MULTI-AGENT SYSTEM FOR MODELLING THE RESTRUCTURED ENERGY MARKET

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Summary

The worldwide deregulation of the traditionally monopolized and vertically integrated electric power utilities in the last decade has lead to a competitive industry. The whole industry of generation, transmission and distribution, wholesale and retail has been unbundled into individual competing entities which need to adopt new efficient economic behaviours.

Each power system has its own specificity and the deregulation of the energy industry can be accomplished through an infinite number of market structures. The choice of a market structure adapted to the transmission system and to the need of both the energy suppliers and consumer is essential to its good operation. The deregulation process has faced many challenging issues that have been addressed differently in different market structures or are yet to be addressed. The development of flexible and versatile market simulators is a way to approach these issues through intensive simulations to assess the efficiency or applicability of market rules or participants behaviours.

This thesis investigates the use of multi-agent technology to model the restructured energy market. Multi-agent modelling capabilities are especially well adapted to effectively model such a distributed market with its many participants spread over wide geographical areas, which are expected to make autonomous rational decisions but also require some coordination. A flexible multi-agent framework that models the market is proposed and implemented in this research.

The Singapore new electricity market structure has been chosen for the implementation of the market simulator since the deregulation of the Singapore energy market is recent and the structure is still evolving. The implementation of such a market was challenging since it requires real-time computation that optimizes the dispatch of several concurrent services simultaneously and subject to several transmission system constraints. It has been achieved with a modified optimal power flow algorithm. A power system simulation package has been interfaced with the simulator to model the transmission system and run the power flow computations on-line.

With the deregulation, generating companies also face new issues, and are required to adapt their behaviours and develop new strategies. This thesis explores the use of evolutionary computation to address the unit commitment (UC) and generation dispatch problem in the deregulated industry. It results in an efficient evolutionary algorithm that can solve the UC problem for large systems in a reasonable computation time and obtains better results than other reported methods.

A bidding strategy for the competitive market based on the unit commitment is also proposed and implemented.

Finally, the developed software, incorporating the multi-agent framework, the implementation of the Singapore energy market, the unit commitment solution, and the bidding strategy module, form a comprehensive tool not only to study the Singapore market but also any restructured energy market, as the platform is generic and versatile in its design.

List of publications related to this thesis

1. D. Srinivisan and J. Chazelas, “Heuristics-based Evolutionary Algorithm for solving Unit Commitment and Dispatch”, accepted for 2005 IEEE Congress on Evolutionary Computation (CEC), Edinburgh, 2-5 September, 2005.
2. D. Srinivisan and J. Chazelas,”A priority list-based evolutionary algorithm to solve large scale unit commitment problem”, In proceedings of the IEEE International Conference on Power System Technology, 2004 (PowerCon 2004), 21-24 Nov. 2004, Volume 2, Page(s):1746-1751.
3. D. Srinivisan and J. Chazelas, “Multi Agent System for simulation of restructured Power Systems”, submitted to International Conference on Computational Intelligence (CIRAS2005), Singapore 15-18 December, 2005.

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N_g	Number of generating units.
N_{eb}	Number of price/quantity blocks of the energy offer for every unit.
N_{rb}	Number of price/quantity blocks of the reserve offer for every unit.
λ_{ib}^{p}	Price corresponding to the b^{th} block of energy offered by unit i.
λ_{ib}^{r}	Price corresponding to the b^{th} block of reserve offered by unit i.
p_{ib}^{bid}	Quantity corresponding to the b^{th} block of energy offered by unit i.
r_{ib}^{bid}	Quantity corresponding to the b^{th} block of reserve offered by unit i.
R_S	Spinning reserve requirement.
P_{Load}	Forecasted total load demand.
P_{Loss}	Transmission losses.
p_i^{min}	Minimum generation output of unit i.
p_i^{max}	Maximum generation output of unit i.
$flow_{kl}$	MVA flow on line kl.
$flow_{kl}^{max}$	Upper limit of MVA flow on line k-l.
A_{kl}^{i}	Linear Sensitivity of the flow on line k-l to the generation at bus i.
p_{ib}	Power produced with the b^{th} energy offer block of unit i.
r_{ib}	Reserve provided with the b^{th} reserve offer block of unit i.
p_i	Power produced by unit i.
r_i	Reserve provided by unit i.

Chapter 1 INTRODUCTION

In this chapter, a brief review on restructured electricity market is given. A survey on present state of the art in electricity market simulator, unit commitment solution, and bidding strategies, is presented. Then motivation for the work done, major contributions, and structure of the thesis are summarised.

1.1 Background on Restructured electricity market

For almost 100 years, the structure of the electricity power industry all over the world has been characterised by the words regulation and monopoly. Some electric utilities have been granted a monopoly on the generation, transmission, and distribution of electricity over a wide geographical area so that they can achieve lower production and transmission costs, greater reliability, and better efficiency. In the meantime, regulation was imposed to ensure that both the consumer and the utility benefited from these improvements [1]. This model has proven to be very efficient since monopoly led to economies of scale at the generation and at transmission levels. The industry continuously installed larger power plants, the generating efficiency increased, production costs fell, and price of electricity declined because regulators required the utilities to pass on cost savings to customers.

In the 1990's the same reasons, improving efficiency, better services, and lower costs for customers, led the authorities to require the initiate the unbundling of services in the vertically integrated companies, to deregulate the market, and to open it to an increased number of independent power producers which could freely compete to sell electricity. These policy changes resulted from technological developments that make it possible for small producers to compete with large ones, the belief that competition is beneficial in every industry, and the large disparities in electricity tariffs across regions [1].

The move from a monopolistic structure to a competitive market in the power industry encountered lots of difficulties but on the long term the shift appears to be beneficial: it has let to new market structures, new technologies are being developed for use in the generation sector, and lessons have been learnt from the experiences in other markets. However, since problems arising from the shift can cause very serious issues, and the dynamic management of energy market is a very complex problem, market structures are still evolving. New tools are needed to help improve market structures and to elaborate efficient behaviours for the large number of actors of the restructured energy market, such as independent generation, transmission and distribution entities, independent system operator, market operator, industrial customers, retail customers, and traders.

1.2 Literature Survey

To simulate market structures and market participants' strategies, this thesis investigates the use of multi-agent technology to develop an energy market simulator that implements a market clearing engine, considering transmission issues and reliability of the system. This market simulator is then used to develop an efficient unit commitment algorithm and bidding strategies for the restructured energy market. This section presents the state of the art in electricity market simulators, unit commitment solution, and bidding strategies.

1.2.1 Market simulators

Several electricity market simulators with specific features and objectives have been reported in the literature [3]-[17]. Some of them only model the power exchange market, disregarding the operation of the power system; they are usually for the study of the spot market [6], bidding strategies [7][17] or market power [13]. Others are for teaching purposes to help understand different market structures or the bidding behaviours [8][12].

Other simulators model both physical and economic aspects [3][4][12][14][16] but implementation of the ISO agent is generally limited, and implemented market structures generally do not model a real structure actually used in a power system with its specific rules.

Contreras et al. have developed several simulators to study the electricity market and its various participants. [6] presented the feature of a Java based simulator simulating communication between the participants with a client-server structure, using Matlab to clear the auction. In [3] a pool-based electricity market considering multiperiod bidding, price elasticity and network modelling, was simulated iteratively to optimize the production of each genco to maximise its profit; Nash equilibria are obtained in a specific case. In [7] different market structures (single round auction with and without special conditions, and multi round auction) have been implemented and their performance compared. Finally in [8] a pool based market inspired by the rules of the Spain electricity market was simulated to teach basic bidding concepts to students.

Madrigal et al. presented a platform to introduce different market structures to students in [12]. The platform also introduced the students to the role of the regulating entities and the concept of market power. Rudnick et al. investigated market power in a hydrothermal market and the mitigation effect of financial and bilateral contracts [13].

Li et al. addressed in [17] the issue of how to efficiently internalise fixed costs in the bid curves through the use of a market simulator.

Few of the existing simulators consider the distributed structure of the electricity market in the implementation of the different participants, or they do not implement the whole market structure, considering only the market and/or system operator. A commonly used distributed structure is a client/server structure [6][16], but it is not well adapted to the electricity market as it implies a rigid distinction of roles between resource requester (client) and resource providers (server). The clients are the market participants (energy sellers, energy buyers, and system operator). The server provides them with a database that gives access to the power system characteristics, the bids, and the dispatch and price schedules, as well as the resources to compute these schedules. The servers have the resources but can't take any initiative; they are reactive and wait for being invocated by client nodes while clients have initiative but no resource. Moreover clients can communicate with the server but not among themselves and servers cannot take the initiative to communicate with clients. For instance the System operator can trigger a recomputation of the dispatch and price schedules, but the server cannot notify the system operator when the computation is completed.

Agent technology can overcome these problems. The autonomous nature of agents would be able to represent various market participants in making rational decisions in such systems. The agents would model each market participant in the network and seek to simulate the complex market environment.

Most of the recent articles agree that multi agent technology fits particularly well to model the electricity market. F. Wu used it to introduce cooperation and coordination among market participants in order to solve the multilateral trading problem with a decentralised approach [9], and proposed in [10] the framework of a general-purpose power market simulator based on multi agent technology. The flexible framework made it possible to cover a wide range of functions and market structures but no specific implementation has been realised yet. In [11], a multi agent system for evaluating rules, behaviours and participants in the different competitive electricity market structures was successfully implemented.

Galarza et al. presented in [4] a market simulator that implemented the New York electricity market structure and requirements. In particular, the market clearing engine accepted and optimised bids for generation and all ancillary services. It included a full network model and used security-constrained unit commitment and economic dispatch to optimize the dispatch of all resources in the market. This simulator, developed to analyze New York market performances, considered only the Independent System Operator (ISO) point of view and did not implement the behaviours of market participants.

1.2.2 Unit Commitment

The Unit Commitment (UC) problem is the problem of determining the on/off schedule of the power generating units of a power system while observing the units' operation constraints. In the regulated vertically integrated industry the objective was to minimise the cost while serving the load and ensuring the reliability of the system. In the deregulated industry, the primary objective is to maximise the generating company's profit. The generating companies are no longer obliged to serve the load.

To solve this challenging problem, several optimization methods have been developed. The most talked-about and commonly used methods in the industry techniques are priority list, dynamic programming and Lagrangian relaxation [34]-[36].

The above mentioned techniques either require an excessive computation time or do not provide near optimal results. The more promising results, in term of computation time and cost minimization, are obtained with methods using Artificial Intelligence including genetic algorithm or evolutionary programming [40]-[47]. Some of these methods are presented here. Most of them report better results than Lagrangian relaxation or dynamic programming methods.

In [41], Kazarlis designed a genetic algorithm with the following characteristics: the initial population of binary encoded solutions was randomly generated; the selection procedure for reproduction used the Roulette Wheel parent selection algorithm that selects an individual with a probability proportional to its relative fitness within the population; standard mutation and cross over operators were applied to evolve the population. In [43], the influence of penalty terms in the fitness function has been investigated and a method using varying penalty terms was proposed.

Juste et al. reported in [40] an evolutionary programming solution to the UC problem which employed a coding representing the UC schedule as a string of integers.

Other algorithms introduced problem specific operators or knowledge-based method to improve the convergence and the cost of the solution [41][44][45][46].

All the above mentioned evolutionary computation techniques modelled the constraints by the introduction of penalty terms in the fitness function. In [47], Arroyo et al. proposed another approach with a repair genetic algorithm that works only on feasible solutions to reduce the solution space and thus the search burden.

1.2.3 Bidding strategies

A significant amount of research has been conducted concerning the development of efficient bidding strategies for power producers. It usually starts with the development of a short-term price forecasting tool that will serve as a base for the bidding design module. [50] and [51] presented two forecasting models based on Neural Networks.

In [52]-[55], game theory has been applied to find a Nash equilibrium of the bidding game, corresponding to the optimal bidding strategies achieved by the participants. This approach takes into consideration the fact that market participants act in response to competitor strategies in order to maximise their pay-off.

Other methods such as ordinal optimization [56], Lagrangian relaxation [57], stochastic optimisation [58], and Markov decision process [59] have also been applied to solve the optimal bidding strategy problem.

All these methods assumed at least a partial knowledge of the competitors' behaviours, and required extensive computation and risk management before the bidding. This is not needed in the case of a multi-round auction such as the one implemented in Singapore, as market participants can adjust their bids at each round in response to other participants' behaviour. Although few models implementing a multi round auction have been proposed [60]-[64], none of them included the simultaneous optimisation of energy and reserve offers.

1.3 Main objectives and focus of the research

The restructuring of the power industry has already been achieved in many countries and has introduced dramatic changes in the way power systems are managed and energy and ancillary services are traded. However there has been no consensus on a specific market structure to obtain the best performances; each power system has its own specific features that the market structure should consider. Moreover market rules are still evolving to take into account the evolution of the power system, the development of new technology, the behaviours of market participants or simply to improve its performance. To achieve these goals intensive simulations are needed.

Restructuring of the industry has also created a totally new and unknown situation for the generation companies since the electricity price is now set by an auction market, and the generating companies can choose not to produce electricity or provide ancillary services when prices do not match their profit expectations. The global competitive market requires companies to take trading decisions in response to a wide amount of information. Autonomous and intelligent software agents can be a very efficient tool to help in this real time decision making process.

This thesis explores the use of multi agent technology, to develop a power electricity market simulator. It focuses more particularly on the restructuring issues pertaining to the Singapore electricity market since the deregulation of the energy market in Singapore is very recent and the process is still evolving. The first step towards deregulation was taken in 1995 with the unbundling of the government owned vertically integrated only utility. A second step was achieved in 1998 with the commencement of operation of the Singapore Electricity Pool. The pool operated as a wholesale electricity market to facilitate the trading of energy between generators and SP services Ltd in a competitive environment. The actual deregulated New Electricity Market (NEM) started its operation in 2003, and its market structure is still evolving.

The simulator presented in this thesis implements the rules and structure of the Singapore New Electricity Market and includes a full network model to take into account the line loss and congestion problems. Implementation of the ISO agent is complete and can be used for optimizing the dispatch of generation and ancillary services. Ancillary services market has to be considered in the bidding strategies, as the generation companies need to optimize the dispatch of their units for energy, reserve and regulation for instance. Moreover, in a market like the Singapore Market, reserve and regulation are provided as an integrated part of the market clearing process. Energy, reserve and regulation are all offered simultaneously, and are co-optimized by the market clearing model.

The behaviour of generation companies is then studied through the development of a bidding strategy based on the optimisation of the Unit Commitment problem in order to maximise the profits of the company. This bidding strategy is implemented and tested with the power market simulator.

1.4 Main contributions

This thesis achieves the development and implementation of an electricity market simulator modelling the Singapore New Electricity Market. This market structure has never been modelled in any publication. Some papers have reported the modelling of multi-round auction markets, but none of them considered both the transmission constraints of the physical power system and the simultaneous optimisation of bids for energy and ancillary services as it is done in the Singapore market. Moreover the developed model is able to perform the market clearing process in real time while reported methods usually perform off-line computation.

While the rules of the Singapore New Electricity Market have been implemented, the developed simulator is generic enough in its design to allow the implementation of other market structures, the platform, the communication technology and the wrapped in tools being the same. To model another structure, only the rules of the market have to be updated in the program. Moreover the modularity of the multi-agent system allows for an easy adaptation to other market participants such as the demand side bidders.

Distributed structure of the energy market is modelled through a multi-agent system. Agent technology has been recognised as a realistic way to model market structure but very few researchers actually implemented it.

The developed software has been interfaced with the power system simulation package *PowerWorld Simulator* to model as realistically as possible the transmission system and make use of its efficient power flow algorithm.

Using this simulator, a new efficient solution to the unit commitment problem and a bidding strategy for generating companies in the restructured energy market have been proposed, successfully implemented, and tested. Better results than other reported methods have been obtained for the UC problem, especially for large scale systems.

The simulator has been designed to be very comprehensive and flexible to allow addition of new modules in response to any future changes.

1.5 Structure of the thesis

The thesis is organised in 8 chapters.

This Chapter provides an overview of restructured energy markets. A survey on electricity market simulators, the generating unit commitment problem, and the design of bidding strategies are also presented. The focus of the thesis and the main contributions are then summarised.

Chapter 2 presents an overview of the key features of the restructured electricity market and highlights some related challenging issues.

In Chapter 3, a power market simulator based on multi-agent technology is developed. Characteristics of the platform, implemented agents and their behaviours are detailed. Wrapping methodology of decision supportive tools in the platform is explained.

In Chapter 4, the Singapore New Electricity Market structure is implemented in the multi-agent based platform. Key features of this market are first presented. Then an iterative mixed integer programming solution with linearized constraints is proposed and implemented to solve the market.

While Chapter 4 concentrated on the market manager behaviour, Chapter 5 and Chapter 6 present the development of generation companies' agents' behaviours. Chapter 5 proposes, implements, and tests a priority list-based evolutionary algorithm to solve large scale Unit Commitment problem. The development of this algorithm is made considering a regulated environment as it allows us to appreciate the performances of the method and to compare the obtained results with other reported techniques.

In Chapter 6, generation companies' objective in a deregulated market is expressed and compared to the objective and constraints in a regulated environment. The algorithm presented in Chapter 6 is adapted to match the new objective. A bidding strategy based on the unit commitment solution is proposed.

Chapter 7 presents simulations of the whole implemented market structure. The performances of the market clearing engine are first explored on a 30-bus system. Competition between two generating companies is then simulated on a simpler system.

Finally Chapter 8 concludes this thesis, highlighting the major contributions of this research. A brief possible future research directive is also included.

In Appendix, two artificial intelligence techniques are introduced to the reader. These two techniques, namely multi-agent technology and evolutionary computation, are used in this thesis to develop a market simulator for the restructured energy industry and an efficient solution to the unit commitment problem.

Chapter 2 RESTRUCTURING AND DEREGULATION OF ELECTRICTY MARKETS

This chapter presents the circumstances that led to the deregulation of the energy industry all over the world. The different models and participants of a restructured electricity market are then presented. Finally, challenging issues relative to the energy industry deregulation are developed.

2.1 From a monopoly to an open market

Until the 1990s the electricity industry was organized as a monopolized entity. Utilities were generally owned and operated by government bodies. A utility was granted a territorial monopoly over a wide area, the whole power system being divided into few vertically integrated utilities. These utilities owned all the generation units, as well as the transmission and distribution networks over a wide geographical area. Hence they had the monopoly in their geographical area to produce, sell and distribute electricity, managing all the components of the system: generation, transmission and distribution. In this monopolistic situation, electricity rates charged to the consumer were usually set by an independent regulatory body that would set a price acceptable to both buyers and sellers: the utility was assured a fair rate of return on its investment, while the consumer was assured not to pay an unreasonably high price [1].

Utilities had the responsibility to maintain the integrity and reliability of the power system; this was done by meeting the predicted time-varying demand, compensating for transmission losses, meeting the operating constraints (as thermal line limit, and voltage stability, balancing the deviations from the anticipated demand in real time, and providing stand-by resources in case of outage.

All these tasks were coordinated with one common goal, which still stands in the deregulated market: to maximize the profit of the utility. But as the selling price was set, the utility could only minimize the total cost of operation to maximize its profit.

Since the early 1990s this traditional monopolized structure of the power industry has been gradually abandoned to move towards a competitive structure where energy producers compete to supply power to consumers. Reasons for the move towards a competitive market include the availability of new smaller and more efficient generation units and the success of the deregulation in other industries.

2.2 Reasons for deregulation

In the traditional power industry, a price that was fair both to the utilities and the consumers was set and the power system was operated in the most economical way while its reliability was guaranteed. So why almost all the power industries over the world have been recently deregulated, introducing competition instead of monopoly?

It is believed, and it has been demonstrated by the introduction of competition in other industries such as airline or telephone industries, that competitive companies can provide services more efficiently; which results in a wider range of products and services to meet consumer particular needs at the lowest cost solution. In the case of the electric power industry, the main objective is to provide a more reliable energy at a lower cost to consumers.

Introduction of competition in the power industry allows new independent power producers to get access to the market. For long the electricity supply has been considered to be a natural monopoly since the generation function exhibited economies of scale, the larger the facility, the lower the cost per unit of output: if the market were reserved to one utility, this utility could achieve the maximum economies of scale and the price of electricity decreased since regulators required the utility to pass on cost savings to customers. But while efficiency of large generators had reached its maximum, technological developments in small generators resulted in units that are cost competitive with large power plants. Hence because bigger did not mean anymore more efficient and economies of scale, small independent producers could provide electricity at a lower cost than large utilities. Several advantages of these new generating units, which include wind turbines, photovoltaic systems, combustion turbines, or fuel cell, should be highlighted [18]. First they have lower production costs. Highly efficient and reliable, they need less input energy, personnel and maintenance. Secondly, they produce less pollution. It is particularly true for renewable energy technologies. It is also important to note that they are more flexible and are well adapted to provide ancillary services such as regulation, reserve or voltage control. They are also smaller, easier to install, and have a lower capital and operating costs. Finally, smaller and less pollution means they can be installed closer to the load, thus minimising the transmission costs.

Deregulation of the power industry gave new independent producers using these new technologies access to the transmission network.

2.3 Market players in the deregulated industry

To obtain a competitive structure, the various tasks which were normally carried out within the traditional organization have been identified and separated to be opened to competition. This process is called “unbundling”. Unbundling of wholesale generation and transmission services was especially important to facilitate competition as it ensured a non discriminatory access to the transmission grid. Limitations came as vertically integrated utilities favoured their own generation when transmission was congested and prevented other utilities or suppliers full access to transmission system.

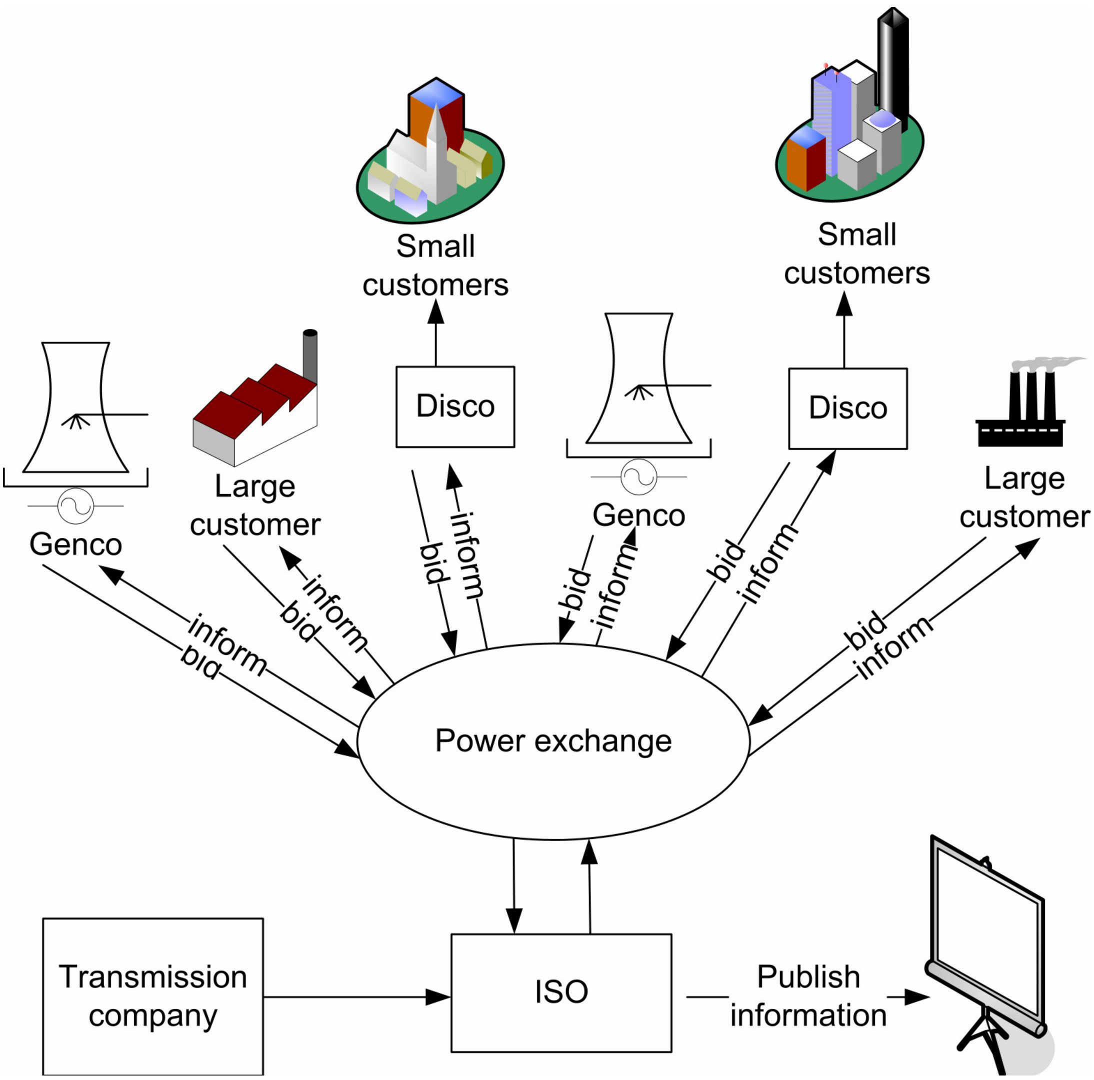

Figure 2.1: Restructured energy market

Hence formerly vertically integrated utilities have been required by law to unbundle into several independent competitive commercial entities: the generation companies, the transmissions companies, and the distribution companies [2]. Moreover two new independent entities have been introduced to manage the market and the system: the Independent system operator and the Power exchange manager. Figure 2.1 shows the inter-relationship of these entities.

2.3.1 Generation companies (Genco)

A Genco operates and maintains generating plants. In the restructured power market, the objective of a Genco is to maximise its profits. To do so, it can take part in energy and ancillary services market to trade real power, reactive power, operating reserves and other services.

2.3.2 Distribution companies(Disco)

Distribution companies buy power from the market and distribute it to consumers. In the restructured power market, the objective of a Disco is to get the supply according to the forecast of energy demand at lowest price. Large users are also regarded as Discos. Their objective is to maximise their profits. To attain it they should purchase electricity at the lowest price but also adapt their energy need to the market prices. For instance if the energy price is higher than the profit a company could get from the use of this energy, the company should not purchase energy.

2.3.3 Transmission companies

The transmission providers are responsible for transmitting and wheeling the energy across power grids of a restructured power system.

Transmission companies are still treated as monopolies. Indeed a transmission network is a natural monopoly since power flows cannot be directly controlled and the power flow due to a contract and a load cannot be guaranteed to flow through a specific generation company but, following the laws of physics, it will flow through the entire network.

2.3.4 The Independent System Operator (ISO)

The generation companies compete for the following services: supply of energy, regulation, spinning reserve or interruptible load, reactive support, voltage control, black start capability.

These unbundled services need to be coordinated because of the strong physical coupling and restrictions between them. A new independent entity has been introduced in the restructured electricity market to carry out this coordination: the Independent System Operator (ISO). This is a non profit organization in charge of maintaining the system security and reliability through the coordination of the participants as well as ensuring a non-discriminatory access to the transmission services. A system is defined as reliable if an adequate amount of capacity resources is available to meet peak demand and if the system is able to withstand changes or contingencies.

Primary objective of the ISO is matching electricity supply with demand to ensure the system reliability, hence its control over generation should only be to the extent necessary to maintain reliability and optimize transmission efficiency.

To maintain system integrity, it is the ISO responsibility to purchase all necessary resources (real and reactive power, reserve, etc.) to balance the system at any time under any circumstances, manage the transmission congestion, and maintain the system frequency at acceptable level. Through contingency planning, the ISO evaluates resources required to meet contingencies and ensures the secure supply of energy. Contingency planning is the backbone for achieving high grade of power quality by ensuring the power systems is able to handle all sorts of abnormalities that will affect the reliability and security of power supply. For instance generating units may fail without warning, hence some reserve capacity has to be made available to the system to quickly correct any imbalance and maintain reliable supply.

To make these services available, the ISO contracts with service providers so that the services are available under the ISO's request. When a service provider is called by the ISO, the provider is paid extra to cover its operating costs. Capacity resources are contracted seasonally by the ISO and providers are required to send their bids to an auction operated by the ISO. The ISO chooses successful providers based on a least cost bid basis.

In case of emergency, the ISO is responsible for the system reliability and therefore has the absolute authority to commit and dispatch system resources.

The ISO is also responsible for providing information on the system to market participants; it usually includes load forecasting, reserve requirements, actual state of the transmission system, and planned maintenance on the transmission system.

2.3.5 The Power Exchange (PX)

The industry restructuring requires the creation of a new market place to trade energy and other services in a competitive manner. This market place, named Power Exchange (PX), permits different participants to sell and buy energy and other services in a competitive way based on quantity bids and prices. The market clearing process takes the form of an electronic auction where consumers and producers submit bids to buy or sell energy. The PX selects the bids according to the specific rules of the market: if it receives bids from buyers and sellers its role is to match as closely as possible the aggregated production curve to the load curve. If only the generators can bid in the market the PX role is to minimize the purchase cost.

Before the start of each trading period, generators enter bids specifying the quantity of power they are offering and the price they are demanding. A generator may divide the power he intends to sell into many smaller bids, so that he can effectively offer a bid curve which reflects its marginal cost curve. At the same time, electricity buyers enter bids specifying the quantity and price of power they want to buy. All supply and demand bids are aggregated into a supply and demand curve as shown in Figure 2.2. The point at which the supply curve intersects the demand curve specifies the clearing price, defined as the price demanded by the most expensive accepted bid. This price will be awarded to all accepted supply bids.

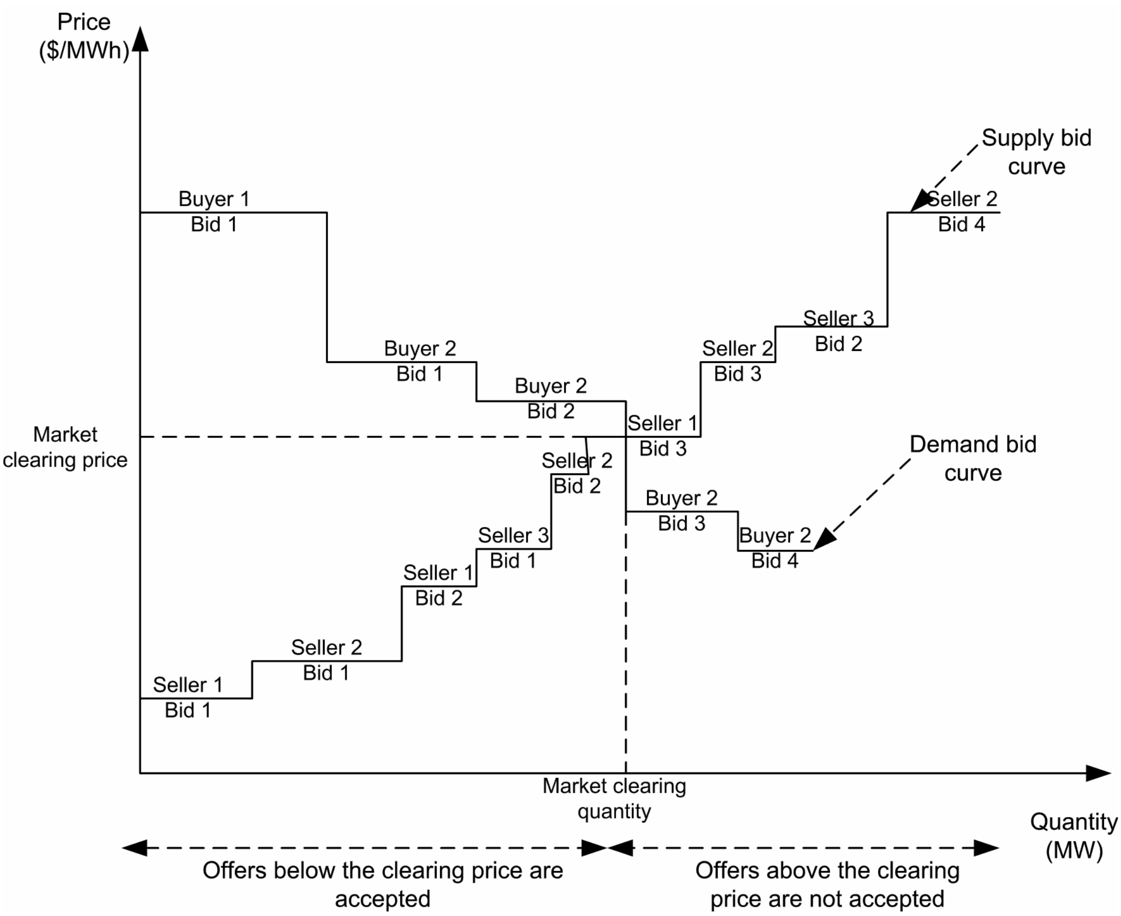

Figure 2.2: Spot market clearing curve

2.4 Restructured market models

Three major models are discussed as alternatives to the vertically integrated models. The three models are PoolCo model, bilateral contracts model, and hybrid model [2].

The main characteristic of the PoolCo model is the establishment of an independently owned wholesale power pool. This pool becomes a centralised clearing market for trading electricity which would implement competition by forcing distribution utilities to purchase their power from the PoolCo instead of trading with generating company. These companies sell power at the market clearing price defined by the PoolCo and usually set as the price of the highest selected bid. Competitive generators submit bids to the ISO on a day-ahead basis specifying the amount of energy available, price, and delivery point, while distribution companies do the same for loads. Based on submitted bids, the ISO solves the market and dispatches generators to balance generation with load and maintain reliability. This is this ISO's role to operate the transmission grid.

The second model is based on bilateral contracts. In this model the ISO's role is more limited and customers are free to contract directly with power generating companies. Contracted parties agree on contract terms such as price, quantity, and locations. Suppliers pay transmission charges to a transmission company to acquire access to the transmission grid. The ISO is responsible for maintaining the system reliability. Therefore suppliers are required to inform the ISO on how their generators will be dispatched and the ISO should implement a congestion management method.

The hybrid model combines various features of the previous two models. Utilizing the power exchange is not obligatory and customers are allowed to sign bilateral contracts. The pool will serve all participants who choose not to sign bilateral contracts.

2.5 Challenging issues in restructured energy market

The move from a regulated industry to a competitive structure encounters many challenging issues. Some of them are explored in the following chapters of this thesis through the modelling of the market participant and the development of algorithms and techniques to simulate their actions.

2.5.1 Impact of transmission losses on the energy dispatch process

As electricity flows through the transmission system, a small percentage of energy is lost in the form of heat due to electrical resistance. This means that if a customer requires a unit of electricity, generators will need to produce more energy than that to allow for the losses incurred in transporting the electricity from the generators to the customer.

Let's consider the power system in Figure 2.3. Losses on the transmission line are assumed to be proportional to the square of the power flow:

$$P_{loss} = 0.0002 \cdot flow^2 = 0.0002 \cdot P_1^2 \tag{2.1}$$

where P_1 is the power generation of generator 1 (similarly P_2 will be the power generation of generator 2).

The bidding offers of the generators are given in Table 2.1. Since units offer only one bid each, the generation cost is computed as follows

$$\text{generation cost} = (\lambda_1^{\mathrm{p}} \cdot P_1 + \lambda_2^{\mathrm{p}} \cdot P_2) \quad (2.2)$$

Table 2.1 Generators bidding offers

	Bidding Offer	
	Quantity	Price
Unit	400MW	$\lambda_1^{\mathrm{p}} = 11.3\$$
Unit	400 MW	$\lambda_2^{\mathrm{p}} = 12.5\$$

Figure 2.3: 2-bus system

If the transmission losses are considered, but their economic influence is not, the market clearing process presented in the last paragraph results in the following dispatch instruction:

$P_1 = 400$ MW; $\mathrm{P_{Loss}} = 32$ MW; $P_2 = 132$ MW with a total production cost of 6170$.

A better alternative is to find the optimal combination of generators output to attain the minimum generation cost that covers demand and losses for the whole system. Mathematically the problem is to minimise the production costs:

$$\text{minimise } (\lambda_1^{\mathrm{p}} \cdot P_1 + \lambda_2^{\mathrm{p}} \cdot P_2) \quad (2.3)$$

While balancing the system

$$P_1 + P_2 = \mathrm{P_{Load}} + \mathrm{P_{Loss}} \quad (2.4)$$

We form the Lagrange equation:

$$L = (\lambda_1^p \cdot P_1 + \lambda_2^p \cdot P_2) + a(\mathrm{P_{Load}} + 0.0002 \cdot P_1^2 - P_1 - P_2) \tag{2.5}$$

Then

$$\begin{aligned} &\frac{dL}{dP_1} = 11.3 + a(0.0004 \times P_1 \text{ -1}) = 0 \\ &\frac{dL}{dP_2} = 12.5 - a \\ &500 + 0.0002 \cdot P_1^2 - P_1 - P_2 = 0 \end{aligned} \tag{2.6}$$

And we obtain the following dispatch

$P_1 = 240$ MW; $\mathrm{P_{Loss}} = 11.5$ MW; $P_2 = 271.5$ MW with a total production cost of 6106\$.

Note that the optimum dispatch does not aim at minimising the losses. The minimum loss solution is obtained by running generator 1 at the lowest possible output; it would result in the following dispatch which production cost is higher:

$P_1 = 102.1$ MW; $\mathrm{P_{Loss}} = 2.1$ MW; $P_2 = 400$ MW for a total production cost of 6154\$.

These calculations demonstrate the economic influence of the transmission system characteristics on the electricity market. Transmission losses, and thus the cost of electricity, differ from one injection point to another. Many modern electricity markets account for this difference through the energy nodal pricing, meaning that prices at each node in the network will be influenced by the physical properties and constraints of the transmission system. This results in the price of energy differing at different physical locations on the network. During the market clearing process, only bidding offers below the market price at their own node will be dispatched.

2.5.2 Impact of line flow limits on the energy dispatch process

Not only transmission losses but also line flow limits can create energy nodal price difference. The power system in Figure 2.3 will be used to demonstrate their influence. We assume that the transmission line is lossless but the line flow is limited to 250MVA. The dispatch solution without considering the line flow limit is given in Figure 2.4. In this case (no loss and no transmission constraint) the energy nodal price is the same for both nodes.

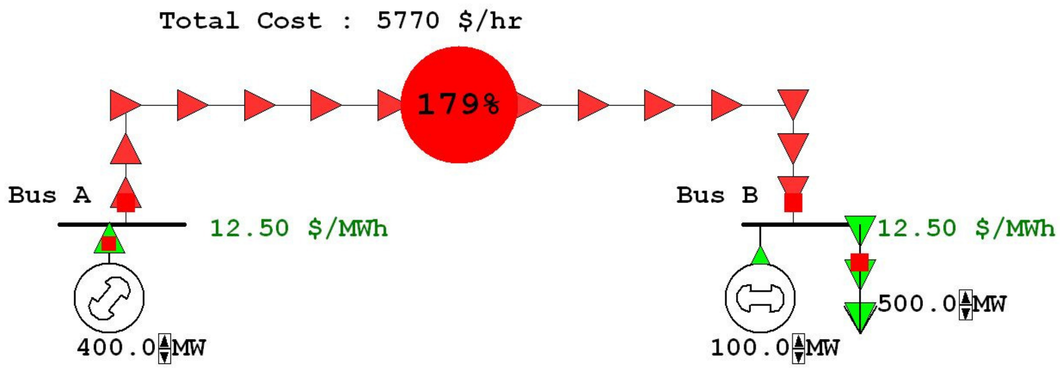

Figure 2.4: Dispatch solution without considering the line flow limit

Figure 2.5 shows the best dispatch solution that respects the transmission line constraint. The cost of serving the demand is higher and the energy price differs at each node.

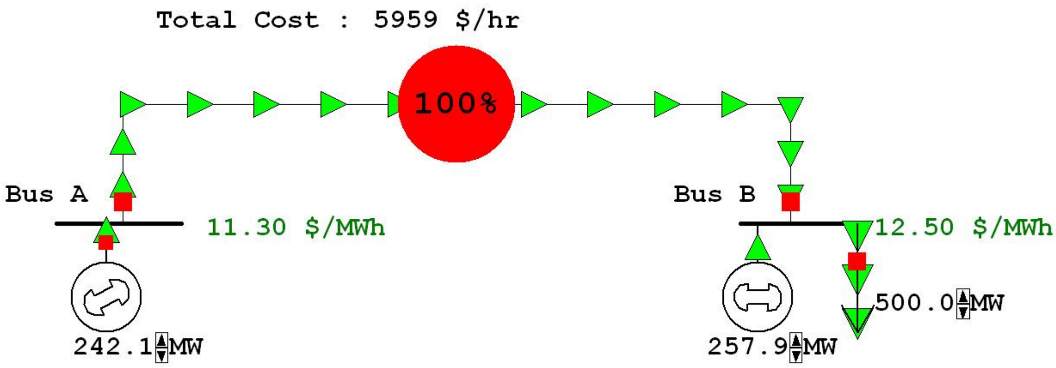

Figure 2.5 Dispatch solution considering the line flow limit

Similar to the transmission loss problem, the economic influence of the transmission system constraints is important. It appears then primordial for the ISO not to dispatch generators only based on the submitted bids, but also to consider the transmission system characteristics. This is usually done through the use of an optimal power flow algorithm that optimizes the dispatch of generators in the most economical way while ensuring system constraints.

2.5.3 Impact of elastic and inelastic demands

An inelastic market does not provide signals or incentives to a customer to adjust its demand in response to the price; the consumer does not have any motivation to adjust its demand for electrical energy to adapt to market conditions. Figure 2.6 shows the market clearing process for two different energy supply offers and inelastic demand. As we see from the figure, supply curves show elasticity, while the demand remains inelastic, i.e. demand for energy is the same, regardless of the price of energy.

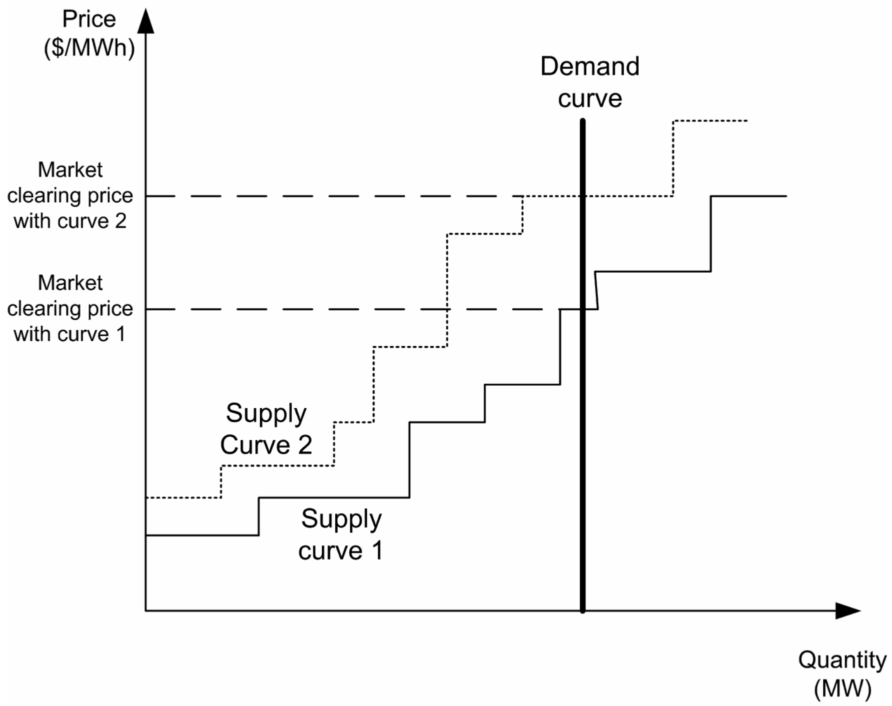

Figure 2.6: Market clearing process with elastic supply curves and inelastic demand

If demand is price sensitive, the market clearing price and quantity are obtained as shown in Figure 2.2. The load responds directly to the price of supply offers and a different supply offer curves would have resulted in different market price and market clearing quantity.

2.5.4 Impact of reliability

The necessity for the ISO to maintain the system reliability has also an impact on the dispatch of energy. For instance the ISO has to make sure that enough reserve capacity is available to correct any imbalance and maintain reliable supply in the event of a generating unit failure. Since a generator usually must be running to be available for reserve, a generating unit might be dispatched for energy even if its offer price is higher than the market clearing price so that the generator can provide reserve.

2.5.5 The new unit commitment problem for generating companies

In the regulated industry generating companies had to commit and dispatch their units so that they can serve the load and maintain the reliability of the system at the minimum cost. In the deregulated energy market, it is no more an obligation for generating companies to serve the load or maintain the reliability. Their only objective is to maximize their profit. To do so, they can sell energy and ancillary services if the prices match their expectations. Therefore, unit commitment planning and generation schedule have to be adapted to the new deregulated environment.

2.6 Conclusion

This chapter discusses deregulation of the energy industry, the structure of restructured markets and some issues pertaining to the operation of these markets. In particular, the market clearing process has been presented and the necessity to consider transmission system constraints has been highlighted.

The concepts developed in this chapter form the grounding for a good and accurate understanding and modelling of the restructured energy market in the later chapters in which a market simulator framework will be developed. A market clearing algorithm considering transmission losses and limits as well as the system reliability, a unit commitment solution, and bidding strategies, will be implemented and tested on this framework.

Chapter 3 DEVELOPMENT OF A POWER MARKET SIMULATOR BASED ON MULTI-AGENT TECHNOLOGY

Agent technology has seen a growth of interest in many fields of engineering and has been successfully applied to many fields such as commodity markets, traffic control simulation, robotics, field combat simulations, ecological simulations, videogames, and many more. This chapter presents the development of the multi-agent based power market simulator for the restructured electricity market.

3.1 Introduction

The autonomous nature of agents would be able to represent various market participants in making rational decisions in the distributed restructured electricity market. The agents would model each market participant in the network and would seek to simulate the complex market environment.

The developed multi-agent system should be able to effectively model the power market as a multiplayer environment where dynamic interactions constantly take place. The objective of the framework design is to provide an efficient tool to support electricity market simulations covering a wide range of functions: market operation, bidding strategies study, interaction of players, system operation, or market power study.

To achieve this goal, a flexible framework to accommodate various market participants, their interactions and their communication is proposed. It allows the study of different market structures and to observe the consequences of power system constraints or market participant’s behaviours. This framework can also help to assess the use of autonomous intelligent agents to assist humans in a market environment.

The design of the framework presented in this chapter had been started by Wong Fook Heng [19]who designed and developed a cross platform multi agent framework complete with self developed customised libraries and tool kits using Java. The design of this framework includes the cutting edge information security capabilities of Secure Socket Layer (SSL) plug-ins via the OpenSSL software. His work has been pursued by Tan Ming Jin [21]who modelled the regulatory functions of the ISO and developed a Graphical User Interface to present the functioning of the market. Lam Kwen Ngian [20] looked more deeply into the Power Exchange entity and simulated the workings and economics of this scheduling body.

The project presented in this thesis synthesised the framework design for the multi-agent system explored by these three students as described in 3.3. However the work done for modelling the Power Exchange or the System operator has been abandoned and a new modelling is proposed in this thesis. New independent and intelligent agents have been developed (3.2) and therefore agents’ actions and interactions (3.6) have been updated. New agents’ decision-supporting systems (section 3.4) have been incorporated. The infrastructure of the simulator has been changed to suit these new agents and decision-supporting systems (3.5). The rules of an existing market and a new market clearing algorithm have been implemented (Chapter 4), and agents have been made intelligent thanks to new algorithms and techniques (Chapter 5 and Chapter 6).

3.2 Market participants / Agents

The agents of the multi-agent systems are the energy market participants presented in Figure 2.1.

3.2.1 Generation companies (Genco)

Each generation company has been modelled through two different types of agents: several generating agents and one genco agent.

Each generating plant is represented in the multi-agent system by a generating agent. It receives dispatch instruction and can submit predefined bidding offers to the market manager. Its capacities, its intelligence and its knowledge of the environment are limited and therefore, even if this agent can act independently of its owner (the generation company), its decisions are not optimised.

The Genco Agent communicates with all the generating units it owns to gather the knowledge shared among them. This agent implements a module of artificial intelligence to optimise its bidding strategies and the coordination between its different units. It can also communicate with other genco agents, for instance to form coalitions, with the objective of increasing its profits.

3.2.2 Independent system operator (ISO) and market manager (PX)

The market manager maintains and operates the competitive market and determines the market clearing prices and dispatch schedules based on the bidding offers.

The independent system operator is responsible for system security and transmission system operation. It takes care of real time power balance with constraints considered and also provides and coordinates the different ancillary services.

In most of the market structures, these two entities are closely linked, and have been modelled as one single entity in the developed framework. This ISO/PX agent is in charge of running the competitive markets for energy and ancillary services, ensuring system security and operating the transmission system.

The ISO/PX agent has a complete knowledge of the environment (transmission system characteristics, generating units' constraints, market participants bidding offers) and it makes use of intelligent optimisation and control tools to operate the market and the system.

This agent answers the request of any other agents, disseminates public information to all agents, requests for action or information from the market participants, and communicates the results of the market clearing.

3.3 Multi-agent framework for the restructured energy market

The multi-agent system that aims at modelling the electricity market is the assembly of the above described agents, their communication and interaction, and their supporting applications.

The Java Agent Development Environment (JADE) [22] has been used to develop the simulator framework. JADE is a software development framework aimed at developing multi-agent systems and applications conforming to FIPA standards for intelligent agents [23]. It includes two main products: a FIPA-compliant agent platform and a package to develop Java agents. The agent platform includes services that allow agents to enter, join, or leave the network at any time as well as to search and discover other agents. These services are the white and yellow page mechanisms that allow publishing and discovering the features and services offered by an agent.

These services are provided by some administrative agents residing in a special node of the network, which provide a service that simplifies the look-up and discovery of the active agents, their list of capabilities, and their list of provided services as shown in Figure 3.1.

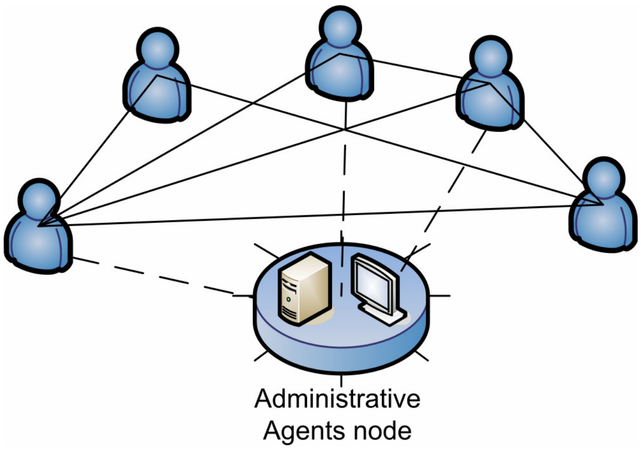

Figure 3.1 Distributed system with administrative agents.

Because of these administrative agents located at a special node, the multi-agent network is not totally decentralized and its functioning depends on the availability of this index node. On the other hand, this network structure generates less traffic and is more secure. The two administrative agents are the Agent Management System (AMS) and the Directory Facilitator (DF). The standard model of an agent platform including these two agents is represented in Figure 3.2 [22].

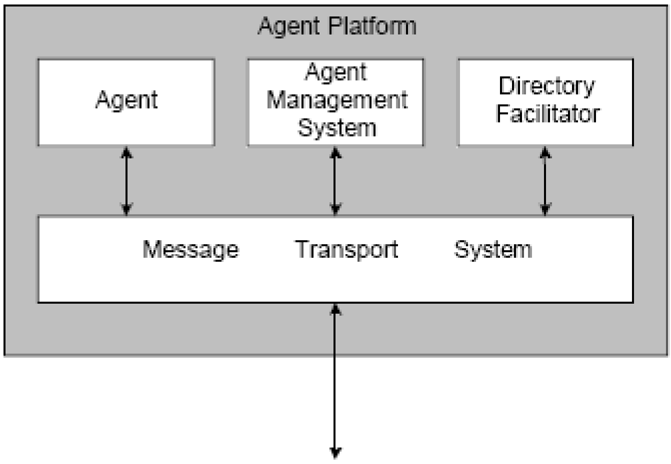

Figure 3.2 standard model of an agent platform

The AMS is the agent which exerts supervisory control over access to and use of the Agent Platform. The AMS provides white-page and life-cycle service, maintaining a directory of agent identifiers and agent states.

The DF is the agent which provides the default yellow page service in the platform. It allows the agents to discover the other agents in the network based on the services they wish to offer or to obtain. For instance an agent can obtain from the DF, the list of the agents which wish to sell energy, or the name of the market manager, and the necessary information to enter in communication with them.

To allow communication between the agents, JADE implements a Message Transport System, this is the software component controlling all the exchange of messages within the platform, including messages to/from remote platforms.

3.4 Agents' decision-supporting system

The whole simulator has been developed in Java language, including the agents' intelligent behaviours. However, several developed algorithms make use of complex but widely used computation methods. Instead of approximately implementing these methods, highly efficient commercial software have been wrapped in the simulator.

Agents are given access to the computational functions of the supporting software through a Java interface.

3.4.1 Wrapping of PowerWorld Simulator

PowerWorld Simulator [24] is a power system simulation package based on a comprehensive, robust Power Flow Solution engine capable of efficiently solving systems of up to 60,000 buses, implementing the full Newton-Raphson method, the fast decoupled power flow, and a DC power flow. It also allows the user to visualize the system through the use of animated diagrams providing good graphical information about both the technical and economic aspects of the transmission network.

PowerWorld Simulator will be used by the PX/ISO agent as:

- A power flow solver: the implemented Newton-Raphson method is the most robust and reliable method available. Moreover it proposes faster solution methods (fast decoupled power flow, and a DC power flow) if the computation time is a limiting factor.
- A database to access the transmission network characteristics. Indeed, PowerWorld provides a user friendly interface to efficiently create, modify, access, and save a power system model.

3.4.1.1.Automation Server (COM interface)

PowerWorld provides an automation server that is intended for enabling a PowerWorld customer with the ability to access PowerWorld Simulator functionality from within a program written externally by the user through COM technology.

The Microsoft Component Object Model (COM) [25] is a platform-independent, distributed, object-oriented system for creating binary software components that can interact. COM is a technology that allows objects to interact across process and machine boundaries. COM enables this by specifying that the only way to manipulate the data associated with an object is through an interface on the object. This interface must be implemented so that it complies with COM standards.

The Simulator Automation Server acts as a COM object, which can be accessed from various different programming languages that have COM compatibility. PowerWorld implements a COM compliant interface that makes some of its functions available to any client who asks for it. The functions made available by PowerWorld include: loading and saving a transmission network file, setting and getting many of the available parameters in the power system, and a script command that allows making use of almost all the computation capabilities of the software.

3.4.1.2.Bridging Java and COM [26]

Because Java is ill suited for some tasks and also because it is necessary to be able to access code libraries not written in Java for evident reasons of time and cost savings, it is needed to interoperate with other languages or environment.

However Java does not have COM compatibility. While Java is a cross-platform language achieving its objective of being write-once, run-anywhere, the COM interface is specific to the windows platform and uses the specificities of this system. However, the Java platform integrates the Java Native Interface (JNI) which is a standard programming interface for writing Java native methods and embedding the Java virtual machine into native application. The primary goal is binary compatibility of native methods libraries across all Java virtual machine implementations on a given platform. JNI allows a Java virtual machine to share a process space with platform native code. It is then possible from Java to find, load, and invoke a native language method, free of the rules of the virtual machine.

In this project, JNI is used to build a communication layer between Java and the PowerWorld automation server through the open source architecture Jawin [27] as shown in Figure 3.3.

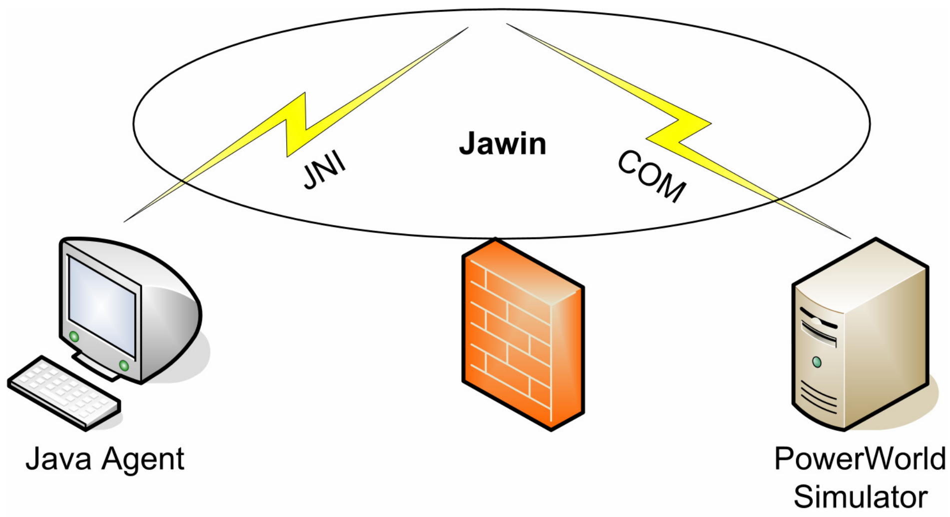

Figure 3.3 Wrapping of PowerWorld Simulator

3.4.2 Wrapping of Ilog Cplex 8.1

Ilog Cplex [28] is an optimization software that solves linear programming (LP) and related problems. Specifically, it solves linearly constrained optimization problems where the objective to be optimized can be expressed as a linear function or a convex quadratic function. The variables in the model may be declared as continuous or further constrained to take only integer values. To solve such linear programming problems, Ilog Cplex implements optimizers based on the simplex algorithms (both primal and dual simplex) as well as primal-dual logarithmic barrier algorithms and a sifting algorithm. Ilog Cplex can also handle certain problems in which the objective function is not linear but quadratic. Such problems are known as quadratic programs (QP). Ilog Cplex is also a tool for solving linear programming problems in which some or all of the variables must assume integer values in the solution. Such problems are known as mixed integer programs or MIPs because they may combine continuous and discrete variables in the objective function and constraints.

In this project, Ilog Cplex has been used to solve LP, MIP, and QP encountered by the PX/ISO agent and the generating companies when trying to optimize the generation dispatch, the use of the transmission network, and the bidding strategies.

Wrapping Ilog Cplex in the Java simulator has been a far easier task than the wrapping of PowerWorld since Ilog provides a set of libraries offering an application programming interface (API) that includes modeling facilities to allow the programmers to embed Cplex optimizers in Java applications.

3.5 Infrastructure of the simulator

Figure 3.4 presents the infrastructure of the multi-agent system simulator. The agents in the infrastructure are:

- The administrative agents AMS and DF that allow other agents to enter, join, or leave the network at any time as well as to search and discover other agents.
- The genco agents and their associated unit agents that model the generating companies. They compete in the market to sell energy and ancillary services in order to make the maximum profits. The genco agent has access to a database of resources and unit commitment and generation dispatch optimization modules to optimize its bidding strategy.
- The PX/ISO agent that operate the market and the transmission system. Market and transmission network operations are optimized with the help of a supporting computational system, as explained in Chapter 4.

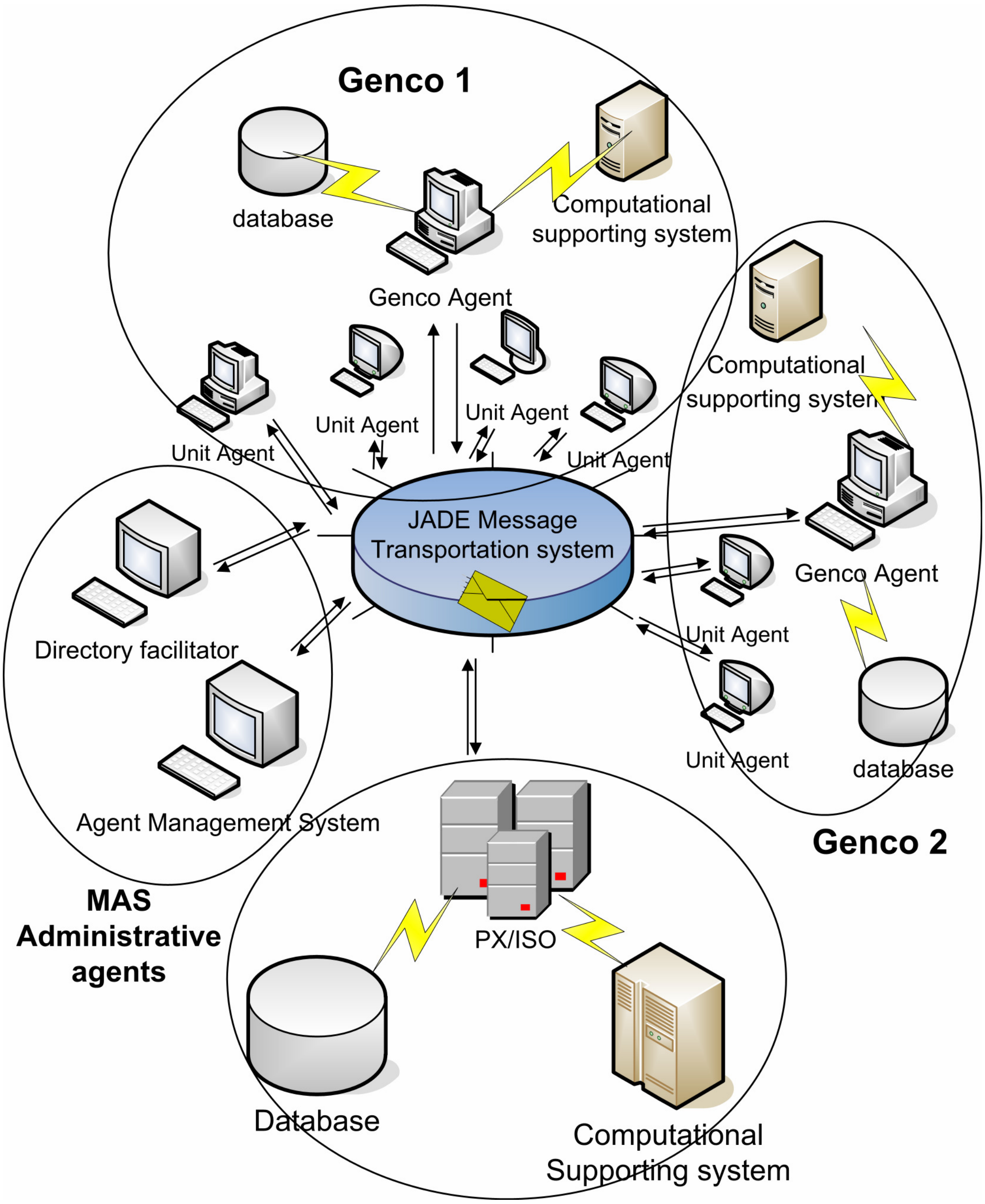

Figure 3.4 Infrastructure of the simulator

Agents can communicate with each other through the JADE message transportation system.

3.6 Agents' actions and interactions

In any multi-agent systems, agents of different nature are endowed with different attitudes, beliefs, and objectives. The interaction with the other agents makes up the simulation environment. Implemented behaviors for each agent are presented in this section.

3.6.1 Common initialization behavior

At the moment of its creation, every agent registers itself with the Directory Facilitator of the multi agent system. It allows other agents to discover who they could do business with, and how to contact them.

3.6.2 PX/ISO agent

3.6.2.1. Request player registration behavior

At the beginning of the market procedure, the PX/ISO agent requests the registration of entities willing to take part in the market. Then upon receiving registration demand, it will acknowledge the demand.

3.6.2.2. Receive bidding offers behavior

Market participants submit their bidding offers for energy and ancillary services to the PX that will check the validity of the offers and inform the participants of the acceptance or refusal of the offer.

3.6.2.3.Market clearing behavior

Before each dispatch period, the PX/ISO agent solves the market based on the bidding offers, the system demand, and the transmission security and constraints. This behavior depends of the specific market rules. An implementation of this behavior in the case of the Singapore New Electricity Market is presented in the next chapter.

3.6.2.4. Communicate dispatch instructions

Before the beginning of a dispatch instruction, the PX/ISO agent communicates to each unit agent its dispatch instruction resulting from the market solving.

3.6.2.5. communicate system related information

The PX/ISO agent provides load demand forecasting and planned contingency information to the market participants so that they can optimize their own behaviors.

3.6.3 Generating Unit agent

3.6.3.1. Registration with the PX behavior

When receiving the request for registration from the PX/ISO agent, unit agent should answer by providing information such as their minimum and maximum output, ramping rates, and their bus of power injection in the system.

3.6.3.2. Send bidding offer to PX

Bidding offer includes the quantities and associated prices of energy or ancillary services the units offer to sell. This offer built either by the unit agent itself based on its narrow knowledge (usually only its own characteristics) or by the genco agent based on the shared knowledge of all the unit agents, is sent to the PX agent before it clears the market.

3.6.3.3. Communication with the genco agent

Unit agents communicate all their knowledge to their genco agent including, unit's characteristics and current state.

Based on the information provided by all its generating units the genco optimizes its bidding strategy and proposes to each unit a bidding offer that considers the coordination of all units.

3.6.4 Genco Agent

3.6.4.1. Get the system related information from the PX/ISO

The Genco agent will make use of the demand load estimation and system constraints in the optimization process of the bidding offers.

3.6.4.2.Get generating units' information

From the combination of the limited knowledge of each unit, the genco agent can build a better understanding of its environment and coordinates the units.

3.6.4.3.Optimization of the bidding offers behavior

Based on the knowledge obtained from the generation units and the PX/ISO agent, the genco agent can optimize the bidding offers of its generators to maximize its profit. The implementation of this behavior makes use of complex artificial intelligence techniques. An implementation is proposed and demonstrated in Chapter 7.

3.7 Conclusion

In this chapter, an electricity market simulator based on multi-agent technology has been developed. The agents modelling the markets participants have been presented as well as their behaviours implementing their action and communication capabilities. The multi-agent platform has been implemented through JADE. Decision supportive tools have been wrapped in the platform.

Next Chapters delve deeper in the implementation of agents. In particular, Chapter 4 investigates the implementation of the ISO agent to model the Singapore New Electricity Market.

Chapter 4 MODELLING OF THE SINGAPORE MARKET

Deregulation of the energy market in Singapore is very recent since the first step towards deregulation was taken in 1995 with the unbundling of the government owned vertically integrated only utility. The actual deregulated New Electricity Market (NEM) started its operation in 2003. The implementation of the Singapore market rules and structure in the simulator will allow studying such a recent market.

This chapter first presents the structure and rules specific to the Singapore New Electricity Market. An efficient market clearing algorithm following these rules is then proposed and implemented in the ISO agent of the simulator modelling the restructured energy market.

4.1 The Singapore New Electricity Market

The Singapore New Electricity Market follows basically the structure of the PoolCo model since participation in the pool is compulsory for all market participants and physical bilateral contracts are not allowed. However this market structure presents several specificities. First the market is not cleared on a day-ahead basis, but through a multi-round auction; market outlook scenarios are issued at regular intervals by the market operator and market participants can modify their offers at anytime. Another important specificity is the simultaneous clearing of the energy and reserve markets in order to optimise the dispatch of the two services. The market structure and operation are explained in [29]-[33] and detailed in this section.

4.1.1 Market structure

Following the example of many energy markets deregulations in the world, the key players in the Singapore market include a market operator, a power system operator, a transmission company, and the generation companies.

The market operator (EMC) operates and administers the wholesale market.

The power system operator (PSO) is responsible for ensuring the reliable supply of electricity to consumers and the secure operation of the power system. The PSO controls the dispatch of facilities in the wholesale market, coordinates outage and emergency planning, and directs the operation of the transmission system.

The *transmission company* (PowerGrid) owns, operates, and maintains the transmission system. The transmission system is a natural monopoly and the transmission company is therefore subject to regulation to ensure open and non-discriminatory access to the transmission network.

The *generation companies* compete to provide energy and ancillary services. Their participation to the market is mandatory to ensure that all generators are subject to the market rules.

Like many other competitive electricity markets, retail competition in Singapore is being introduced progressively. Contestable consumers can select a Market Participant Retailer (MPR), or purchase directly from the wholesale market, or, if they do not want to participate in the market, they can be supplied by SP Services Ltd., the Non-Market Participant Retailer (NMPR).

Figure 4.1 shows the inter-relationships of these four entities in the New Electricity Market [29].

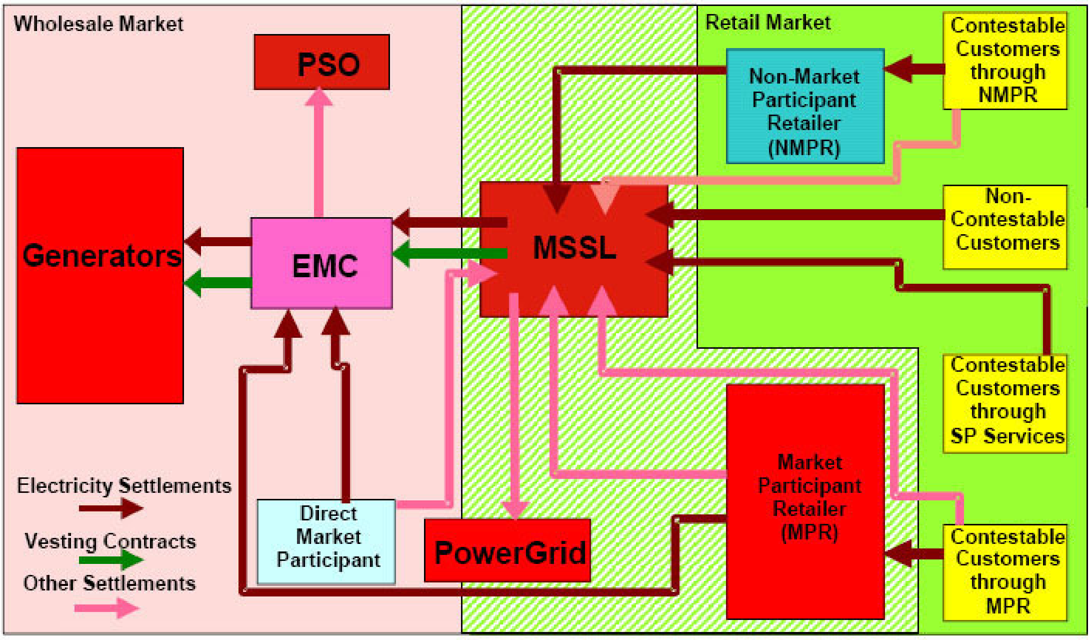

Figure 4.1: Singapore's New Electricity Market Structure

The wholesale electricity market in Singapore comprises two markets: the real time market and the procurement market.

The real time market for trading energy, reserve and regulation, uses a form of auction pricing to settle transactions. This encourages the economically efficient scheduling of generations facilities in the short term (market outlook scenarios are issued starting seven days before the dispatch period), and provides incentives for new power system investment in the long term.

The procurement market is for trading ancillary services (other than reserve and regulation) required to maintain the secure operation of the power system. These services, such as reliability must-run service, reactive support and voltage control service, are supplied under long-term contracts negotiated by the PSO. The procurement market has not been modelled in this thesis since it is based on long-term contracts and has little influence on the real time dispatch studied in this thesis.

The implementation of the real time market is a challenging issue because of the simultaneous optimisation of energy, reserve, and regulation, the consideration of the transmission system characteristics, and the need to obtain results in real time.

This spot market, run every half-hour, determines the real-time dispatch of electricity, scheduling generators to supply energy, reserve and regulation, as well as the corresponding spot market prices. To achieve this, generators offer their capacity, specifying price/quantity pairs into the market and the PSO provides a prediction of the expected load along with any system constraints for the time period under consideration. The market then determines the least-cost dispatch quantities and the corresponding market clearing prices based on the offers made by generators agents. This results in a dispatch schedule that is at minimum cost to the market while respecting transmission and system conditions and constraints, reserve and regulation requirements and the dynamic characteristics of generation plant and meeting the projected load at each node on the transmission system [29].

Prior to each dispatch period, a series of indicative market and pre-dispatch scenarios are run to indicate the likely load and supply levels in that dispatch period. The indicative scenarios help to ensure that market participants have good information upon which to infer expected supply and demand conditions. This in turn allows generators to offer efficiently and reduce their risks. Daily market outlook scenarios are prepared commencing seven days before each dispatch period. Commencing on the day before the dispatch period, pre-dispatch market scenarios are prepared every two hours through to the actual dispatch period.

Each generator is paid the market price for energy at the node to which it has been assigned. Energy prices vary at different points on the network to reflect the transmission losses and physical restrictions on the transmission system.

Energy buyers pay the Uniform Singapore Energy Price (USEP) so that no consumers are disadvantaged due to their location. This is a weighted-average of the nodal prices. Because the Singapore transmission system is well developed and has few instances of constraints that will impact the nodal prices, uniform pricing is an acceptable compromise between accurate economic signalling and social policy objectives.

In addition to trading in the spot market, participants can enter into bilateral contracts. These are purely financial arrangements whereby participants buy and sell on the spot market and settle between themselves any financial differences implied by their bilateral contracts. Such contracts create price certainty for the parties and limit their exposure to spot market volatility. Bilateral contracts do not affect dispatch and consequently have not been modelled in this project.

4.1.2 Market operation

4.1.2.1.The offer process

Generators agents make offers to supply energy, reserve and regulation for each of their units in each dispatch period in which they want to operate. Offers can vary for each period. Market participants are allowed to continually adjust their offers up to 5 minutes prior to the dispatch period. Generators may make energy offers consisting of up to 10 price/quantity bands for each facility for each period, and reserve and regulation offers consisting of up to 5 price/quantity bands. An example of energy offer is shown in Figure 4.2.

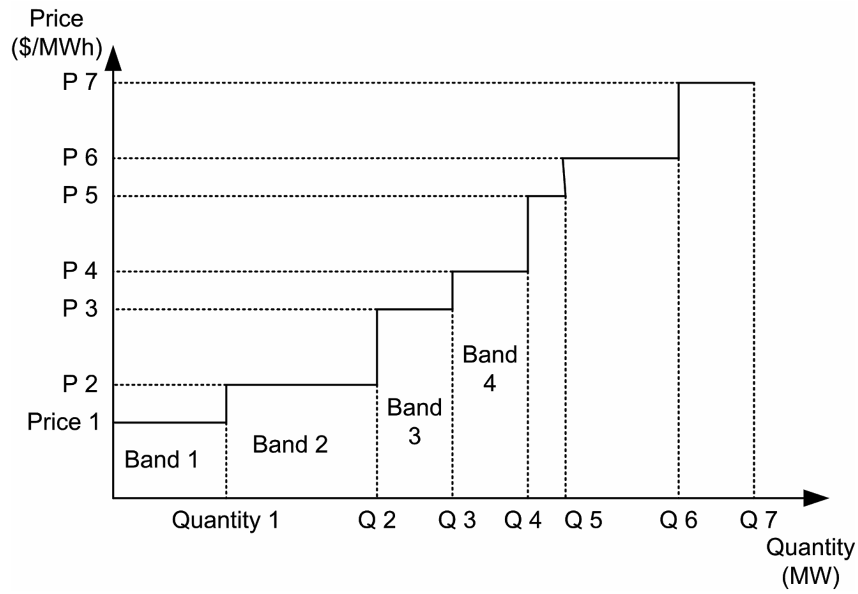

Figure 4.2: An example of energy offer

Energy, reserve and regulation are all offered simultaneously, and are co-optimised by the market clearing model.

The Singapore New Electricity Market is a self-commitment market. This means that unit commitment is the responsibility of each generation company and no start-up and shutdown payments are made; generators are expected to integrate these costs into their bidding strategy. This point will be studied more extensively in Chapter 6.

There is no demand-side bidding for energy in the Singapore electricity market at this time.

4.1.2.2.Market Operations timetable

From 8 days to 5 minutes before the dispatch period market participants can submit and continuously update their bidding offers. The market clearing engine always uses the most recent offer to solve the market.

Starting 7 days before the considered dispatch period, market outlook scenarios are issued daily. Starting between 12 to 36 hours before the considered dispatch period, pre-dispatch schedules are issued every 2 hours. Starting 6 hours before the considered dispatch period short-term schedules are issued every 30 minutes. These 3 schedules provide indicative dispatch and prices to market participants; they are not binding and create no financial commitments.

The real-time dispatch schedule is issued at least 30 seconds before the dispatch period. It constitutes the dispatch instruction for facilities and gives the market prices. At this point, generators agents are committed to their offer prices and quantities.

4.1.2.3.The market clearing engine(MCE)

The objective of the MCE is to find a set of dispatch instructions that minimises the cost (based on the generators offers) of supplying the load at all nodes, as well as meeting the reserve and regulation requirements.

The computation of this optimal dispatch takes into account constraints on the electricity system such as: the offers made by generators, estimated demand on the network, reserve and regulation requirements, ramping rate, losses, physical limitations of the power system, constraints related to system security.

The MCE solution includes market prices associated to the optimal dispatch.

4.2 PSO/EMC Implementation

In the Singapore New Electricity market, the market operator (EMC) and the system operator (PSO) are separate entities but they are closely linked. Therefore the developed model of the Singapore market combined them to form a single entity in charge of the bidding and scheduling process, the network stability and reliability, and information dissemination to participants. The communication processes for information dissemination have been highlighted in the previous chapter. This chapter concentrates on the scheduling process while ensuring the network stability and reliability. This task is done through the use of the market clearing engine. The Market clearing engine problem formulation is presented below. Then an iterative approach to solving this problem using linear sensitivity factors to linearize the constraints about a power flow solution and a branch & bound method to optimise the dispatch is proposed.

4.2.1 Market clearing engine problem formulation

The objective of the MCE's optimization process is to minimize the cost of supplying the load and the reserve requirements. Hence the objective function is given as:

$$\text{minimize} \sum_{i=1}^{N_g} \left[\sum_{b=1}^{N_{eb}} \mathrm{p_{ib}} \lambda_{\mathrm{ib}}^{\mathrm{p}} + \sum_{b=1}^{N_{rb}} \mathrm{r_{ib}} \lambda_{\mathrm{ib}}^{\mathrm{r}} \right] \tag{4.1}$$

The first term inside the bracket is the cost of providing energy (this is the sum of accepted production bids $\mathrm{p_{ib}}$ times their corresponding bidding price $\lambda_{\mathrm{ib}}^{\mathrm{p}}$), while the second term is the cost of providing reserve (sum of accepted reserve bids $\mathrm{r_{ib}}$ times their corresponding bidding price $\lambda_{\mathrm{ib}}^{\mathrm{r}}$). Both are based on generators offers. The total cost to be minimised is the sum of these two terms for the N_g units.

The prevailing constraints are as follows:

The accepted bids $\mathrm{p_{ib}}$ and $\mathrm{r_{ib}}$ must be greater or equal to zero, and lower than the offers $\mathrm{p_{ib}^{bid}}$ and $\mathrm{r_{ib}^{bid}}$:

$$\begin{aligned} 0 \le \mathrm{p_{ib}} \le \mathrm{p_{ib}^{bid}} \\ 0 \le \mathrm{r_{ib}} \le \mathrm{r_{ib}^{bid}} \end{aligned} \tag{4.2}$$

A generator must be dispatched for energy at least at its minimum output P^{i}_{gmin} or not dispatched at all. If the generator is not dispatched for energy it cannot be dispatched for reserve. Moreover the sum of the dispatch quantities for energy and reserve must be lower than the generator's maximum output P^{i}_{gmax}:

$$\begin{cases} p_i \ge P^{i}_{gmin} \\ or \begin{cases} p_i = 0 \\ r_i = 0 \end{cases} \end{cases}$$
$$and \tag{4.3}$$
$$p_i + r_i = \sum_{b=1}^{N_{eb}} p_{ib} + \sum_{b=1}^{N_{rb}} r_{ib} \le P^{i}_{gmax} \quad i = 1,..., N_g$$

Enough reserve must be available to maintain the reliability of the system:

$$\sum_{i=1}^{N_g} r_i \ge R_S \tag{4.4}$$

The required quantity of reserve R_S is determined by the expected size of a contingency. It is usually calculated dynamically from the size of the largest unit generating, the stability of the unit under contingencies and the correlation of unit failure with other contingencies. However in this thesis R_S is defined as being 10% of the forecasted load:

$$R_S = P_{Load} \cdot 0.1 \tag{4.5}$$

The generation must supply the forecasted load P_{Load} and transmission losses P_{Loss}:

$$\sum_{i=1}^{N_g} p_i = \sum_{i=1}^{N_g} \sum_{b=1}^{N_{eb}} p_{ib} = P_{Load} + P_{Loss} \tag{4.6}$$

Finally, the line flow on line kl $flow_{kl}$ must be lower than the transmission line limit:

$$flow_{kl} \le flow_{kl}^{max} \tag{4.7}$$

4.2.2 An iterative MIP solution for the market clearing engine problem

This is a highly constrained problem with non-continuous variables because of Equation (4.3) since generators should be either dispatched to produce more than their minimum output or not dispatched at all.

This problem is similar to a traditional optimal power flow, its objective is to minimise the generation cost and it must solve so that the solution satisfies the entire set of power constraints. However the optimisation process is here slightly more complicated since we can choose to commit or not a generator introducing non-continuity in the problem, and several services (generation and reserve) are to be optimised simultaneously.

Optimal power flow is usually solved using linear programming methods that solve the problem by iterating between solving a power flow and then solving a linear program to change the system controls to remove any limit violations.

Similarly, we adopt an iterative procedure between a mixed integer programming (MIP) algorithm and a standard power flow. The basic steps in the algorithm are:

- Obtain an initial solution without considering the transmission constraints using the mixed integer programming algorithm.
- Solve the power flow with a Newton-Raphson method.
- Linearize the power system about the current power flow solution. Both constraints and controls are linearized.
- Solve the linearly-constrained MIP problem using a branch & bound algorithm, computing the incremental change in the control variables.
- Update the control variables and resolve the power flow.

If the changes in the control variables are below a tolerance then the solution has been reached. Figure 4.3 presents a flowchart of the market clearing algorithm.

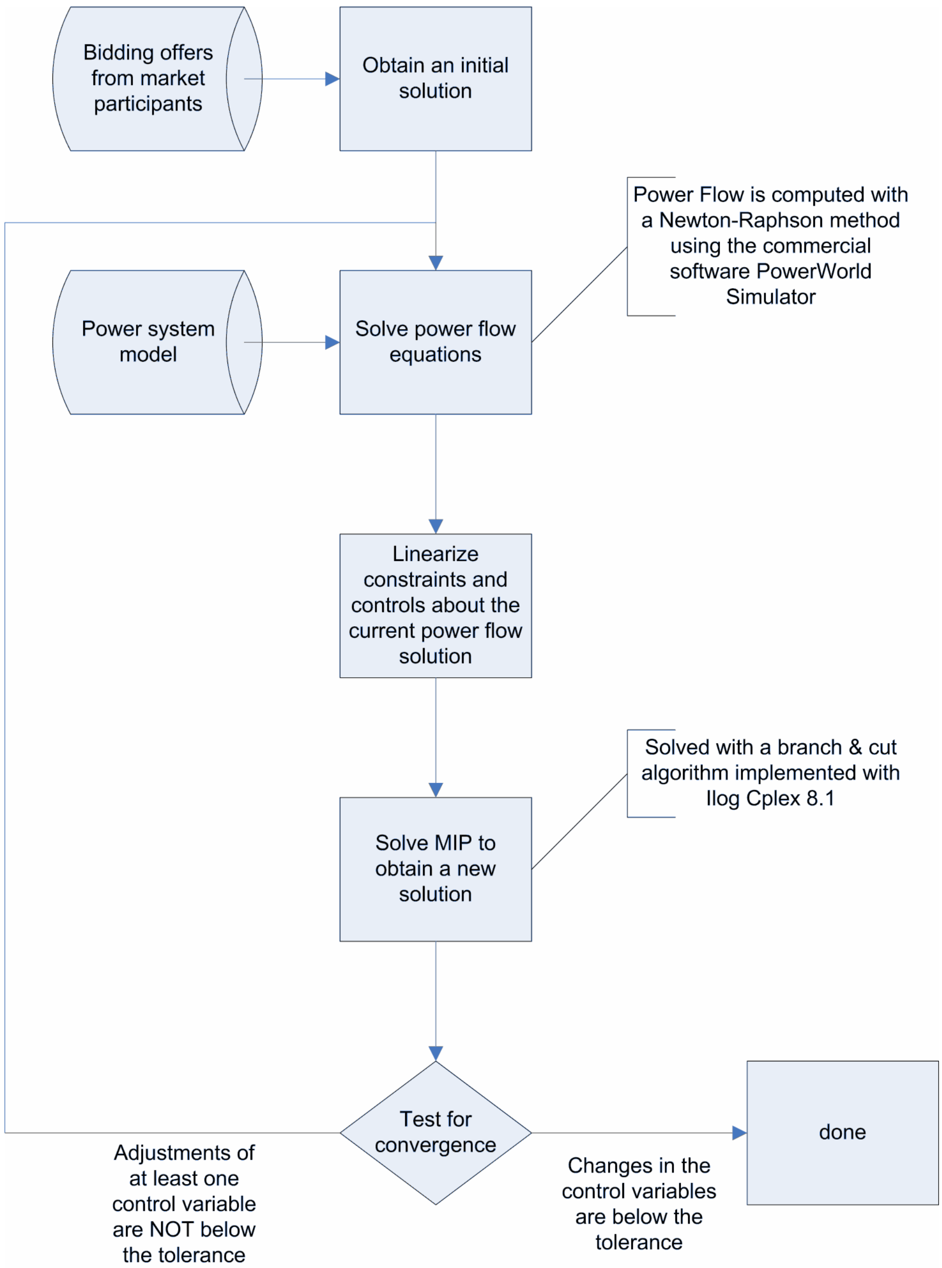

Figure 4.3: Flowchart of the market clearing algorithm

4.2.2.1.Obtaining an initial solution

An initial solution is obtained by solving the optimization problem without considering the transmission constraints or losses. To do so, the MIP algorithm presented in paragraph 4.2.2.4 is used without modelling these constraints.

In that case, the problem is to minimise the objective function(4.1), while respecting the bid limits(4.2), ensuring the generation unit limits(4.3), meeting the reserve requirements(4.4) and balancing the system(4.6) with losses taken to be equal to 2% of the load in this initial solution.

This initial solution allows us to start the iterative procedure that consists of 3 steps: solving the power flow, linearizing the network constraints about the power flow solution, and solving the linearly-constrained mixed integer programming problem.

4.2.2.2.Solving the Power Flow

Ensuring the transmission system constraints requires to model the transmission network and to monitor the currents, voltages and power flows at every bus in the system.

Power flow is a traditional power engineering calculation that is performed to determine the flows on all lines and the voltages at all buses in the system given the power injections at all buses and the voltage magnitudes at some of them. It gives us the electrical response of the transmission system to a particular set of loads and generation units output [34].

The power flow problem entails solving a system of nonlinear equations. Several methods are commonly used to solve this nonlinear system including iterative and robust methods like the Gauss-Siedel method or the Newton-Raphson method, faster processes like the fast decoupled power flow, and fast non-iterative method like the DC power flow [34].

In this project, the transmission network has been modelled using the commercial software PowerWorld Simulator [24]. PowerWorld Simulator is a power system simulation package based on a comprehensive, robust Power Flow Solution engine capable of efficiently solving systems of up to 60,000 buses, implementing the full Newton-Raphson method, the fast decoupled power flow, and a DC power flow. It also allows the user to visualize the system through the use of animated diagrams providing good graphical information about both the technical and economic aspects of the transmission network.

4.2.2.3.Linearization of network constraints

Linear sensitivity factors are used to formulate transmission constraints and to approximate the losses function.

Generation shift distribution factors [34][35] show the approximate change in line flows for changes in generation on the network configuration and are derived from a DC load flow as follows:

The flow on line k-l is a expressed as a function of the bus phase angles δ_k and δ_l and the reactance for line k-l x_{kl}:

$$\mathrm{flow}_{\mathrm{kl}} = \frac{\delta_k - \delta_l}{x_{kl}} \tag{4.8}$$

Hence the sensitivity of the flow on line k-l to the generation at bus i $\mathrm{A}^{\mathrm{i}}_{\mathrm{kl}}$ is:

$$\begin{aligned} \mathrm{A}^{\mathrm{i}}_{\mathrm{kl}} &= \frac{d\mathrm{flow}_{\mathrm{kl}}}{d\mathrm{p}_{\mathrm{i}}} = \frac{d}{d\mathrm{p}_{\mathrm{i}}}\left[\frac{\delta_k - \delta_l}{x_{kl}}\right] \\ &= \frac{1}{x_{kl}}\left[\frac{d\delta_k}{d\mathrm{p}_{\mathrm{i}}} - \frac{d\delta_l}{d\mathrm{p}_{\mathrm{i}}}\right] = \frac{1}{x_{kl}}\left[X_{ki} - X_{li}\right] \end{aligned} \tag{4.9}$$

where $X_{ki} = \dfrac{d\delta_k}{d\mathrm{p}_{\mathrm{i}}}$.

X_{ki} is obtained from the standard matrix calculation for the DC load flow that expresses the bus phase angles $\boldsymbol{\delta}$ as a linear function of the bus power injections $\mathbf{P}$:

$$\boldsymbol{\delta} = [X]\mathbf{P} \tag{4.10}$$

The generation shift distribution factor A_{kl}^{i} expresses that an increase of 1MW in generation at bus i, will result in an approximate change in line flow of A_{kl}^{i} at line k-l.

Linearizing, i.e. retaining only the linear terms of the Taylor's series expansion the line flow about the power flow solution obtained at the last iteration, we get:

$$\mathrm{flow}_{kl} = \mathrm{flow}_{kl}^{\text{last iteration}} + \sum_{i=1}^{N_g} \frac{d\mathrm{flow}_{kl}}{d\mathrm{p_i}} \Delta \mathrm{p_i} \tag{4.11}$$

Using the generation shift distribution factors, the line flow constraints expressed in equation (4.7) are then modelled by:

$$\mathrm{flow}_{kl}^{\text{last iteration}} + \sum_{i=1}^{N_g} A_{kl}^{i} (\mathrm{p_i} - \mathrm{p_i}^{\text{last iteration}}) \le \mathrm{flow}_{kl}^{\max} \tag{4.12}$$

In a similar manner loss sensitivity factors are computed, it indicates how losses would change if one more MW of power were injected at bus i. Stated mathematically, the loss sensitivity factor LSF_i is so that:

$$LSF_i = \frac{d\mathrm{P_{Loss}}}{d\mathrm{p_i}} \tag{4.13}$$

The loss sensitivities are calculated by modelling an injection of power at a bus and then assuming that this injection is absorbed by the system slack bus. The sensitivity then shows how much the losses (for the region of interest) increase when 1MW is transferred from the injection bus to the system slack.

Hence using the loss sensitivity factors, losses are linearized about the power flow solution obtained at the last iteration:

$$\mathrm{P_{Loss}} = \mathrm{P_{Loss}^{\text{last iteration}}} + \sum_{i=1}^{N_g} \frac{d\mathrm{P_{Loss}}}{d\mathrm{p_i}} \Delta \mathrm{p_i} \tag{4.14}$$

Equation (4.6) that states that in steady-state power system operation, total generation must always equal total load plus losses can be modified as:

$$\sum_{i=1}^{N_g} \mathrm{p_i} = \mathrm{P_{Load}} + \mathrm{P_{Loss}^{last\ iteration}} + \sum_{i=1}^{N_g} LSF_i (\mathrm{p_i} - \mathrm{p_i^{last\ iteration}}) \tag{4.15}$$

4.2.2.4.Solving the linearly-constrained mixed integer programming problem

The system constraints have been linearized about the power flow solution obtained at the last iteration and the problem is now to minimise the objective function(4.1), while respecting the bid limits(4.2), ensuring the generation unit limits(4.3), the reserve requirements(4.4), the linearized line flow constraint(4.12) and the linearized system balance equation(4.15).

Considering that each one of the $\mathrm{N_g}$ unit offers $\mathrm{N_{eb}}$ bids for energy and $\mathrm{N_{rb}}$ bids for reserve, the control variables to be optimised are:

- Power produced with the b[th] energy offer block of unit i:

  $\mathrm{p_{ib}}$ for i=1,2,...,$\mathrm{N_g}$ and b=1,2,...,$\mathrm{N_{eb}}$

- Reserve provided with the b[th] reserve offer block of unit i:

  $\mathrm{r_{ib}}$ for i=1,2,...,$\mathrm{N_g}$ and b=1,2,...,$\mathrm{N_{rb}}$

It is important to note that the variables $\mathrm{p_{i1}}$ (for i=1,2,...,$\mathrm{N_g}$) are non-continuous.

This problem is implemented and solved with the optimisation software Ilog Cplex 8.1, using a branch and bound technique [36]. The basic philosophy in this procedure is to divide the overall non continuous problem into a series of continuous subproblems solved with traditional linear programming optimisation technique. Subproblems are enumerated following a tree structure. The root of the tree is the continuous relaxation of the original MIP problem. Subproblems are then developed by imposing constraints on the non-continuous variables to force them in their feasible range. Each subproblem is a node of the solution tree.

The fundamental steps in this technique are:

- Step 1: initialisation. We obtain the continuous relaxation of the original problem. If all control variables are in their feasible range (i.e. no generating unit has been dispatched for less than its minimum output), this is the optimal solution. Else perform the iteration procedure below.
- Step 2: Branching. Select the subproblem that was created most recently. Choose one variable in the LP relaxation of the subproblem that is not in its feasible range to be the branching variable. Let p_{i1} be this variable. Create 2 new subproblems by adding the respective constraints,

$$p_{i1} = 0 \text{ and } p_{i1} \geq p_i^{min} \tag{4.16}$$

- Step 3: bounding. For each new subproblem, obtain its linear programming relaxation.
- Step 4: optimality test. For each new subproblem, if the linear programming relaxation has no feasible solution or if the solution is more expensive than the best solution found so far, the subproblem is dismissed from further consideration. If the solution has all its variables in their feasible range and its cost is lower than best solution found so far, save as the new best solution found so far.

The procedure is illustrated below using a simple numerical example. The results with a larger system and considering line losses, line flow limits, and simultaneous optimisation of energy and reserve, are presented in Chapter 8. The objective here is only to demonstrate the solution procedure of a branch and bound algorithm. Let's consider the dispatch for energy in a 3 unit system. The units' bidding offers are given in Table 4.1. The power demand is 224MW.

Table 4.1: generators bidding offers for energy

	Minimum output	Maximum output	Offer 1		Offer 2		Offer 3	
			Quantity	Price	Quantity	Price	Quantity	Price
Unit 1	50	200	100	11.0	50	11.5	50	12.0
Unit 2	20	60	20	12.5	20	12.8	20	13.2
Unit 3	5	25	8	12.3	8	12.7	9	13.1

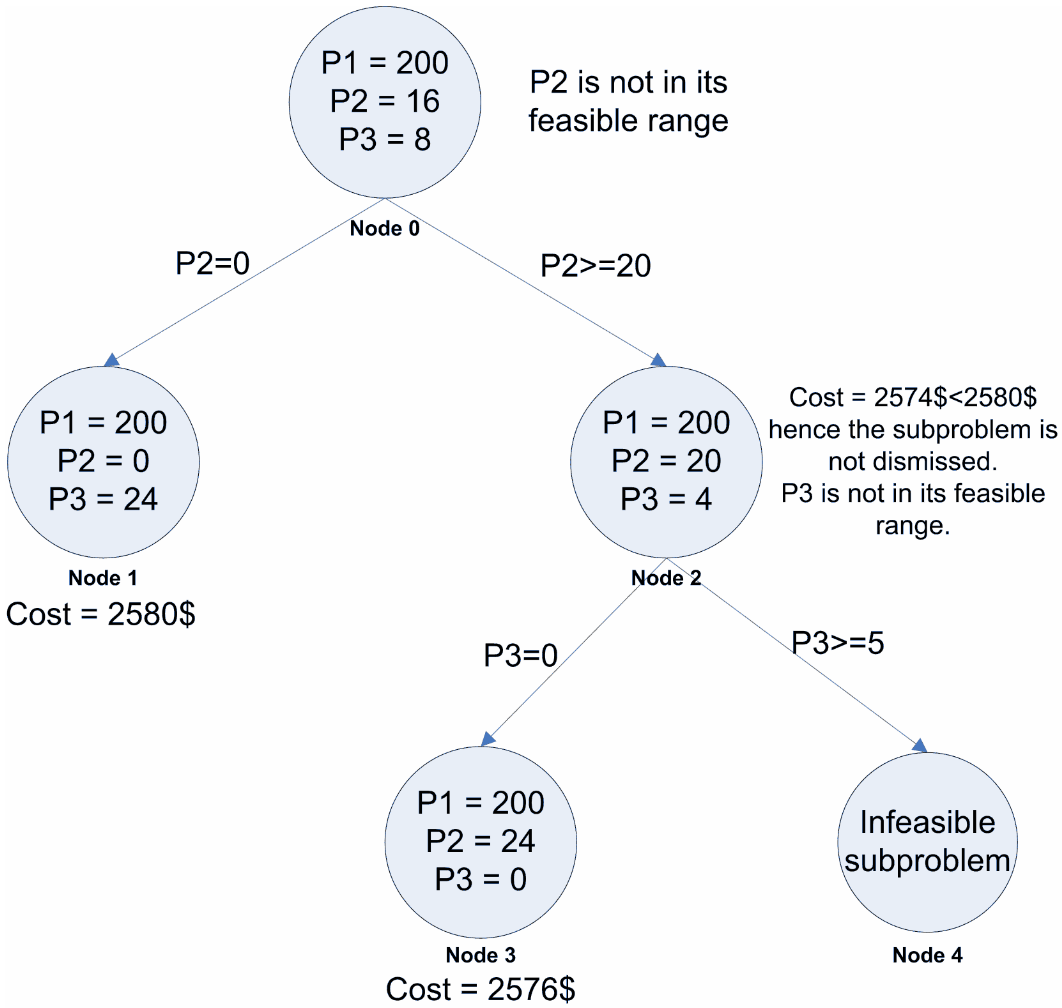

Figure 4.4: Solution tree for the dispatch of the 3 generators system

The control variables are P1, P2 and P3, power produced by unit 1, 2, and 3 respectively.

The solution tree is represented in Figure 4.4. Node 0 gives the continuous relaxation of the original problem. In this solution the variable P2 is not in its feasible range hence we create 2 subproblems (node 1 and 2) by adding the respective constraints, $P2 = 0$ and $P2 \geq 20$. The continuous relaxation of the subproblem at node

1 gives a feasible solution with a cost of 2580$. This solution is saved as the best solution obtained so far. Then we solve the subproblem at node 2, the solution of the continuous relaxation has a cost lower than the saved best solution, hence we can explore this subproblem further. The variable P3 is not in its feasible range, so we create 2 subproblems (node 3 and 4) by adding the respective constraints, $P3 = 0$ and $P3 \geq 5$. We obtain a feasible solution at node 3 for a cost of 2576$, while the subproblem at node 4 has no solution. The solution tree has been totally explored hence the iterative procedure is over. The optimal solution is P1=200, P2=24, P3=0, for a minimised cost of 2576$.

4.3 Conclusions

This chapter presents a new iterative approach to solving the transmission constrained economic dispatch simultaneously for energy and reserve using linear sensitivity factors to linearize the constraints about a power flow solution and a branch & bound method to optimise the dispatch.

The rules of the market clearing engine of the Singapore New Electricity Market have been used to implement the algorithm that has been integrated in the ISO agent of the multi-agent framework that aims at modelling the electricity market.

The following chapter explores the use of an evolutionary algorithm to solve the unit commitment problem; this algorithm is then use in Chapter 6 to design combined energy and reserve bidding strategies in a multi-round competitive market.

Chapter 5 A PRIORITY LIST-BASED EVOLUTIONARY ALGORITHM TO SOLVE LARGE SCALE UNIT COMMITMENT PROBLEM

In this chapter, a priority list-based evolutionary algorithm to solve large scale Unit Commitment problem is proposed, implemented, and tested. The development of this algorithm is made considering a regulated environment as it allows us to appreciate the performances of the method and to compare the obtained results with other reported techniques.

5.1 Introduction

The Unit Commitment (UC) problem is the problem of determining the on/off schedule of the power generating units of a power system so that the committed units meet the forecasted demand plus the spinning reserve, the units' operation constraints are observed, and the production cost is minimized.

The exact solution of this problem could be obtained by a complete enumeration of all feasible solutions and the computation of the economic dispatch and total production cost for each of them.

However, modern power systems are usually large scale systems, and as the number of solutions to the UC problem grows exponentially with the number of units, the computation time would be excessive. This is even truer with the actual development of Distributed Generation (DG). DG units are small-scale electricity generation units located throughout the distribution system, close to the consumer. As the technology is now ready to produce these small-scale units that can provide better power quality , higher reliability, and fewer environmental problem, DG should take an important place in the future power systems, what will lead to an increasing number of generating units [18].

5.2 Problem formulation

The objective of the UC problem is to find the feasible combination of the generating units over the scheduling period that minimizes the total production cost. This cost is the sum for the N units and for the T time intervals of the unit fuel costs $F_i(p_i(t))$, the start-up costs $SU_i(t)$ and the shut-down costs $SD_i(t)$. Hence the objective function of the UC problem is

$$TC = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[F_i(p_i(t)) + SU_i(t) + SD_i(t)\right] \tag{5.1}$$

The fuel cost rate F_i of unit *i* is a function of the unit power output $p_i(t)$. The most frequently used cost function is:

$$F_i(P_i(t)) = a_i + b_i \cdot p_i(t) + c_i \cdot p_i^2(t) \tag{5.2}$$

The start-up cost is a function of time the unit has been down:

$$\begin{aligned} &SU_i = CSC_i \text{ if } T_i^{off} > T_{i\min}^{off} + T_i^{cold} \\ &SU_i = HSC_i \text{ in the other cases} \end{aligned} \tag{5.3}$$

The shut-down cost is usually a constant value.

$$SD_i(t) = \text{Constant value} \tag{5.4}$$

What make the search of the optimal solution difficult are the many constraints which must be taken into account.

First, generating units usually cannot run below a minimum level p_i^{min} and their maximum output is also limited by the value p_i^{max}. Unit power output must be within these two limits.

$$p_i^{min} \le p_i(t) \le p_i^{max} \tag{5.5}$$

Then enough units should be committed to supply the load. The system must be constantly balanced.

$$\sum_{i=1}^{N_g} p_i = P_{Load} + P_{Loss} \tag{5.6}$$

The total load on the system will generally be higher during the daytime and early evening when industrial loads are high, lights and TV are on…, and lower when most of the population is asleep. The supply should also follow this cycle. Hence, as it costs money to keep a unit on even if it is not supplying power to the network, units should be turned off when they are not needed.

Another constraint to be considered is the spinning reserve constraint. Committed units must have some reserve so that the loss of one of these units does not cause a drop in system frequency. If a unit experiences an unexpected contingency, other units should have enough reserve to compensate for the loss.

$$\sum_{i=1}^{N_g} [p_i^{max} - p_i(t)] \ge R_S(t) \tag{5.7}$$

Finally thermal units also have operating constraint. It can only undergo gradual temperature changes, hence once the unit is running, it should not be turned off immediately (minimum up time), similarly once the unit is decommitted, it cannot be turn on immediately (minimum down time).

5.3 Review of solution techniques

To solve this still challenging problem, several optimization methods have been applied. The most talked-about and commonly used in the industry techniques are priority list, dynamic programming and Lagrangian relaxation [34]-[36].

5.3.1 Priority List

The simplest unit commitment solution consists of arranging the generating units in a start-up heuristic ordering by operating cost combined with transition cost so that least expensive units are placed at the top of the list, and then proceeding to the most expensive ones. Units are committed in the list order until the load is satisfied and they are decommitted in the reverse order when they are not needed anymore. A number of refinements including minimum up- and down-times, different start-up and shut-down orderings, dynamic techniques, have been made to this priority list method resulting in complex heuristic techniques[38][34].

It remains one of the primary methods in use in actual industrial applications.

5.3.2 Dynamic programming

Dynamic programming is an optimization approach that transforms a complex problem into a sequence of simpler problems; its essential characteristic is the multistage nature of the optimization procedure [36]. By using the recursive relationship, the solution procedure moves stage by stage, each time finding the optimum policy for that stage, until it finds the optimum policy starting at the initial stage. For the UC problem, the stages of the procedure are the time periods of the study horizon. Starting at the initial stage, the procedure is to compute the cost at each stage of X combinations of units and to save the path to the N best (most economical) solutions. When the last stage is reached, the minimum total cost is calculated and it is possible to trace back the path to find the optimal solution. The dynamic programming method suffers from the curse of dimensionality since the problem grows exponentially with the number of generating units. Moreover an optimal solution is not guaranteed. Several approaches have been adopted to reduce the search space and hence the dimension of the DP problem, most of them being based on the above priority list technique.

5.3.3 Lagrangian relaxation

Lagrangian relaxation is based upon the observation that many difficult programming problems can be modelled as relatively easy problems complicated by a set of side constraints. The LR method uses Lagrange multipliers for the system constraints and adds the associated penalty terms in the objective function to form the Lagrangian function. For fixed values of the Lagrangian multipliers, the problem can be decomposed in smaller subproblems (each subproblem determines the commitment of a single unit) that are solved iteratively until a near optimal solution is obtain.

Lagrangian relaxation is the most explored and commonly used technique. Research on this method is still active and improvements in term of costs and computation time are made through new Lagrange multipliers updating procedures [39][42], new decomposition methods [39], and the addition of multipliers to handle more constraints.

5.3.4 Evolutionary computation methods

The above mentioned techniques either require an excessive computation time or do not provide near optimal results. The more promising results, in term of computation time and cost minimization, are obtained with methods using Artificial Intelligence including genetic algorithm or evolutionary programming.

Generally a simple binary alphabet is chosen to encode the solution. A binary string of length T*N (number of periods in the time horizon * number of units) is needed to represent the solution. Each bit of this string indicates the state (1 for “On”, 0 for “Off”) of one unit for one period as shown in Figure 5.1.

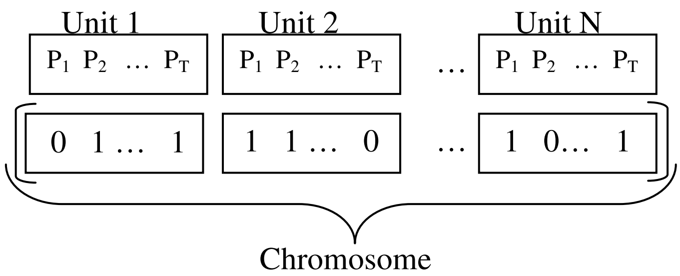

Figure 5.1 binary representation of a unit commitment solution

5.4 Proposed algorithm

An evolutionary algorithm is proposed, developed and implemented to solve the Unit Commitment problem. It is an iterative procedure acting on a population of chromosomes, each chromosome being the encoding of a candidate solution to the problem. A fitness, which depends how well it solves the problem, is associated with each chromosome. Computed from the objective function, penalty terms being added if problem constraints are not fulfilled, this fitness determines the solution's ability to survive and produce offspring. New generations of solutions are obtained by a process of selection, cross-over, and mutation. During the evolution process, new generations should give fitter solution and evolve towards an optimal solution.

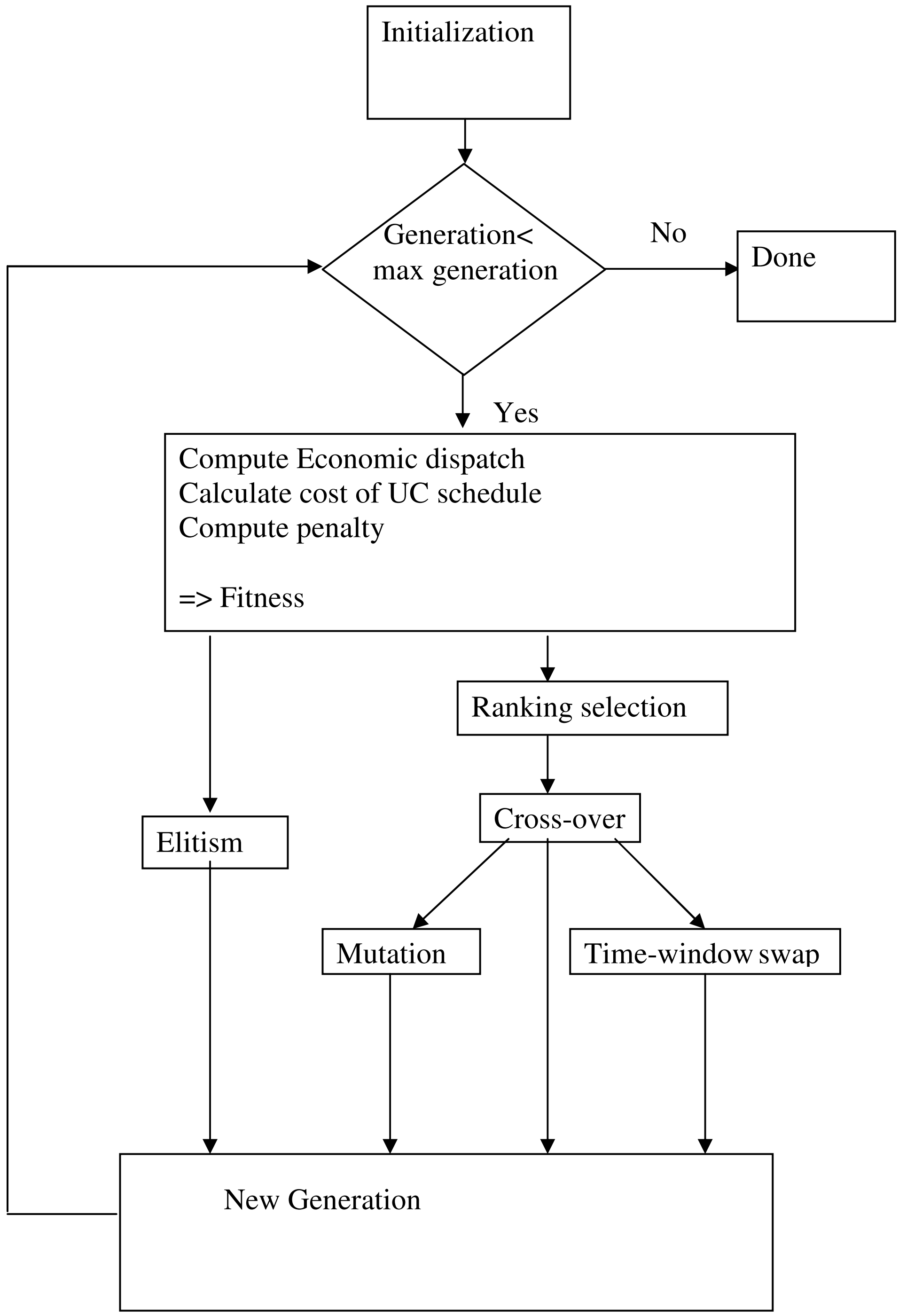

Figure 5.2: Evolutionary Algorithm flowchart

The proposed algorithm evolved an initial population made of good solutions obtained by a Priority List method. Evolution was characterized by the elimination of the less fit, the survival of the fittest, a reproduction ability based on the fitness, and the genetic operators: cross-over, mutation and time-window swap. Figure 5.2 gives a flowchart of the proposed algorithm.

5.4.1 Solutions encoding

Each chromosome of the population represented a UC schedule that could be a solution to the problem. These schedules were encoded in a binary way, a solution was represented by a set of bits, each bit representing the state of a given unit at a given time (1 for ON, 0 for OFF). Hence, for a *N*-units system over a period of *T*-hours, a chromosome was an array of *T*N* bits as shown in Figure 5.3.

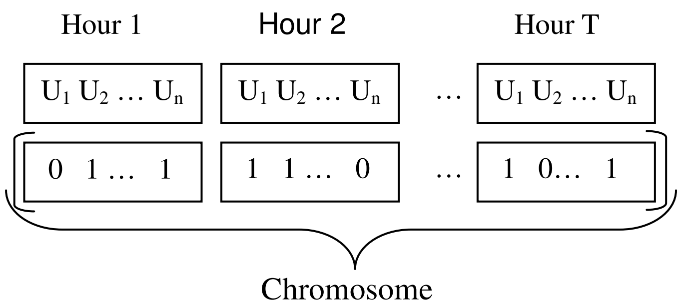

Figure 5.3: Solution Encoding

5.4.2 Initialization of the population

Initial population is usually obtained from randomly generated solutions. However, these randomly generated solutions are generally far from the optimal solution in the solution space, thus the convergence is slow and likely to get trapped in a local minimum during the exploration of the solution space.

In this paper, a part of the initial population was still generated randomly to maintain the population diversity, but remaining chromosomes were generated using a priority list method.

In a Priority List (PL) method, for each time interval of the scheduling period, units are connected in a preset order until load and reserve requirements are observed. This order is set based on the knowledge available about units. It was chosen to connect units in the ascending order of their per MW cost at maximum power output, i.e. in the ascending order of:

$$\frac{a_i + b_i \cdot \mathrm{p}_\mathrm{i}^{\max} + c_i \cdot \mathrm{p}_\mathrm{i}^{\max 2}}{\mathrm{p}_\mathrm{i}^{\max}} \tag{5.8}$$

The less costly units are committed first and the more costly units are committed only if the load demand is high. A good (cheap) UC schedule is then expected.

More solutions were obtained from this one by mutation of a few last connected units or next to be connected units in the PL order as shown in Figure 5.4.

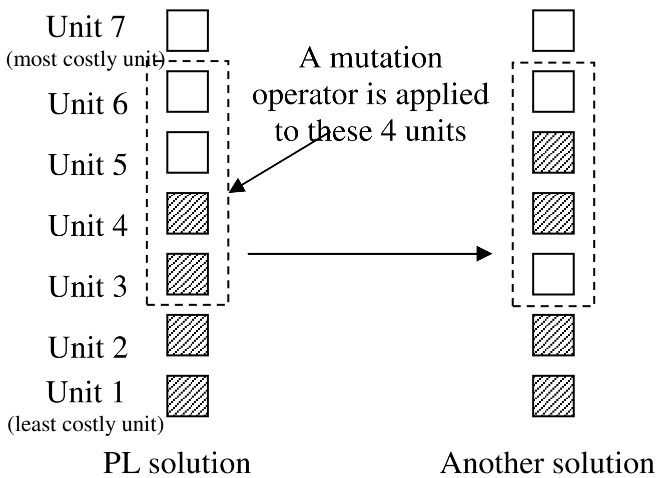

Figure 5.4: Another PL solution is obtained from the initial one

Introduction of these "good" solutions in the initial population, even if they are not feasible solutions, makes the search starts closer to the optimum, leading to a faster convergence and better results.

5.4.3 Fitness computation

The fitness function to minimize is the sum of the total production cost (objective function) and the penalty costs (if constraints are not observed).

To calculate the penalty term, constraints (minimum up/down time, load and spinning reserve requirements) were checked and a penalty cost was computed for the infeasible solutions. The more constraints were not observed, the more this cost was high. Penalty costs had to be chosen carefully so that the population evolved towards feasible solutions but diversity was maintained not to be trapped in local minimum.

The total production cost was obtained from (5.1),(5.2),(5.3),(5.4), the output of each unit being obtained by the economical dispatch, computed with a classical lambda iteration method [34].

5.4.4 Creation of the new generation of solutions

To obtain the new generation from the current one, several mechanisms and operators were applied.

5.4.4.1.Conservation of the best solutions

The chromosomes having the best fitness were copied directly into the new generation without any change. It permits the best solutions not to be lost if they are not selected to reproduce or if they are altered by a genetic operator during the reproduction process, because a small change to a chromosome can completely change its fitness (for instance if a constraint is no more fulfilled) and a good solution can become a bad one that will be discarded by the evolution process.

Thanks to this mechanism, the population can only progress.

5.4.4.2.Ranking Selection

Solutions from the current generation were ranked according to their fitness.

Worst solutions from the current generation were discarded and were not allowed to produce an offspring. Only the fittest could enter the reproduction pool, this way, infeasible solutions or chromosomes that did not search in the right direction were eliminated, the search becoming then more efficient.

Solutions from the reproduction pool were selected for reproduction according to a probability proportional to their rank. Thus a fitter solution had more descendants but a less fit solution still had a chance to reproduce even if its fitness was far lower. This selection method avoided giving the far largest share of offspring to a small group of highly fit individuals and then prevented a too quick convergence.

5.4.4.3.Cross-over

A 2 points cross-over as presented in [69] was used. Two parents were selected and their genotypes were combined as shown in Figure 5.5 to form a new one. The idea is to combine existing good blocks to obtain a better solution [67].

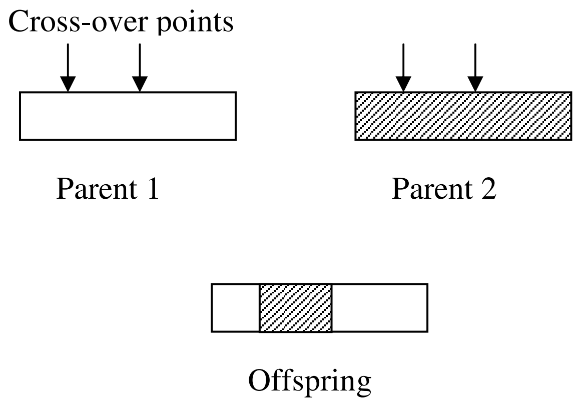

Figure 5.5: 2 parents' genotypes are recombined by cross-over to form a new chromosome.

Suppose that parent 2 proposes a better UC schedule than parent 1 between the two cross-over points and that parent 1 has a better schedule for the remaining time interval. Combination of these 2 chromosomes can give a UC schedule that outperforms its parents.

5.4.4.4.Mutation

To introduce innovation and diversity in the population, a standard mutation operator as described in [69]was used. Bits of the chromosomes (the mutation points) were randomly chosen and inversed as shown in Figure 5.6.

New good building blocks (part of the schedule) can be discovered thanks to this operator.

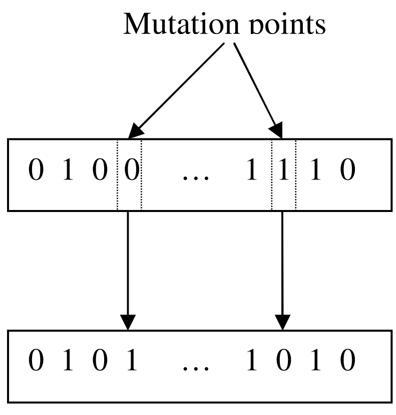

Figure 5.6: Mutation: selected bits of the chromosome are inversed.

5.4.4.5.Time-window swap operator

Two units, a starting and ending time were randomly chosen. The operator swapped the states of these 2 units between these 2 instants as shown in Figure 5.7. This last operator acts on building blocks rather than bits according to the theory stating that EAs work by discovering, emphasizing, and recombining good building blocks, good solution being made of good building blocks [67].

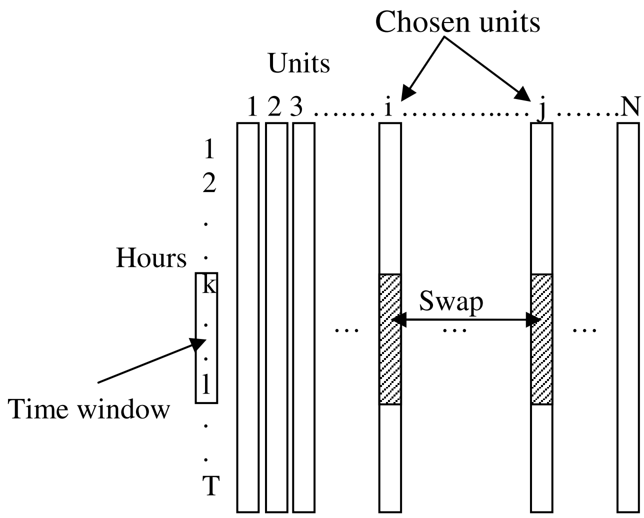

Figure 5.7: Time window swap operator.

The behaviour of an evolutionary algorithm is too complicated to be totally controlled but to simplify, it can be said that the 3 presented operators acts in a complementary way: the mutation operator introduces new building blocks, the cross-over produces and recombines good space blocks (a combination of units for a given time interval), the time-window swap operator recombines good time block (the schedule of a unit over several time intervals).

The efficiency of the algorithm presented in this paper comes from the combination of these 3 operators which work on a near optimal initial solution obtained by the PL method.

5.5 A repair evolutionary algorithm

Recent works using evolutionary computation to solve problem in different fields including the UC problem have emphasized the efficiency of repair algorithms [47][48][49]. In a repair genetic algorithm, all the individuals considered for evaluation are feasible solutions of the problem. A repair algorithm presents two advantages compared to penalty based genetic algorithms: 1) it does not work on a broad search space full of infeasible solutions, but on bounded search spaces (consisting of feasible solutions), thus reducing the search burden and increasing the efficiency of the algorithm and 2) the problem of choosing penalties of different nature for each of the constraints disappears. On the other hand repair algorithms require high computing time to turn infeasible solutions into feasible.

The algorithm presented in the previous paragraph has been modified to create a repair priority list based evolutionary algorithm. Results obtained with the 2 methods are compared in the next section.

The repair procedure is as follows:

- After its generation, each solution is first repaired so that the total available generation capacity covers the load demand and reserve requirements. To do so, randomly chosen units are committed until the generation capacity is sufficient.
- Then, each solution undergoes another repair process to fulfil the minimum up- and down-time constraints.
- After this last repair, the minimum generation capacity is not assured to be covered; hence a penalty term proportional to the deficit capacity is added to the fitness function.

With this method, all the solutions are not feasible but the algorithm converges quickly towards only feasible solutions and it avoids to increase the computation time dramatically as with a more elaborate repair process.

5.6 Simulation results

The Evolutionary Algorithm was implemented in Java Language and the simulations were carried on an AMD Athlon XP 2400. Because of the stochastic nature of the GA, 20 runs with different initial population were carried for each test.

5.6.1 Test systems

The algorithms have been tested on systems ranging from 10 to 100 units. Units' characteristics and load demand for the 10-units system are given in Table 5.1 and Table 5.2. Spinning reserve was assumed to be 10% of the load demand.

For the 20 units problem, the initial 10 units were duplicated and the demand and reserve were multiplied by two. The problem data were scaled appropriately for the systems with more units.

Table 5.1 Problem data for the 10-units system

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
P max (MW)	455	455	130	130	162
Pmin (MW)	150	150	20	20	25
a ($/h)	1000	970	700	680	450
b ($/MWh)	16.19	17.26	16.60	16.50	19.70
c ($/MW^{2}h)	0.00048	0.00031	0.002	0.00211	0.00398
Min up (h)	8	8	5	5	6
Min down (h)	8	8	5	5	6
Hot start cost ($)	4500	5000	550	560	900
Cold start cost ($)	9000	10000	1100	1120	1800
Cold start time (h)	5	5	4	4	4
Initial status (h)	8	8	-5	-5	-6

	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P max (MW)	80	85	55	55	55
Pmin (MW)	20	25	10	10	10
a ($/h)	370	480	660	665	670
b ($/MWh)	22.26	27.74	25.92	27.27	27.79
c ($/MW^{2}h)	0.00712	0.00079	0.00413	0.00222	0.00173
Min up (h)	3	3	1	1	1
Min down (h)	3	3	1	1	1
Hot start cost ($)	170	260	30	30	30
Cold start cost ($)	340	520	60	60	60
Cold start time (h)	2	2	0	0	0
Initial status (h)	-3	-3	-1	-1	-1

Table 5.2 Load Demand

Hour	Demand(MW)	Hour	Demand(MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

5.6.2 Parameters adjustments of the penalty-based algorithm

The penalty-based evolutionary algorithm was first tested and its parameters adjusted on a 40-units system.

5.6.2.1.Operators weight

After adjustment, the population size was set to 150 chromosomes, the best 4% of the current population were copied unchanged in the new population, the best 80% entered the reproduction pool, cross-over was applied to 40% of the chromosomes selected for reproduction, mutation operator was then applied to 15% of the new population while the time window swap operator was applied to another 55%.

5.6.2.2. Priority list influence

The priority list was obtained as explained in previous section and is presented in Table 5.3.

Table 5.3 Priority List

Unit Number	Priority Order	Unit Number	Priority Order
1	1	6	6
2	2	7	7
3	4	8	8
4	3	9	9
5	5	10	10

Initial solution from PL fulfilled lot more constraints than a randomly generated one and the search began nearer to the optimal solution. As shown in Figure 5.8, the algorithm gave better results and the convergence was faster when the initial population was seeded with PL solutions.

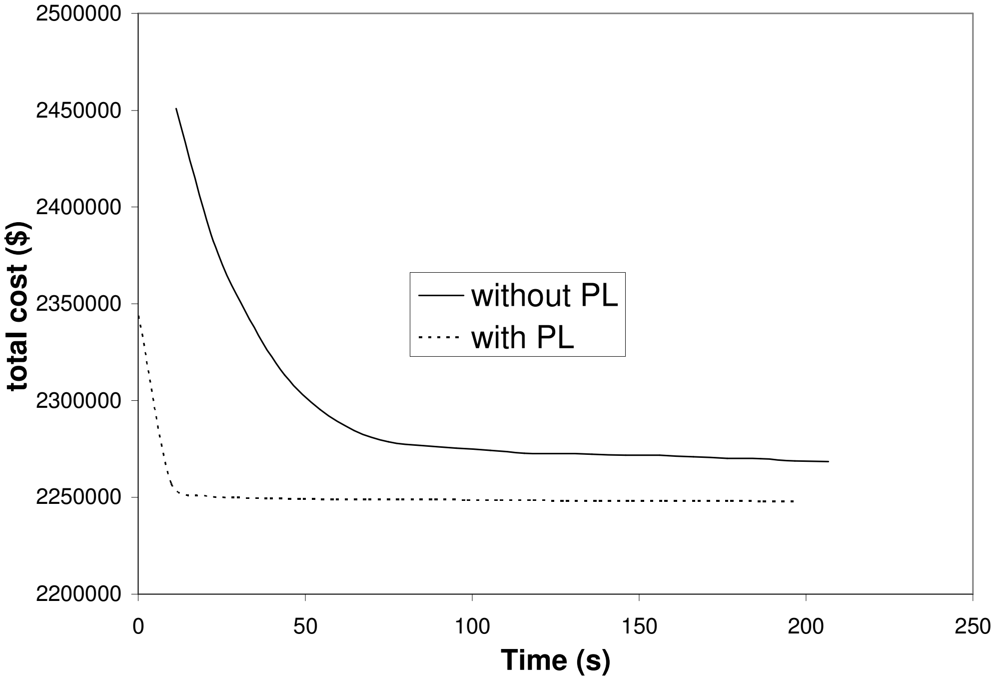

Figure 5.8: Average performance over 20 runs with and without priority list solutions in the initial population

Figure 5.9 shows that the proportion of priority List solutions in the initial population, has little influence on the final result as long as at least one PL solution has been generated. However introducing too much PL solutions (and so less randomly generated solutions) in the population can lead the algorithm to premature convergence as the randomly generated chromosomes bring to the population the diversity needed to evolve towards an optimal solution. Consequently the algorithm is designed with only one PL solution in the initial population, remaining solutions being generated randomly.

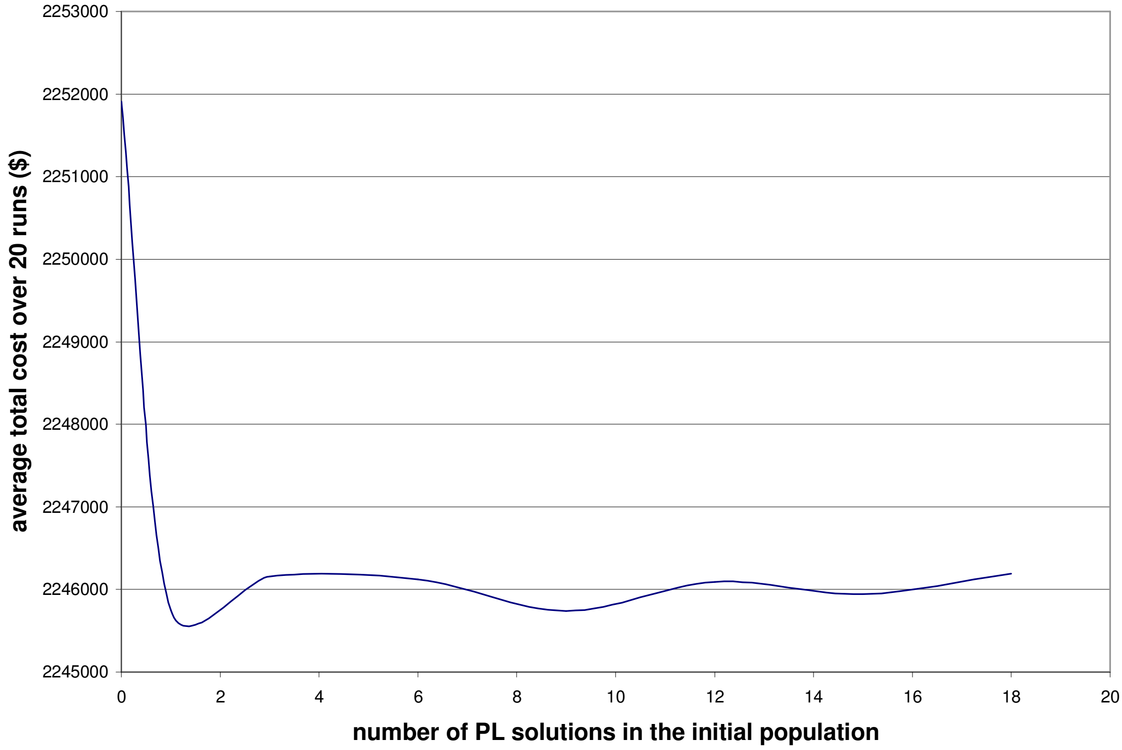

Figure 5.9 : Average performance over 20 runs with increased number of priority list solutions in the initial population

Table 5.4 and Table 5.5 present 2 solutions to the UC problem for a 10-units system. The first one is the non feasible PL solution obtained as explained in 5.4.2. The second solution is the one obtained after convergence of the algorithm presented in this paper. All constraints are now fulfilled and the total production cost is much lower. However these solutions are close to each other, the PL order being observed main of the time. Changes brought to the commitment scheduling along the evolution process were mainly to fulfil the constraints and to connect cheaper units for the reserve requirements; indeed, units that provide reserves often run near their minimum power output, hence the previously applied PL order was not adapted any more.

Table 5.4 PL solution to the UC problem for the 10-units system

PL solution; total production cost: $584799

unit\hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
unit 1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
unit 2	245	295	265	235	285	360	410	455	455	455	455	455	455	455	455	335	285	360	455	455	455	360	315	345
unit 3	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0
unit 4	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0
unit 5	0	0	0	0	0	25	25	30	85	162	162	162	162	85	30	0	0	25	30	162	85	25	0	0
unit 6	0	0	0	0	0	0	0	0	20	33	73	80	33	20	0	0	0	0	0	33	20	0	0	0
unit 7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	0	0	0
unit 8	0	0	0	0	0	0	0	0	0	10	10	43	10	0	0	0	0	0	0	10	0	0	0	0
unit 9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
unit 10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0

Table 5.5 PL-EA solution to the UC problem for the 10-units system

PL EA solution; total production cost: $563977

unit\hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
unit 1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
unit 2	245	295	370	455	390	360	410	455	455	455	455	455	455	455	455	310	260	360	455	455	455	455	420	345
unit 3	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
unit 4	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
unit 5	0	0	25	40	25	25	25	30	85	162	162	162	162	85	30	25	25	25	30	162	85	145	25	0
unit 6	0	0	0	0	0	0	0	0	20	33	73	80	33	20	0	0	0	0	0	33	20	20	0	0
unit 7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
unit 8	0	0	0	0	0	0	0	0	0	10	10	43	10	0	0	0	0	0	0	10	0	0	0	0
unit 9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
unit 10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0

5.6.2.3.Mutation rate

Choice of the mutation rate has a great influence on the efficiency of the search algorithm, as we need to prevent pre-mature convergence and excessive diversity. If it is too small the search won't cover all the search space and if it is too big, the algorithm won't converge. As shown in Figure 5.10, best results are obtained with a mutation rate of 1.5/(size of the chromosome), i.e. for a 10-units system over a period of 24 hours, we chose a value of 1.5/240.

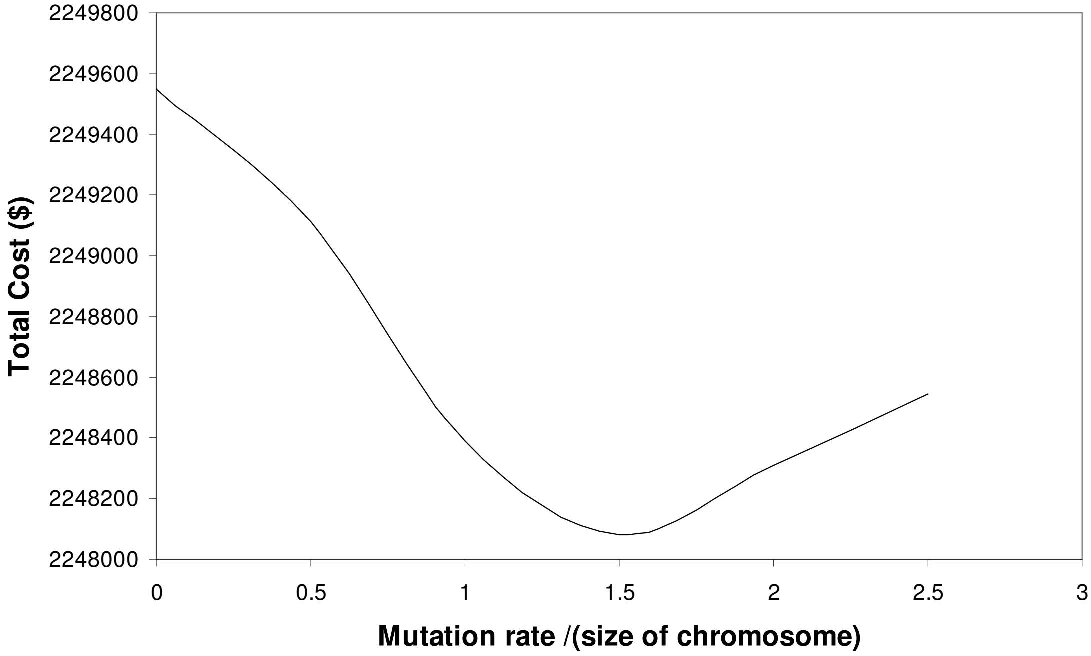

Figure 5.10: Average performance over 20 runs with increased mutation rate

5.6.3 Penalty-based versus repair algorithm

Convergence properties and best solution obtained by the 2 algorithm have been compared and are reported in Figure 5.11. The 2 algorithms make use of exactly the same genetic operators, except that only the repair algorithm applies a repair procedure on the chromosomes. Results demonstrate that the penalty-based algorithm converges faster and towards a better solution than the repair algorithm. The assumption that stated that by working only on feasible solutions, thus reducing the search space, the efficiency would be improved proved to be false. In the unit commitment problem, the feasible solutions are spread all over the solution space, and a good feasible solution can be far from another feasible solution and surrounded only by infeasible solutions. Hence the penalty-based method can be more appropriate to approach this solution that has few chances to be discovered with the repair method.

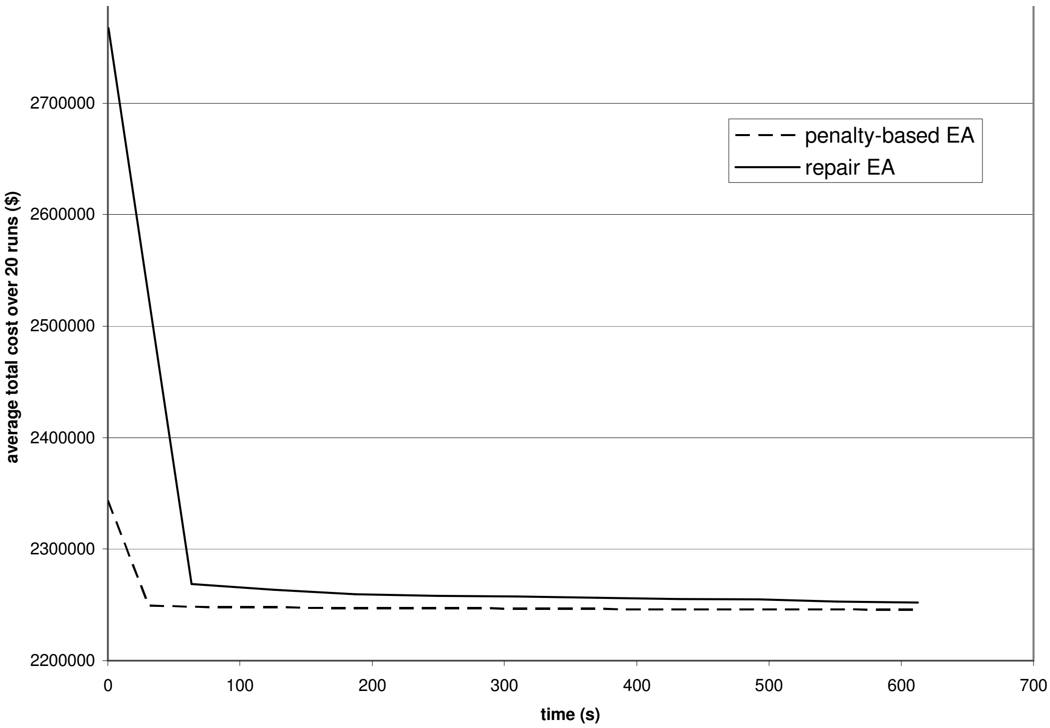

Figure 5.11 Penalty based versus repair algorithm

5.6.4 Comparisons with other reported methods

Once the parameters of the algorithm adjusted, simulations were conducted on systems from 10 to 100 units in the same conditions as [40][41][38]. Test results obtained during these simulations as well as results obtained in [40][41][38] are shown in Table 5.6 and Table 5.7. The best and the worst solution over 20 runs are reported with their difference as a percentage of the best results.

Table 5.6 Simulation results

	average best				Lagrangian
Units	PL EA	EPL [4]	GA[3]	EP[2]	Relaxation [3]
10	563977	563977	565825	564551	565825
20	1124295	1124369	1126243	1125494	1130660
40	2243913	2246508	2251911	2249093	2258503
60	3363892	3366210	3376625	3371611	3394066
80	4487354	4489322	4504933	4498479	4526022
100	5607904	5608440	5627437	5623885	5657277

Table 5.7 Simulation results (continued)

	average worst			difference (%)		
Units	PL EA	GA	EP	PL EA	GA	EP
10	565451	570032	566231	0.26	0.74	0.30
20	1126446	1132059	1129793	0.19	0.51	0.38
40	2247495	2259706	2256085	0.18	0.34	0.31
60	3369524	3384252	3381012	0.17	0.23	0.28
80	4495737	4510129	4512739	0.19	0.12	0.32
100	5613081	5637914	5639148	0.09	0.19	0.27

The times needed by the Priority list based evolutionary algorithm to compute the UC schedule were ranging from 1 minute for the 10-units system to 20 minutes for the 100-units system.

In comparison with results obtained in [40][41][38], the priority list based EA gave satisfactory solutions since lower costs were obtained for all systems. Moreover the difference between the best and the worst results over 20 runs was very small; that proves the algorithm converged near the optimal solution at each run in spite of the stochastic nature of evolutionary algorithm.

It is interesting to note that, compared to the GA presented in [41], the algorithm reported in this paper contains less problem-specific operator and no other optimization techniques than EA. These techniques can help to obtain better solutions but they augment the computation time to a great extent. Nevertheless our results are better, proving that the use of PL in the initial population is very efficient.

In [38], a PL solution was also used to create the initial population, but this population was then modified using only heuristic methods and not an evolutionary algorithm. Results presented in Table and Table 5.7, show that the priority list based evolutionary algorithm is more efficient. This is especially true for large scale system since for small systems near optimal or optimal solutions were already obtained in [38] in a shorter computation time. But for larger systems, the solution space being much larger, the PL EA search more efficiently and can obtain much lower cost in a reasonable time.

5.7 Conclusion

An Evolutionary Algorithm to solve the Unit Commitment problem has been developed and explained in details in this chapter.

The initial population was seeded with Priority List solutions to obtain a faster and better convergence.

This algorithm was tested on a problem previously solved by other methods. Better results were obtained in a reasonable computation time even for large scale systems. This ability to handle large scale systems is important for actual and future power systems that will comport more and more units due to the restructuring of the power industry and the development of the distributed generation.

This technique can be adapted very easily to handle any sort of constraints through the modification of the penalty terms.

In the next chapter, the unit commitment solving method is adapted to the new deregulated environment and its use for the design of bidding strategies is explored.

Chapter 6 PROFIT-BASED BIDDING STRATEGIES

The UC solution technique developed in the previous chapter is here adapted to solve the less constrained problem in the deregulated environment. The new profit-based solution is then exploited to develop good bidding strategies in a competitive market.

6.1 Introduction

The unit commitment problem presented and solved in the previous chapter corresponds to the problem that generating companies encountered in the regulated market. To match the needs of today's companies the solution has to be adapted. Indeed, while the unit commitment problem still aims at optimizing the generation resources, the objective changed from satisfying load demand and security at least cost to maximising the generating company profit. Minimising the cost and maximising the profit are different problems since generation companies no longer have the obligation to satisfy the load demand and the profit is equal to the revenue minus the cost. Hence a generation company should generate energy only as long as the incremental revenue is larger than the incremental cost. Moreover security constraints are unbundled from energy and are provided and priced separately as ancillary services.

Load and security are not considered as hard constraints for the generating companies anymore. However, as consumers still need their load to be served and the ISO needs to ensure the system security, these constraints are reflected in the market prices for energy and ancillary services. As a result, the profit-based unit commitment formulation presented in the next section requires considering fewer constraints and the solution is driven by the market prices.

The profit-based unit commitment solution is useful to the generation companies to appreciate the contract opportunities in the competitive market. Contracts are obtained through bidding in the energy and ancillary services. As bidding efficiently is now an essential task for gencos, tools are needed to define and optimise their bidding strategy.

6.2 Profit-based Unit Commitment problem formulation

The objective of the profit based UC problem is to find the feasible combination of the generating units over the scheduling period that maximise the genco profit. This profit is equal to the revenue for the N units and for the T time intervals from the energy and reserve supply minus the generation cost TC defined in(5.1). Hence the objective function of the UC problem is

$$\text{maximise} \sum_{t=1}^{T}\sum_{i=1}^{N}\left[p_i(t)\cdot MCP_i^{energy}(t) + r_i(t)\cdot MCP^{reserve}(t)\right] - TC \tag{6.1}$$

where $MCP_i^{energy}(t)$ and $MCP^{reserve}(t)$ are the forecasts of the market clearing prices for energy and reserve for the period t. The market clearing price for energy is specific to the generator bus to include the influence of transmission constraints on prices.

Equality Constraint (5.6) that modeled the obligation to serve the load is changed to an inequality constraint. Indeed, the generating company should not produce more power than the expected demand.

$$\sum_{i=1}^{N_g} \mathrm{p_i} \leq \mathrm{P_{Load}} \tag{6.2}$$

Similarly, constraint (5.7) stating the obligation to provide reserve is suppressed.

Unit minimum and maximum output constraints are modified as follows to account for the dispatch of reserve

$$\begin{aligned} &\mathrm{p_i^{min}} \leq p_i(t) \\ &p_i(t) + r_i(t) \leq \mathrm{p_i^{max}} \end{aligned} \tag{6.3}$$

Finally, thermal units minimum up and down time constraints are kept unchanged.

6.3 Modifications to the priority list-based evolutionary algorithm to solve the profit-based unit commitment problem

The basic flowchart of the algorithm is still the same. Only minor changes have been made to some steps of procedure considering the objective function and modified constraints.

6.3.1 Priority list solution

Units are still connected in the ascending order of their per MW cost at maximum power output. However the procedure now stops when

$$\sum_{i=1}^{N_g} \mathrm{p^{max}}_{\mathrm{i}} \geq \mathrm{P_{Load}} \tag{6.4}$$

while we previously connected units until we obtained

$$\sum_{i=1}^{N_g} \mathrm{p^{max}}_{\mathrm{i}} \geq \mathrm{P_{Load}} + \mathrm{R_S} \tag{6.5}$$

Indeed, it is rather inefficient to connect a unit only to provide reserve (unless the price for reserve is very high). Similarly it could have been possible not to connect units that are running near their minimum output as the price paid for generation is not likely to compensate for the fixed costs. However, the priority list solution being only a rough estimate of the optimum solution and being evolved by the evolutionary algorithm, it has been chosen not to complicate the procedure.

6.3.2 Penalty cost computation

The load and minimum reserve requirements are not considered as hard constraints anymore and consequently do not contribute to the penalty cost anymore. Penalty costs are computed only if the minimum up and down time constraints are not satisfied.

6.3.3 Economic Dispatch procedure

The non obligation to serve load and reserve requirements also modify the economic dispatch procedure and the previously applied lambda-iteration method is no longer suitable to the problem.

For the same unit commitment, different dispatch solutions are possible to sell either more reserve or more energy. For instance, depending on the price of the two products, it could be more interesting to keep some capacity available to sell it as reserve if the energy price minus the incremental cost is lower than the reserve price.

Given a unit commitment solution, for each dispatch period, the economic dispatch problem is to find the optimal dispatch variables $p_i(t)$ and $r_i(t)$ for the committed units to maximise the profit defined as revenues minus costs:

$$\sum_{i \,\in\, \text{comitted units}}^{N} \left[p_i(t) \cdot MCP_i^{energy}(t) + r_i(t) \cdot MCP^{reserve}(t) - b_i \cdot p_i(t) - c_i \cdot p_i(t)^2 \right] \qquad (6.6)$$

$p_i(t)$ and $r_i(t)$ satisfying to the constraints (6.2) and (6.3).

This is a continuous and linearly constrained quadratic programming problem. It is implemented with the Ilog Cplex 8.1 Java interface and solved for each unit commitment solution (each chromosome) to allow the computation of the fitness function.

6.3.4 Fitness function

As the fitness function to minimise in chapter 5 was the cost plus the penalty term, we now have to minimise the penalty terms minus the profit. Hence the fitness function is:

$$\text{penalty function} - \sum_{t=1}^{T}\sum_{i=1}^{N}\left[p_i(t) \cdot MCP_i^{energy}(t) + r_i(t) \cdot MCP^{reserve}(t) \right] + TC \qquad (6.7)$$

The penalty function is computed by checking all the time constraints in the solution, while the revenues and costs are computed from the results of the economic dispatch and the forecasted market clearing prices.

6.4 Profit-based UC case study

Similarly to the algorithm presented in the last chapter, the profit-based unit commitment solution method is able to handle large scale problems, the results and computation times being similar to those in Chapter 5. A 10-units system is used in this section to investigate the results of the algorithm, as this system is small enough for the results to be presented in few pages, and large enough to highlight the performances of the method.

The profit-based unit commitment algorithm has been applied to the 10 units test system presented in section 5.6.1 except that load and reserve requirement were considered as upper limits. The generation company which owns the 10 generating units aims at maximising its profits in a competitive environment.

The impact on the generation schedule of energy prices, reserve prices, and the relative difference of these 2 prices were investigated.

Two cases are presented here:

Case 1: the market prices for energy and reserve were 100$/MWh at every periods of the schedule.

Case 2: the time varying market prices for energy and reserve were those given in Table 6.1 and Table 6.2.

Table 6.1 Market prices forecasts for energy

Period	Energy Price ($/MWh)							
1-8	17.42	17.48	17.53	20.68	22.10	22.30	22.43	22.86
9-16	26.19	34.75	36.21	39.13	33.81	22.59	22.25	21.24
17-24	21.09	21.95	22.5	31.5	26.54	22.14	20.48	20.18

Table 6.2 Market prices forecasts for reserve

Period	Reserve Price ($/MWh)							
1-8	0.01	0.05	0.03	1.04	2.5	2.1	2.2	2.4
9-16	7.51	7.18	13.54	13.87	8.62	2.5	2.1	1.87
17-24	1.85	2.6	5.27	11.48	6.25	1.84	0.18	0.15

Dispatch results of case 1 were obvious and, as expected, exactly the same results than the ones already reported in Table 5.5 were obtained, i.e. the whole load and reserve requirements were served. Since the prices are much higher than the generators' marginal costs, the more the generating company provides energy, the higher its profits. Similarly, the high prices for reserve incited the generating company to commit more units than needed for energy, so that it could sell reserve.

Dispatch results of the profit maximisation unit commitment for case 2 are presented in Table 6.3 to Table 6.5.

Table 6.3 Energy dispatch results for the profit-based UC

	1	2	3	4	5	6	7	8	9	10	11	12
Unit 1	455	455	455	455	455	455	455	455	455	455	455	455
Unit 2	245	295	387	455	390	455	455	455	455	455	455	455
Unit 3	0	0	0	0	0	0	0	130	130	130	130	130
Unit 4	0	0	0	0	130	130	130	130	130	130	130	130
Unit 5	0	0	0	0	25	60	67	30	92	162	162	162
Unit 6	0	0	0	0	0	0	0	0	20	43	40	80
Unit 7	0	0	0	0	0	0	0	0	0	25	25	25
Unit 8	0	0	0	0	0	0	0	0	0	0	10	10
Unit 9	0	0	0	0	0	0	0	0	0	0	0	10
Unit 10	0	0	0	0	0	0	0	0	0	0	0	0

Table 6.4 Energy dispatch results for the profit-based UC (continued)

	13	14	15	16	17	18	19	20	21	22	23	24
Unit 1	455	455	455	455	455	455	455	455	455	455	455	455
Unit 2	455	455	455	440	390	455	455	455	455	445	445	345
Unit 3	130	130	0	0	0	0	0	0	0	0	0	0
Unit 4	130	130	130	130	130	130	130	130	130	130	0	0
Unit 5	162	49	57	25	25	52	102	82	92	0	0	0
Unit 6	43	0	0	0	0	0	20	20	20	0	0	0
Unit 7	25	0	0	0	0	0	0	0	0	0	0	0
Unit 8	0	0	0	0	0	0	0	0	0	0	0	0
Unit 9	0	0	0	0	0	0	0	0	0	0	0	0
Unit 10	0	0	0	0	0	0	0	0	0	0	0	0

Table 6.5 Reserve dispatch results for the profit-based UC

Period	Reserve provided ($/MWh)							
1-8	70	75	68	0	100	102	95	120
9-16	130	97	145	150	97	113	105	105
17-24	100	110	120	140	130	0	10	80

These results highlight three features of the profit-based unit commitment solution: the impact of energy prices, the impact of reserve prices, and the trade-off between the dispatch of energy and reserve.

A comparison of the dispatch results in Table 6.3 and Table 6.4 with Table 5.5 shows that units that were running near their minimum output are not committed anymore for a lower price since the revenue does not compensate their costs. For instance at hour 3, generator 5 that was producing 25MW is not committed anymore since the expected energy price (17.53$) is lower than its marginal cost (19.80$). At hour 4, the expected price (20.68$) is larger than its marginal cost, but the benefit is not high enough to compensate for the fixed costs of the generator, hence the unit is still not committed.

However a generator can be committed even if the expected energy prices do not cover its costs if the reserve price is high enough to provide a sufficient pay-off. For instance unit 6 is dispatched from period 19 to 21 even if the revenues from the selling of energy do not cover its costs. The generator compensates by selling reserve at a high price

For many periods the generating company chose not to serve the whole load and reserve while it could serve the whole load or the whole reserve with the committed units. An arbitrage between energy and reserve was realised. At hour 3, the company chose to provide only 842MW for energy and 68MW for reserve while the demand and reserve requirements were 850MW and 85MW respectively. This trade-off between energy and reserve assured the maximum benefit. Unit 2 was dispatched at 387MW, its marginal cost was 17.50$/MWh. As the forecasted price was 17.53$, the marginal benefit for energy was 0.03$, which was equal to the marginal benefit for reserve.

As shown in Table 6.6, the profit maximisation algorithm allowed increasing the profit of 4.5%. The generation company should decide to produce only 83% of the reserve and 97% of the energy.

Table 6.6 Profit comparison

	Cost	Income	Profit	Energy supply	Reserve Provided
Traditional UC	563977	701960	137983	27100	2710
Profit max. UC	532477	676635	144158	26199	2262

6.5 Bidding strategies based on the UC solution

As seen in the last section, since the profit-based unit commitment optimises energy and reserve simultaneously, it allows discovering arbitrage opportunities between energy and ancillary services. This characteristic can be used to design a bidding strategy for a multi-round auction market. Multi-round auction markets allow market participants to progressively discover the market prices and to build their generation schedules and bidding offers based on this information.

6.5.1 Bidding curve design

The bidding curve has been built from the generation schedule obtained from the unit commitment as follows. We assume that p_{uc} and r_{uc} are the dispatch quantity for energy and reserve obtained from the unit commitment and generation schedule solution. The bid curve shown in Figure 6.1 has been obtained as follows:

- Bid p_{uc} at a price below the forecasted market clearing price
- Then bid the incremental cost curve for the quantity (p^{max}- p_{uc} - r_{uc})
- Last, bid the remaining quantity r_{uc} at the incremental cost plus the reserve price.

If the generating company bids follow this curve, it is not assured to be dispatched exactly according to its optimal generation schedule but it should at least obtain the same benefit.

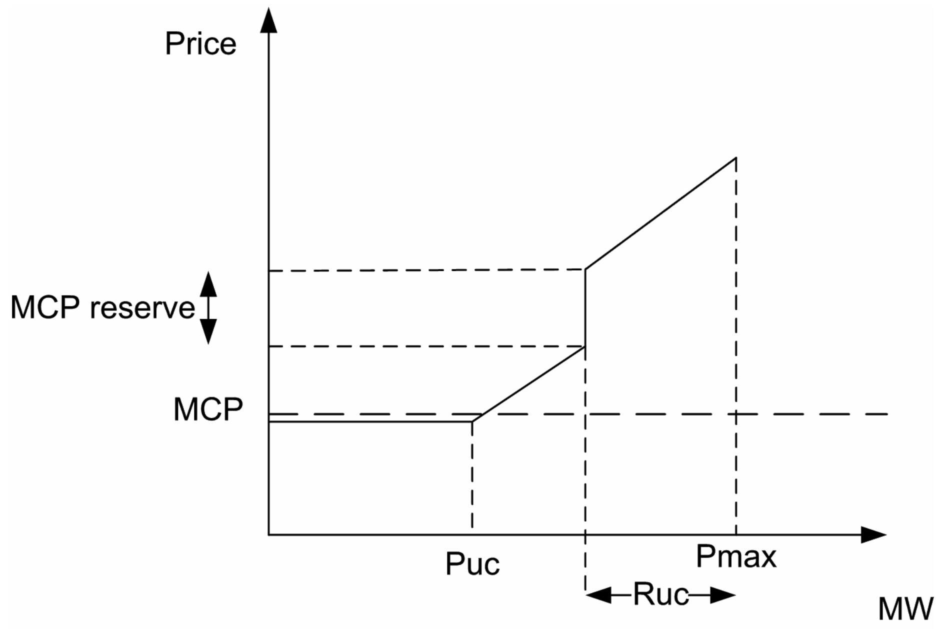

Figure 6.1: Energy bid curve

We obtained the reserve bid curve shown in Figure 6.2 similarly:

- Bid the quantity (p_{max}-p_{uc}) at a price below the forecasted market clearing price.
- Then bid the remaining quantity (p_{uc}-p_{min}) at the energy price minus the decremental energy cost curve.

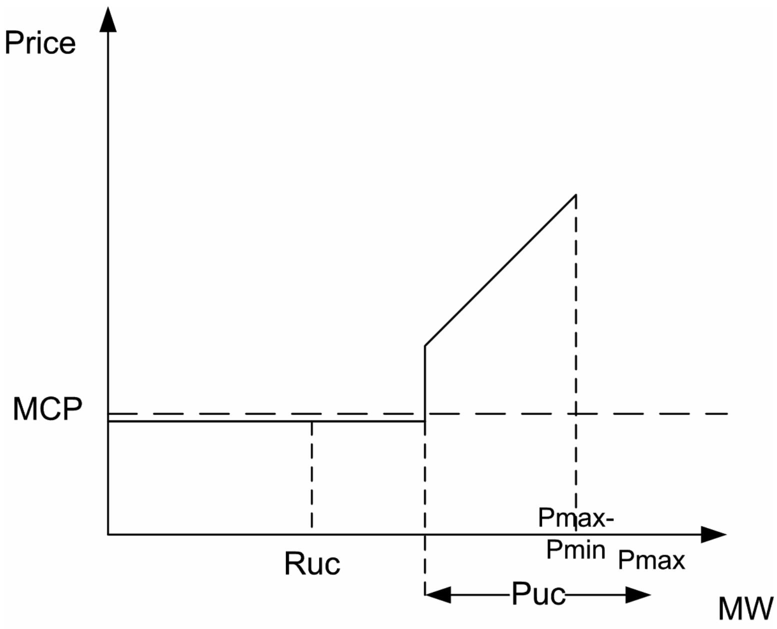

Figure 6.2: Reserve Bid Curve

6.6 Conclusion

In this chapter the new objectives of a generation company in a deregulated environment have been investigated. This investigation emphasizes the influence of the price factor in the unit commitment problem that now aims at maximising profits instead of minimising costs. The solution technique developed in the last chapter has been adapted to the new problem and simulations on a 10 units system have shown how the selling prices influence not only the unit commitment solution but also the dispatch of energy and reserve since the supplies of these 2 services are co-optimised.

A bidding strategy based on the unit commitment solution has been proposed and implemented in the genco agent of the multi-agent framework.

Chapter 7 MARKET SIMULATIONS AND RESULTS

In the previous chapters, a multi-agent based simulator for modelling the restructured energy market has been developed. The market structure of the Singapore New Electricity Market has been implemented in this simulator through a market clearing engine that optimises in real time the dispatch of reserve and energy while considering the impact of the transmission network. An efficient profit-based unit commitment solution method has also been developed and applied to the design of bidding strategies.

This chapter presents market simulations that make use of all the above mentioned developed modules. The performance of the market clearing engine is first explored on a 30-bus system. Competition between two generating companies is then simulated on a simpler system.

7.1 Simulations of the market clearing process

A modified IEEE 30-bus system represented in Figure 7.1 is used to illustrate the market clearing algorithm proposed in Chapter 4. Load distribution, transmission line data, and generators characteristics and bidding offers are given in Table 7.1, Table 7.2, and Table 7.3 respectively.

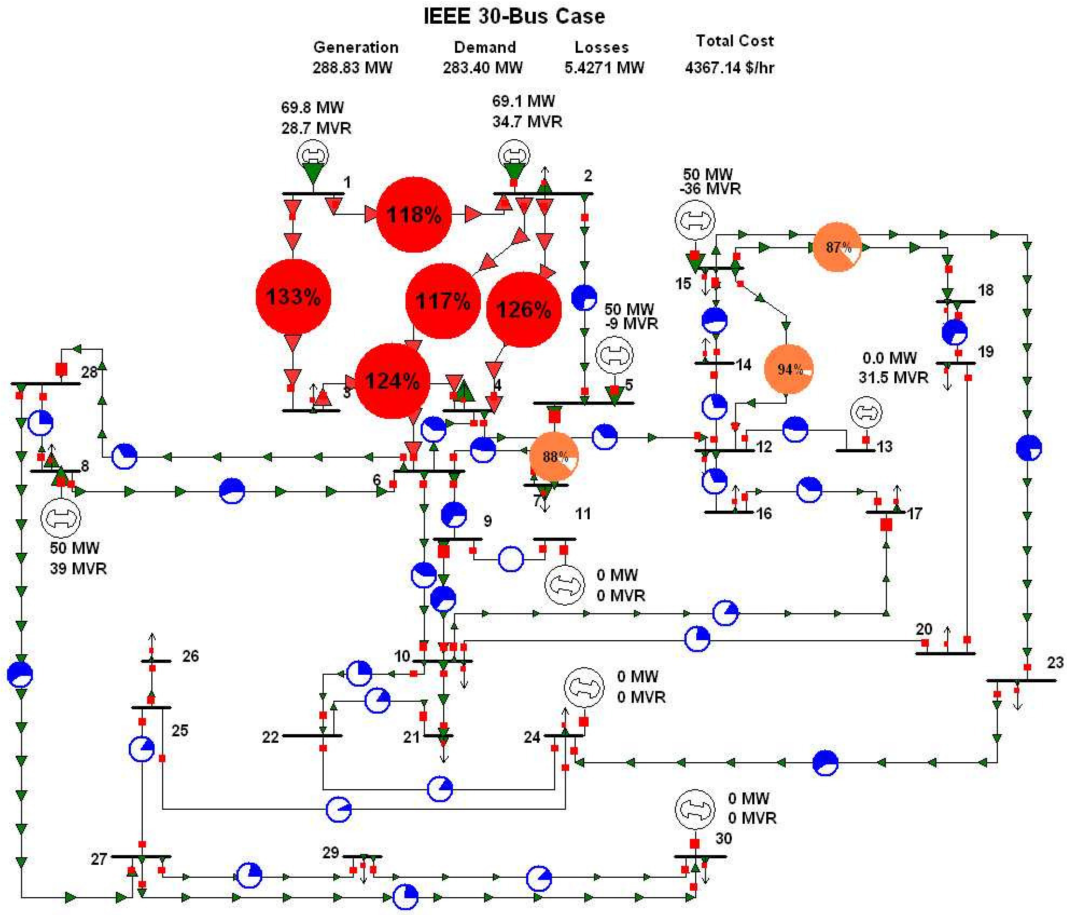

Figure 7.1 State of the system when the dispatch does not consider network constraints

Table 7.1 Load distribution

Bus	Load (MW)	Bus	Load (MW)
2	21.7	**17**	9
3	2.4	**18**	3.2
4	67.6	**19**	9.5
5	34.2	**20**	2.2
7	22.8	**21**	17.5
8	30	**23**	3.2
10	5.8	**24**	8.7
12	11.2	**26**	3.5
14	6.2	**29**	2.4
15	8.2	**30**	10.6
16	3.5		

Table 7.2 Transmission Lines data

Line No	From bus	To bus	R p.u.	X p.u.	Lim MVA	Line No	From bus	To bus	R p.u.	X p.u.	Lim MVA
1	1	2	0.0192	0.0575	30	22	12	13	0	0.14	65
2	1	3	0.0452	0.1852	30	23	12	14	0.1231	0.2559	32
3	2	4	0.057	0.1737	30	24	12	15	0.0662	0.1304	32
4	2	5	0.0472	0.1983	30	25	12	16	0.0945	0.1987	32
5	2	6	0.0581	0.1763	30	26	14	15	0.221	0.1997	16
6	3	4	0.0132	0.0379	30	27	15	18	0.1073	0.2185	16
7	4	6	0.0119	0.0414	30	28	15	23	0.1	0.202	16
8	4	12	0	0.256	65	29	16	17	0.0824	0.1923	16
9	5	7	0.046	0.116	30	30	18	19	0.0639	0.1292	16
10	6	7	0.0267	0.082	30	31	19	20	0.034	0.068	32
11	6	8	0.012	0.042	30	32	21	22	0.0116	0.0236	30
12	6	9	0	0.208	30	33	22	24	0.115	0.179	30
13	6	10	0	0.556	30	34	23	24	0.132	0.27	16
14	6	28	0.0169	0.0599	30	35	24	25	0.1885	0.3292	30
15	8	28	0.0636	0.2	30	36	25	26	0.2544	0.38	30
16	9	10	0	0.11	30	37	25	27	0.1093	0.2087	30
17	9	11	0	0.208	30	38	28	27	0	0.396	30
18	10	17	0.0324	0.0845	32	39	27	29	0.2198	0.4153	30
19	10	20	0.0936	0.209	32	40	27	30	0.3202	0.6027	30
20	10	21	0.0348	0.0749	30	41	29	30	0.2399	0.4533	30
21	10	22	0.0727	0.1499	30						

Table 7.3 Generators data and bidding offers

		Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Bus No		1	2	5	8	11	13	15	24	30
p_i^{min}		20	10	10	10	5	10	10	5	10
p_i^{max}		70	80	50	50	20	70	60	20	20
Energy Offer 1	Quantity	30	24	18	18	8	22	20	8	12
	Price	10.92	18.31	13.57	13.60	38.07	19.66	18.51	40.10	49.86
Energy Offer 2	Quantity	10	14	8	8	3	12	10	3	2
	Price	11.01	18.48	13.71	13.74	38.16	19.90	18.65	40.20	49.96
Energy Offer 3	Quantity	10	14	8	8	3	12	10	3	2
	Price	11.10	18.65	13.85	13.89	38.25	20.15	18.80	40.3	50.06
Energy Offer 4	Quantity	10	14	8	8	3	12	10	3	2
	Price	11.20	18.82	13.99	14.03	38.33	20.40	18.94	40.39	50.16
Energy Offer 5	Quantity	10	14	8	8	3	12	10	3	2
	Price	11.29	18.99	14.13	14.17	38.42	20.65	19.08	40.49	50.25
Reserve Offer	Quantity	10	10	10	10	10	10	10	10	10
	Price	1.1	1.05	0.95	1.9	3.0	2.0	1.5	1.6	2.2

Three cases have been simulated. In the first one, the energy and reserve dispatch were optimised but network constraints were not considered. The second case included the transmission constraints but there were no reserve requirements. Finally, in the last case energy and reserve dispatch, as well as transmission constraints were considered.

7.1.1 Energy and reserve dispatch without network constraints

In this first case, line flows were assumed to be unlimited, and losses were assumed to be constantly equal to 2% of the load. The dispatch for energy without reserve requirement (scenario 1.1) is shown in Table 7.4, while dispatch for reserve and energy when reserve requirements were equal to 10% of the load (scenario 1.2) are shown in Table 7.5.

Table 7.4 Energy dispatch without network constraints and without reserve requirements

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Energy dispatch	70	69.07	50	50	0	0	50	0	0
Energy nodal price	18.99	18.99	18.99	18.99	18.99	18.99	18.99	18.99	18.99

Table 7.5 Energy dispatch without network constraints, reserve requirements=10% of the load

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Energy dispatch	70	66	50	50	0	10	43.07	0	0
Energy nodal price	18.99	18.99	18.99	18.99	18.99	18.99	18.99	18.99	18.99
Reserve dispatch	0	10	0	0	0	8.34	10	0	0
Reserve price	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0

Scenario 1.1 corresponded to the simple market clearing process described in section 2.3.5. The energy price was set by the last accepted offer that belonged to generator 2. Only offers below the market clearing price were accepted. Consequently, generators 1, 3, and 4 had all their five energy offers accepted, generator 7 had only 4 of its offers accepted, and generator 2 had 4 of its offers accepted while its last offer

was only partially dispatched since this was the marginal bid. The cost of providing energy in this case was 4369.88$.

The dispatch for energy in scenario 1.2 was similar to the one in scenario 1.1, except that unit 6 was dispatched for energy even though its energy offer was higher than that of the marginal plant since the committed units of the first scenario couldn't provide the whole reserve. This was acceptable because there was no cheaper energy and reserve solution for the system as a whole. The reserve price received by unit 6 compensated for the shortfall between its energy offer price and the energy spot price. It is clear from the reserve dispatch quantities and prices in Table 7.5 that in this case, the market clearing process did not simply dispatch the resources when price was lower than the market clearing price. Since it optimised the dispatch of energy and reserve simultaneously, more expensive units could be dispatched for reserve if less expensive units were totally dispatched for energy, and thus not available for reserve. For instance generator 3 offered the lowest price for reserve but overall, it was cheaper to dispatch generator 3 for energy and to get the reserve from another unit. In this scenario, the cost of providing energy was 4376.93$ and the cost of reserve was 42.18$.

In these two scenarios the energy nodal price was the same at each node since the physical properties and constraints of the transmission system were not considered. This price was set by the offer of the marginal unit.

7.1.2 Energy dispatch with network constraints and without reserve requirements

As shown on the network diagram in Figure 7.1, the dispatch solution of Table 7.4 violated several line flow limits. After 6 iterations of the market clearing algorithm, the dispatch presented in Table 7.6 is obtained. As shown in Figure 7.2, all the line flows were then within the limits and the generation exactly balanced the demand and losses. The cost of providing energy was 4625.14$, which was higher than that of the case without network constraints since the generation had been redispatched in favour of more expensive units and one more unit had been committed to satisfy the line flow limits.

Energy nodal price differences arose due to transmission losses and physical limitations on the transmission system.

Table 7.6 Energy dispatch with network constraints, and without reserve requirements

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Energy dispatch	41.93	57.20	50	50	0	57.06	31.71	0	0
Energy nodal price	11.09	18.82	19.77	21.30	22.56	20.40	18.80	21.97	22.95

Energy nodal prices created price signals that encouraged market participant to relieve the congestion. Congestion on the transmission system was mainly due to generator 1, hence the lower energy price at bus 1 pushed the generating unit to produce less. Generation at bus 13 by generator 6 helped to relieve the congestion hence the energy price at bus 13 was higher.

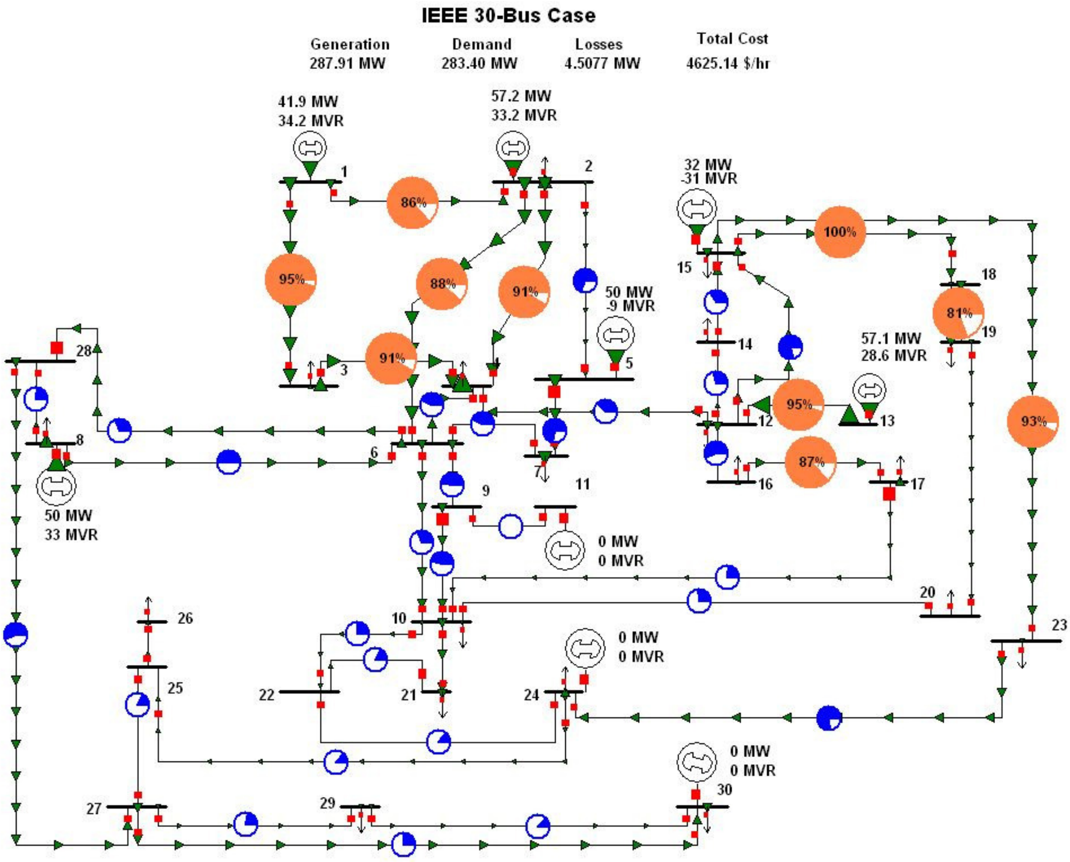

Figure 7.2 State of the system after congestion management

7.1.3 Energy and reserve dispatch with network constraints

The energy and reserve dispatch with network constraints and reserve requirements equal to 10% of the load are given in Table 7.7. The energy dispatch was the same as the case without the reserve requirements since committed units had enough reserve to fulfil the requirements, and no other unit proposed a price for reserve low enough to justify its commitment. The total cost of providing reserve and energy is 4662.93$.

Table 7.7 Energy dispatch with network constraints, reserve requirements=10% of the load

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Energy dispatch	41.93	57.20	50	50	0	57.06	31.71	0	0
Energy nodal price	11.09	18.82	19.77	21.30	22.56	20.40	18.80	21.97	22.95
Reserve dispatch	10	10	0	0	0	8.34	0	0	0
Reserve price	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0

It has then been assumed that, due to congestion, the ISO established two zones as shown in Figure 7.3. Generators could only provide reserve for their own zone, since congestion on the transmission system could prevent more energy exchanges between the two zones. Each zone had a reserve requirement equal to 10% of its own load.

Dispatch results are presented in Figure 7.3 and Table 7.8. The cost of energy is 4712.80$, and the cost of reserve is 34.06$, resulting in a total cost of 4746.86$, that is higher than the previous case. The market clearing prices for reserve are different in the 2 zones. Unit 8 has been dispatched to provide energy even if its offer price is higher than the MCP so that it is available to provide reserve.

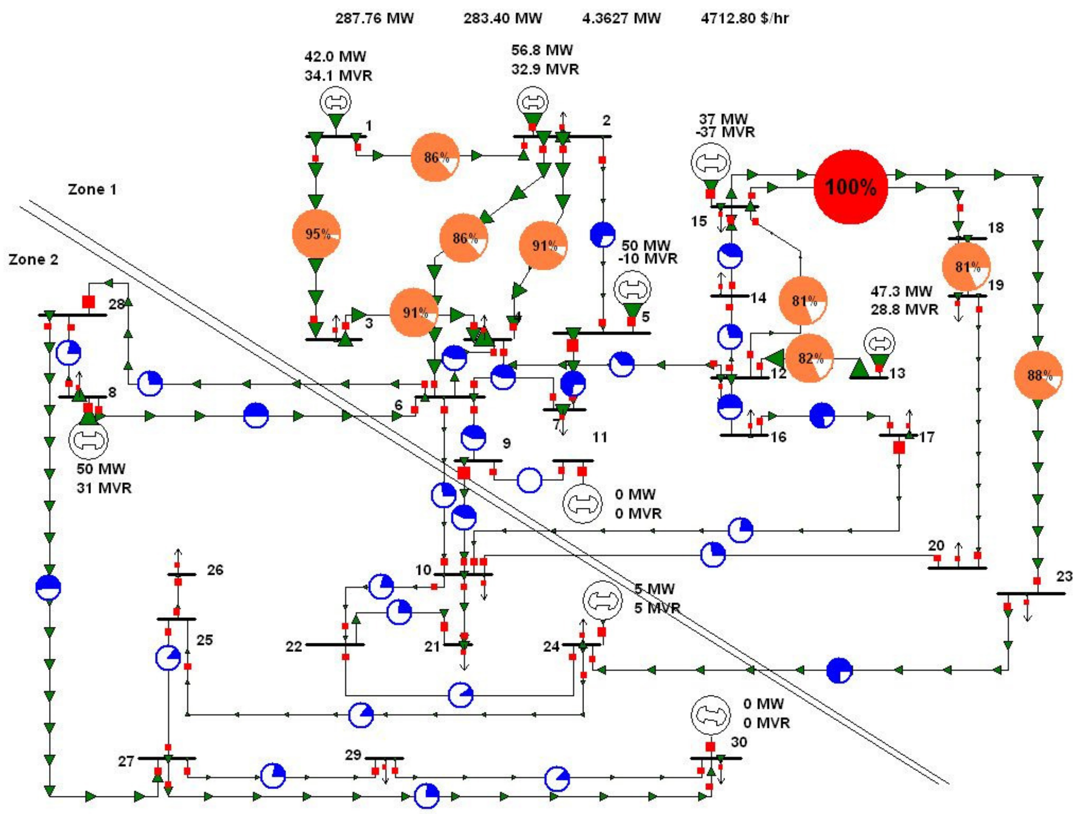

Figure 7.3 the system is divided in 2 zones for the reserve market

Table 7.8 Energy dispatch with network constraints, reserve=10% of the load in each zone

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9
Energy dispatch	41.99	56.79	50	50	0	47.27	36.70	5	0
Energy nodal price	11.10	18.82	19.68	21.11	22.33	20.40	18.80	21.58	22.88
Reserve dispatch	10	10	0	0	0	0	0.49	7.85	0
Reserve price	1.5	1.5	1.5	1.6	1.5	1.5	1.5	1.6	1.6

7.2 Market competition simulation for energy and reserve

The efficiency of the market simulations have been demonstrated in the previous section on a 30-bus system since the market clearing engine was able to compute the optimal dispatch and agents have been able to communicate either to submit offers or to inform of the dispatch results.

The simulation platform has then been used to simulate the market competition between two generating companies competing for the supply of energy and reserve. Each generation company owned two units and made use of the unit commitment algorithm introduced in Chapter 5 and adapted to the profit maximisation problem in Chapter 6, to optimise its generation schedule and to define its bidding strategy.

The simulation results presented here only consider one time period. Consequently the unit commitment solution is trivial but the efficiency of the different methods and algorithms has been demonstrated in the previous chapters; the focus here is to run an easy to understand simulation that highlights the basic functionalities of the comprehensive simulator that has been built.

The 2 bus power system used for the simulation is represented in Figure 7.4. The system has been kept simple in order to make results clearer. Simulations on a larger system have been carried out and presented in the previous section.

Three scenarios were explored. The first two cases did not consider any line flow limit. In the first scenario, the two generating companies competed only for energy while in the second one, they also competed for reserve. The last scenario considered line flow limit in a competitive market for energy and reserve.

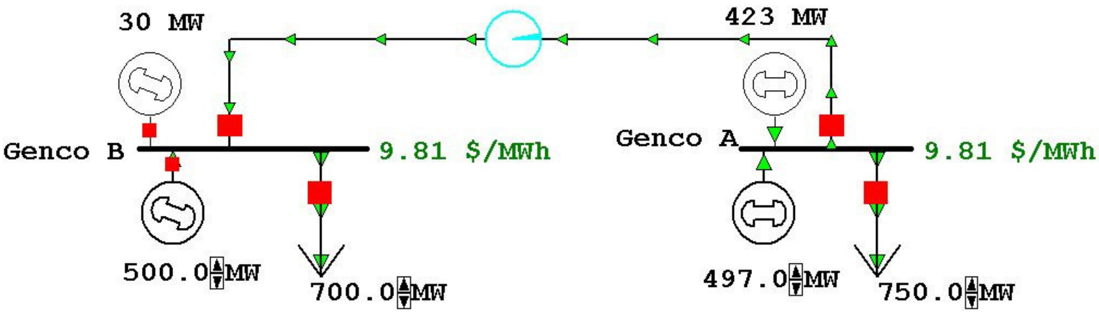

Figure 7.4 2-bus test system

Generation units' characteristics are given in Table 7.9.

Table 7.9 Units' characteristics

	Genco A		Genco B	
	Unit 1	Unit 2	Unit 3	Unit 4
Cost coefficient b	7.82	7.7	9.9	7.7
Cost coefficient c	0.002	0.0025	0.0025	0.002
p_i^{min}	30	30	30	30
p_i^{max}	500	500	500	500

In the first scenario, the 2 gencos competed only for energy; there was no reserve to provide in the market. After few rounds of auction, the market clearing prices and quantities converged. The dispatch results and market price are presented in Table 7.10. As there were no transmission constraints in this case, the market prices were the same at each node and only generators whose marginal cost was lower than the market prices were dispatched.

Table 7.10 Disptach results without reserve

	Genco A		Genco B	
	Unit 1	Unit 2	Unit 3	Unit 4
Energy dispatch	500	450	0	500
Energy price	9.95	9.95	9.95	9.95

In the second scenario, the reserve market was considered. Reserve requirements were 150MW for the whole system. Once again the gaming of the 2 players converged in few iterations and the results in Table 7.11 were obtained.

Table 7.11 Dispatch results with reserve

	Genco A		Genco B	
	Unit 1	Unit 2	Unit 3	Unit 4
Energy dispatch	500	420	30	500
Energy price	9.84	9.84	9.84	9.84
Reserve dispatch	0	80	70	0
Reserve price	0.04	0.04	0.04	0.04

Unit 3 was dispatched at its minimum output even if its marginal cost (and its bidding offer) was higher than the market price so that it was available to provide reserve. The loss of energy is compensated by the revenue from the reserves. The 3 units dispatched in the previous scenario couldn't serve the whole load and reserve because of the units' limits.

For the last scenario, a 60MW line flow limit has been imposed on the transmission line between the 2 buses.

Table 7.12 Dispatch results with reserve and transmission line limit

	Genco A		Genco B	
	Unit 1	Unit 2	Unit 3	Unit 4
Energy dispatch	436	374	140	500
Energy price	9.56	9.56	10.06	10.06
Reserve dispatch	0	75	75	0
Reserve price	0.01	0.01	0.01	0.01

Dispatch results are given in Table 7.12. The transmission constraint caused an energy nodal price difference between the 2 generation buses and the genco A decreased its offer. Since units 2 and 3 were both available to provide reserve and receive enough pay-off from their energy bids, they both bid for reserve at the minimum price.

7.3 Conclusion

The different modules developed in this thesis have been incorporated in the multi-agent based simulator to model the electricity market and its participants. The rules and the structure of the Singapore New Electricity Market have been used for the implementation.

The simulator proved to be efficient since communication and interactions between the market participants were achieved.

Implementation of the Singapore market structure and rules has been successful, with the market clearing engine managing to optimise the dispatch of energy and reserve in a constrained power system.

Finally, competition between two agents to sell energy and reserve has been simulated. Results similar to an OPF solution have been obtained. Consequently we can affirm that the genco agents perform efficiently.

Chapter 8 CONCLUSION

In this thesis, several issues related to the deregulated electricity market have been addressed and incorporated in a comprehensive electricity market simulator that models the restructured energy market and its participants using a multi agent approach. The multi agent modelling capabilities are especially well adapted to effectively model such a market with its many participants spread over wide geographical areas, and the need for coordination associated to the policies of independent participants. A distributed multi agent system framework has been successfully implemented to model the restructured electricity market and its participants, as well as their communications and interactions.

The rules of the Singapore Electricity market have been implemented in this framework and the resulting system is able to simulate in real time the spot market for trading energy and reserve. The market clearing engine that solves the spot market based on participants bidding offers uses a full network model to represent the physical system and to consider the transmission constraints.

The behaviour of the generation companies has also been modelled through the design of an efficient evolutionary algorithm to solve the unit commitment problem. This algorithm has first been implemented, tested and compared to other techniques considering the problem faced by a generation company in the regulated industry. The algorithm has then been adapted to the need of a Genco in the deregulated environment and has been used as a supportive tool to design simultaneous and optimised bidding strategies for energy and reserve.

Last, an optimisation and power flow software have been interfaced with our Java simulator using the COM technology to give the agents access to efficient decision supportive computational tools.

The possible applications and uses of the developed simulator and tools are numerous. This is especially true with the implementation of the Singapore market structure since the actual deregulated New Electricity Market (NEM) started its operation in 2003 and as a recent structure it is still evolving, it has not attained its maturity and its rules must accordingly be adapted and improved. The market simulator developed in this thesis can help to design new rules for the market. Particularly three major applications can be considered: consumer bidding, financial transmission rights, and emission allowances.

The Singapore transmission system knows few instances of constraints that will impact the nodal prices. It has therefore been decided not to disadvantage consumers due to their location when it happens and that's why buyers pay a uniform overall average price. Consequently, there is actually no consumer bidding for energy in the Singapore NEM. Load for each period is estimated by the market operator based on information provided by the system operator. However in many other markets all over the world, load side bidding has been seen as a really efficient way to mitigate market power. Moreover, in the future, depending on the evolution of the transmission system, the load demand, and policy, nodal pricing could be considered for load, and demand-side bidding could be introduced in the market. Simulations of the demand-side bidding influence on the market can be a precious tool to appreciate the opportunity to implement it.

As supply and demand grows, and depending on the expansion of the transmission system, prices at various nodes may begin to diverge. Generators may then wish to take nodal price differences into consideration when offering plant to the system. A form of financial hedging contract, called a financial transmission right (FTR), can be used to manage volatility in prices between nodes. FTR are contracts between the transmission system operator and market participants that lock in nodal price differentials. They can be used to compensate a generator if the generator is denied access to the market because of a transmission constraint exacerbated by the actions of another participant. Provision has been made for FTRs in the Singapore market rules, but it is not available yet. The implementation of FTR in the market simulator can be study as a congestion management method. The trade of FTR could take place in a specific competitive market, or it could be interesting to make use of the communication and collaboration possibilities between agents offered by the multi-agent framework to solve this problem.

Similarly the multi-agent framework could be used as a trading platform for emission allowances. In accordance with the emission allowance trading program implemented in the US, the environmental protection agency distributes a limited number of emission allowances to power generating plants and requires plants to hold enough allowances to cover their emissions in each year. To clarify, each allowance covers one ton of SO_2 emissions and can be used in its designated year or later years. The core element of the emission allowance system is that the overall cost of meeting the mandated emission cut is determined by market forces. While market forces induce trading which allows multiple power generation units of different utilities to take advantage of economies of scale in emission control, competition among the range of compliance options drives down the cost of each one. The market provides a financial reward to those who can devise new ways to cut pollution at a lower cost.

The implemented market clearing engine, while already considering many system constraints, can be further improved to include all the constraints considered in a real market. For instance the resulting dispatch should fulfil the units' ramping rate constraints. Contingency constraints have not been considered in this thesis either; it is possible to include an n-1 contingencies rule while ensuring the transmission line flow limit.

The developed market simulator is an efficient tool to study the Singapore electricity market, to optimise participants' behaviours, and to carry simulations to design its future. However it is generic enough in its design to allow the implementation of other market structures, the platform, the communication technology and the wrapped in tools being the same.

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Appendix A MULTI-AGENT SYSTEMS

Modelling of complex structures such as the restructured energy market, and the design of autonomous, intelligent, and efficient agents, require the use of artificial intelligence technology. In this thesis, multi-agent technology is investigated to model the market structure, while an evolutionary computation solution to the generation scheduling problem is explored. The basic backgrounds of these two techniques are presented in these appendices.

A.1 Introduction

The current trend in software engineering methodology to build software system is the object oriented methodology. Its ability to structure data based on inheritance and composition structures, the reusability property of objects, and its ability to account for the generic characteristic of behaviours or concepts, make it very attractive for software implementation.

Another requirement of today's software engineering is to account for the distributed nature of data, processing power, and computer systems. Computer systems are more and more complex, including large numbers of different subsystems with numerous functionalities, interacting with each other and distributed over the physical space. Each of these subsystems has only a partial view of the whole system, and subsystems need to be coordinated efficiently.

Not only the computer systems are distributed but the problems to be solved are also often physically distributed over a wide area; solving a problem includes considering many heterogeneous functions that require a large number of experts in different domains, coordinating their knowledge and their local view of the problem to reach a global solution.

Multi-agent systems can be seen as an extension of the object oriented technology, accounting for the distributed nature of systems and problems, agents being active objects that are used to model parts of a real-world system, which operate independently and interact with each other. That's why it is believed that software engineering methodology of tomorrow should be 'agent-oriented' as that of today is 'object-oriented' [65][65].

A.2 Agent's definition

A.2.1 Agent's Characteristics

Intelligent agents are software entities that carry out some set of operations on behalf of a user or another program with some degree of independence or autonomy, and in so doing, employ some knowledge or representation of the user's goals or desires

Intelligent agents continuously perform three functions: perception of dynamic conditions in the environment; reasoning to interpret perceptions, solve problems, draw inferences; and determine actions.

These agents communicate by sending messages to other agents with the intent of requesting and delivering services or information. Agents control their actions and are able to take decisions, they can take initiative without human intervention, aim for a goal or react to state changes, and they are able to interact with other agents.

There are different types of agent corresponding to different approaches: Some agents perform tasks individually ... others need to work together; some are mobile ...

some static; some communicate via messages ... others do not communicate at all; Some learn and adapt ... others do not.

Despite this diversity, we can identify some common properties that differentiate them from conventional programs; an agent can be define through the following keywords: action, autonomy, communication, adaptation, and perception [65][66],as detailed below.

First, agents are capable of acting in an environment; hence they are going to modify their environment and thus their future decision making. This is a fundamental difference with classic artificial intelligence since agents are no longer ‘thinkers’ sealed within their own reasoning, and ignorant of their environment, but they constitute veritable societies of beings which plan, communicate, perceive, act and react. Reasoning is followed by action.

Secondly, an agent exercises a certain degree of autonomy in its operation. Its actions are not controlled by the user but by itself trying to achieve its individual goals. It acts on behalf of the user.

Another important feature is the capacity to communicate and collaborate. An agent should be able to engage in complex communications with other agents, including human agents, in order to obtain information or request for their help in accomplishing its goals. Communication allows collaboration and exchange of information between agents in the environment to improve the decision making quality of each agent.

Agents are also capable of adaptation, responding to changes in the environment.

Finally agents are capable of perceiving their environment (usually only a part of it) and to model it.

A.2.2 The Different types of agent [71]

A.2.2.1 Collaborative agents

Collaborative agents are modular, for instance they can be interface, task and information agents. They negotiate in order to resolve conflicts (e.g., meeting time). Some of them also collaborate to integrate information.

This type of agent provides solutions to inherently distributed problems as air traffic control or telecommunications network management.

A.2.2.2 Interface agents

Interface agents support and provide assistance; they cooperate with the user in accomplishing some task in an application. Interface agents can learn by observing and imitating the user (from user), through receiving feedback from the user, by receiving explicit instructions, or by asking other agents for advice (from peers).

A.2.2.3 Reactive agents

Reactive agents do not have internal symbolic models; they act by stimulus-response to the current state of the environment. Each reactive agent is simple and interacts with others in a basic way. However, complex patterns of behaviour emerge from their interaction. These are robust and fast responsive agents.

A.2.2.4 Information agents

Information agents manage the explosive growth of information, manipulating or collating information from many distributed sources.

A.3 The different models of Agency [72]

A.3.1 Rational agency

A rational agency can be logical or economic. A logical rational agency is characterised by the constituency of beliefs and the suitability of actions given beliefs and intentions (e.g.: Knowledge-based inference systems).

In an economic rational agency, agent holds preferences over world states and selects actions that result in maximizing its preferences. The decisions may be made with complete knowledge, or partial uncertainty. Rational agents might negotiate deals among themselves.

A.3.2 Social agency

Social agency is characterised by the cooperation, competition, or coordination between agents; Agents might make social commitments with other agents and work to achieve common objectives.

A.3.3 Interactive agency

Agents might interact with each other through intended or unintended interactions; Intended interactions involve communication among agents, e.g., by means of a shared language (syntax, semantics, pragmatics).

A.3.4 Adaptive Agency

Agents learn by interacting with their environment (which might include other agents).

A.3.5 Evolving Agency

While individual agents may or may not learn or adapt, self-replicating agent populations adapt to their environments through evolution

A.4 Inter-agent Communication

Communication among homogeneous agents in narrow, precisely defined domains (e.g., distributed routing in communication networks) is relatively straightforward to handle using suitably defined protocols with precisely specified syntax and semantics.

Communication among heterogeneous agents in open information systems or collaborative problem solving environments is much more challenging. Effective communication requires:

- Shared knowledge of syntax,
- Shared understanding of semantics and pragmatics,
- Some means of exchanging sentences (or even signs or symbols) to communicate.

Therefore an Agents' Communication Language (ACL) has to be designed to define:

- A common protocol, Knowledge Query Manipulation Language (KQML), for messages that reflect an agent's attitude about the content that is being carried. KQML is based on the theory of speech acts and supports a collection of performatives such as ask-if, tell, achieve, reply, etc.
- A common interchange format, Knowledge Interchange Format (KIF) as a means of representing and encoding knowledge
- A set of ontologies for various domains that describe concepts and their relationship.

A.5 Multi-agent systems and their applications

Multi-Agent System (MAS) is a way to artificially reproduce real life system through a model made of autonomous, independent and interacting agent objects.

Agent technology is one of the most important emerging technologies in computer science and has been successfully applied to many fields as commodity markets, traffic control simulation, robotics, field combat simulations, ecological simulations, videogames, and many more.

In particular, multi-agent systems allow having a new insight in the field of theoretical or real models simulations since it makes it possible to study individual behaviours and to link them to observations at the macro level. Indeed, most collective phenomena are the result of a set of decisions taken by individuals who take into account the behaviours of other actors in the system; hence there is a need to account for phenomena emerging from interaction of individual behaviours.

Apart from the simulation point of view, agent technology is widely used to assist or replace humans in various tasks now too complex in the era of information explosion and globalisation. The necessity for efficient and quick decision taking processes in the increasing global competition requires the assistance of intelligent system. In the business field they will be used to deal with competition, markets and customers, while in the manufacturing field they will help for the optimisation of processes.

To attain the state of an autonomous, acting, and communicating entity, agents should be gifted with some intelligence capacities. Artificial intelligence is a very prolific field in today's engineering and many techniques have been developed. This thesis investigates more particularly the use of evolutionary computation.

Appendix B EVOLUTIONARY COMPUTATION

To attain the state of an autonomous, acting, and communicating entity, agents should be gifted with some intelligence capacities. Artificial intelligence is a very prolific field in today's engineering and many techniques have been developed. This thesis investigates more particularly the use of evolutionary computation.

B.1 Introduction

The idea of using evolution as an optimization technique for engineering problems goes back to the 1960's. Since then, using the metaphor of natural selection and genetics proved to be a very efficient search and optimization technique. The main characteristic of evolutionary algorithms is the intensive use of randomness and genetics-inspired operations to evolve a set of candidate solutions. Basically, a mapping is done between the problem solving and a simple model of evolution: the evolving population represents a set of solutions for the problem, each individual in the population being a candidate solution; a fitness that represents the quality of the solution is associated with each individual; the environment the population is evolving into represents the problem characteristics [69].

Different evolutionary computation models have been developed at this time [68][69][70]: the genetic algorithms, evolutions strategies and evolutionary programming.

In the early 60's, John Holland developed the Genetic Algorithms. Simple biological models based on the notion of survival of the fittest were considered to design robust adaptive systems. Holland's method evolves a population of chromosomes. The chromosomes are binary strings and the search operations are crossover, mutation and inversion. The chromosomes are evaluated by using a fitness function.

An alternative approach to simulating evolution was adopted by Rechenberg and Schwefel. This model, traditionally named Evolution Strategies, emphasizes the behavioural link between parents and offspring, or between reproductive population, rather than the genetic link. The method focuses on building systems capable of solving difficult real-valued parameter optimization problems. The natural representation is a vector of real-valued genes that are manipulated primarily by the mutation operator. Mutation perturbs the solution vector in various useful ways.

Evolutionary Programming was devised by L.J. Fogel in 1962 as an attempt to simulate intelligent behaviour by means of finite-state machines.

Many advantages are usually recognized to evolutionary algorithms. In particular, they can solve a wide range of problem; they search from a set of solutions and not from a single solution; they are not derivative-based; they can work with discrete and continuous parameters; they explore and exploit the parameter space; and they have low development and application costs. More over, they can easily be incorporated into other methods or incorporate other method solution and also provide many alternative solutions to the problem.

However, they also have some disadvantages compared to other techniques since there is no guarantee for optimal solution within finite time, the theoretical basis is weak, they are often computationally expensive, and good performance generally requires a fine and long process of parameters tuning.

B.2 Description of a genetic algorithm

A genetic algorithm involves randomly generating a population of solutions, measuring their suitability or *fitness*, selecting the better solutions for breeding which produces a new population. The process is repeated to guide a highly exploratory search through a coding of a parameter space, and gradually the population evolves towards the solution. GAs are based on the heuristic assumptions that the best solutions will be found in regions of the parameter space containing a relatively high proportion of good solutions and that these regions can be explored by the genetic operators of selection, crossover, and mutation [73].

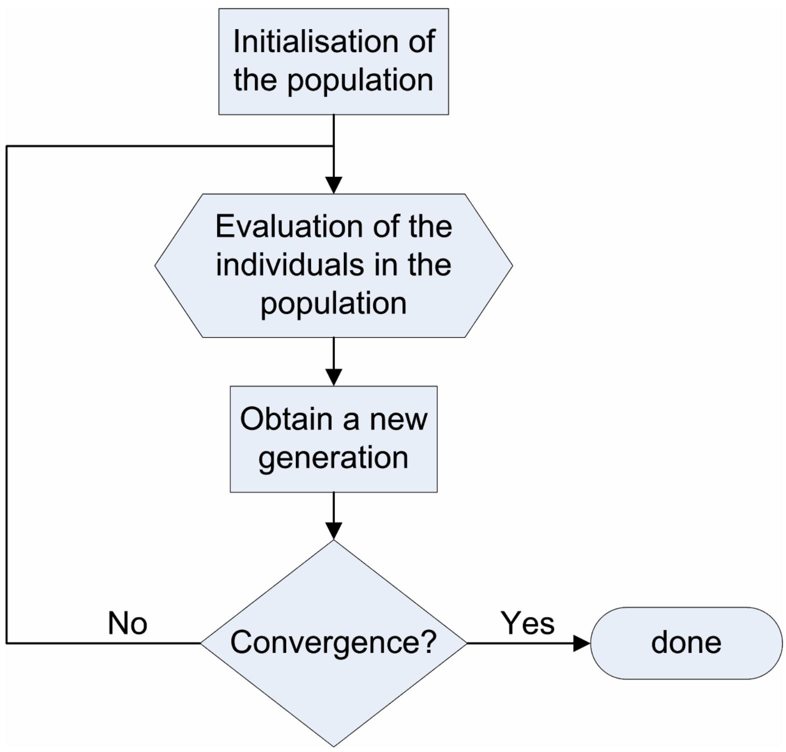

Figure B.1: General evolutionary algorithm

A general evolutionary algorithm may be outlined as an iterative procedure as exposed in Figure B.1. A set of candidate solutions (the population) is first randomly created.

Then the GA will produce new sets of solution from the previous ones. Successive populations are called generations. New generations are obtained through a process of evaluation, selection, and the use of search operators.

Every evolutionary algorithm shares this basic structure; however they differ from each other through a wide set of components including the representation scheme of potential solutions, the evaluation mechanism, the search operators, the selection strategy, and the environmental selection.

B.3 Representation scheme

The search is generally not performed directly in the solution space, but rather in the representation space. Each candidate solution is represented as an individual (or chromosome) of a population. Therefore, an individual encodes (or represents) a point in the search space of a given problem. Deciding on a good representation is fundamental to the performance of evolutionary computing techniques. The algorithms work on numbers but we are trying to design a solution to a physical problem. The choice of the representation scheme will decide the size of the representation space and therefore the complexity of the problem.

B.4 Selection strategy

The selection operator involves choosing the candidate solutions among the current population that will be used to produce the next generation. Individuals are generally selected according to their relative fitness in the population; a good solution is likely to be selected for breeding or to be kept unchanged in the next generation, while a bad solution is likely to be discarded. The selection operator can be implemented in different ways, the more common being the roulette wheel selection. According to this technique, individuals are selected with a probability directly proportional to their fitness. The probability P_i of the individual i to be selected is:

$$P_i = \frac{Fitness_i}{\sum_{k=1}^{N} Fitness_k} \tag{0.1}$$

where $Fitness_k$ is the fitness of individual k and N is the number of individuals in the population.

However, the roulette wheel selection method can cause the far largest share of offspring to be given to a small group of highly fit individuals and then cause a too quick convergence.

Other methods, as the ranking selection can avoid this problem. Solutions are selected for reproduction according to a probability proportional to their rank. Thus a fitter solution had more descendants but a less fit solution still had a chance to reproduce even if its fitness was far lower.

Other frequently used techniques include the tournament selection. The population is divided into random tournaments and the fittest individual of each tournament is selected.

B.5 Search operators

The main search operators are recombination (cross-over) and mutation. The recombination operator is used to create new individuals by combining the genetic information of two parents or more. The mutation operator generates new individuals by variations of a single individual. Many other generic or problem specific operators have been developed and new ones can be helpful to design an efficient evolutionary algorithm.

B.5.1 Cross-over operator

The cross-over operator allows the creation of two new solutions from the information provided by two individuals, called parents. Portions of the parents' strings are exchanged with a probability determined by the cross-over rate. There are different methods to select the information to be exchanged. With a single point cross-over, the information following a randomly chosen cross-over point is exchanged between the two strings. With a two points cross-over, the information between two randomly chosen cross-over points is exchanged as shown Figure B.2 to produce two new solutions.

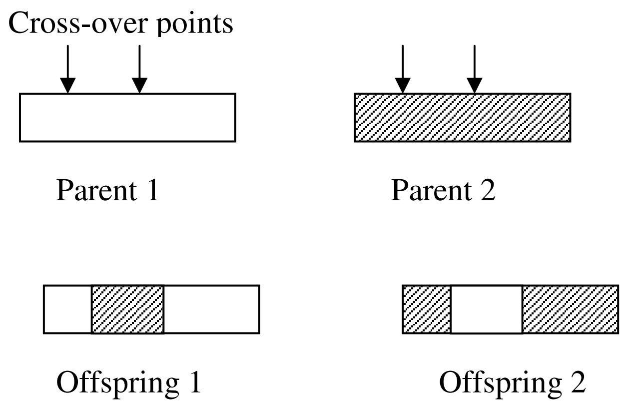

Figure B.2: 2 parents' genotypes are recombined by a 2 points cross-over.

No new material is introduced during the cross-over process. New individuals incorporate genetic material from their two parents.

B.5.2 Mutation operator

To introduce innovation and diversity in the population, the mutation operator is used. Bits of the chromosomes (the mutation points) are randomly chosen and inversed with a probability determined by the mutation rate as shown in Figure B.3.

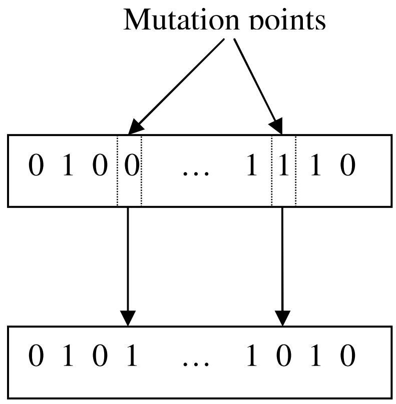

Figure B.3: Mutation: selected bits of the chromosome are inversed.

Mutation operator allows to explore new areas of the solution space or to make a local search around a given solution.

Typical mutation rates are in the order of $\dfrac{1}{\text{length of the chromosome}}$. However during the GA process, the need for mutation is not constant. Therefore, variable mutation rate are often introduced to improve the algorithm's performances.