive product marketing package drives the market share of the Retailer One even higher. The higher spending on the product marketing package is later recovered by the benefit obtained from increasing energy prices and decreasing incentives. As a result, the profit of this Retailer at the end of the simulation increases almost 5 folds of the profit the Retailer attained at the beginning of the simulation. And the time-series of the daily profit has similar pattern as the market share, indicating maximizing profit through expansion in the market as one attractive option.

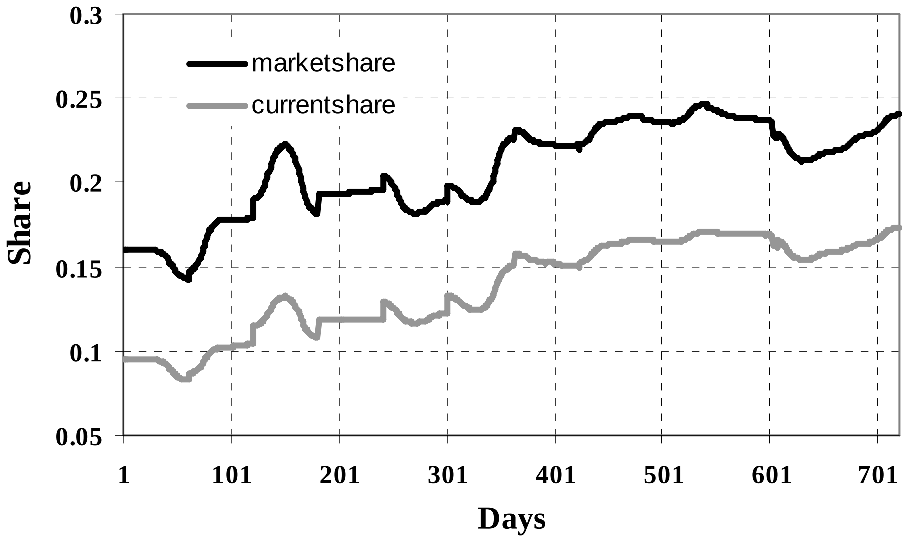


Fig. 5.18. Share variations of Retailer One during simulation

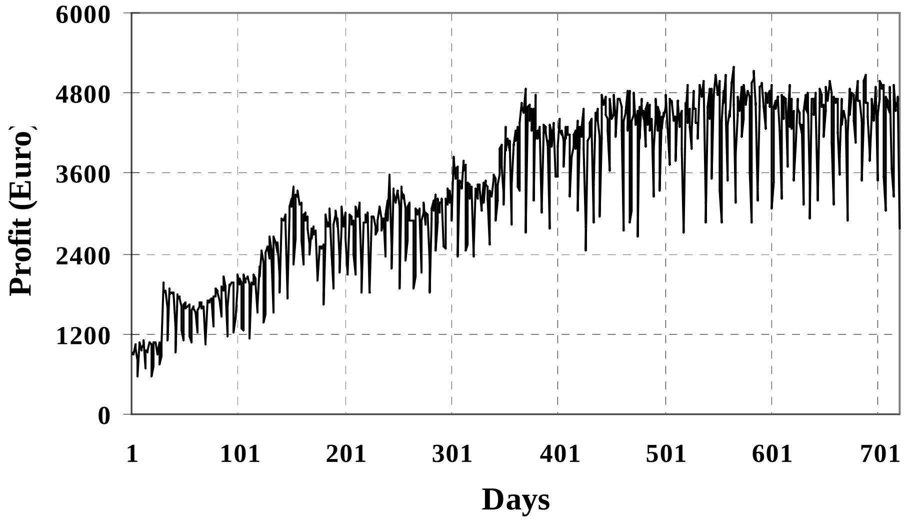


Fig. 5.19. Profit variation of Retailer One during simulation

The results from Retailer Two, another Retailer supplying electricity to different Consumer classes, indicate the application of the same strategy by both electricity marketing Retailers. The marketing decisions made by this Retailer such as changing of energy prices, incentives, and product marketing matters are displayed in Fig. 5.20 and Fig. 5.21 respectively.

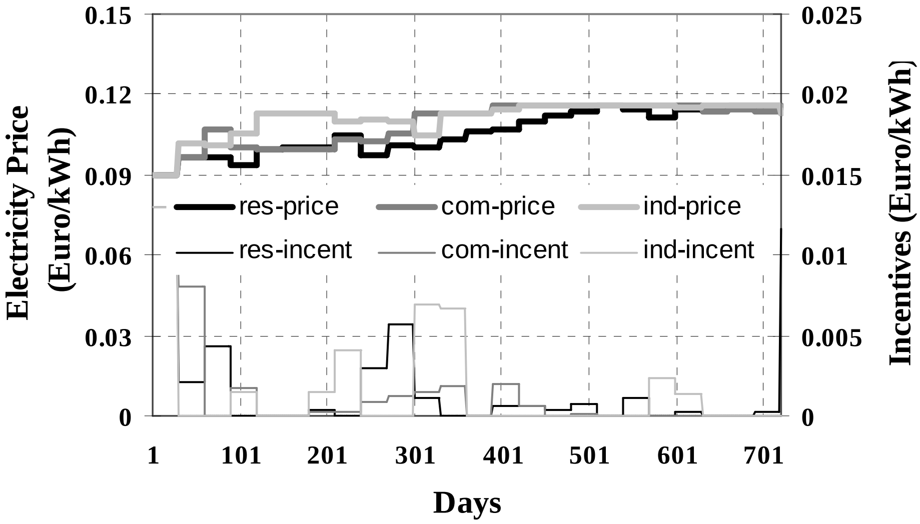


Fig .5.20. Retailer Two's marketing decisions regarding prices and incentives during simulation

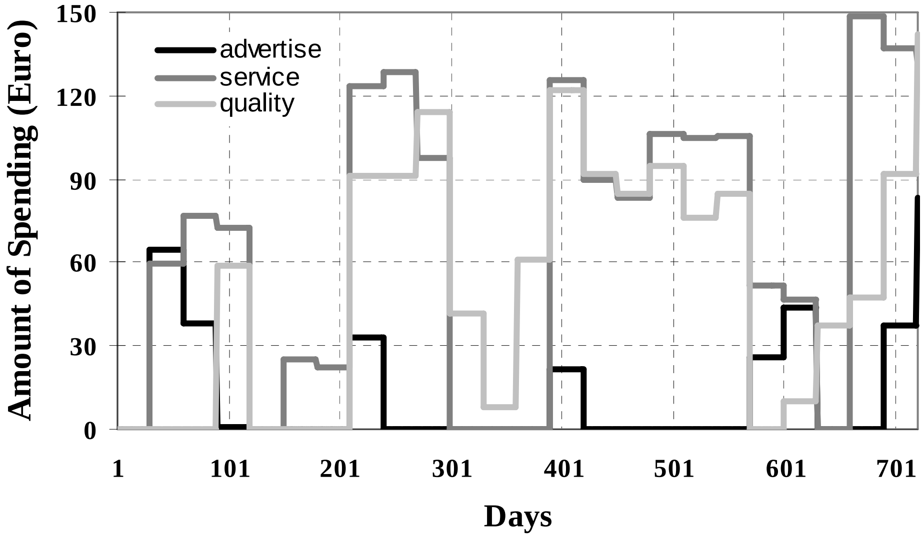


Fig. 5.21. Retailer Two's marketing decisions regarding product marketing during simulation

Basically, this Retailer follows the strategy that the Retailer One has applied, maximizing profit through increasing energy prices and decreasing incentives while increasing spending on product marketing. Consequently, the market share of this Retailer is on the rise along the simulation, as shown in Fig. 5.22. A huge surge in market share in the middle of simulation is the effect of increasing spending on incentives and product marketing measures simultaneously. Therefore, the market share later drops significantly when cutting costs happens.

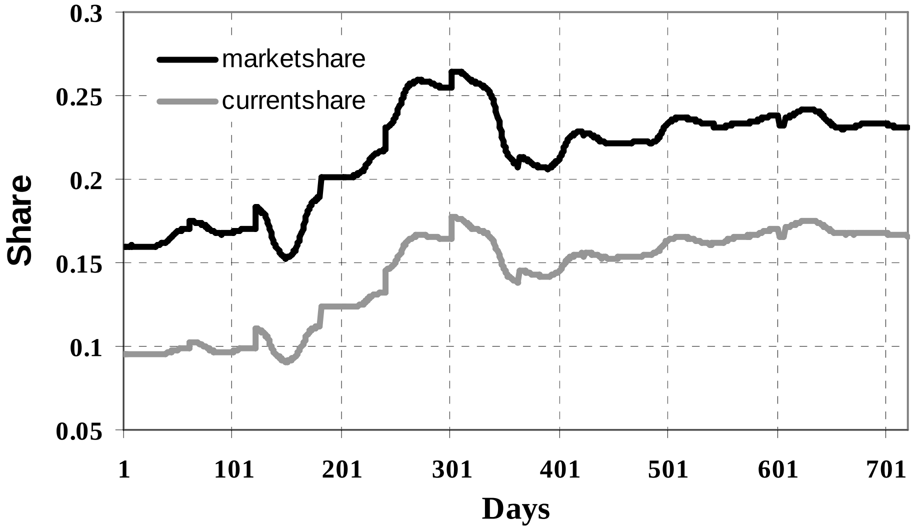


Fig. 5.22. Share variation of Retailer Two during simulation

According to Fig. 5.23, the daily profit of the Retailer at the end of the simulation expands to nearly 5 times of the profit obtained at the beginning of the simulation. It is noticed that rising of the daily profit at the early stage of the simulation has been primarily contributed by the market share expansion of the Retailer; however, maintaining the rising daily profit at the later stage of the simulation is much more related to the direct profit taking measures such as increasing energy prices since the market share of the Retailer turn to be flat toward the end of the simulation.

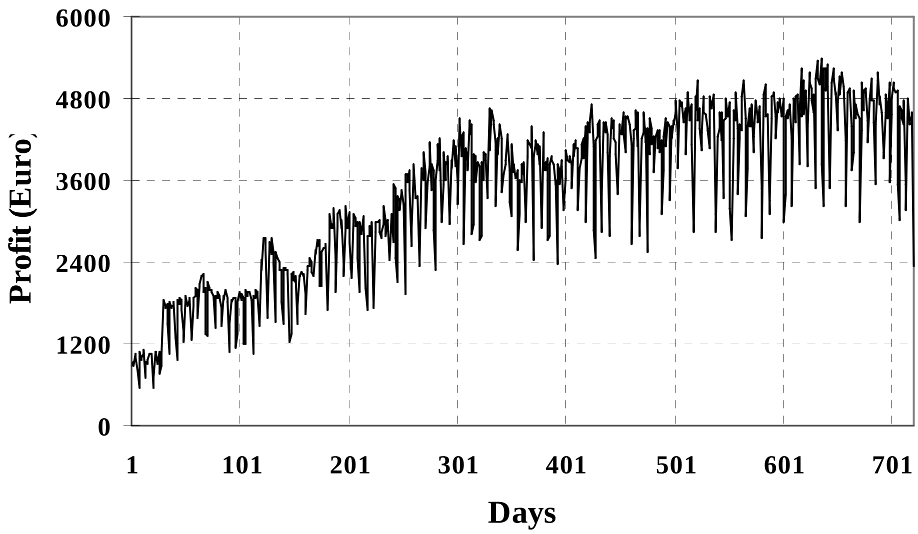


Fig. 5.23 Profit variation of Retailer Two during simulation

The marketing results obtained from Retailer Three, which delivers natural gas to consumers, is shown in Fig. 5.24 and Fig. 5.25. The overall review of these results indicates that the Retailer has the behavior of making profit from increasing energy prices and reducing on all spending. Ever increasing natural gas prices along the simulation and spending almost nothing on incentives and product marketing measures in the most of the time highlight the action of the Retailer.

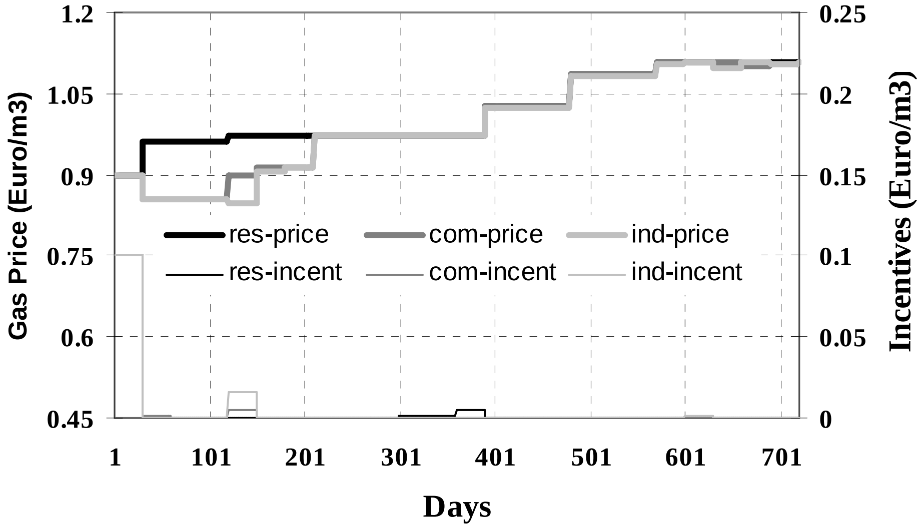


Fig. 5.24.Retailer Three's marketing decisions regarding prices and incentives during simulation

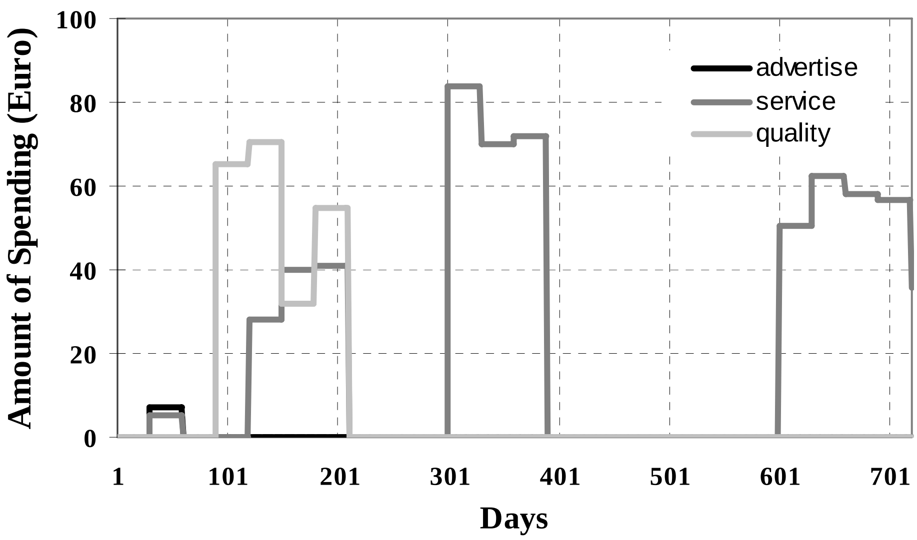


Fig. 5.25.Retailer Three's marketing decisions regarding product marketing during simulation

According to the approach of the Retailer Three that simultaneously raises natural gas prices and cuts expenses, no measure prevent its market share from falling. Therefore, the gradual rising of natural gas prices and cutting expenses in incentives and product marketing measures lead this Retailer to a gradual loss of market share, as shown in Fig. 5.26. Despite losing market share, the daily profit of the Retailer is on the rise; the profit gained from increasing natural gas prices and cutting expenses effectively compensates the lost market share. The sudden surges that appear in Fig. 5.27 indicate that immediate profit rising occurs after the Retailer has increased the natural gas prices; however, the profit again drops afterward due to the loss of market share that results from the counter measures of consumers. This behavior emphasizes the effect of significantly increasing in energy prices. Moreover, the strategy to increase the natural gas prices while cutting expenses without considering the effect of market share loss may not be as successful as the strategy applied by electricity marketing Retailers since the profit of the Retailer at the end of the simulation is barely 2 folds of the profit achieved at the beginning of the simulation.

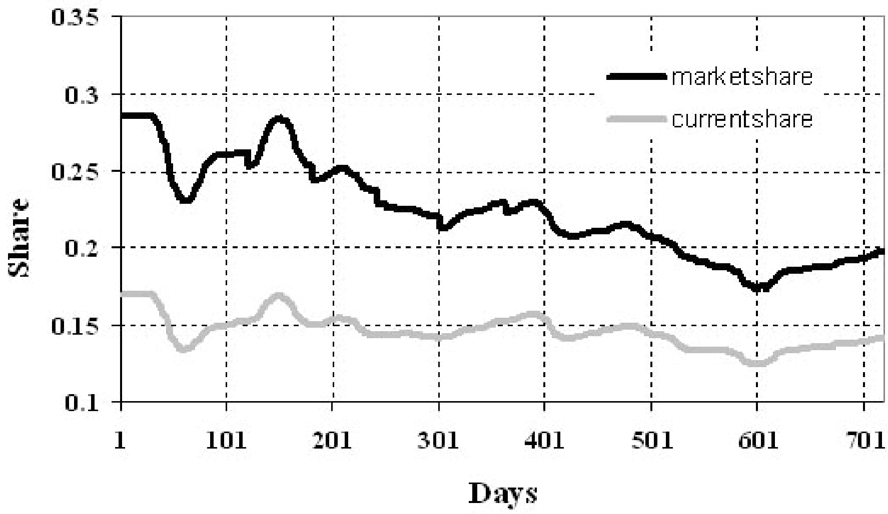


Fig. 5.26. Share variation of Retailer Three during simulation

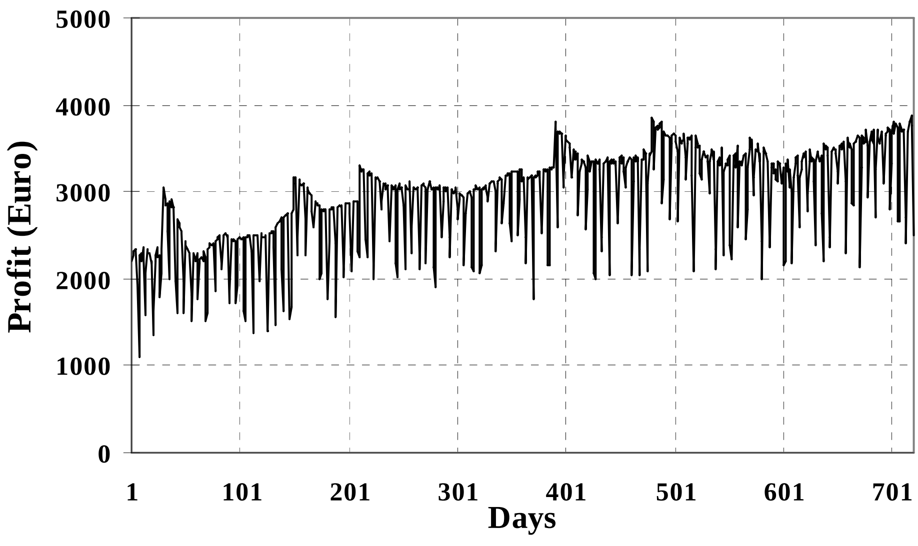


Fig. 5.27. Profit variation of Retailer Three during simulation

The results obtained from Retailer Four, one of the two natural gas marketing Retailers, indicate that the behavior of Retailer Four is almost identical to the Retailer Three. According to Fig. 5.28 and Fig. 5.29, it is clearly noticed that the increasing-prices-while-cutting-expenses strategy is also applied by this Retailer.

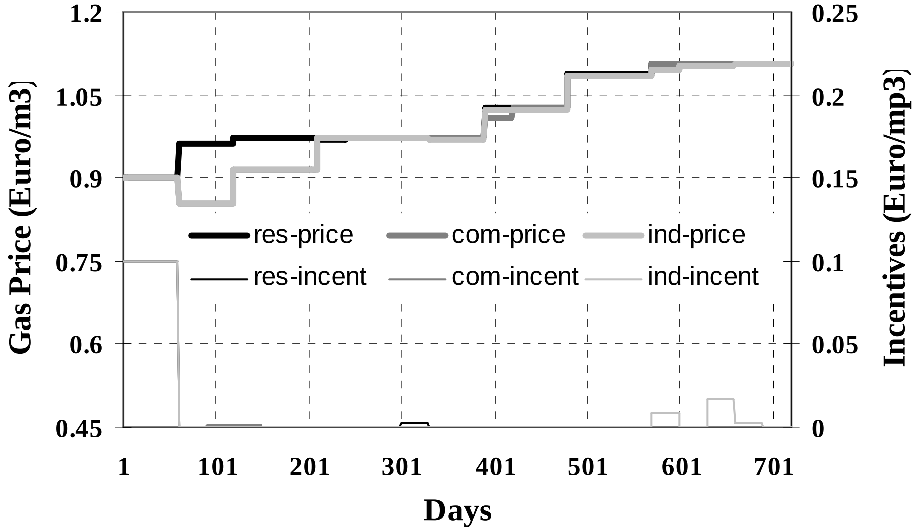


Fig. 5.28. Retailer Four's marketing decision on prices and incentives during simulation

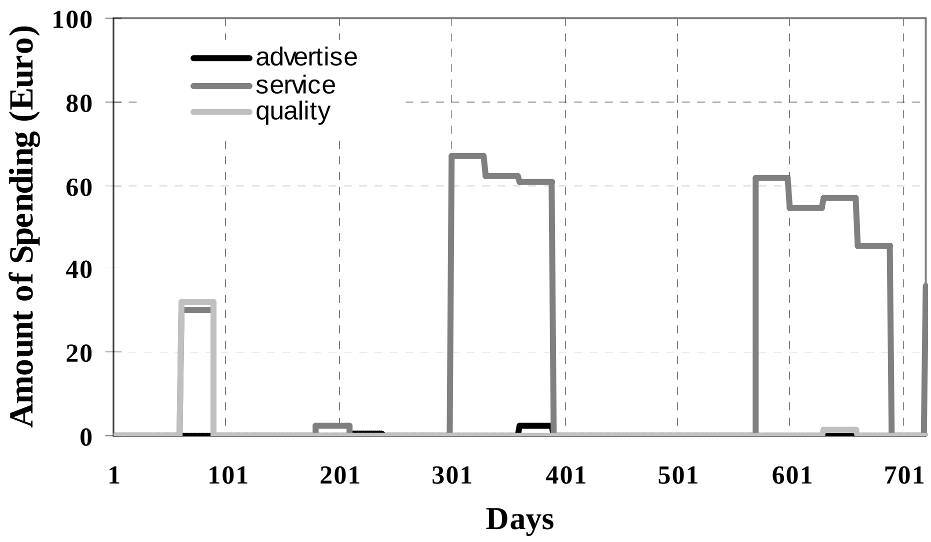


Fig. 5.29. Retailer Four's marketing decisions regarding product marketing during simulation

Unsurprisingly, the typical outcome of the increasing-prices-while-cutting-expenses strategy, slightly increasing in profit and gradually decreasing in market share, is seen in Fig. 5.30 and Fig. 5.31. The ratio of the profit of the Retailer at the end of the simulation to that of at the beginning of the simulation is just over 1.5 times.

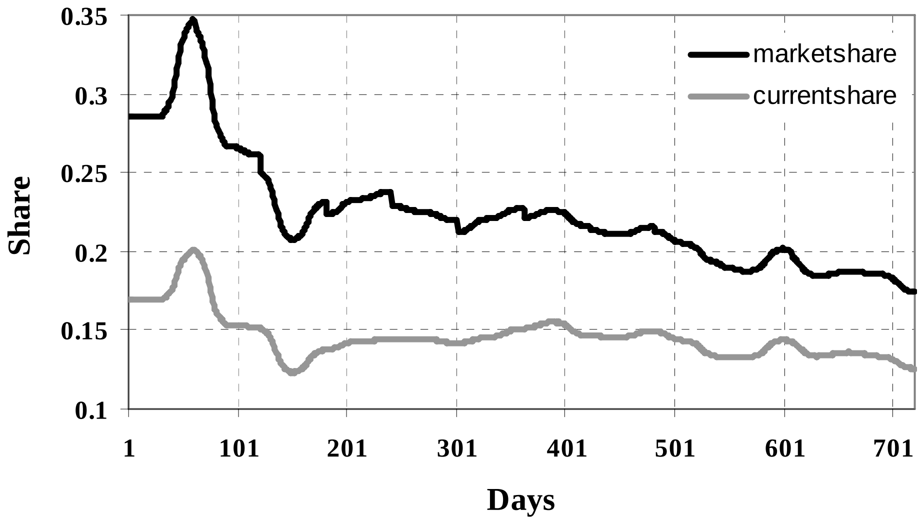


Fig. 5.30. Share variations of Retailer Four during simulation

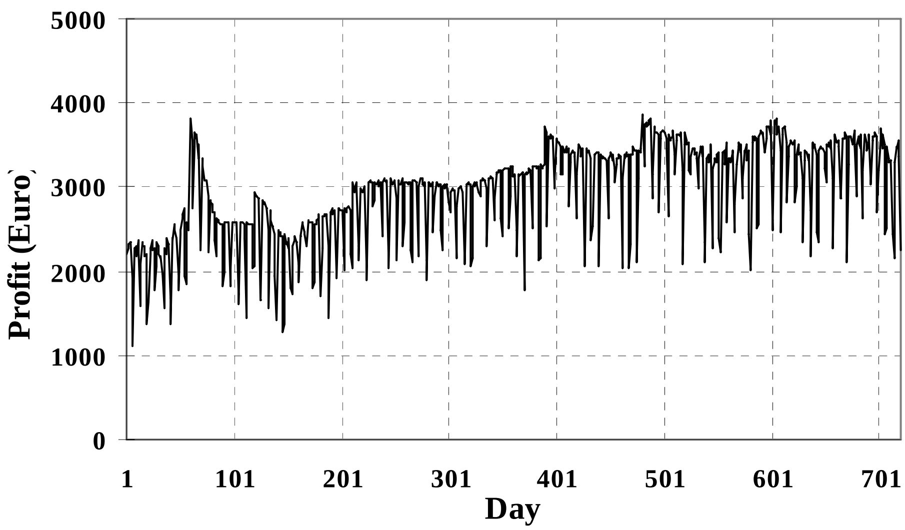


Fig. 5.31. Profit variations of Retailer Four during simulation

Retailer Five, which provides heat to consumers, has developed different strategy to maximize its profit. In order to maximize the profit, this Retailer employs a strategy that maneuvers the prices, incentives and the spending on product marketing measures in a timely manner. The results shown in Fig. 5.32 and Fig. 5.33 display the variation of heat prices, incentives given to consumers, and spending on product marketing measures along the simulation. The constantly changing prices, incentives, and spending on product marketing measures indicates the Retailer's busy attempt on finding optimal solutions.

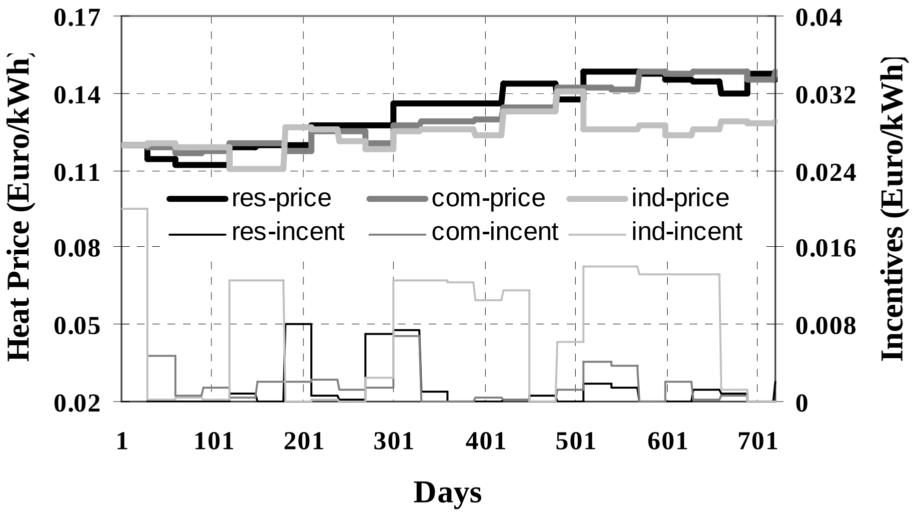


Fig. 5.32. Retailer Five's marketing decisions regarding prices and incentives during simulation

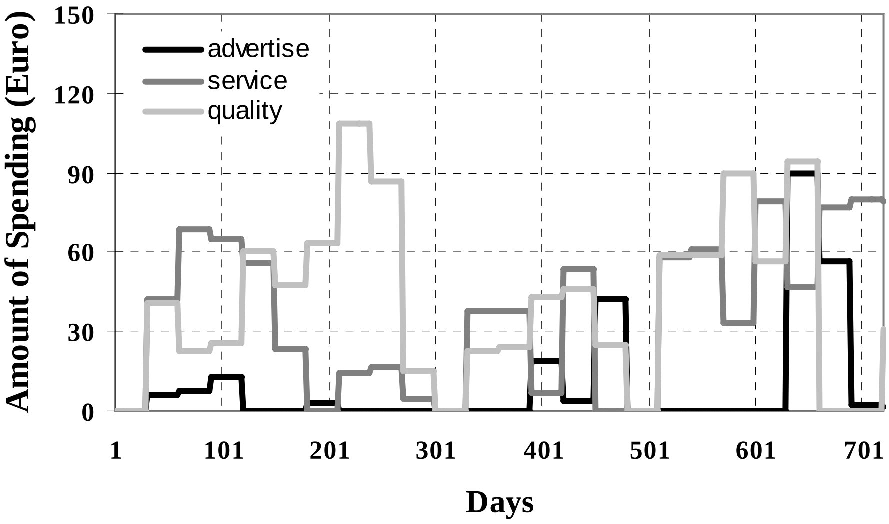


Fig. 5.33. Retailer Five's marketing decisions regarding product marketing during simulation

Due to the optimal strategy applied by this Retailer, its market share fluctuates along the simulation. Fig. 5.34 indicates that the Retailer has tried to keep its market share constant along the simulation; however, it chooses to increase the market share at the ending stage of the simulation with increasing the spending on product marketing.

Despite the fluctuation of the market share, the profit of the Retailer steadily increases along the simulation, and it reaches to 5 times at the end of the simulation comparing with the profit at the beginning of simulation, as shown in Fig. 5.35. Apparent contrast between the pattern of the market share and profit indicate that the profit maximization occurred in this Retailer comes from the combination of several factors; market share gains, rising energy prices and reduction of expenses.

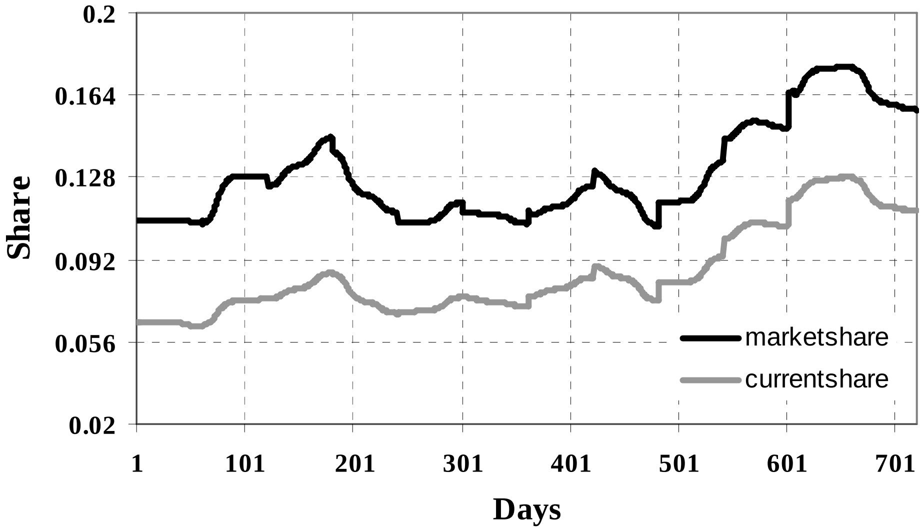


Fig. 5.34. Share variations of Retailer Five during simulation

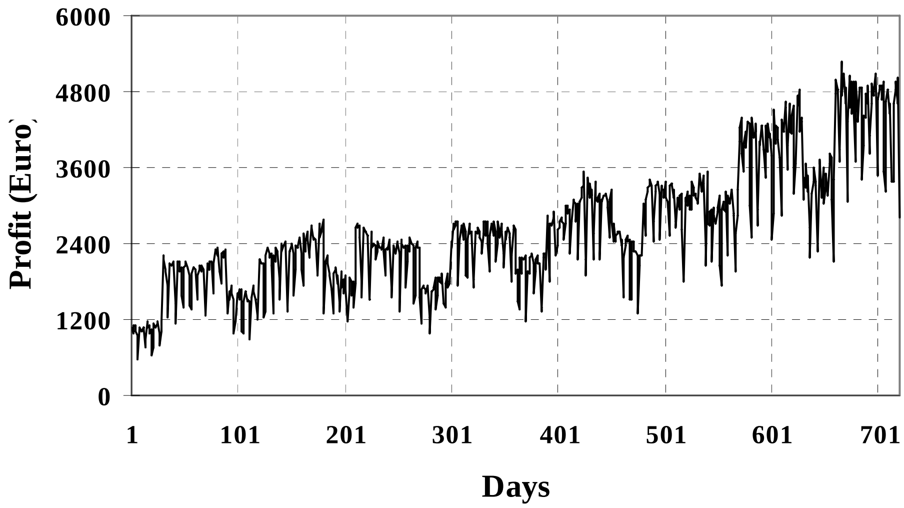


Fig. 5.35. Profit variation of Retailer Five during simulation

5.5 Conclusions

In order to show the potential of the multi-energy retail market simulation platform, test simulations have been run on the platform. The results obtained from these test simulations indicate that the behavior of the market actors clearly exhibits the complexity required in developing a realistic market simulation, and far more complex behaviors resulted from simple local interactions among the market actors indicate the development of emerging behaviors.

Especially, the results from the Consumer classes provide the detail effect of the consumers' choice on the decisions of the Retailers. Moreover, the level of complexity displayed in those results is the evidence of the successful development of complex adaptive consumers in the simulation.

The optimal network expansion schemes developed by the Energy Deliverers highlight the effectiveness of the network expansion method based on graph theory. This method offers the advantage of being able to expand networks economically without consuming too much computational power.

According to the results, the Retailers clearly develop different marketing strategies in order to maximize their profitability. The Retailers perfectly adapt to the environment and successfully create marketing strategies that suit their objectives. The development of different marketing strategies in the Retailers indicates the complex adaptive behavior emerged from the Retailers.

The complex behaviors that appear in the results of the test simulation indicate the effectiveness of the simulation platform, and it is certainly a pioneer approach in the field of open energy markets and opens a window of opportunity to study complex adaptive systems.

In the case of the study that pays attention on the performance of the programming platforms, sequential programming platform provides perfect performance for problems that can only be solved sequentially. However, the drawback of the sequential programming approach is visible when the problem can be represented by many different ways including semi-parallel or parallel. The large time savings achieved by running the test simulation on the concurrent-programming platform further emphasizes the disadvantage of using sequential programming approach on non-sequential problems. Further time savings are achieved with the parallel-programming platform. However, the savings are only half of what is achievable in theory. The reason that holds back the time-saving in the parallel programming platform is that the problem is only representable in semi-parallel. As a result, the test simulation is unable to exploit the full potential of parallel programming. The valuable conclusion that can be made from this study is that choosing the appropriate programming approach is vital when computation efficiency is important.

6. Evolution of Energy Retailers

Abstract

An energy retailer plays the role of a financial-oriented actor in energy markets, manipulating marketing decisions for better profitability. In the multi-energy retail market simulation platform, Energy Retailers have been developed as autonomous agents that mimic the behaviors of actual retailers; forecasting the development of the market, predicting every move made by opponents, and making decisive moves to improve their profitability. Evolutionary based algorithms have been considered as suitable approaches for providing artificial intelligence (AI) required by these agents. According to their merits and popularity, particle swarm optimization and several algorithms from evolutionary computation – Evolutionary Particle Swarm Optimization and several variant algorithms of Genetic Algorithms – have been chosen as candidate algorithms for developing the AI in the Retail agents. In order to determine the effectiveness of the candidate algorithms, three scenarios have been created. In each scenario, the candidate algorithms have employed different population sizes, which include standard population, enlarged population and reduced population. After a thorough analysis has been performed on the competing algorithms, the order of the algorithms is established according to their problem solving performance and computational efficiency. For a brief conclusion, Evolutionary Particle Swarm Optimization exhibits its superiority over other competing algorithms not only in problem solving quality but also in computational performance.

6.1 Introduction

The open multi-energy retail market is a complex system composed of many interconnected market actors vying to improve their profitability. Each market actor of this open retail market at least holds a part in making the market workable; however, some actors play more than an ordinary part, forming backbones of the market, and their activities clearly shape the behavior and direction of the market. One of those vital components of the multi-energy retail market is a retailer. An energy retailer is defined as a newly created entity in competitive energy industry that obtains legal approval to sell retail energy [1]. Moreover, the energy retailer is a market actor entitled to provide available energy and other services to its end-use consumers, which involves a series of commercial functions – procuring, pricing, and selling, and also metering its use, billing for it, and collecting payment.

Since retailers have been created as a way to introduce or promote competition in energy retail markets, postulating actual activities of the retailers in the development of a multi-energy retail market simulation platform is important. In the multi-energy retail market simulator, a Retailer agent is designed to handle typical functions of a retailer such as monitoring its own economical performance, exploring available marketing choices, and making optimal decisions in a timely manner. Among various duties, achieving maximum profit while providing reliable service to consumers is the ultimate goal for the profit-oriented Retailer. In order to perform such complex functions in a dynamic environment, the Retailer is designed to be a complex adaptive agent. Adaptation of the Retailer not only plays as the complimentary part in performing complex optimization functions but also acts as the basic requirement for the market simulator to perform competitively.

In order to develop complex artificial intelligence for Retailers, several approaches have been initially considered regarding their merit in multi-objective optimization domain. These selected approaches include many expected approaches such as game theory, reinforcement learning, and evolutionary computation (EC). However, EC has appeared to be the most suitable approach in producing the artificial intelligence for the Retailer. Some of the advantages of EC over other methods – robustness, solution to problems unsolved by analytical techniques, hybridization, flexibility, and parallelism – have perfectly fulfilled the general requirement of a particular algorithm in producing high-level intelligence for the Retailer.

Several algorithms have proven record in solving optimization problems. These algorithms include classical evolutionary algorithms (EAs) such as genetic algorithms, new EAs such as evolutionary particle swarms optimization, and particle swarms optimizations. Therefore, five variant algorithms derived from the above algorithms – steady-state genetic algorithm, deterministic-crowing genetic algorithm, multiple-population genetic algorithm, particle swarm optimization, and evolutionary particle swarm optimization – have been selected for further study regarding agent learning process. This chapter explains the detailed development of intelligence in Retailers using the selected algorithms and their performances. Extensive research work has been performed to measure the capability of each selected algorithm, and their advantages and disadvantages are discussed in this chapter.

In the process of discussing the evolution of Retailers, this chapter is arranged as follows: The mathematical structure of the Retailers is again described in section 6.2. Then, section 6.3 provides the implementation of the algorithms considered in this study. Afterward, the performances of the competing algorithms are compared using the results obtained from the simulations in section 6.4. Finally, the summary from the evolution of the Retailers is discussed in section 6.5.

6.2 Mathematical formulation

As explained before, the intelligence that controls the capability of decision making power of Retailers has been developed with selective evolutionary-based algorithms. The Retailers apply those algorithms to manipulate parameters that have influence on profitability in a timely manner. An individual, a set of influential parameters on profitability, acts as a possible decision or solution of the given problem in evolutionary approach and fitness function that evaluates the quality of each individual is developed using following objective function.

Maximize $\mathrm{OBJ} = \sum_{d=1}^{n} \left[\mathrm{Eco}_d - \mathrm{Pen}_d\right]$ (6.1)

subject to:

$$\mathrm{Price}_a^{min} < \mathrm{Price}_a < \mathrm{Price}_a^{max}$$

$$\mathrm{DevPrice}_a < \mathrm{Limit}$$

$$\mathrm{Incentive}_a^{min} < \mathrm{Incentive}_a < \mathrm{Incentive}_a^{max}$$

$$\mathrm{Advertise}_a^{min} < \mathrm{Advertise}_a < \mathrm{Advertise}_a^{max}$$

$$\mathrm{Service}_a^{min} < \mathrm{Service}_a < \mathrm{Service}_a^{max}$$

$$\mathrm{Quality}_a^{min} < \mathrm{Quality}_a < \mathrm{Quality}_a^{max}$$

$$\mathrm{Management}_a^{min} < \mathrm{Management}_a < \mathrm{Management}_a^{max}$$

where

n – number of days of an internal simulation

Eco_d = Economic performance at day d

Pen_d = Penalty assigned at day d

Price_d = Energy prices charged to residential, commercial and industrial consumers

Incentive_d = Incentives given to residential, commercial and industrial consumers

Advertise_d = Spending on advertisement

Service_d = Spending on customer service improvement

Quality_d = Spending on quality improvement of the product

Management_d = Spending on management efficiency improvement

The objective function can be broken down into two parts: economic performance and penalty for violating constraints. The economic performance of the Retailers can be evaluated using following generalized formula.

$$\text{Eco}_d = P_d \times UP_d + S_d \times US_d \tag{6.2}$$

where

UP_d = Unit profit of the Retailer at day d

US_d = Unit market share of the Retailer at day d

P_d = Profit weight factor at day d

S_d = Share weight factor at day d

The Retailers are designed to use different evaluation methods in different marketing strategies. When the basic marketing strategy is profit-oriented, the economical performance is evaluated as follow:

$$\text{Eco}_d = \begin{Bmatrix} P_d^1 \times UP_d + S_d^0 \times US_d \quad \text{if } \delta P_d \geq 0 \\ P_d^2 \times UP_d + S_d^0 \times US_d \quad \text{if } 0 > \delta P_d \geq \delta P_{\lim it}^{lower} \\ P_d^3 \times UP_d + S_d^0 \times US_d \quad \text{if } \delta P_d < \delta P_{\lim it}^{lower} \end{Bmatrix} \tag{6.3}$$

subject to:

$$S_d^0 < P_d^1 < P_d^2 < P_d^3 < 1$$

where δP_d represents the derivative of the current profit with respect to the reference profit. The value of profit weight factor changes with respect to the condition of δP_d. The predetermine value, $\delta P_{\lim it}^{lower}$, is set as the lower limit of the profit derivation.

When the basic marketing strategy is share-oriented type, the economical performance is evaluated as:

$$Eco_d = \begin{cases} P_d^0 \times UP_d + S_d^1 \times US_d & \text{if } \delta S_d \geq 0 \\ P_d^0 \times UP_d + S_d^2 \times US_d & \text{if } 0 > \delta S_d \geq \delta S_{\lim it}^{lower} \\ P_d^0 \times UP_d + S_d^3 \times US_d & \text{if } \delta S_d < \delta S_{\lim it}^{lower} \end{cases} \tag{6.4}$$

subject to:

$$P_d^0 < S_d^1 < S_d^2 < S_d^3 < 1$$

where δS_d is the derivative of the current share with respect to the reference share. The value of share weight factor changes with respect to the condition of δS_d.The predetermined value, $\delta S_{\lim it}^{lower}$, is also set as the lower limit of the share derivation.

In the case of the neutral strategy, the formulation for the economical performance of the Retailers become:

$$Eco_d = \begin{cases} P_d^1 \times UP_d + S_d^1 \times US_d & \text{if } \delta P_d \geq 0 \\ P_d^2 \times UP_d + S_d^2 \times US_d & \text{if } 0 > \delta P_d \geq \delta P_{\lim it}^{lower} \\ P_d^3 \times UP_d + S_d^3 \times US_d & \text{if } \delta P_d < \delta P_{\lim it}^{lower} \end{cases} \tag{6.5}$$

subject to:

$$P_d^1 < P_d^2 < P_d^3 < 1$$

$$S_d^1 < S_d^2 < S_d^3 < 1$$

where δP_p is the derivative of the current profit with respect to the reference profit. The value of profit and share weight factor changes with respect to the condition of δP_p. The predetermined value, $\delta P_{\lim it}^{lower}$, is also set as the lower limit of the profit derivation.

Then, the penalty is determined along the internal simulation according to the status of profit, market shares, and predefined limits on profitability and market share of the Retailers. When a profit-oriented move is foreseen, the formulation for calculating the penalty becomes:

$$Pen_d = C + \delta S^2 \times F \tag{6.6}$$

It is evaluated as follows when action prepared is share-oriented.

$$Pen_d = C + \delta P^2 \times F \tag{6.7}$$

Furthermore, it is calculated as follows when the action is decided by a neutral strategy.

$$Pen_d = C + (\delta P^2 + \delta S^2) \times F \tag{6.8}$$

where

C = Constant

F = Penalty factor

δS = Deviation of market share with respect to a reference share

δP = Deviation of profit with respect to a reference profit

6.3 The Development of Selected Algorithms

Although many evolutionary-based algorithms have been successfully developed and employed in many different problems, they all share similar implementation structure. As a result, the implementation of the selected algorithms in this comparison study can be generalized through following flow.

At the beginning of the market simulation, individuals formed with real number variables are randomly created as a population inside a particular Retailer. Whenever the evolution of the Retailer has been triggered, the surrounding environment is analyzed first.

Simultaneously, forecasting the moves of opponents is done using artificial neural networks. The artificial neural networks applied in this study have 3 layers and employ back propagation approach was for training. Learning rate of 0.3 and sigmoid activation functions are also used in training process. Both historical prices offered by Retailers to Consumer classes and associated historical market shares of the Retailers are taken as input data of the training process while prices offered by a particular Retailer is considered as output data. Moreover, the input and output data are normalized in order to make the learning process of the neural networks faster. In order to train the neural networks with latest available data, training data sets are limited to 20 data sets, and they are updated by gradually replacing old training data sets with new available data sets. When the training process is over, future energy prices of a particular Retailer is ready to be forecasted by the neural networks using prices and market shares of the Retailers at a particular time.

After the possible moves of opponent Retailers had been predicted with the back propagating neural networks, the Retailer performs a fitness evaluation on the population through its internal simulation process, which is equipped with an inner capacity for simulating the market. Then, selection process is performed on the population according to the individuals' fitness.

In case of the selected algorithms that employ crossover, pairs of individuals are randomly chosen from the selected pool and undergo recombination process with a particular probability called crossover. Afterward, mutation process is performed on the individuals, and a new generation of individuals was produced. For particle swarm related algorithms, the movement rule is applied for producing new individuals.

Then, replacement scheme allows competition among individuals from old and new generation and produces an improved generation with the best individuals left from the competition. This cycle is repeated until the stopping criteria are met. Then, the best individual emerged from the process is taken as the candidate decision of the Retailer to be applied. The generalized implementation of the selected algorithms is graphically displayed in the following flow chart.

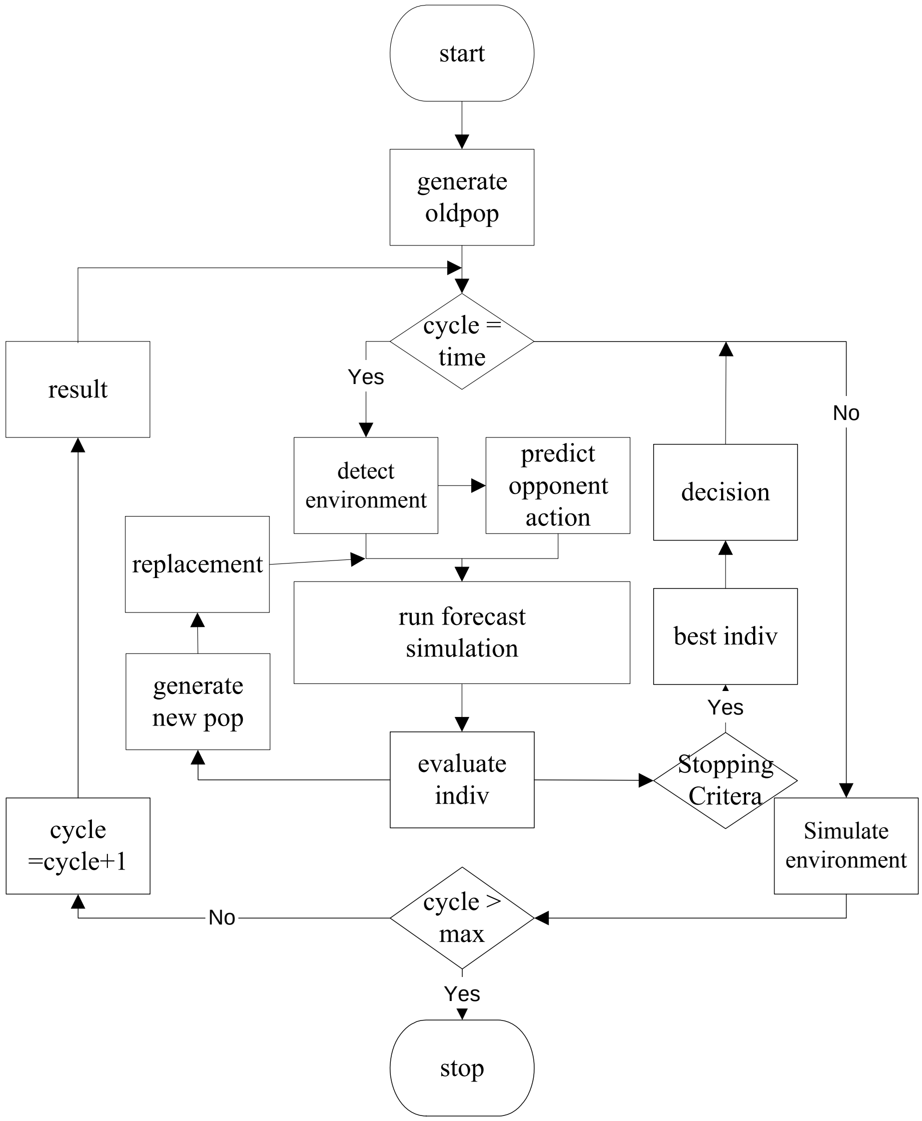


Fig. 6.1 Flow chart of the selected evolutionary algorithms in the simulation platform

In order to determine the best performing algorithm for developing intelligence in the Retailer, several algorithms and their variant versions have been considered. According to their merit and popularity, algorithms such as genetic algorithm (GA), particle swarms optimization (PSO) and evolutionary particle swarms optimization (EPSO), have been selected to participate in this comparison study. Since GA has been the most popular algorithm in evolutionary computation [2], its reputable record has earned itself a place in the study. PSO has been considered for its merit and simplicity over conventional EAs [3]. EPSO, a new emerging technique that shows great potential in optimization domain [4], has been included for testing its actual potential.

Five algorithms have been developed in order to seek the capable algorithm for developing intelligence in Retailers. These algorithms include EPSO, PSO, and three variant algorithms of GA – steady-state GA, multi-population GA, and deterministic-crowding GA. Detail of the development of each algorithm is described in the following sections.

6.3.1 Genetic Algorithms

GAs are general-purpose, parallel search procedures based upon genetic and evolutionary principles [5]. A GA works by repeatedly modifying a population of artificial structures through the application of genetic operators. GA is typically a black-box method that uses fitness information exclusively; they do not require gradient information or other internal knowledge of the problem. GAs became the most popular evolutionary algorithm due to their successful application in optimization and search problems, particularly in those problems in which the size or complexity of the search space renders infeasible the use of other optimization techniques [6].

Following Holland’s original genetic algorithm proposal, many variations of the basic algorithm has been introduced; however, the important and distinctive feature of all GAs is in the population handling technique. All candidate GAs of this study – steady-state GA (SSGA), multi-population GA (MPGA), and deterministic-crowding GA (DCGA) – intend to outperform the classical GA by modifying the population handling technique in different ways. The implementation of each variant algorithm of GAs is further explained in the following sections.

6.3.1.1 Steady-state GA

The classical GA adopts a generational replacement policy in which the whole population is replaced in each generation. However, the steady-state policy used by many subsequent GAs employs a selective replacement for the population [7]. The idea is to keep one or more individuals within the population for several generations as long as those individuals sustain a better fitness than the rest of the population. SSGA applied in this study can be explained through the following flow.

Individuals, each formed with real number variables, are randomly created as a population. Each individual is then evaluated by using the objective function mentioned in the previous section, and a quantitative fitness value is assigned to each individual. The selection of the population is later performed by the roulette wheel selection on the fitness of the individuals. Probabilistic roulette wheel selection chooses individuals through n simulated spins of a roulette wheel, which contains one slot for each population element and the size of each slot is directly proportional to its respective probability. After finishing the selection procedure, pairs of individuals are randomly chosen from the selected pool and undergo recombination with a particular probability. A uniform crossover with 0.9 probability rate is applied in this particular algorithm. Mutation process is later performed on newly produced individuals. Gaussian mutation with 0.1 probability rate is chosen to present the mutation process of this algorithm. A new generation of individuals is eventually generated after the mutation process. Then, replacement scheme of overlapping population approach, which transfers certain percentage of the best individuals from the previous generation into the new generation, is utilized to replace 80% of old individuals. This cycle is repeated until a stopping criterion is met.

6.3.1.2 Deterministic Crowding GA

Deterministic Crowding is inspired by a corresponding ecological phenomenon – the competition among similar members of a natural population for limited resources [6]. Similar individuals in a natural population, often of the same species, tend to occupy the same environmental niches, and therefore must compete against each other for limited resources.

DCGA technique in this study is designed to maintain genetic diversity throughout the evolution. In DCGA, the following steps are typically done:

a) two individuals are first selected randomly
b) using crossover and mutation, two new individuals are generated
c) a technique of similarity is applied to the set of two parents and two descendent

individuals to group them in two pairs, maximizing the similarity within each pair

d) an elitist selection is applied to each group of similar individuals, finally selecting two individuals to form the next generation
e) this process is repeated until the following generation has the desired number of individuals.

Since DCGA has been entirely based on SSGA, the characteristics of its genetic operators – selection, crossover and mutation – are set the same as the one from SSGA.

6.3.1.3 Multi-population GA

The fundamental technique for locating multiple solutions with GAs is to perform multiple and independent runs of the GAs and to keep the best solution from each run afterward. When this process is performed in parallel, it is equivalent to parallel GA. MPGA is a variant algorithm of parallel GA, in which independent GAs are designed to separately run on local subpopulations within a single CPU architecture [8].

MPGA developed in this study is designed to run a number of SSGAs in parallel on its subpopulations. The same parameter set previously utilized in SSGA has been reapplied to the selection, crossover, and mutation processes of each SSGA applied to each subpopulation under MPGA. During evolution, MPGA introduces communication among subpopulations with migrating individuals. The objective of this process is to trade the diversity among subpopulations throughout the run, making each subpopulation less likely to prematurely converge. In the work reported, only two sub-populations have been used, and these have exchanged two randomly selected individuals from one of the sub-populations to another before crossover takes place.

6.3.2 Particle Swarm Optimization

The flow of PSO applied in this study starts with randomly initializing a population of individuals with positions and velocities on 10 dimensions in the problem space. Afterward, the fitness is evaluated using the desired optimization fitness function for each individual. Then, the process of modification on the best fitness available of the population as well as each individual is performed by comparing the current fitness of a particle with its best ever fitness as well as with the best overall fitness of previous population and updating them accordingly. Then, changing of the velocity and position of the particles is taken place according to the movement rule, which is specifically mentioned in chapter 3. These steps are repeated until a stopping criterion is satisfied.

In this study, the maximum velocity on each dimension has been set as about 10% of the dynamic range of the variable on each dimension. Regarding weighs in the movement rule, the weight associated with the velocity of the particle has been developed to be linearly decreasing from 1 to 0.5 during a run while other weights have been set at 1 respectively.

6.3.3 Evolutionary Particle Swarm Optimization

The general scheme of EPSO is the followings: First, a population of individuals with positions and velocities on 10 dimensions in the problem space is randomly initialized as in PSO. Then, replication process is taken place with the individuals being duplicated 2 times. Afterward, mutation is performed on strategic parameters of each individual. Furthermore, offsprings are produced from the individuals according to the movement rule. Utilizing the desired optimization fitness function, the fitness value of each individual is later evaluated. Afterward, the process of comparing fitness of the individuals for determining the best ever fitness of each particle and the best overall fitness of the population is performed as in PSO. Finally, selection process is performed by stochastic tournament and the best individuals survive to form a new generation.

6.4 The Comparison Results

The same test system mentioned in the previous chapter has also been used in this comparison study; however, the network expansion scheme of Energy Deliverers has been set not to perform in this work so that the results from test simulations has not had interference from the expansion of the networks. Moreover, only one Retailer has supplied energy to consumers in each industry.

The test simulation has been fixed at 24 months for market simulation and at 2 months for internal simulations inside evolutionary process. Each evolutionary process has been designed to start at the beginning of each month and the stopping criterion has been the same: in the first episode, when performing the first internal simulation, the evolutionary process would be stopped if there were no improvement in the fitness function after 50 consecutive generations; in all the following internal simulations, during the market simulation of 24 months, the threshold of 10 generations has been used instead of 50. In order to compensate for the influence of random events, the simulation has been run for 5 times each. During market simulation, only one retailer has been equipped with one type of the selected algorithms while other retailers have been set to idle in decision making process.

In order to determine the potential of selected algorithms in this study, the market simulation has been repeatedly run for a chosen retailer (Gas Retailer in this analysis) equipped with one type of algorithm at a time. Several results that indicate the effectiveness of the marketing decisions produced by the selected algorithms are presented in this section. These results include the Retailer's weekly profit and accumulated present worth profit at the end of the market simulation. Number of evaluations performed on given objective function to obtain the solution is also included as an indication that reflects the computational efficiency of the algorithms.

Since stopping criteria of the algorithms has not been tied to the number of generations in this study, making strict comparison among the algorithms regarding computational efficiency has been a difficult task. However, three scenarios have been created in order to keep the number of function evaluations of the algorithms comparable during the performance testing of the competing algorithms. Generalized population of 20 individuals has been applied by all selected algorithms in the first scenario, paying no attention to computational effort. Then a second scenario has been developed by increasing the number of individuals to 80 in SSGA, 40 in PSO, and 100 in DCGA so that the number of function evaluation among the algorithms are nearly equal. Finally, the number of individuals of EPSO has been reduced to half, 10 individuals, in third scenario in order to levelized the evaluation number of EPSO with other algorithms. The results from these three scenarios are discussed in the following sections.

6.4.1 Scenario One

This scenario intends to concentrate on the optimization performance of the algorithms regardless of their computational performance. One of the results that compares the capacity of optimization power in this study, the weekly profits of the Gas Retailer being equipped with one of the selected algorithms – DCGA, MPGA, SSGA, PSO, and EPSO – at a time and run 5 simulations each, are shown in the following figures.

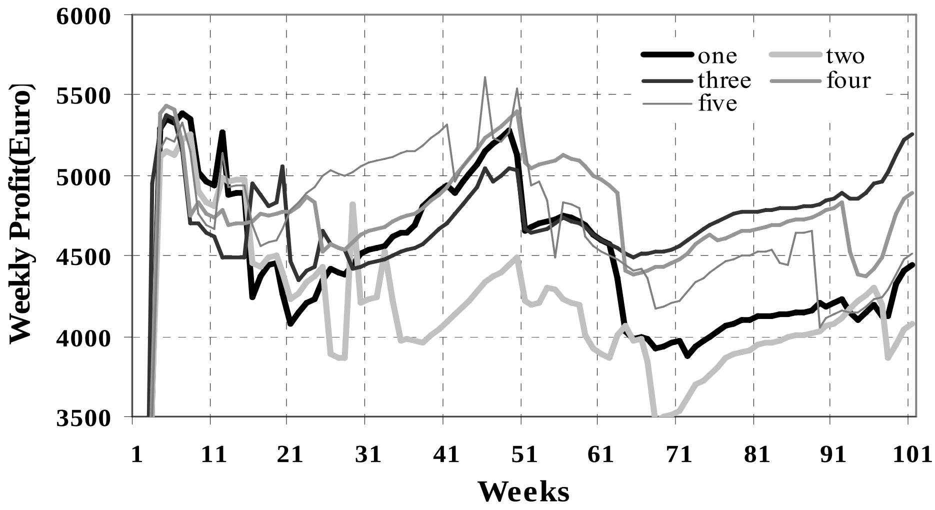


Fig. 6.2. Weekly profit of the Gas Retailer with DCGA

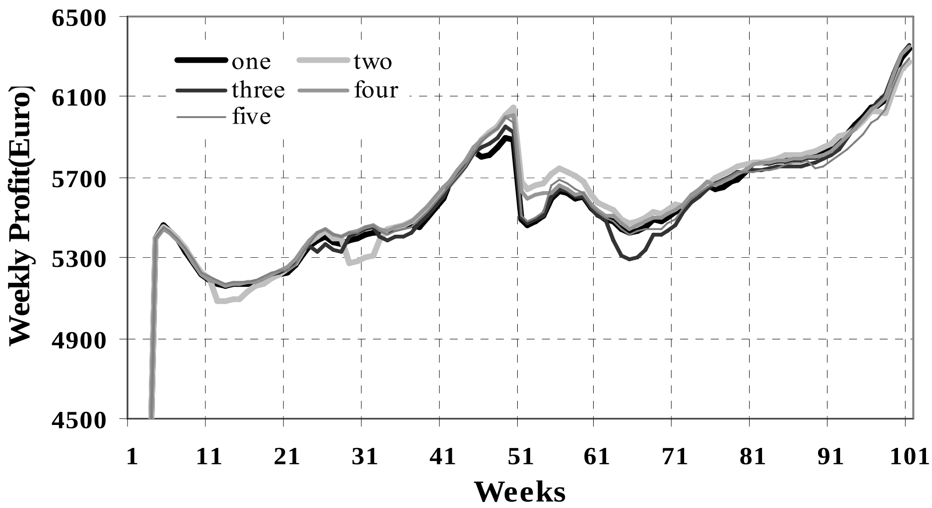


Fig. 6.3. Weekly profit of the Gas Retailer with MPGA

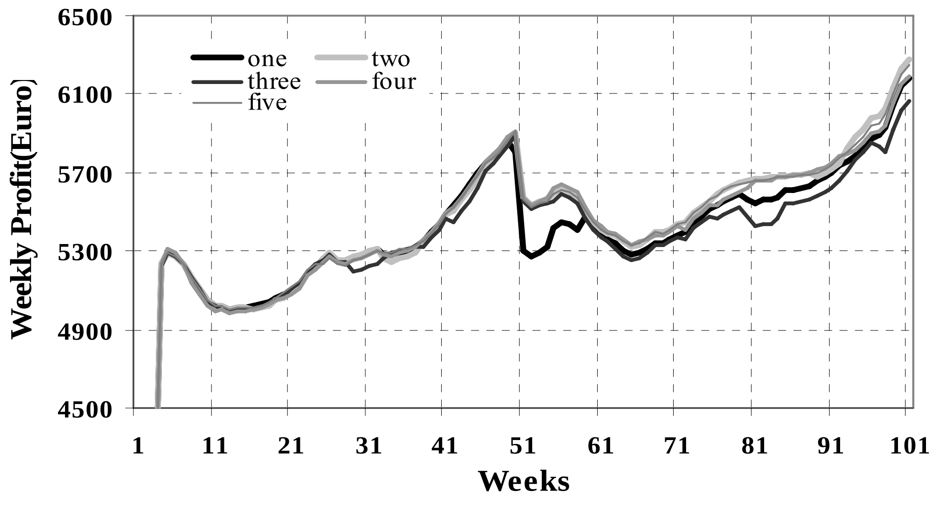


Fig. 6.4. Weekly profit of the Gas Retailer with SSGA

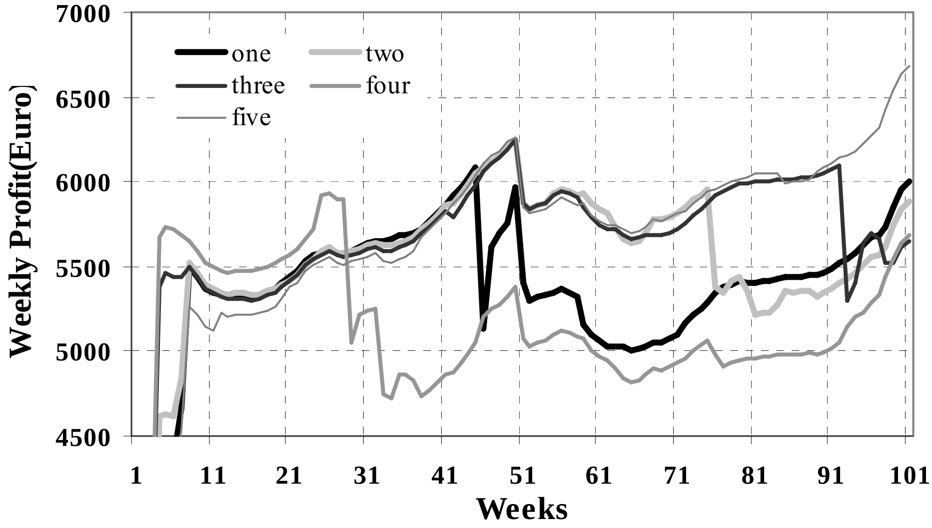


Fig. 6.5. Weekly profit of the Gas Retailer with PSO

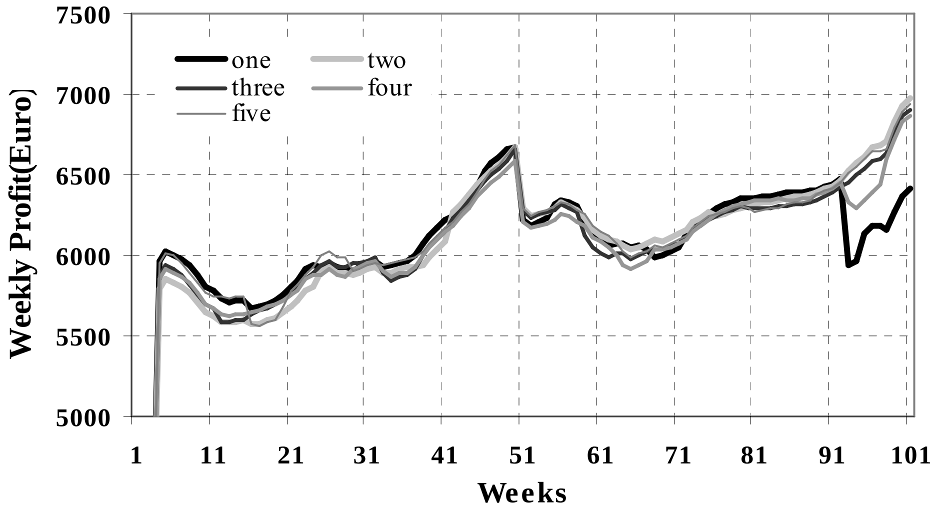


Fig. 6.6. Weekly profit of the Gas Retailer with EPSO

According to the weekly profit graphs of the Gas Retailer with different selected algorithms, EPSO, SSGA and MPGA has produced similar marketing decisions in 5 simulation runs. As a result, there is similar pattern among the 5 weekly profit curves of the Gas Retailer, indicating these algorithms as consistent and reliable approaches. However, other selected algorithms, DCGA and PSO have developed less consistent results. Significant variation among their 5 weekly profit curves indicates the requirement of repeated testing in order to get reliable results.

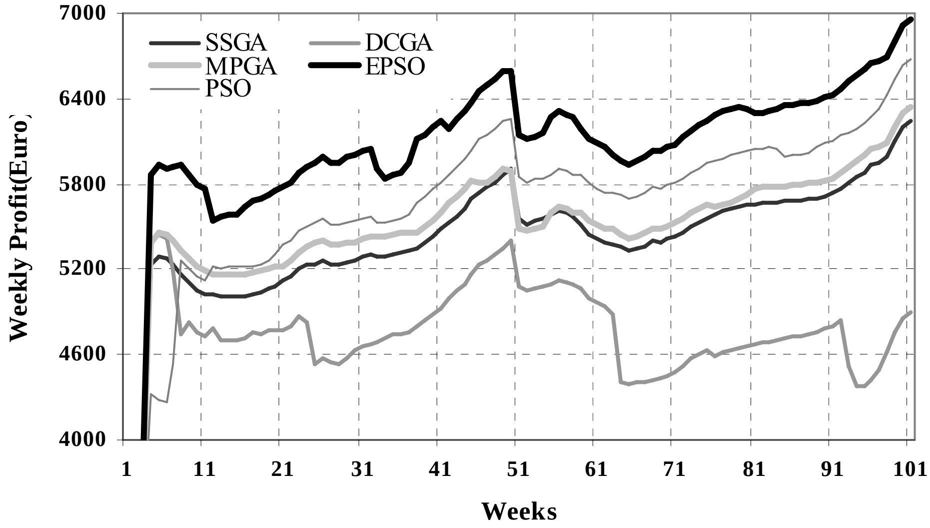


Fig. 6.7. Comparison of weekly profit of the Gas Retailer obtained from the best run of the selected algorithms

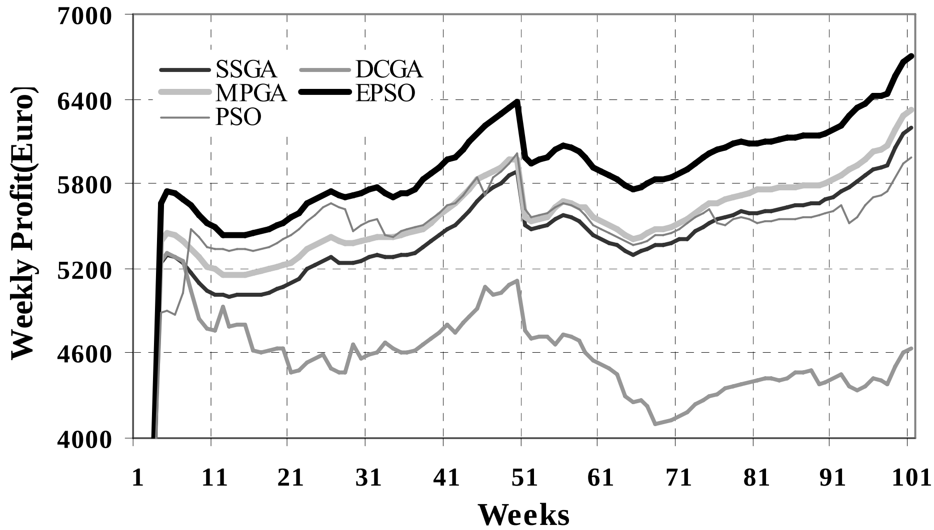


Fig. 6.8. Comparison of average weekly profit of the Gas Retailer obtained from 5 simulation runs of the selected algorithms

In order to make comparison among the performance of the selected algorithms clear and visible, the weekly profit results are reorganized into the weekly profit of the best run and average weekly profit for each algorithm. The weekly profit of the best run represents the best weekly profit curve occurred during 5 simulation runs. The average weekly profit simply indicates an average weekly profit produced from the weekly profit curves of all 5 simulation runs. According to the comparison among the weekly profit of the best runs shown in Fig. 6.7, EPSO is clearly the leader, producing the highest weekly profit during entire simulation. The second best is PSO. Afterward, MPGA is in third while SSGA is closely following it from behind. The last one is DCGA.

The average weekly profits of the competing algorithms, as shown in Fig. 6.8, endorse the order of the effectiveness of the competing algorithms, replicating the order of the algorithms mentioned previously with PSO as an exception. In case of PSO, it tends to perform less competitively in the second half of most of its simulation, dropping behind EPSO, SSGA and MPGA. The accumulated present worth profits obtained by the Gas Retailer with different competing algorithms also portray the same picture. Fig. 6.9 indicates that the order of present worth profit achieved with different algorithms is the same as the order mentioned just before; EPSO, MPGA, SSGA, PSO, and DCGA.

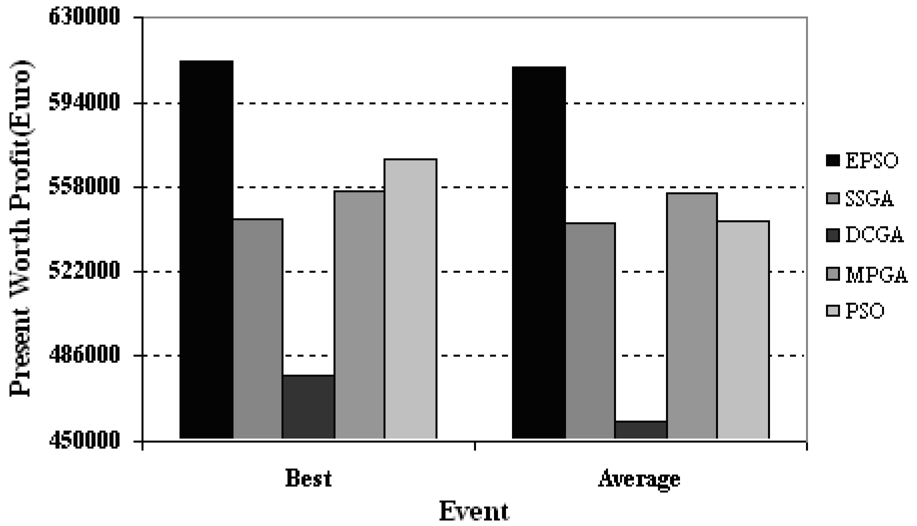


Fig. 6.9. Accumulated present worth profit of the Gas Retailer with the candidate algorithms

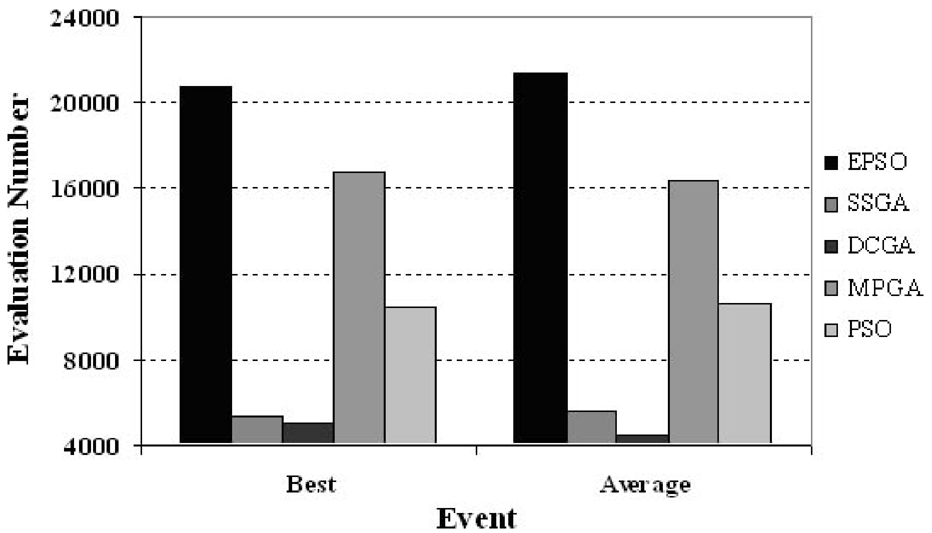


Fig. 6.10. Number of evaluations performed by the candidate algorithms

Fig. 6.10 depicts the different picture regarding the computational performance of the selected algorithms. According to the figure, time-consuming algorithms such as EPSO and MPGA perform many more evaluation of the objective function than their time-saving counterparts, SSGA and DCGA, introducing the dilemma of functional performance vs. computational performance. Furthermore, the findings of algorithms' computation performance lead us to do more analysis for answering intriguing questions such as "will increasing evaluation number of the time-saving algorithms perform better than the time-consuming algorithms" or "will reducing evaluation number of time-consuming algorithms still perform better than time-saving algorithms?" These questions eventually drive me to develop two more scenarios.

6.4.2 Scenario Two

After scenario one has been analyzed, the functional performance of the selected algorithms is being able to put in order; beginning with EPSO as a leading performer and MPGA, SSGA, PSO, and DCGA following the EPSO in order. However, large differences in the number of evaluations between the time-consuming algorithms and the time-saving algorithms have highlighted the need of further analysis. In order to determine the computational performance of the selected algorithms, this scenario has been developed by increasing the evaluation numbers of the time-saving algorithms to the similar level as the time-consuming algorithms. This has been done by increasing the size of the population of the time-saving algorithms. As a result, the number of evaluations performed in those algorithms has also increased proportionally.

In this scenario, population size of EPSO and MPGA has been kept constant at 20 individuals while the population size of DCGA, SSGA, and PSO has been increased to 100, 80, and 40 respectively. The weekly profit curves of the Gas Retailer equipped with the modified population algorithms – DCGA, SSGA, and PSO – are shown in the following figures.

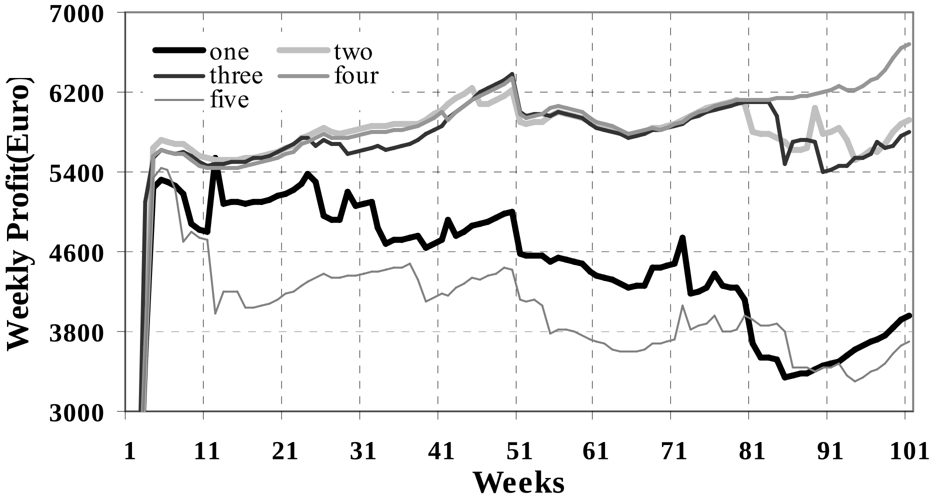


Fig. 6.11. Weekly profit of the Gas Retailer with DCGA

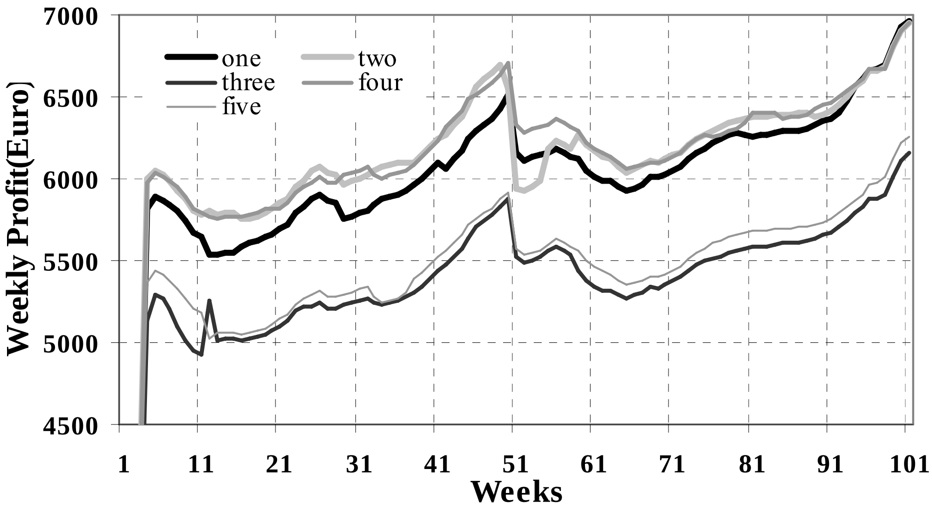


Fig. 6.12. Weekly profit of the Gas Retailer with SSGA

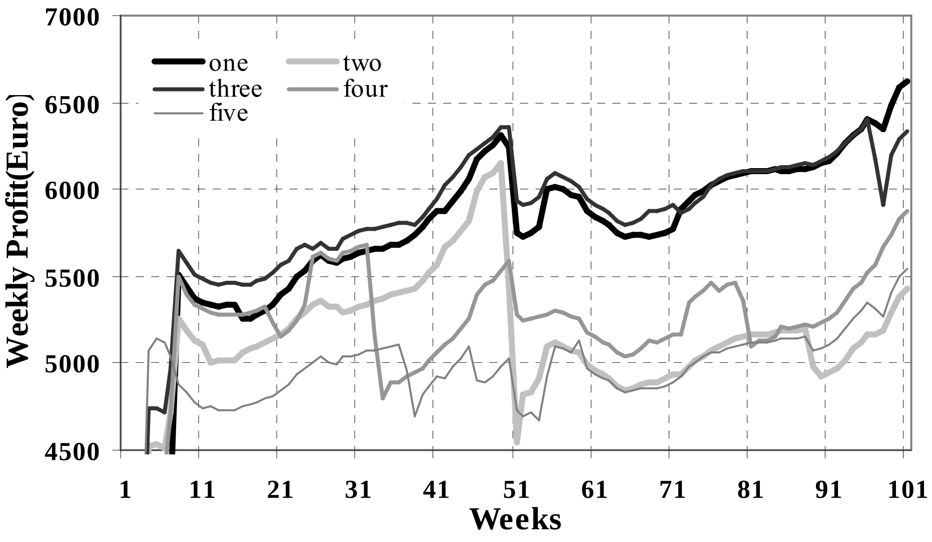


Fig. 6.13. Weekly profit of the Gas Retailer with PSO

The algorithms with modified population sizes seem to produce two types of weekly profit; higher weekly profit occur when the global optimum point has been found in the simulation while lower weekly profit is the result of the simulation that has been locked in a local optimum point. Moreover, the effect of the application of bigger size population is clearly seen in SSGA and DCGA. The weekly profit from several simulations of those algorithms reaches to the new level, indicating the possibility to reach the global optimum point of the problem with bigger population in those algorithms. However, the functional performance of PSO has been hardly changed even if its population has been increased to 2 times of its original population.

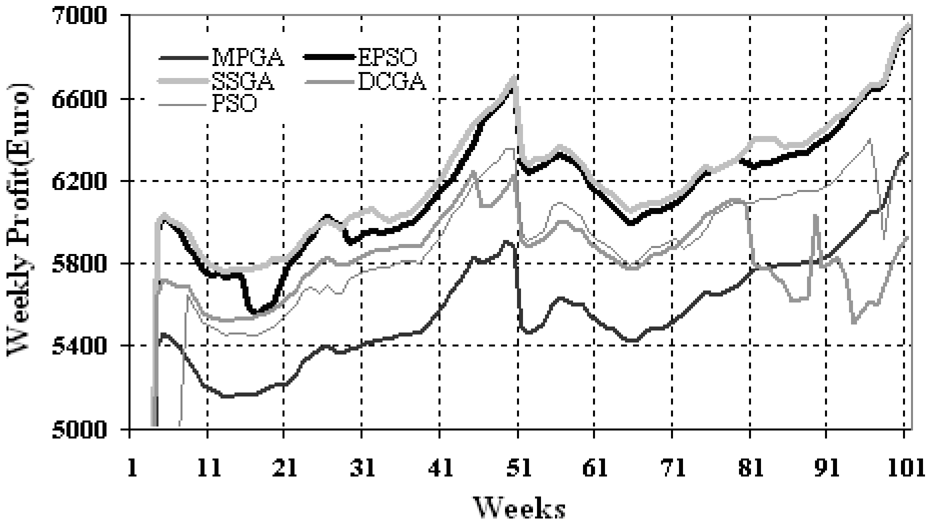


Fig. 6.14. Comparison of weekly profit of the Gas Retailer obtained from the best run of the selected algorithms

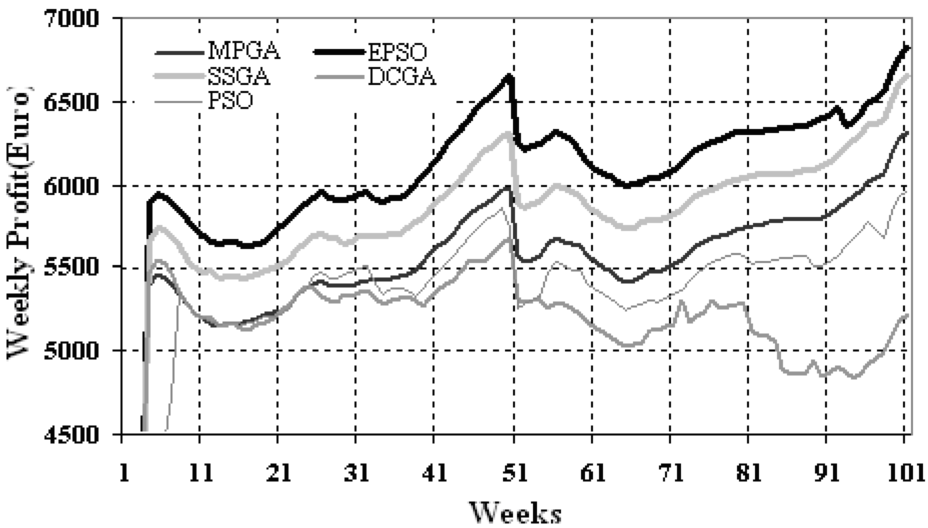


Fig. 6.15. Comparison of the average weekly profit of the Gas Retailer obtained from 5 simulation runs of the selected algorithms

Due to the better outcome from the algorithms with modified population, the functional performance order of the selected algorithms changes slightly. According to the results shown in Fig. 6.14 and Fig. 6.15, SSGA is slightly ahead of EPSO while DCGA and PSO outperform MPGA in most part of the simulation in the comparison based on the weekly profit of the best runs. However, the results from average run describe the similar order that previous scenario has established except SSGA outperforming MPGA in this scenario. The new order resulted from this scenario is EPSO, SSGA, MPGA, PSO, and DCGA.

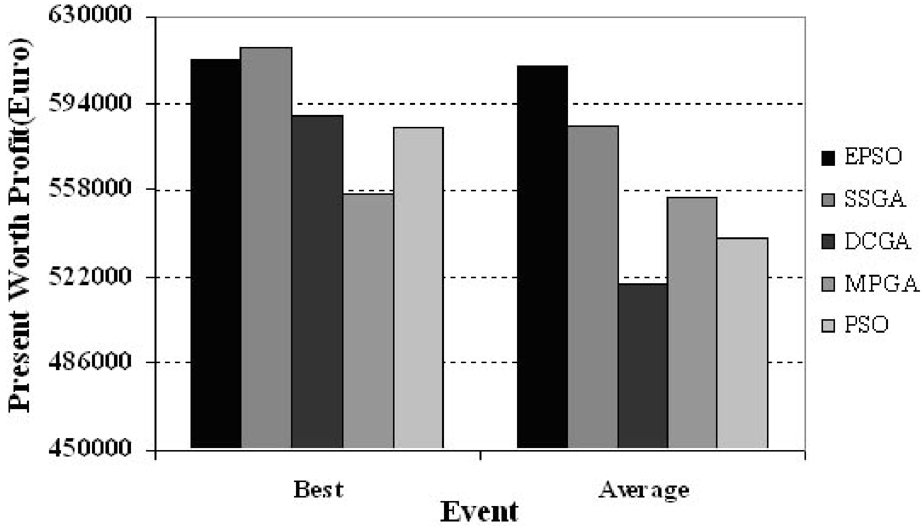


Fig. 6.16. Accumulated present worth profit of the Gas Retailer with the candidate algorithms

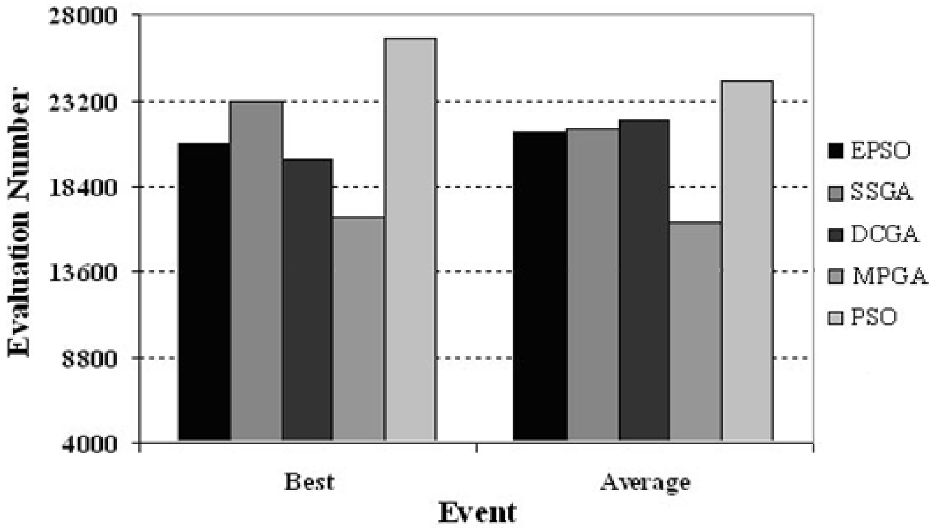


Fig. 6.17. Number of evaluations performed by the candidate algorithms

Accumulated present worth profits of the Gas Retailer with the selected algorithms represented in Fig. 6.16 further validate the functional performance order of the selected algorithms. Fig. 6.17 displays the number of evaluations performed by the competing algorithms during test simulations. Roughly equal numbers of evaluations of the competing algorithms indicate that the functional performance of the selected algorithms in this scenario is based on the same computational performance.

6.4.3 Scenario Three

This scenario has been created as a way to determine the performance of the time-consuming algorithms with downsized evaluation numbers. Downsizing evaluation numbers has been done with reducing the size of the population of the time-consuming algorithms. However, the population size of MPGA, one of the time-consuming algorithms, has kept unchanged as reducing the population size from its original size would severely degrade the outcome of the MPGA.

In this scenario, only the population size of EPSO has been reduced to 10 while the population size of other competing algorithms has been kept constant at 20 individuals. The weekly profit of the Gas Retailer equipped with EPSO is shown in following figure.

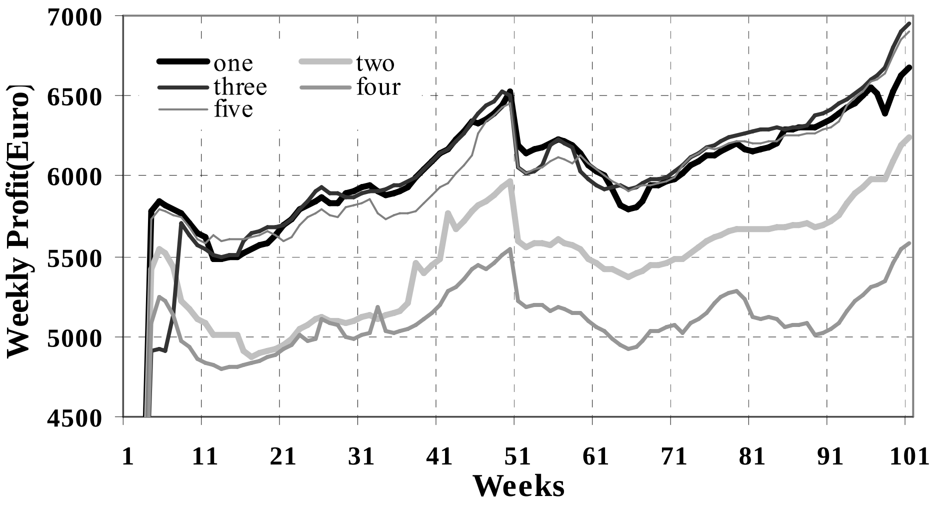


Fig. 6.18. The weekly profit of the gas Retailer with EPSO

As the population size of EPSO has been reduced to half, its functional performance has degraded significantly. Variation in the weekly profit curves as well as the development of two different level of the weekly profit curves from 5 simulation runs clearly indicate the sign of trapping in local optimums when the population size of EPSO has been reduced.

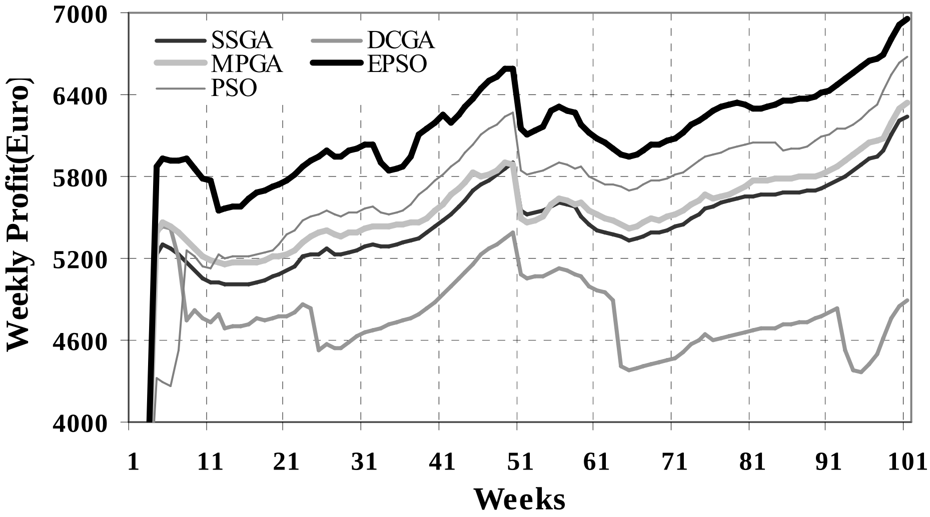


Fig. 6.19. Comparison of the weekly profits of the gas Retailer obtained from the best run of the selected algorithms

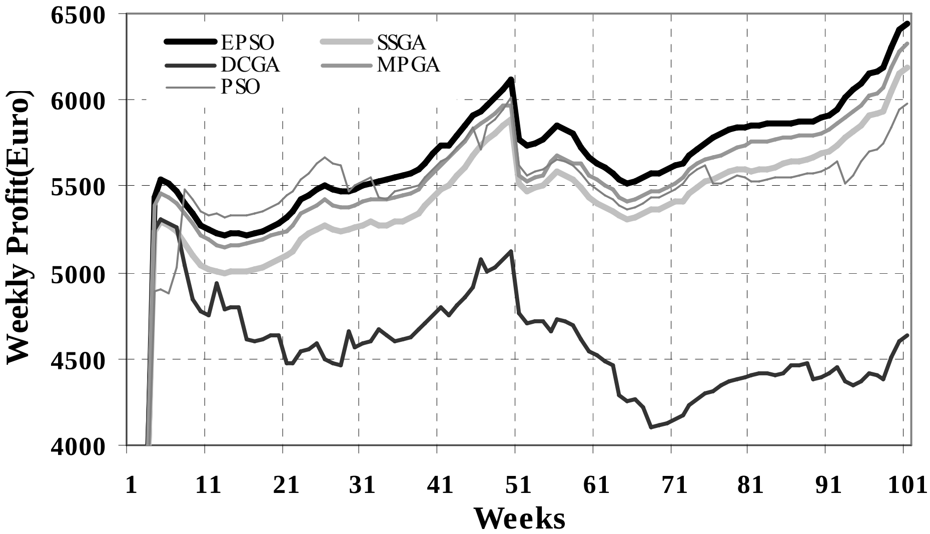


Fig. 6.20. Comparison of the average weekly profits of the gas Retailer obtained from 5 simulation runs of the selected algorithms

Although EPSO with reduced population has shown signs of becoming trapped in local optima, it is still the best among the competing algorithms. Fig. 6.19 and Fig. 6.20 indicate that EPSO still maintain its superiority over other competing algorithms even when its population has been reduced to half of the original population.

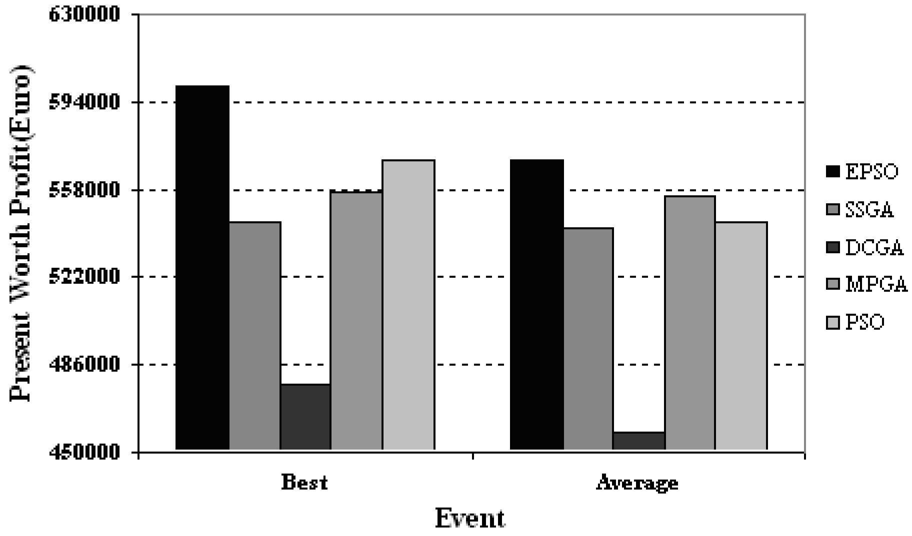


Fig. 6.21. Accumulated present worth profit of the Gas Retailer with the candidate algorithms

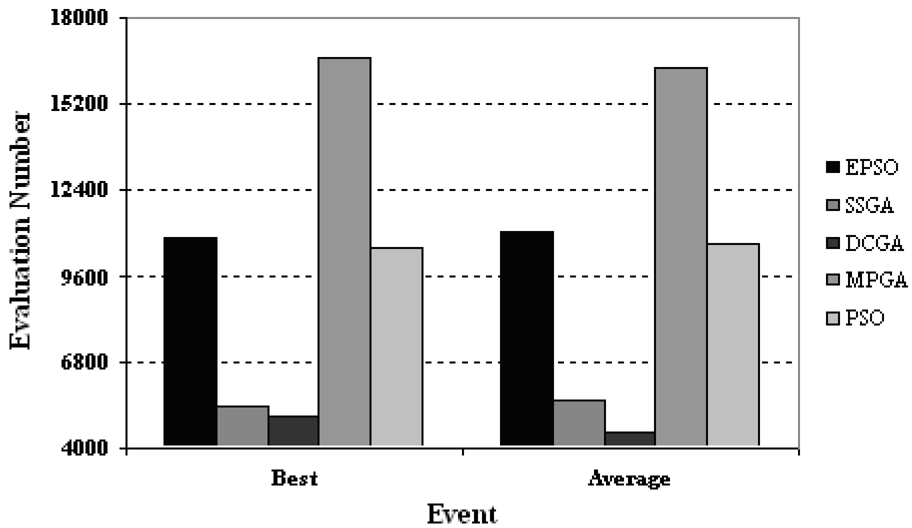


Fig. 6.22. Number of evaluations performed by the candidate algorithms

As usual, accumulated present worth profit shown in Fig. 6.21 indicates the same idea presented in the weekly profit findings. Fig. 6.22 shows the number of evaluations performed by each algorithm in this scenario.

6.5 Conclusions

In order to extensively study the performance of the selected algorithms and their merit and weakness, three scenarios have been developed for determining the performance of these algorithms in terms of optimization as well as computational efficiency. The findings from these scenarios clearly help to find the order of performance of algorithms considered in this study. The detail summary of each method is discussed as follow.

Deterministic crowding GA, which has unique replacement scheme among parents and offsprings, intends to keep diversity intact. However, the noise associated with higher diversity approach leads DCGA to provide inconsistent solutions. Furthermore, the marketing decisions provided by this algorithm with standard population have often trapped in local optimum points, resulting in low profitability. The profitability of the Gas Retailer with DCGA has been significantly improved with a larger population size, ranking as third in comparison among the best runs; however, it is down to last in 5 competing algorithms when consideration is fixed on average results.

The findings from PSO indicate that the profitability developed by PSO hardly changes between standard population size and reduced population size. Moreover, PSO with both population sizes could not lift the marketing decisions to the global optimum, providing less competitive results. As a result, the ranking of this method is the second last in the list when comparison is performed with average results. Although PSO with standard population size has been ranked higher in the comparison of the best runs, it is considered as unreliable according to its one-time-only nature.

MPGA introduces the idea of running GAs in parallel with some level of communication among them. One interesting character appeared from the results of this algorithm is its consistency. Although the marketing decisions developed by this method do not reach to the global optimum point, strikingly similar results produced by 5 simulation runs endorse the reliability of the method. Through out the comparison, this algorithm is closely competing with SSGA for second best position in the list. When the population size is set to standard size for both methods, MPGA develops better optimization scheme with more profitability. However, the population size of SSGA is increased to the level the evaluation numbers of both methods can be compared, the ranking becomes reverse.

SSGA is one of the most popular GAs, and it has been successfully employed in vast array of problems. With standard population size, this algorithm provides competitive and consistence results. However, it only discovers the global optimum after its population size has been increased. Although it has produced the best result in the comparison of the best runs in the second scenario, its position generally stands at the second best after EPSO.

EPSO claims to be developed as the better algorithm with borrowing the best idea of particle swarm optimization and evolutionary strategies. The results obtained from the Gas Retailers who employ EPSO endorses this proclaim. Through out the competition, EPSO has been come up as the best algorithm among the competing algorithms considered in this study. With standard size population, this method has reached the global optimum level every simulation run. The global optimum has also been achieved in approximately half of the simulation runs even if the size of the population has been reduced to half.

The extensive analysis has been performed to determine the performance of the selected algorithms and to choose the best out of 5 competing algorithms for developing artificial intelligent of Retailers. According to the results received during the analysis, the performance of EPSO is the best considering both functional performance and computational performance. The general order of other competing algorithms is broadly considered as SSGA, MPGA, PSO and DCGA. However, each method considered in this study can always be considered as a candidate in different situations and different needs.

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7. The Role of Regulators in Open Energy Markets

Abstract

Regulatory body has been an integral part of energy industries. Its dominant role in vertically integrated energy industries has particularly created market structures that offer financially secured condition for the investment of energy utilities as well as physically reliable energy service to consumers. However, recent restructuring developments in the energy industries have resulted in the transition of energy markets from monopoly nature to competitive nature, and the existence of the regulatory body has been threaten in open energy markets. This study is designed to study the role of regulators in open energy markets. Three scenarios, which depict the market behavior at initial transition stage, final transition stage, and progressive transition with regulators involvement, has been developed in order to analyze the effect of the regulators' existence in the market.

7.1 Introduction

Regulators have played an important role in energy industries. They have had the role of controllers having responsibility to formulate acceptable conditions for both utilities and consumers when energy systems had been operating as vertically integrated systems. However, recent developments in energy industries – privatization and reform – have changed the role of the regulators. Deregulation has become a famous term for referring the transformation of energy industries from monopolistic nature to competitive nature, and therefore, the role of regulators has diminished in the new market structure. It has been a popular concept of the deregulation supporters that invisible hands of open market, instead of regulators, would control the behavior of the market.

Recently, the term "re-regulation" has been used more often as the restructuring process of energy industries around the world has progressed in full swing. Several market transition failures in energy markets have prompted the requirement of the regulations in the energy markets. This study focuses on understanding the behavior of a regulator and redefining its role under the open market structure.

This chapter presents the findings of the study that intends to establish the role of regulators in open energy markets using the multi-energy retail market simulation platform. Establishing test scenarios and the interesting results from those scenarios are discussed in next section. Then, important conclusions are reported in conclusion section.

7.2 Testing the role of regulators

Similar parameter setting of the test case described in chapter 5 is used in this study. The test simulation is designed to run 24 months for market simulation and 2 months for internal simulations inside evolutionary process. During market simulation, all five retailers are equipped with evolutionary particle swarm optimization, and their evolution process runs every month. Each EPSO employs a population of 20 individuals and uses the same stopping criterion: the evolutionary process would stop if there is no improvement in the fitness function of the best solution after 50 consecutive generations in the first internal simulation; however, it changes to 10 generations in all the following internal simulations.

Three scenarios, which depict the market behavior at initial transition stage, final transition stage, and progressive transition with regulators involvement, has been developed in order to analyze the effect of the regulators' existence in the market. The observation has focused on how competitive nature of energy market would have developed from interaction among evolving agents in the suggested scenarios, and the information that explains the behavior of the energy market is represented detail in the following sections.

7.2.1 Scenario One – Initial Transition Stage

First scenario emulates the situation, in which the energy market is in early transition stage from vertically regulated market to competitive market. In this particular situation, competitiveness of consumers is low due to the lack of awareness regarding open market situation as well as accustomed to the habit of existing under the protection of regulators. This situation has been implemented by placing a low index value on the sensitivity of Consumers classes throughout the simulation. The results from this scenario are shown in the following figures.

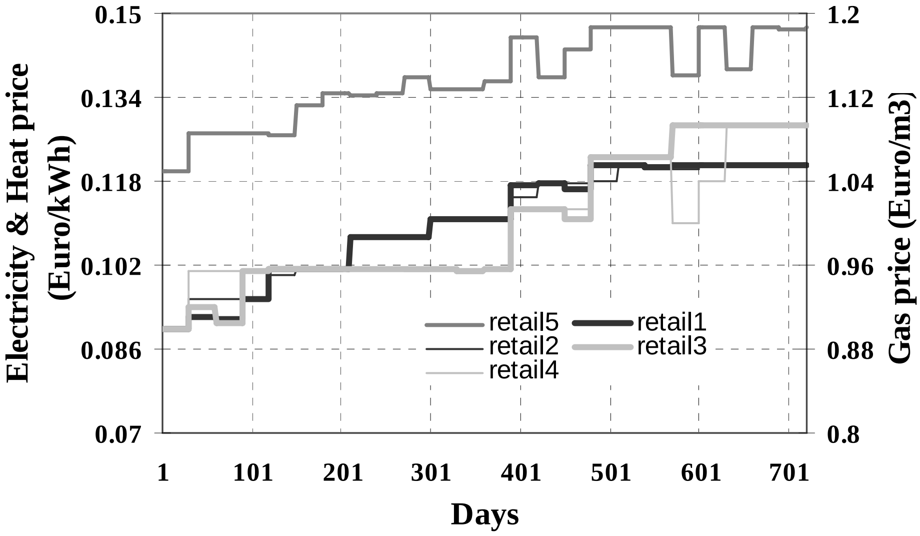

Fig. 7.1. Evolution of energy prices of residential consumer in scenario one

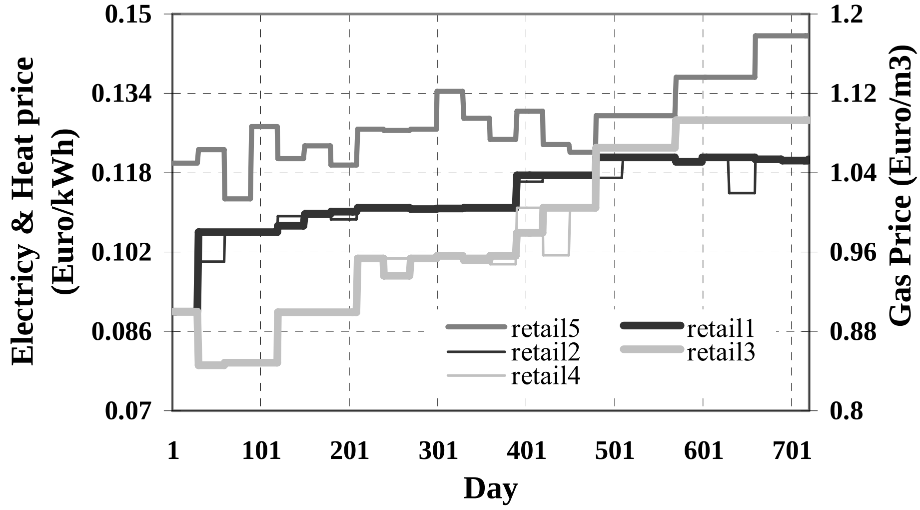

Fig. 7.2. Evolution of energy prices of commercial consumer in scenario one

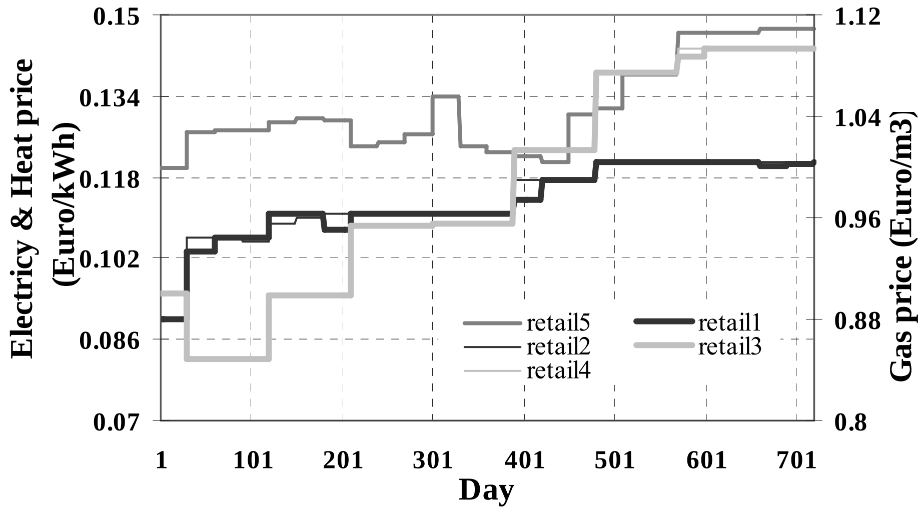

Fig. 7.3. Evolution of energy prices of industrial consumer in scenario one

Due to the lack of awareness, the Consumer classes are less competitive. Consequently, their responses to the actions of the Retailers are not strong enough to make the Retailers compete with one another. The Retailers take the advantage of this unique situation by increasing prices gradually without losing substantial amount of market share. This behavior is seen in Fig. 7.1, Fig. 7.2 and Fig. 7.3 where the energy prices set by the Retailers are gradually rising for all consumer types, residential, commercial and industrial.

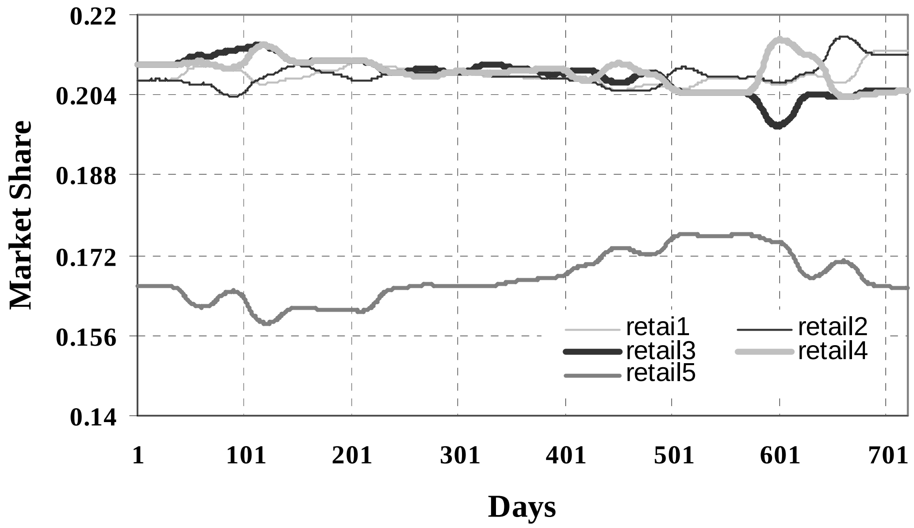

Fig. 7.4. Market share of the Retailers in scenario one

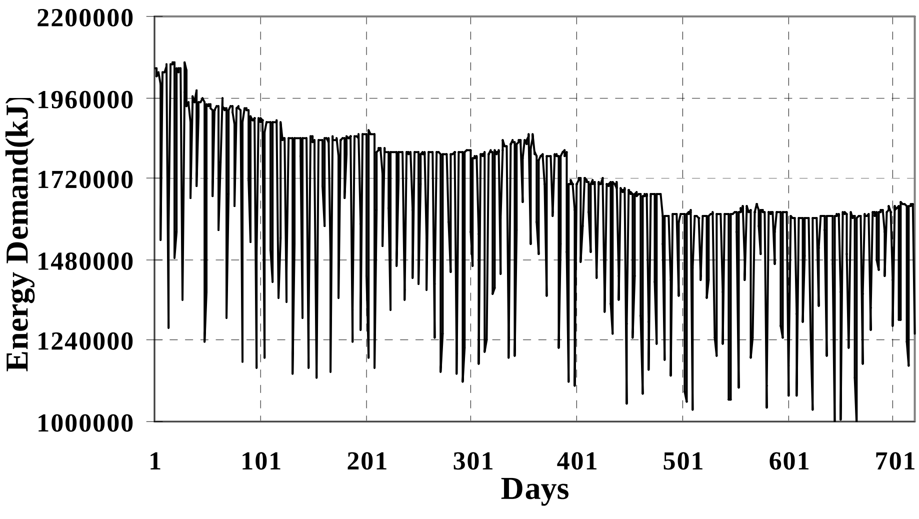

Fig. 7.5. Energy demand in scenario one

Although the energy prices gradually raise, the market shares of the Retailers, as shown in Fig. 7.4, is still in stable condition with only minor fluctuations. The results from this scenario indicate the situation in which the Retailers develop cooperative behavior unintentionally. However, the negative effect of rising energy prices is seen in

Fig. 7.5, where energy demand is in decline throughout the simulation due to the measures taken by the consumers to balance their spending on energy.

7.2.2 Scenario Two – Final Transition Stage

Scenario two is developed as a case in which consumers are well alerted to the competitive market situation, possibly as a result of public campaigns that educate the consumers about the new market structure and the pro's and con's of new level of freedom given to them. The formulation of this scenario is the opposite of the first scenario, setting higher index value on the sensitivity of the consumers throughout the simulation.

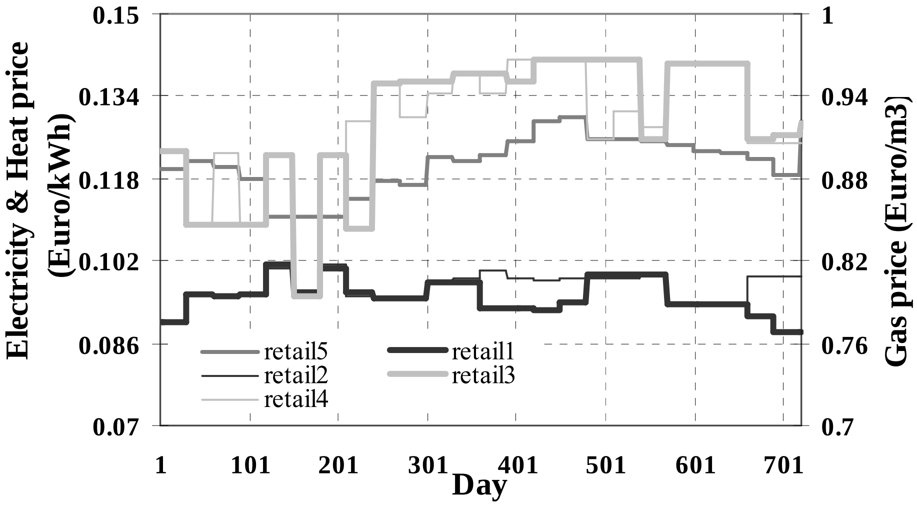

Fig. 7.6. Evolution of energy prices of residential consumer in scenario two

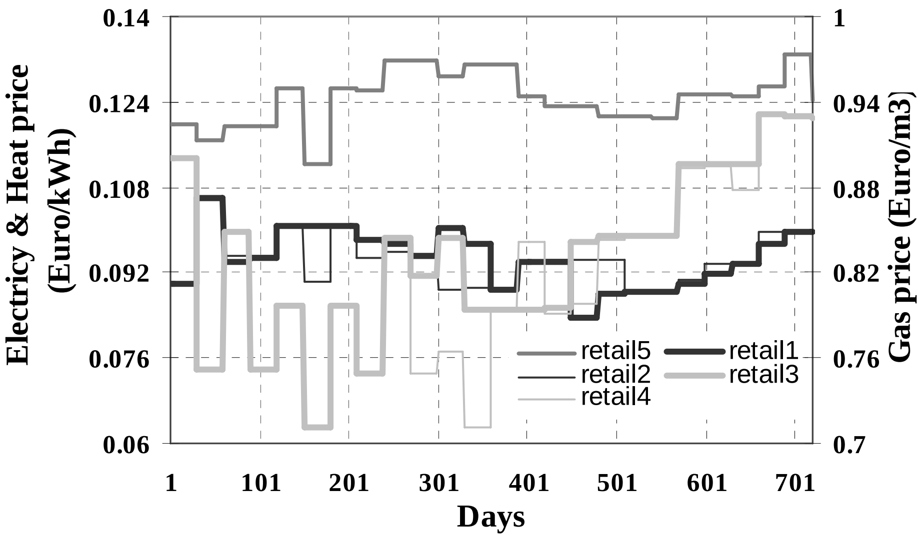

Fig. 7.7 Evolution of energy prices of commercial consumer in scenario two

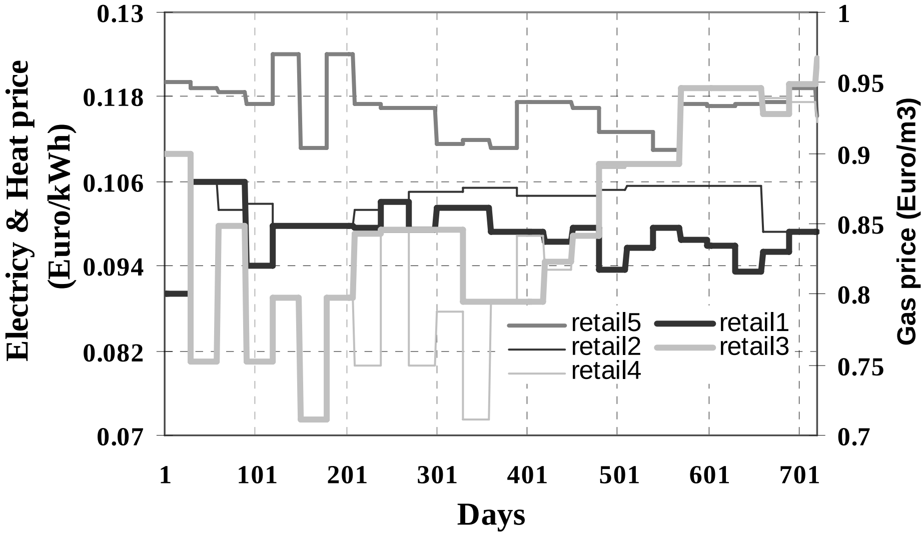

Fig. 7.8. Evolution of energy prices of industrial consumer in scenario two

Due to the public awareness campaigns or other educational programs, the Consumer classes are well aware of the competitive market situation, unlike the Consumer classes from scenario one. Therefore, the Retailers are unable to take the advantage of the Consumer classes even if they are equipped with the same methodology applied in scenario one. Since the Consumer classes have responded well to the advances of the Retailers, they have no choice except competing with one another to make profit. Since competition among retailers has been fiercely contested, the movement of energy prices oscillates around the prices introduced at the beginning as shown in Fig. 7.6, Fig. 7.7, and Fig. 7.8.

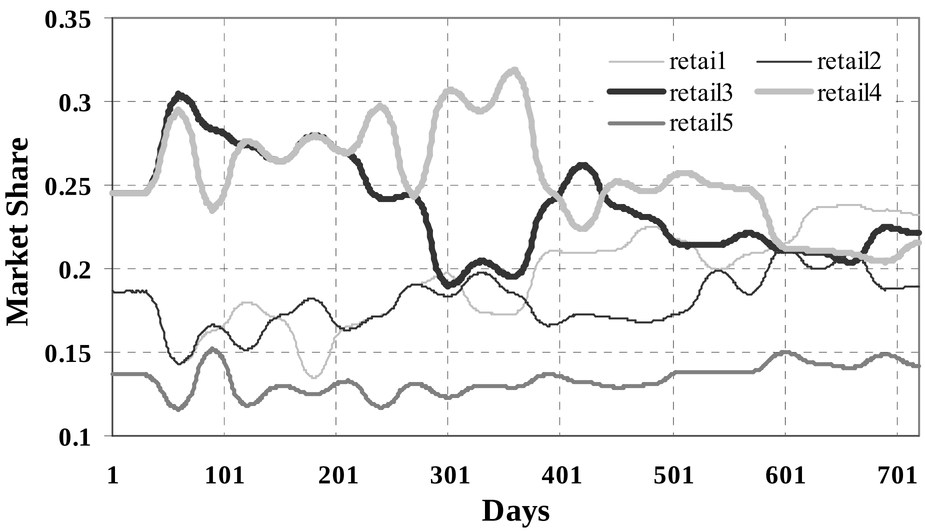

Fig. 7.9. Market share of retailers in scenario two

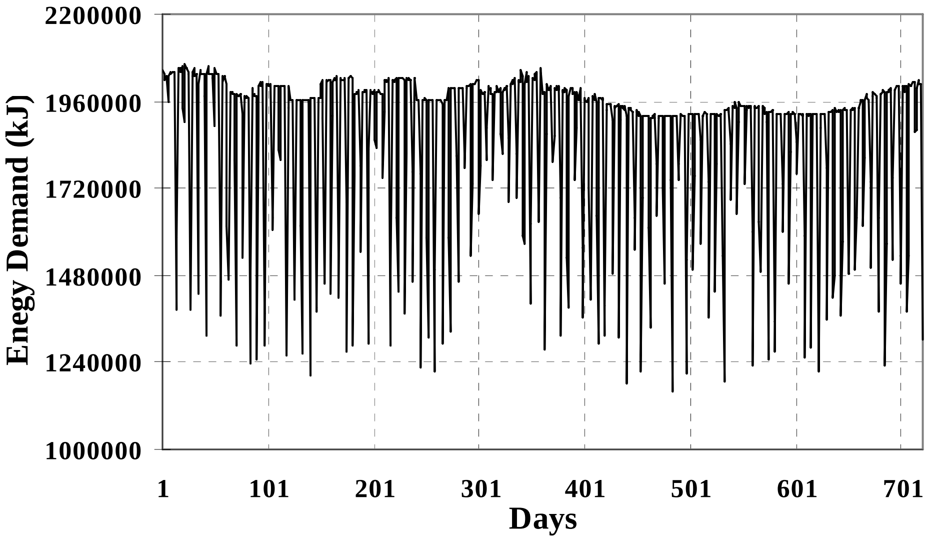

Fig. 7.10. Energy demand in scenario two

The higher fluctuation of market share resulting from fierce competition among the Retailers can be seen in Fig. 7.9. Strong pressure given by the Consumer classes directs the Retailers to compete one another and lefts the Consumer classes out of the exploitations of the Retailers. Moreover, stable energy demand, as shown in Fig. 7.10, is seen as a proven fact that the characteristic of the consumers plays an important role in shaping the behavior of the market. High awareness and strong consumer response are forces that drive the market to perform efficiently.

7.2.3 Scenario Three – Progressive Transition with Regulators

Scenario three has an environment similar to that of scenario one except that the regulators are intelligent enough to understand how to stimulate consumers and guide them into competitive market structure smoothly. In this scenario, the sensitivities of Consumer classes are set to low index value as in scenario one; however, it is allowed the Consumer classes to evolve along with the Regulators through out the simulation.

In order to evolve the Regulators along the simulation, they are provided with new capabilities, which include the ability to monitor the changing of the market and deviation pattern in energy demand and to manipulate the market with a simple yet efficient method adopted from feedback control procedure. The procedure of this control method is as follow:

a) First, a particular Regulator carefully monitors the development of the market. It carefully checks the pattern of energy demand.

b) If the energy demand is below the acceptable limit set by the Regulator using historical data and there is no major changes in energy demand influential parameters except energy prices, then the Retailer further checks the status of energy price deviation. Otherwise, it does nothing.

c) If there is a positive price deviation, then the Regulator formulates plans to combat the advances of profiteers. The formulation of each plan includes determining the amount of spending on a campaign that spreads the useful information among public and duration of the campaign. The size and duration of the campaign are partially determined by the level of deviation of the energy prices.

d) Then, the plan is turned into the public campaign, and the changing in energy prices from the beginning to the end of the campaign is recorded for further assessment regarding future campaigns.

e) The process is repeated again from (a) throughout the simulation.

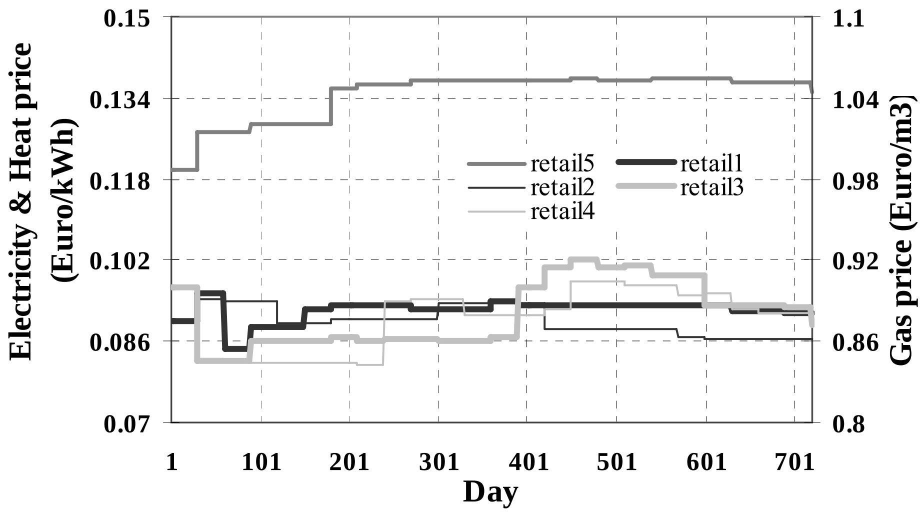

Fig. 7.11. Evolution of energy prices of residential consumer in scenario three

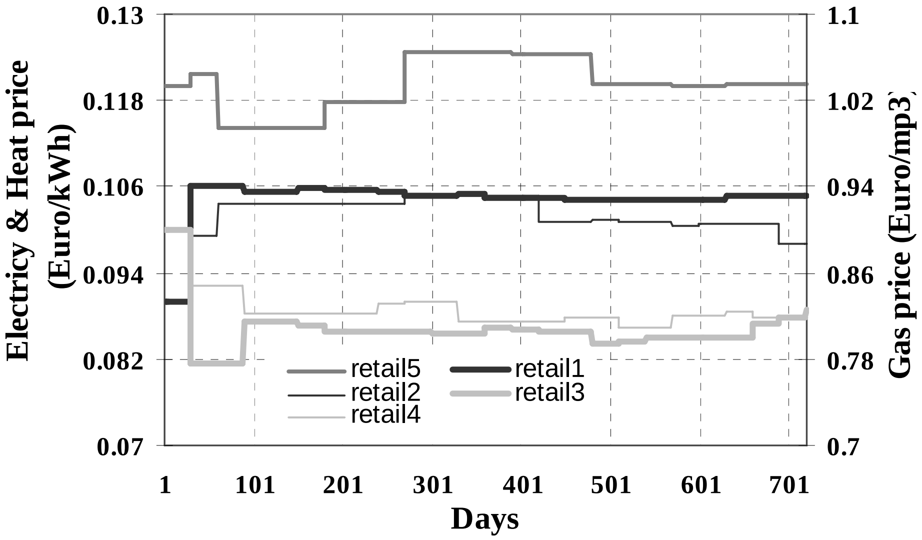

Fig. 7.12. Evolution of energy prices of commercial consumer in scenario three

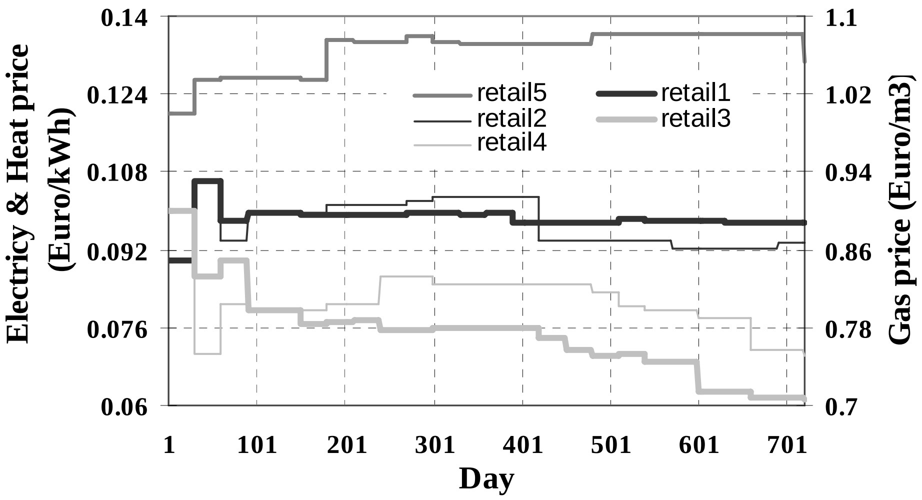

Fig. 7.13. Evolution of energy prices of industrial consumer in scenario three

Although scenario three has started with the same initial condition as in scenario one, the gradual rise of energy prices is not seen in this scenario. The credit for this improvement goes to the attention that the Regulators have paid on the behavior of the market. The Regulators have monitored the market continuously and spend optimal amount of money and time to educate market participants whenever necessary. Due to the intense campaigns from the Regulators, the Retailers have no choice but to compete with one another to stabilize their market share. With intense involvement from the Regulators, the stabilizing of the energy prices around the prices introduced at the beginning is seen in Fig. 7.11, Fig. 7.12, and Fig. 7.13.

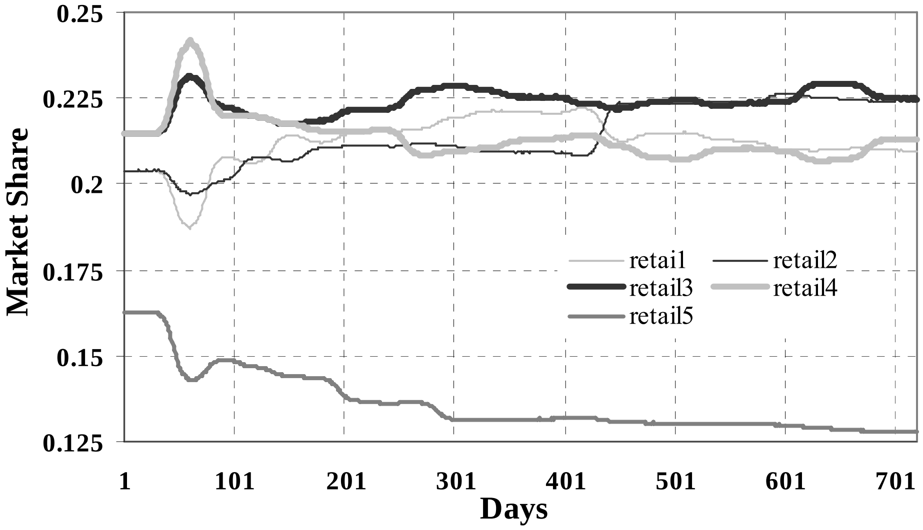

Fig. 7.14. Market share of retailers in scenario three

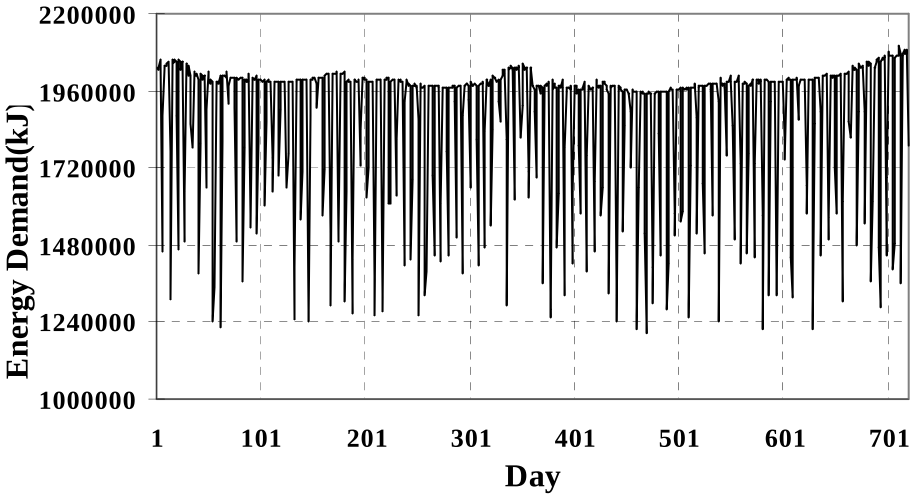

Fig. 7.15. Energy demand in scenario three

In case of market share, relatively large market shares gains and losses are seen at an early stage of the simulation as in Fig. 7.14; however, they later stabilize around the initial value throughout the rest of the simulation except the share of the Retailer five, which has traded its share for profit. The stable energy demand as shown in Fig. 7.15 further emphasizes the requirement of regulator involvement in energy markets at least at the early stage of the market transition. Without the Regulators and their rigorous attempts, the Consumer classes will be surely exploited by the Retailers as in scenario one, and the development of the market and its demand will suffer consequently.

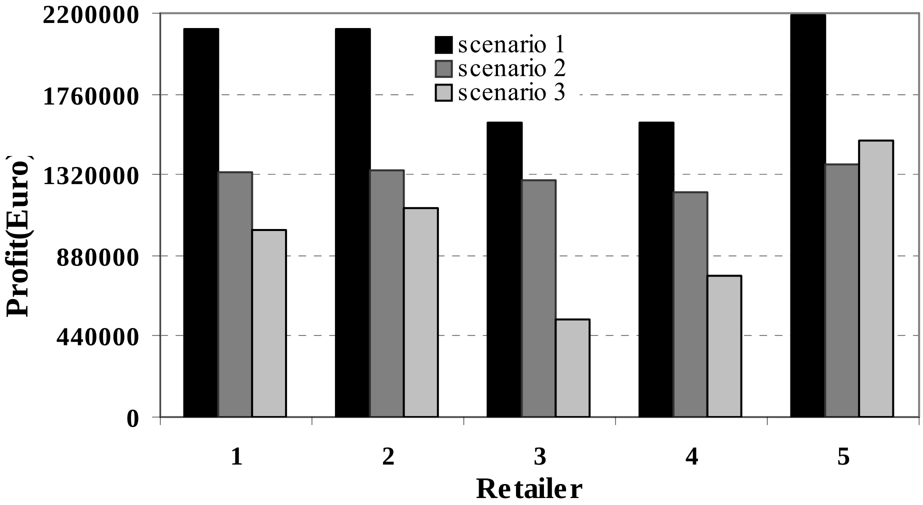

Fig. 7.16. Profit comparison of three scenarios

Results shown in Fig. 7.16 confirm the existence of the exploitation of Retailers on Consumer classes. The comparison among the profits of the Retailers in the suggested scenarios indicates that the Retailers are more profitable in scenario one, in which the Consumer classes were less-informed about the behavior of competitive market. However, the exploitation of the Retailers can be effectively reduced with developing market awareness as in scenario two, in which consumers were well-informed about the behavior of competitive market from the beginning. Scenario three provides the closest situation that we are facing in this moment: the market is in transition state in which no participant is fully aware of the behavior of competitive market. With proper understanding and rigorous attempts from the Regulators, the transition of the market from monopolistic nature to competitive nature can be smoothly performed as in scenario three.

7.3 Conclusions

Using the multi-energy retail market simulation platform as a test-bed, better understanding of the behavior of the multi-energy market and other valuable knowledge can be gained by developing case studies that emphasize particular problems. The study mentioned in this chapter is one of the studies that explore the capability of the simulation platform. It analyzes the behavior of energy market through simulation and establishes the role of the regulators.

The first scenario in this case study imitates the situation of the market at early stage of market transition, in which consumers are unaware of competitive nature and its consequences. The second scenario emulates the behavior of the market that can be seen in a fully developed competitive market. The behavior of consumers in this scenario is designed to be fully aware of open market situation and its threats. The results from these two scenarios clearly indicate the emergence of exploitation from profit-oriented market actors when the consumers do not possess the agility required in a competitive market.

Scenario three provides the possible solution for the problem that scenario one and two have shown. The setting of third scenario is exactly the same as in scenario one. However, the regulators in this scenario are designed to evolve along the simulation. The regulators impose proper regulations to curb the advances of business-oriented market actors and develop proper approaches to improve the level of awareness of the consumers. As a result, the behavior of the market in scenario three is similar to scenario two even if the initial condition of the market is the same as scenario one.

These scenarios highlight the role of regulators in open energy markets. Although it is a convincing idea that open-markets are guided by invisible hands, not by regulators, this concept may not be entirely correct when the market is in transitional state. The results from these three scenarios prove that regulators play crucial role in a transitional market.

8. Closure

8.1 Conclusions

The development of extensive restructuring in electricity, natural gas and district heating industries, recent technological advances in energy conversion among electricity, natural gas and heat, and the similarity of the organization structure of these industries have resulted in the emergence of the multi-energy retail market in which market players from the mentioned industries vie to sell their products to residential, commercial, and industrial energy users. Traditional approaches that consider only one industry at a time may no longer be appropriate for the emerging market as the market players from each industry not only need to consider the threat of their immediate rivals in a particular industry but must also concentrate on the rivals resulting from cross-industry competition in this new market structure.

Computational tools have been widely used in solving complex problems in energy systems; however, very few tools have the ability to successfully uncover the secrect associated with the behavior of energy markets. It becomes very difficult to study the behavior of the overwhelmingly complex energy retail market in which trading of multiple energies occurs among energy retailers and consumers. Agent-based simulation, which employs both computer simulation and agent-based modeling, is considered as an appropriate approach for solving complex problems of the multi-energy retail market due to its simplicity, modeling flexibility and production of emergent behaviors.

The multi-energy retail market simulation platform is based on a bottom-up approach that produces the behavior of the retail market at the macro level as a result of interaction among market actors at the micro level. Therefore establishing individual agents with distinct behaviors is the foundation of the simulation platform, and what remain is to allow those individual agents to interact with one another along the simulation and to analyze the outcomes.

One of the foundation entities of the simulation platform is Consumer entity. This entity employs a methodology that emulates consumer choice behavior. This methodology turns the Consumer entity into a bounded rational agent. Moreover, multi-energy decision-making ability allows this entity to be able to adjust its consumption of different energies to economically optimal condition.

Another important foundation entity of the simulation platform is Retailer. This type of entity utilizes evolutionary-based algorithms to develop attractive marketing packages to lure the consumers. Then, the profitability of these packages is evaluated using internal simulation and possible marketing movements of opponents predicted by the back propagating artificial neural networks. Much needed adaptability of the Retailers is fulfilled by employing computer simulation, evolutionary-based algorithms, and artificial neural networks together.

In order to perform network expansion geographically, Energy Deliverer is equipped with an efficient network expansion method based on graph theory. This method offers the advantage of being able to expand networks economically without consuming too much computational power.

The results from the test simulation indicate that market actors have developed emerging behaviors. Energy Deliverer agents offer the evidence that these agents have adapted to the environment and developed different strategies to maximize their benefits even if initial behavior setting of these agents has been the same. Similar development is also seen in Retailers where different marketing packages resulted from different strategic choices.

The comparison study on computational performance of several programming approaches – sequential programming, concurrent programming, and parallel programming – identify one important aspect of software development, namely choosing an appropriate programming approach for the problem.

The extensive study on the optimization quality of the selected evolutionary algorithms indicates that, in this study, evolutionary particle swarm optimization is the best performer among competing algorithms; steady-state genetic algorithm, deterministic-crowding genetic algorithm, multiple-population genetic algorithm, particle swarm optimization, and evolutionary particle swarm optimization. Moreover, this test study conducted on the simulation platform not only has provided the information on the quality of the selected algorithms but also has opened a window of opportunity to use the simulation platform as a test bed.

Another attempt to use the simulation platform as a test bed is seen in the study on the role of the regulators in the multi-energy retail market. According to the prediction of the simulation platform, consumers have high risk of being exposed to the exploitation of the profit-oriented retailers during transitional period, and the transition of energy markets from monopolistic nature to competitive nature can be smoothly performed with intensive guidance from the regulators.

Above of all, this dissertation offers an innovative methodology to study the behavior of the multi-energy retail market in advance, and to use the knowledge obtained from those studies in real-world problems. Although this simulation platform introduces pioneering approaches in the study of the multi-energy retail market, it does not present itself as a market simulation platform for industrial use. The main idea of this dissertation is simply to state that developing a full comprehensive methodology for studying complex multiple-energy retail markets is now possible, and the present study should be viewed as an important step in that direction.

8.2 Future Works and Assessment on the Simulation Platform

The multi-energy retail market simulation platform is capable of emulating the behavior of real-world multi-energy markets. The results obtained from test simulations clearly indicate the potential of the simulation platform. Moreover, modification in each component of the simulation platform has minimal effect on the structure of the platform since the simulation platform has been based on the bottom-up modeling approach. Therefore, the simulation platform has plug-and-play ability in which each component of the platform can be easily removed, replaced or modified, and provides the extra-flexibility in modeling.

However, the potential of the platform to be used in industrial area is somehow limited by the primitive behavior of some market actors resulted from limited resources and knowledge. In order to improve the simulation platform to the level of industrial use, the following modifications are considered to be required:

- Replacing or modifying Economy entity – This entity generates energy demand of the understudy territory. Therefore, this entity can be replaced with historical time-series energy demand data if it is available for a particular study. If it is not the case, then the modification of the existing Economy entity is required. It can be done with developing more realistic forecasting model on parameters that affect the growth of energy demand, and properly correlate them with the energy demand. Further study should be emphasized on the detailed analysis on the relationship between energy growth and demand sensitive factors, such as weather condition, seasonal effect, economic growth, population growth, income of consumers and so on.

- Improving Regulator entity – This type of entity now issues minor regulatory rules such as setting restrictions on Retailers' marketing ability, and provides public education services to consumers. The activities of this entity can be improved with developing sophisticated regulatory rules such as setting rules that may shape the generation mix of the market in future.
- Modifying Consumer entity – This entity postulates consumer choice. Although consumers in this simulation platform has ability to make optimal choices under specific conditions, they may not be able to be represented as replicas of real consumers unless thorough analysis has been performed to study the detailed link between decision-making behavior of consumers and parameters considered as influential on the behavior of the consumers. Using traditional statistic approach and historical consumer related data, the effect of advertisement about products, quality of products, after-sale and other related services provided by products on the perception of consumers should be properly studied and implemented proportionally in the factorial part of the consumption adjustment formulation employed by the consumers in this study. Furthermore, more studies need to be done on the formulation of consumers' consumption adjustment on competing energies as very little is known about interrelationship among competing energies.
- Replacing Market Operator entity with wholesale energy markets – The duty of this entity, producing the daily spot price, can be replaced by developing full-scale wholesale energy market in which energy suppliers and wholesale consumers bid for trading energy. Developing the wholesale energy market can be done with modeling energy suppliers and wholesale consumers based on the methods used in Retailer entity, and letting them interact round-the-clock.
- Modifying Energy Delivery entity – This kind of entity employs efficient graph theory based network expansion planning to expand its network economically. Although this method has provided interesting results, lack of attention on technical issues and a naïve approach in choosing a potential consumer is its down-sizing. However, this disadvantage can be overcome with developing the model as complex as the one seen in Retailers. Regarding with technical issues of network expansion, load flow analysis of a particular network can be formulated

according to the physical properties of energies, and included in the existing graph theory based expansion planning. Moreover, the functions of network expansion should not be restricted to finding energy consuming customers only. Although the network expansion from this entity is adequate for consumers who entirely take the role of energy consuming entities, the heavy involvement of independent energy producers in competitive energy markets highlights the requirement of the model to be modified in order to accommodate economic-oriented consumers who not only consume energy but also may inject the energy back to the system.

- Modifying Energy Retailer entity – This entity emulates the decision-making behavior of real-world resellers. Although this entity has exhibited its capability with developing complex marketing behaviors, translating its complex marketing strategy into simple quantitative profit and market share constraints is the area need to be improved. Factors that retailers considered as their foundation behaviors need to be established, and how these factors individually shape the overall strategy of the retailers require to be studied thoroughly. When the factors and their influence on the overall strategy of the retailers have been properly defined, one may use systems like fuzzy or expert system to translate the factors into quantitative values. Moreover, forecasting decisions of opponent retailers should expand to cover all decisions instead of concentrating on price and incentive related decisions as in existing platform. Furthermore, evaluation on the optimal marketing decision of a particular retailer should include both short-term and long-term consideration so that the retailer' short-term marketing decisions comply with its long-term policy.

Apart from the above details, the simulation platform as a whole could be improved with switching current client/server type platform to a peer-to-peer type platform in order to gain more computational power. Moreover, the simulation platform should be transformed into a model that can fully take the advantage of using GIS-based approaches.

The last and most important future work is to calibrate the simulation platform. This can be done by solving a specific problem, which is simple enough to be modeled by equation-based approaches, using both a model based on the simulation platform as well as a traditional analytical model based on reliable theories. Then, the solutions of both models are compared to confirm the reliability of the simulation platform. For a complex problem, the cross-checking on the solution of the simulation platform can be performed with real data. If the simulation platform is reliable, then it should produce the similar type of solution obtained from the analytical model or real data.

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