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# Optimal investment portfolio management with hierarchical control for energy markets: An hierarchical control approach for smart grids


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# Optimal investment portfolio management with hierarchical control for energy markets: An hierarchical control approach for smart grids

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Esta tesis está dedicada a todas las personas que han estado conmigo a lo largo de proceso de formación académica, especialmente mi señora madre y a mi director. Este es el resultado de un proceso de formacion y personal que involucró muchas personas, lugares y experiencias y que dejan no solo un aporte académico sino que también (espero) una mejor persona.
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"We make a living by what we get. We make a life by what we give."

Winston S. Churchill

# Abstract

In the energy supply-demand chain, the connection between generators and load is generally performed by energy retailing companies. As such, they must fulfill the agreements and obligations signed with their customers by acquiring energy from generation companies and delivering it to the purchasers with quality and efficiency. In an ideal scenario, the retailer can maximize its operation's returns by monitoring energy demand and prices, buying the energy at the lowest available price and providing the exact amount of energy a given client will consume. However, it is a fact that power system dynamics are too complex, especially in recent years, when the implementation of smart grid technologies (such as: renewable and green energy generation, policies to decrease $CO_2$ emissions and small distributed generators, among others) has increased. Therefore, power system dynamics and the tools customarily used for power system planning and operation are becoming inefficient. As a result, it has become necessary to deal with several technical, financial and exogenous variables that may have different models and scales in order to improve energy retail performance; which, in turn, creates the need to propose new models, tools and management strategies to face the challenges of the emerging power system.

Traditionally, energy retailers reduce operation uncertainties by making use of hedging strategies and energy portfolio diversification. These strategies require the trade of medium and long term energy assets. The use of assets such as energy derivatives or generation investments helps retailers reduce energy price uncertainties but, at the same time, introduces additional costs that must be considered in the retailer's cash flow. In the short term operation and planning process, spot market is an additional instrument used to buy the energy required to meet inelastic demand or to sell energy excess. Short term portfolio is considered to be in charge of the market clearing process. Thus, a short term operation is the realization of the assumptions made within the management strategy design, and is reflected as positive or negative profits compared with previous cash flow expectations. Subsequently, tackling the issues of the inclusion of new retailer hedging strategy dynamics, it becomes increasingly relevant to update traditional management methodologies to meet future power system requirements and maximize operational returns.
Making use of tools widely used for dynamic problems with high uncertainty levels, constraints and mixed time scales, this thesis proposes a new energy retailer management strategy. Considering system load dynamics, a methodology for an optimal generation plan expansion with technical constraints is used to design a generation matrix; with this result, a medium and long term generation investment plan is obtained, including an expected system operation schedule. The designed generation expansion plan provides technical operation parameters that allow for the safe inclusion

of certain amounts of non conventional generation in the operation. Thereupon, future incomes and expenses related to planned generation are used to estimate energy prices while providing the expected energy retailer cash flow. Lastly, from the expected cash flow, a generation budget is provided to the short term portfolio. This budget is used as economic constraint in the short term optimization. In turn, this optimization is in charge of managing the joint operation of: generation plants, alternative generation and energy assets (spot market and forward agreements), to perform feasible market clearing. The market clearing process is made minimizing the operation costs with a dynamic optimization, the obtained short term returns become feedback for the estimated cash flow by measuring the real cash input into the economic balance, and using the profits to pay economic obligations of investments made. Interactively solving the entire problem in proper time scales, an optimal closed loop planing tool for energy retailers is provided. As planning tool, the proposed management strategy requires the use of forecasted data or scenarios that should be integrated with power system elements models, economic models and financial functions to reach a solution. All the aforementioned elements are included in dynamic optimization techniques used to solve the previously described energy retailing problem in a joint and coordinated way.

**Keywords: Portfolio management, Energy markets, Control theory, Optimization**

## Resumen

En la cadena de oferta y demanda de energía, en general, la conexión entre los generadores y la carga se establece por medio de las empresas comercializadoras de energía. Las empresas comercializadoras deben cumplir con los acuerdos y obligaciones suscritos con sus clientes, comprando energía proveniente de los generadores y suministrando la misma con calidad y eficiencia a los consumidores. En un escenario ideal, el comercializador busca maximizar las ganancias de esta operación, haciendo seguimiento de la demanda y los precios de la energía, se busca comprar la energía al menor costo posible y preveer la cantidad exacta de energía que utilizarán los clientes. Sin embargo, es un hecho que las dinámicas de las variables del sistema de energía son demasiado complejas, especialmente en los últimos años, donde la introducción de tecnologías de redes inteligentes o Smart grids (tales como: tecnologías de generación alternativas y verdes, políticas para disminuir emisiones de $CO_2$ , generación distribuida entre otros) va en aumento. Esto implica que las dinámicas del sistema potencia y las herramientas que tradicionalmente se utilizan en la planificación y operación del sistema eléctrico se están haciendo obsoletas. En consecuencia, con el fin de mejorar el rendimiento de los comercializadores de energía es necesario incluir las nuevas variables técnicas, económicas, exógenas y escalas de tiempo que pueden tener las nuevas dinámicas del sistema; se hace necesario proponer nuevos modelos, herramientas y estrategias de gestión para hacer frente a los nuevos desafíos que traen las trasformaciones que están sufriendo el sistema de potencia.

Tradicionalmente, los comercializadores de energía mitigan las incertidumbres de operación haciendo uso de estrategias de apalancamiento y diversificación de su portfolio energético. Esta estrategia de administración requiere hacer uso de instrumentos financieros y derivados energéticos de medio y largo plazo. El uso de derivados de energía o inversiones en generación ayuda a reducir la incertidumbre de los precios, pero, al mismo tiempo, el uso de estos introduce costos adicionales que deben ser considerados en el flujo de caja del comercializador. En la operación y planificación del portafolio de corto plazo de un comercializador, el mercado spot es un instrumento adicional que se utiliza para comprar la energía necesaria para satisfacer la demanda inelástica o vender excesos de energía. El portafolio de corto plazo se considera que es el encargado de igualar la oferta y demanda de energía (Market clearing). Por lo tanto, la operación a corto plazo es la materialización de las suposiciones hechas durante el diseño de la estrategia de gestión y que se ven reflejadas en ganancias positivas o negativas que son comparadas con los flujos de caja proyectados durante el diseño. Por último, para abordar los problemas que implican la inclusión de las nuevas dinámicas del sistema de potencia en las estrategias de apalancamiento de los comercializadores, se deben proponer nuevas estrategias de gestión que sean capaces de operar con las futuras tecnologías del sistema y de maximizar los rendimientos de los comercializadores.

Para abordar el problema mencionado, este trabajo propone una nueva estrategia de gestión para comercialización de energía la cual integra herramientas ampliamente utilizadas en problemas dinámicos con alto nivel de incertidumbre, restricciones y que operan en problemas con varias escalas de tiempo. La estrategia propuesta, basada en la curva de carga del sistema, soluciona el problema de planeamiento de la expansión de generación de manera óptima, la metodología usada incluye restricciones técnicas que se utilizan para diseñar una matriz de generación; con este resultado, se obtiene un plan que incluye inversiones en generación mediano y largo plazo y una planeación de la operación esperada del sistema. El plan de expansión diseñado proporciona parámetros de operación técnica que permite incluir de forma segura una cierta cantidad de tecnologías de generación alternativa en la operación. A continuación, los gastos e ingresos esperados relacionados con la generación planificada se utilizan para estimar precios de venta de energía y a su vez el flujo de caja esperado para el comercializador de energía. Por último, a partir del flujo de caja esperado, se crea un presupuesto de generación que se proporciona al portafolio de corto plazo. Este presupuesto se utiliza como una restricción económica en la optimización de este portafolio. Esta optimización está a cargo de la gestión de la operación conjunta de: plantas de generación, la generación de energía no convencional y activos financieros energéticos (mercado spot y contratos forward) para llevar a cabo el equilibrio de la oferta y demanda. Los costos de operación comercializador se minimizan resolviendo la optimización dinámica y ecoómica del balance de energía a lo largo de un horizonte de predicción, los rendimientos producidos en el portafolio de corto plazo se convierten en una retroalimentación para el flujo de caja calculado; midiendo los ingresos reales producido se usan las ganancias para pagar las obligaciones financieras de las inversiones hechas por el comercializador. Resolviendo todo el problema de forma interactiva en escalas de tiempo apropiadas, se crea una herramienta de planificación optima retroalimentada para comercializadores de energía. Como herramienta de planificación, la estrategia propuesta requiere de datos pronosticados o escenarios que deben ser integrados con: modelos de los elementos del sistema de potencia, modelos económicos, funciones financieras y técnicas de optimización dinámica que, operan de una manera conjunta y coordinada para resolver el problema de comercialización de energía descrito anteriormente.

**Palabras clave: Administración de portafolios, Mercados energéticos, Teoría de control, Optimización**.

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# Nomenclature

| | |
|---|---|
| $E^{pv}$ | Energy produced by photovoltaic generation |
| $E^{w}$ | Energy produced by wind generation |
| $\hat{y}_l(k)$ | Forecast short term load function $[MWh]$ |
| $\theta$ | Load duration curve (LDC) discretized blocks duration |
| $a$ | $a-th$ Energy forward agreement |
| $B^s$ | Short term generation budget [$] |
| $C_i^0$ | Installed capital cost of the $i$ generation technology $\left[\frac{\$}{kW}\right]$ |
| $C_a^{fw}$ | Cost of $a$ energy agreement |
| $C_i^f$ | Fixed cost of the $i$ generation technology $\left[\frac{\$}{kW}\right]$ |
| $C_i^g$ | Variable generation cost of the $i$ generation technology $\left[\frac{\$}{kWh}\right]$ |
| $C^{nr}$ | Energy selling price for the non regulated users $\left[\frac{\$}{kWh}\right]$ |
| $C^r$ | Energy selling price for the regulated users $\left[\frac{\$}{kWh}\right]$ |
| $C_{pv}^r$ | Photovoltaic energy price $\left[\frac{\$}{kWh}\right]$ |
| $C_w^r$ | Wind energy price $\left[\frac{\$}{kWh}\right]$ |
| $C^s$ | Cost of the energy traded in the spot market $\left[\frac{\$}{MWh}\right]$ |
| $E_a^f$ | Energy available in the $a-th$ forward agreement$[MWh]$ |
| $E_j^{nr}$ | Non regulated user energy demand in the $j$ LDC discretized block $[kWh]$ |
| $E_j^r$ | Regulated user energy demand in the $j$ LDC discretized block $[kWh]$ |
| $E^s$ | Energy traded in the spot market $[MWh]$ |

| | |
|---|---|
| $E_{ij}$ | Energy produced by the $i$ generation technology in the $j$ LDC discrete block in the $l$ scenario $[MWh]$ |
| $i$ | $i-th$ generation technology |
| $j$ | $j-th$ LDC discretized block |
| $l$ | $l-th$ long term scenario |
| $N_a$ | Set of Energy agreements |
| $N_b$ | LDC discrete blocks |
| $n_c$ | Compounding frequency |
| $N_p$ | Number of long term scenarios |
| $N_s$ | Short term prediction horizon |
| $N_t$ | Set of generation technologies |
| $P_j^s$ | Cost of energy purchased in the spot market for the $j$ block in the $l$ scenario[$] |
| $R^a$ | Alternative generation returns [$] |
| $R^l$ | Long term returns [$] |
| $R^r$ | Energy retailer cash [$] |
| $R^s$ | Short term returns [$] |
| $r_1$ | Bank risk free rate $[\%]$ |
| $r_2$ | Bank loan annual effective rate $[\%]$ |
| $r_3$ | Bank loan annual effective rate for traditional generation $[\%]$ |
| $r_4$ | Bank loan annual effective rate for alternative generation $[\%]$ |
| $U_{\lambda ij}$ | Participation weight of the $i$ generation technology in the $j$ block control action |
| $U_{Xi}$ | Installed capacity of the $i$ generation technology control action $[MW]$ |
| $U_{yij}$ | Expected use of the $i$ generation technology control action $[MWh]$ in the $j$ block |
| $v$ | Cash transfer between loans function and retailer cash flow[$] |
| $V_i$ | Ramp velocity of the $i-th$ generation technology $\left[\frac{MW}{min}\right]$ , $\left[\frac{MW}{h}\right]$ |

$X_i$ Installed capacity of the $i-th$ generation technology in the $l-th$ scenario $[MW]$

$y_{ij}$ Use of the $i-th$ generation technology in the $j-th$ block in the $l-th$ scenario $[MWh]$

$y_l(k)$ Load time series $[MWh]$

$y_p(k)$ Forecast short term spot price function [ $\frac{\$}{kW}$ ]

# 1. Introduction

## 1.1. Context and motivation

Traditional power system models represent involved participants such as: Generation companies (GENCO), Transmission companies (TRANSCO), Distribution companies (DISTCO) and customers (Regulated and non-regulated). The desegregated model presented in figure **1-1** shows a model of power system markets composed by several companies that may participate in their respective markets: The Generation market is represented by $G_n$ generators, the transmission market by the possible presence of $T_n$ companies, and then, the retailing and distribution companies are presented together for the sake of simplicity in the same market as $R_n$ and $D_n$. They are the components on charge of delivering the energy to the customers. Each market has a particular set of dynamics and models that makes them significantly different, but at the same time, all of them are strongly correlated as they work together to bring the consumption asset known as energy to the customers.

| Customers | | |
|---|---|---|
| $D_1$ | $\dots$ | $D_n$ |
| $R_1$ | $\dots$ | $R_n$ |
| $T_1$ | $\dots$ | $T_n$ |
| $G_1$ | $\dots$ | $G_n$ |

**Figure 1-1**.: Power system business model composed by $n$ Distribution ($D$), Retailing ($R$), Transmission ($T$) and Generation ($G$) companies

As an example of possible dynamics involved in one specific problem, [1] details one possible representation as a causal loop model (shown in figure **1-2**) of variables considered to solve a long term generation planning with stochastic techniques. As it can be seen, the loop model includes a series of technical, financial, operative and regulatory variables. Each problem variable can be represented by different models or data and have totally different natures. For example: wind velocity, a natural stochastic variable, changes the wind power generation, a technical operation value, and, in turn, could modify the energy spot price, an economic variable.

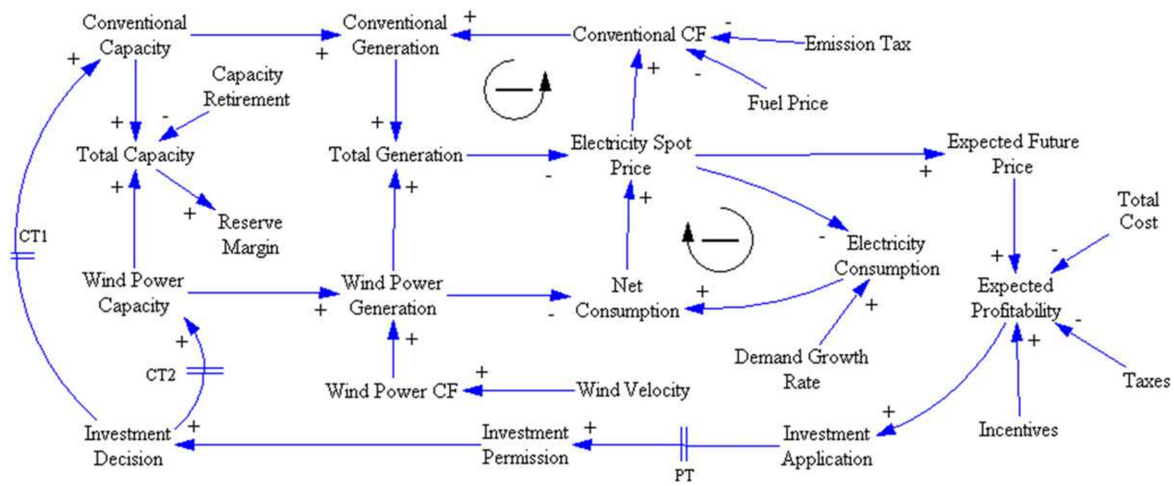


**Figure 1-2**.: Causal loop model for long term assessment in power systems. Taken from: [1]

Analogously, describing the dynamics that surrounds the energy retailing activity in general, and analyzing the system dynamics from this perspective, retailing companies get the power required from generation companies or from the energy spot market, as shown in figure **1-3**. Omitting transmission companies in charge of big scale energy transport, retailing and distribution companies are focused on the sale of energy to their customers (classified as regulated and non-regulated), and their profits are based on the spread produced by the difference between energy buy and sell prices. An important independent variable in energy retailing processes is related with generation companies. Generation participants consider expected demand and other technical and economic variables in order to sell or bid their energy production in generation markets. They can sign agreements directly with the non-regulated customers, confer part of their produced energy to energy retailers, participate in market clearing operations by means of the spot market, or sell their capacity in frequency regulation or system compensations. Generation company profits are related to production cost and energy demand.

Consequently, regulated and non-regulated customers' consumption habits creates the energy demand required by the power system. Non-regulated customers are the largest per client consumers, as big scale industries are characterized by defined operation hours and predictable amounts of energy consumption. Non-regulated users usually have energy agreements with retailers or generators, buying future energy with fixed negotiated prices. Non-regulated users represent long term and stable energy consumption in power system markets and usually get lower prices, thus becoming fixed incomes with low volatility and profits for retailers and generators.
On the other hand, regulated users represent higher expected returns with significantly high volatility. For an energy an provider, regulated users usually pay higher energy prices, but, their consump-

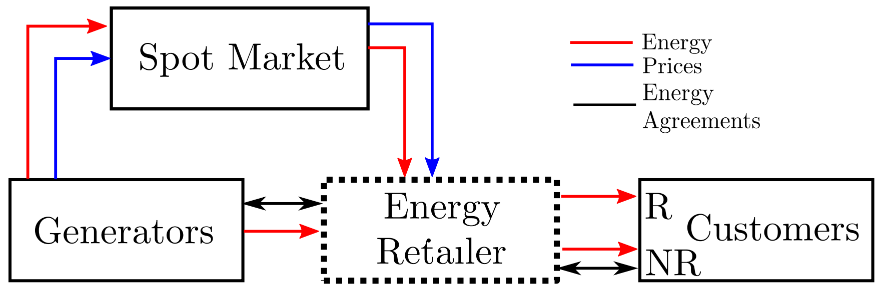


**Figure 1-3**.: Energy retailer interactions in the power system

tion habits are not desirable within generation and retailing companies' operation plans. Firstly, as a representation of a significant amount of the average citizens, regulated users present synchronized consumption patterns, creating high energy demand peaks along the day and forcing the power system to their limits for short periods of times. These peaks force retailers and generators to ensure a robust system capable of meeting the energy demand peaks is installed.
Despite demand peaks being predictable, regulated users have a high volatility throughout the day while non-regulated users consume a stable amount of energy, thus forcing generators and retailers to have fast response energy sources available to cover real time consumption spikes and, at the same time, have cheap base generation technologies to supply steady consumption. In short, regulated and non-regulated customers are complementary obligations for generators and retailers. Low prices with predictable consumption habits and high prices with high consumption volatility forms a system load that demands a complex generation supply plan that needs to be reliable, efficient and with the minimum possible cost in response to a complex dynamic system.

### 1.1.1. Energy markets future

The power dynamics described previously have been increasing their complexity due to emerging smart grid technologies. New energy roadmaps are changing traditional power system perceptions around the world. Current efforts are focused on pollution and green house gas reduction, and promoting a sustainable energy generation matrix. This new scenario is possible by taking advantage of smart grid promoted innovations, such as: distributed generation, alternative generation technologies, and demand side management, among others. Emerging power systems are becoming more eco-friendly. The **"100% Clean and Renewable Wind, Water, and Sunlight (WWS) All Sector Energy Roadmaps for 139 Countries of the World"** roadmap is a document, currently under development, created by a group of researchers from: Stanford university, U.C Berkeley and the Technical University of Berlin, that review energy roadmaps in 139 countries. The document has a projected power system growth, as shown in figure[1] **1-4**. The 2012 to 2050 projected power demand and expected generation matrix presented was obtained from 139 roadmap reviews, and

[1] Avaliable in: `http://web.stanford.edu/group/efmh/jacobson/Articles/I/CountryGraphs/TimelineWorld.jpg`

shows how alternative generation technologies will completely replace all the fossil, bio and nuclear fuels by the year 2050. In the future Wind and Solar generated power will count for 94.5% of installed capacity. On the demand side, within the projected timeframe, power demand has an expected growth of 47.50% as raw value (there are power consumption reductions associated with conversion and use efficiency improvements).

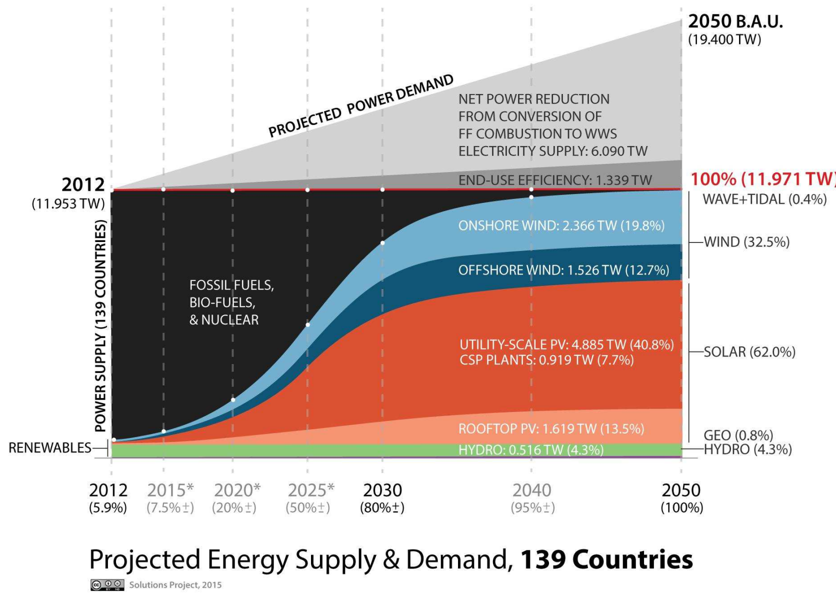


**Figure 1-4**.: Projected energy supply and demand according Solutions Project from Stanford roadmap `http://tinyurl.com/mcy8lfx` , 2015

Nevertheless, high alternative generation penetration implies changes in the entirety of power system planning and operation. A wide research field has been created around this. Industry, governments and research communities are aware of the need to redefine several energy systems concepts. In [2] an interesting discussion about the previously mentioned actor interactions and their influence on the power system operation is presented where mixing information could lead to take better decisions related to the optimal mix of energies; the reader must understand that information is all the data (technical and economic) related to each generation technology. This information represent advantages and disadvantages of the technologies, the information cloud be used to find the optimal mix of generation technologies. This thesis proposes an optimal operation solution by mixing generation technologies. This proposed optimal solution is different from traditional technical solutions, as the integration of additional data and models related to new generation technologies pushes forth a new optimal point. The new optimal defines the perfect solution with a generation mix that considers, in addition to classic system variables, green gases reduction and sustainable politics as part of the objective.

In sum, future power system scenarios will be a mix of alternative and classic generation technologies, as the transitional period towards a future 100% renewable system has begun. All models and variables of power systems are changing, including energy markets and new management methodologies are necessary to face the challenges that the promise of an eco-friendly future brings with it.

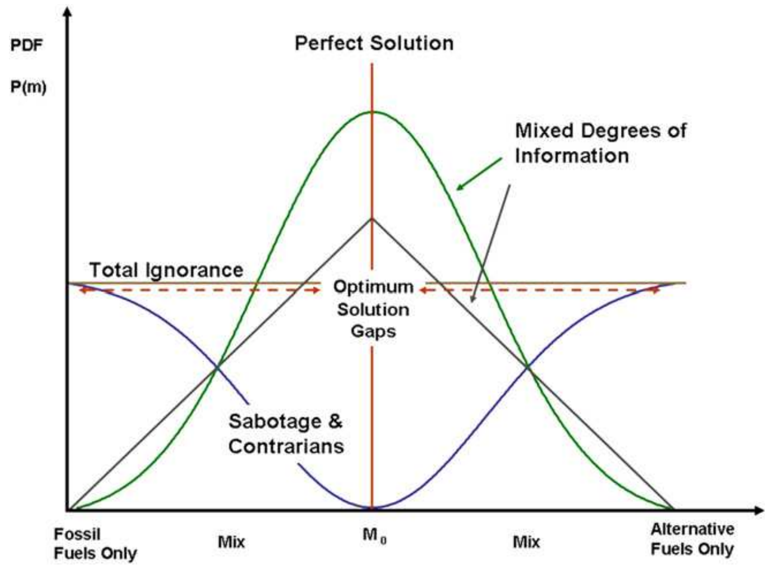


**Figure 1-5**.: Fuel mix optimization based on system analysis. [2]

### 1.1.2. Scope

Now, revisiting our energy retailer operation analysis and considering the described possible future changes in the power system, changes in the generation matrix and user consumption habits will be reflected on retailing planning and operation. As it was previously mentioned, energy retailing operations are based on the capacity to obtain cheap energy and sell it to costumers. Facing medium and long term consumption uncertainties, retailers often makes use of finance derivatives to minimize their exposure to energy price volatility and availability.
Buying future energy is an effective strategy used to guarantee future operation and avoid losses, commonly known as hedging. Various hedging strategies can be found within related literaure as it is a vast and complex financial research field. This paper will consider Back-to-Back hedging (B2B), a strategy commonly used in the market of commodities, such as energy. In general terms, in B2B strategy applied to energy as a commodity, energy retailers decide an exact amount of energy with a calculable price during the negotiation. Price calculation represents the main problem of this strategy, as the base price is usually attached to spot energy prices. After the price and the amount is a agreed upon, retailers pay the agreed cost. The downside of B2B is the exposure to a large volume agreements and liquidity risk. In [3] a complete analysis of the use of commodities applied to risk mitigation in energy markets suggests a lack of effectiveness in the strategy. It is out of energy retailers' control to guarantee promised energy availability, as there is a chance that the generator decides not to honor signed agreements. Although these failure possibilities are covered by regulation entities, they are not desirable in planning exercises and future cash flows

estimations. Furthermore, a future generation matrix will have a high renewable penetration rate, increasing generation and demand uncertainties interpreted in the energy market as liquidity risk. In short, traditional hedging strategies applied to energy retailing tasks are becoming obsolete in the face of future generation and demand scenarios. Obtaining operation reliability and positive expected returns based on traditional management strategies are emerging as a complex challenge. It is increasingly relevant to propose new management and planning methodologies capable of working efficiently with future scenarios and dynamics of the power system. The integration of different tools used in similar problems could be used to innovate solutions for risk management and planning operations within energy retailing companies.

### 1.1.3. Objective

This thesis's general objective is to propose a diversified planning methodology to deal with energy retailing portfolio management. Based on hedging strategy, this proposal focuses in the integration of different financial, technical and economic variables with management models to optimize energy retailing operations. This work considers simplified versions of the models given that, the objective is the integration at technical and economic level. Thus this, several assumptions are made in order to reduce the models complexity. Then, considering future energy market evolution, an energy retailer portfolio diversification in short, medium and long term systems is used to minimize risk exposure. In agreement with the reviewed energy roadmaps and global trends, this proposed strategy has the ability to include alternative and renewable generation technologies into the equation.

This thesis is the construction of a solution for several problems based on energy retailer diversification strategy, beginning with an analysis of hedging strategy which has been used in several applications to minimize risk exposure. In energy retailing, hedging strategy minimizes risk by means of energy derivatives. The use of derivatives in the retailing portfolio ensures companies have energy in the future (medium and long term). With a fixed price negotiated in the Over The Counter (OTC) market, energy derivatives present some risk for energy retailers. By exploring the derivatives operation, it was determined that the financial assets could be seen as virtual energy plants.
Consequently, a new portfolio arrangement is proposed in order to minimize the risk exposure of energy derivatives. This paper explores the opportunity of using investments in generation plants to mitigate the risk associated with the use of energy derivatives. Participation in the generation market allows a company to have energy in the future with a known price and avoids the uncertainty related to bilateral price negotiation. Upon this premise, a wide set of new options will be available for integration to the energy retailer portfolio. Building generation plants within medium term installation timeframes, such as gas based technologies, represent low installation cost and medium-high generation cost to the portfolio, and provide fast response to fast load dynamics, including the required backup should renewable generation technologies be present in the generation

scheme. On the other hand, bigger generation plants, such as hydro or coal, present a much higher installation cost and building time (long term), but the operation costs are low or null. These kind of plants are used to supply base load energy and their flexibility to deal with fast changes is compromised. Finally, to deal with retailer energy market clearing operation, an instant and reliable energy source is required: the spot market. This asset is in charge of balancing the energy retailer obligations, but despite being a permanently available energy source, its price is usually higher that those of energy agreements and the production cost of generation plants. Furthermore, its price volatility is excessive and makes the asset only desirable for small adjustments in real time hourly energy demand. The portfolio described used in this paper in order to propose the management strategy is presented in figure **1-6**.

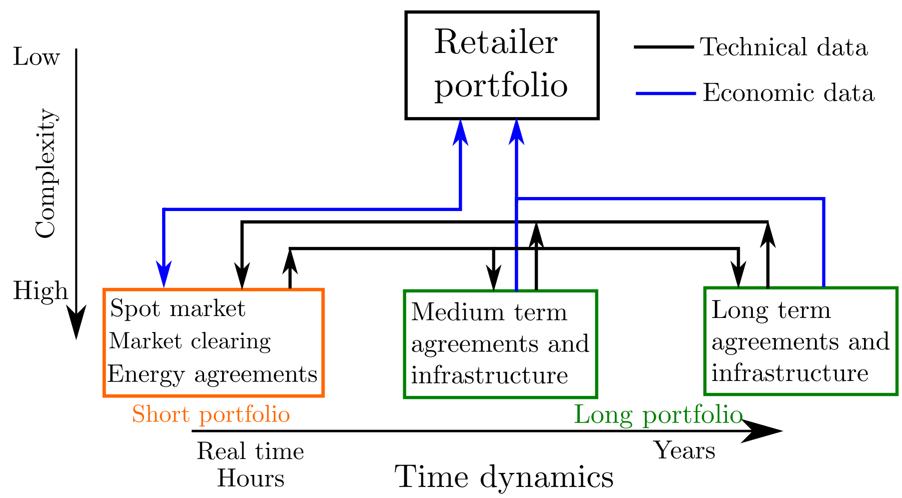


**Figure 1-6.**: Description of the iterations in the proposed energy retailer portfolio

The presented hierarchical portfolio involves several variables and models with varying degrees of complexity and different time scales. Exploring the previously mentioned structure and based on relevant works related to similar hierarchical systems as [4, 5, 6]. The first approach to the described portfolio was published in [7]. Afterwards, with the models, data and variables required, a set of optimization techniques were used to solve each problem. Making use of control theory, this paper proposes an integrated solution for each optimization formulated in a prediction horizon. Extending the solution to a planning horizon, a planning tool is created. As consequence, the use of prospective information requires prediction models and future scenarios. As such, proper assumptions and prediction models are used to solve each optimization problem. It is to be noted that by splitting the management problem in sub-systems, the inclusion or modification and constraints for each portfolio is simplified. This provides universality to the proposed methodology.

Concerning each sub system solution in this paper, long and medium term portfolios are integrated by dealing with generation plants investments in order to solve a proposed modified generation expansion plan problem, the Load Duration Curve (LDC) of an energy retailer is used to calculate future generation plant investments. With installed capacities, technical operation parameters such as ramp velocities and expected plant production schedule as a result, the economic and technical assumptions and results are discussed, and make two contributions in this section: technical design parameters that allow the inclusion of alternative generation plants in the generation schedule and expected returns, plus the option to avoid the use of energy derivatives as hedging assets. The obtained information is used in the energy retailer optimization to estimate the future retailer cash flow.

The retailer functions at the top of the hierarchy consider all the economic problem variables. Expected returns including fixed and variables costs are used to optimize in a prediction horizon retailer cash flow. Here the use of financial functions such as compound interest, preset value and loans models are used to determine the best choices related to cash management in the most accurate way. This function is clearly different to other sub systems as it does not include technical parameters related to energy retailing operations. This fact simplifies the solution and interpretation if results are used in economic analysis, and the hierarchical structure avoids compromising detailed information that is contained in other subsystems. Lastly, considering expected generation schedules with traditional and alternative generation plants, a generation budget is calculated and assigned to the short term portfolio subsystem. This approach extends the use of this methodology, allowing for a more detailed solution closer to a daily operation plan. It is not the objective of this thesis to solve the ideal dispatch problem, but rather the discussion is focused on the economic postulations made and their impact on the optimization problem.

With the generation budget obtained from the retailer optimization as an economic constraint, the short term portfolio subsystem optimizes the use of: all available generation plants (any renewable generation is included in the operation), possible energy derivatives (if included), and energy spot market transactions. Making use of two short term forecast models to estimate the expected user consumption and the energy spot price in a time horizon, the optimization maximizes the expected returns of market clearing operations along the given prediction interval. The optimization results are a set of control actions that act as feedback in the energy retailer function. Updating and comparing the operation results with expected cash flow updates, the real energy retailer returns are visible. Solving the process interactively, and updating the models and variables in proper times creates a resourceful optimal solution for the energy retailing portfolio management problem.

In close, the scope of this thesis is the interaction of different subsystems in order to supply energy with the maximum expected return, minimizing liquidity and operation risks, including alternative generations. The case study considers Colombian energy retailer data. The future scenarios and assets used are selected with the purpose of illustrating solution features and the idea may be applied to any region with the proper modifications. Discussions on the results are focused on results and assumptions made, avoiding disregard of weaknesses in the solution and providing future work options to problems detected..

## 1.2. Thesis outline

The presented thesis was subject to an earlier review made by an academic committee. Approved items in the defense that guided the development of this thesis named, *Optimal investment portfolio management with hierarchical control for energy markets* are listed under the following hypothesis: *It is possible to make optimal management of an investment portfolio composed by stocks with varying time characteristics and behaviors as an energy market portfolio with smart grid features, based on hierarchical control theory.* The general objective proposed was: *To propose a strategy for optimal portfolio management in an smart grid energy market.* Specific objectives considered in this work are listed as:

- To define the models to be used to represent the portfolio
- To assign the models to each level of the hierarchical structure and to choose the information to be shared between the layers
- To determine the optimization problem for each level of the portfolio hierarchy
- To validate the proposed portfolio management strategy in a simulated scenario

The development of this document is guided as follows:

- Chapter one introduces the context and motivation of management problems in power systems. Here, exploring the future of power systems, the scope and objectives of dissertation are presented.
- Chapter two describes the energy retailing operation then, the management problem is presented with a description of a standard retailer management strategy. Afterwards with the problem description serving as a prelude, the state-of-the-art is presented as follows: A general review of management publication related to energy markets is summarized. Subsequently, considering the gap created with penetration of smart grid technologies retailing management strategies focused in new markets are reviewed. Last, considering the new management challenges explored, the use of hierarchical solutions in power systems control is explored an alternative to solve the energy retailing management problem.
  Next, a new proposal for the energy retailer management problem is presented. Assets used in the portfolio such as: short, medium and long term energy assets including renewable sources are described. Then, their models and the management strategy based on a hierarchical structure are discussed. Later, a management optimization problem is formulated and extended to a dynamic optimization problem that allows the proposed solution to be solved in a prediction horizon creating an energy retailer planning tool.
- Chapter three explores medium and long term assets of the energy retailer portfolio. Here, as part of the management strategy, investments in medium and long tern generation plants are analyzed and used to solve a modified generation expansion plan problem. This problem

is used to plan in a prediction horizon the optimal generation mix that will be used in the energy retailing portfolio.

- Chapter four corresponds to short term assets management problem. Here, a dynamic optimization is used to solve a market clearing problem. Proposed optimization, takes into account medium and long term assets and other short term financial instruments to estimate expected returns of energy retailing operation. This information is the feedback that provides to the retailer model returns obtained in the retailing operation.
- Chapter five makes use of models presented in chapter two, three and four to simulate the management strategy proposed. This chapter is used to discuss final details of model integration, financial and technical assumptions made and discusses identified drawbacks and advantages.
- Chapter six presents the conclusions of this dissertation.

# 2. Energy retailer portfolio problem

## 2.1. Introduction

Section 1 discussed the impact of the power system evolution and its impact on operation and consumption habits, and consequently on energy market operations. Considering the detailed energy retailing problem explained in section 2.2 , this chapter's objective is to explain in detail the energy retailer's function and operation strategies. Then, taking into account future power grid scenarios, the state-of-the-art is presented in section 2.3 as follows: First, a review of power market management strategies is made by providing a context for energy markets management. Second, considering a power system timescales partition, the relevance of hierarchical structures in power systems and methodologies used to solve the problem are reviewed.
Afterwards, this thesis contribution is presented in section 2.4.A formal problem statement and solution formulations are described in this section. In addition, the proposed system data flow is explained with a work flow diagram, providing a guide to follow the problem solved by each subsystem and the data it brought, and other systems and their required data as well. As a coordinated strategy, the first problem explained is the system coordinator that corresponds to the energy retailing model presented in section 2.5. Here, the financial relationship between retailer portfolio assets (Short term portfolio, presented in section 4 and, Medium and Long term portfolios solved in section 3) returns are described. The retailer model includes finical functions as present values in compound interest to estimate present time incomes and outcomes real values. Taking advantage of generation investments, renewable energy production is included in the model, just as traditional generation plants, future fixed and variables cost are projected in present time. Short term portfolio results are used as market clearing instrument, representing the energy operations (energy sales and production costs) the energy retailer made in the power market.

Finally, section 2.6 describes the optimization equation used to solve the management strategy, maximizing the expected returns. The optimization problem is used in section 2.7 to formulate the management problem in a prediction horizon. The dynamic optimization is solved by means of Model Predictive Control (MPC) theory. The use of MPC allows to include dynamic constraints in the problem, and combined with financial economic functions that allows to valuate cash flow in present time and the proper prediction models. MPC provides an optimal planning tool for energy retailer portfolio management. Lastly, the discussion in this chapter focuses on model assumptions, how they can be extended or improved, management strategy highlights and downsides, and the impact of MPC use in the solution and the interactions with the different portfolios shown in chapter 5.

## 2.2. The energy retailing portfolio management problem

Energy retailing operations take place in the middle of the supply-demand relationship between generators and customers. Generators have several options to participate in the electricity market, such as: capacities market, ancillary services, transactions in the spot market, and bilateral energy agreements. The last two operations are significantly relevant for energy retailers. In traditional energy markets, energy is a not storable commodity which is bought and consumed instantly with an inelastic demand. Energy retailers must provide, in real time, energy from generators to their customers. In an ideal scenario, knowing the required amount of energy, the energy retailer could buy the energy in the spot market and sell it to the customers, earning some profit in the operation.

However, spot market energy prices are highly volatile and lack of energy purchase planning exposes energy retailers to high market risk. Additionally, customer consumption habits are difficult to predict; regulated user patterns imply a management challenge for the whole system's operation. They create short demand peaks that stress the power system capacity, while at the same time, their consumption habits are variable throughout the year. On the other hand, non-regulated customers present more predictable assumptions, but usually generators or energy retailers have information related to the amount and even the operation time of costumers; whereas, non-regulated customers are used to having lower energy prices. In short, energy retailers face the challenge of providing an uncertain amount of energy to their clients by buying energy in a highly volatile market. Considering that energy retailers' expected returns relies on the price gap between buy and sell prices they could obtain, their operation needs management strategies that minimize the risks mentioned before and maximize the expected returns.

In addition to the previously described management problem and considering the future of energy markets discussed in section 1.1.1, the increase of market uncertainties due to a new eco-friendly generation matrix should be included in the proposal of energy retailing management strategies. Now and in the future, the objective is to maximize energy retailer returns while decreasing market risk exposure in these new scenarios. Traditionally, buying future energy contributes to minimizing market risk exposure, assuming that the energy retailer only wants to buy the expected energy that will be used by their customers later. As discussed in section 1.1.2, energy agreements known as back to back (B2B) are the chosen financial instrument for this task, which provide the forward energy agreement as result of a bilateral negotiation, where the energy price and the energy amount are used to calculate the agreement cost to be paid by the retailer. It is a well-known fact that hedging future energy mitigates market risk exposure. At the same time, some problems related with strategy effectiveness have been identified: there is a remaining risk exposure to market price, especially if the acquired energy is purchased in the long term and agreements with considerable energy amounts are susceptible to a liquidity risk from generators. A common solution to this problem was provided by Nobel winner Harry Markowitz in 1952 [8]: diversification. The use of several energy agreements has been enough to minimize risk exposure in the energy retailing operation, but this assumption basically requires a measurable or estimated variance of considered energy assets. This is where the increasing uncertainties of energy markets imposes new challenges to future retailing management strategies.

Increasing alternative generation sources in the system could reduce firm energy indicators. Many alternative generation technologies are considered non-dispatchable (or not completely), decreasing the information to predict future availability and, consequently increasing the risk to sign future energy agreements. Currently, alternative generation plants are included in power system generation markets by using fast response generations plants or energy reserves as backup. This opens the opportunity to explore new possibilities in the retailer management strategy, including a renewable and conventional generation technologies combination in the problem, in order to improve reliability and reduce uncertainties for future energy agreements.

## 2.3. State-of-the-art

To contextualize the reader and show the precedents of this dissertation, a brief literature analysis where the research fields involved and their contributions are used to evidence the relevancy of this work is presented. Making use of Scopus search analysis tools, the keywords: *power, energy, market and management* are used to collect some general data about researches made in recent years. Figure **2-1** shows that around the year 2000, the amount of related research started to gain more influence and the peak is happening at this moment (2016).

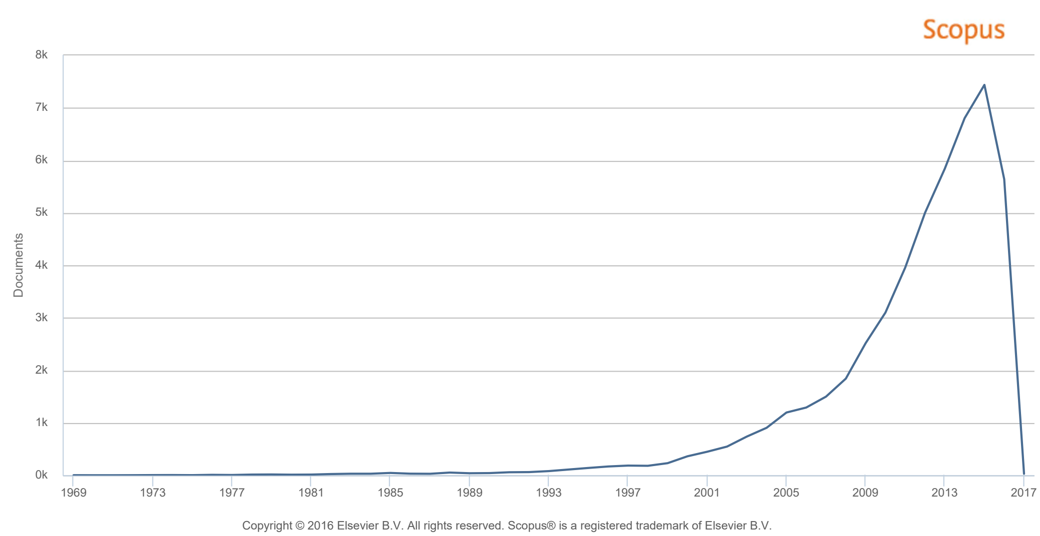


**Figure 2-1**.: Historical publications with power energy markets management in Scopus

By analyzing the described production by publication source in figure **2-2**, some interesting information allows us to form an idea of how research around the different topics has evolved. Firstly, between 1990 and 2005, the majority of research published was on:*Transactions on Power Systems* and *Energy policy*. Secondly, with an emerging interest in smart grids, production in all the sources started to examine growth significantly since 2006; *International Journal of Electrical Power and Energy Systems* and *Energy* suddenly started to increase research in the used keywords. Finally, starting in the year 2008, *Renewable and Sustainable Energy reviews*, *Energy*, *Applied energy* and *energy policies* got sustained and considerable growth rate, especially in *Renewable And Sustainable Energy reviews* which easily overcomes remaining sources. Extrapolating the result of the combination of the keywords used and the publication sources, it is possible to say that since 2008, research related to energy management became a relevant and opportune research topic at the same time as smart gird technologies penetration became a real fact.

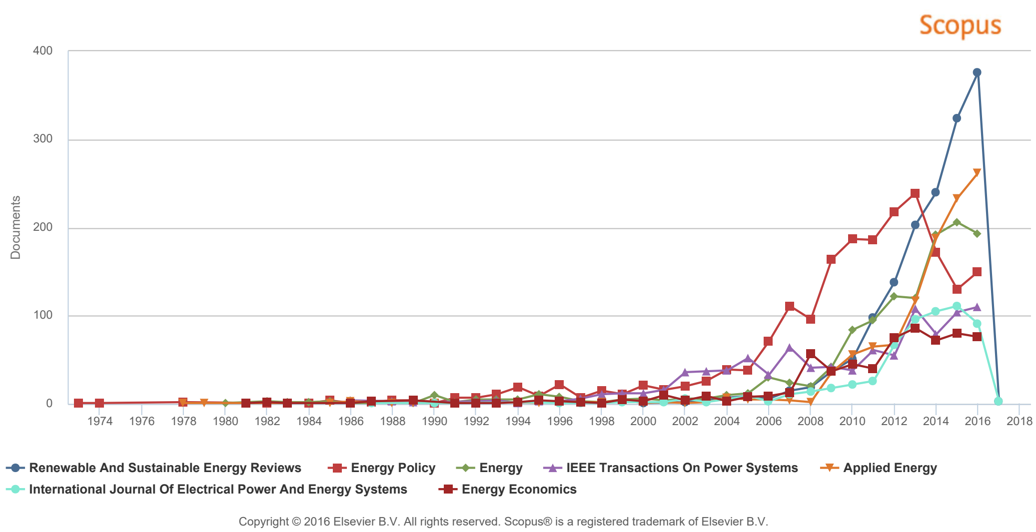


**Figure 2-2.**: Publications Sources related with power energy markets management in Scopus

Now, considering almost all relevant publications since 2008, this state-of-the-art is presented as follows: Firstly, retailing related management strategies used in power markets are visited. Secondly, a review of general applications of hierarchical control in power systems is presented, exploring this tool as a feasible methodology to counter the needs identified in the management review. Thirdly, a summary of mathematical tools used in power markets problems is discussed as context for the solution of problem described.

### 2.3.1. Energy retailing management strategies

In this section, our objective is to review current power market management strategies focused on energy retailing. A short brief of the retailing stages is presented in figure **2-3**, consider this figure as a guide to read the next sections related to this energy retailing literature review. First, a

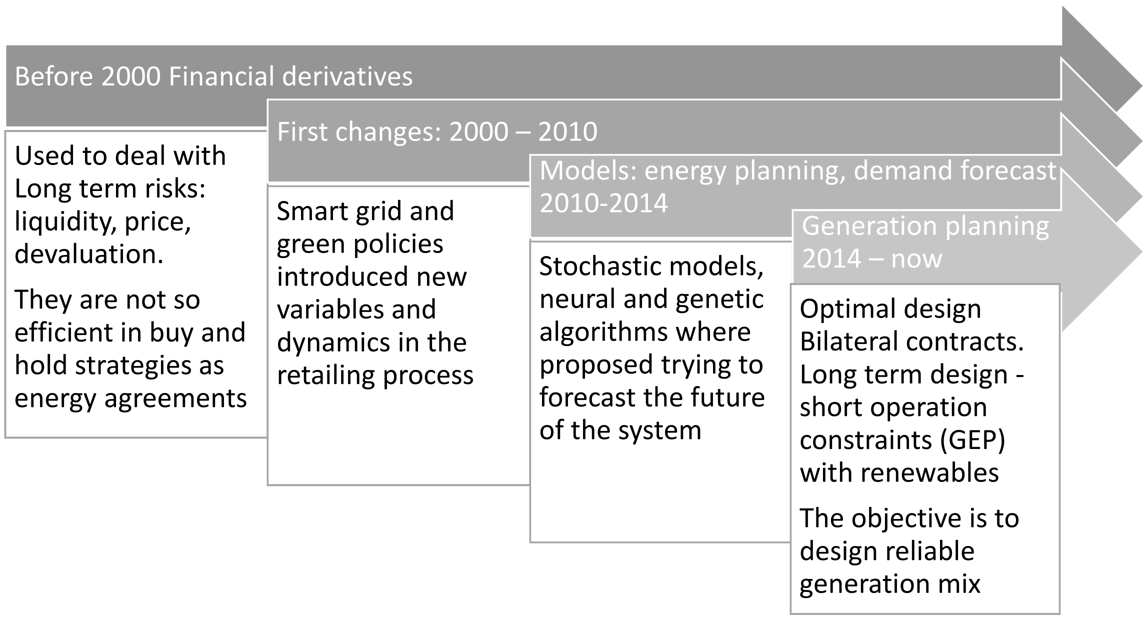


**Figure 2-3**.: Brief of state-of-art related to energy retailing strategies

quick review of financial management methods is presented in order to have a general context of management strategies solutions. The portfolio optimization formulation had its first conveyances through Harry Markowits [8] in 1952. Markowitz proposed portfolio diversification as the solution to minimize risk exposure. From that point onward, a whole research topic became an area of study. Consequent tactics were directed to optimize single-period problems; including the capital asset pricing model (CAPM) by [9] in 1964. Later on, finance derivatives and hedging strategies gained popularity as computational capabilities began to grow. Black's zero-beta CAPM and Black-Scholes model [10] published in 1973 were the beginning of a new financial age. Stochastic methods, probability functions and partial differential equations were used to estimate future prices and risk in portfolios; from that moment on, financial derivatives have been used as assets in risk diversification. It wasn't until early 2000, with the new computational power scenario, that the use of dynamic tools, such as control theory and dynamic optimization techniques, were used for portfolio management problems. By allowing for the exploration of these tools in more complex models, constraints and long term prediction horizons were utilized to find new optimal solutions to the problem, as can be seen in [11, 12, 13, 14, 15, 16, 17])

In regards to the work scope described in 1.1.2, it is of particular interest to this state-of-the-art to review market problems that include supply-demand portfolio problems with feasible future energy scenarios. Considering this, classic energy management related problems will be mentioned briefly. Extended reviews made between 2000 and 2010 are cited as summary of works made before the smart grid and green policies influence in energy markets gained significant relevance as a research topic. This can be seen in figure **2-2**. In [18], models such as: energy planning models, energy supply demand models, forecasting models, emission reduction models and optimization models have been reviewed and presented. Linear, non-linear models, econometric and stochastic models predominate in the review, as well as solutions that mainly focus on linear optimization methods and a strong component of computational intelligence, such as: genetic algorithms and neural networks methods. A paper section is dedicated to renewable energy, but focuses on plant and generation models, but their inclusion in management strategies is omitted. In [19], another examination related to electricity models is presented, and a series of proprietary models is discussed. The models discussed are not available in the literature, but in the conclusion section, the author identifies a lack of integration of ancillary services, energy storage and renewable (all future incoming technologies in the power system). This conclusion is consequent with [20, 21], where a full smart grid vision is described in generations, and third and fourth generations mention the relevance of integration of smart grid technologies to energy markets. As presented in the problem description 2.2, this work focuses on energy retailing portfolio management considered risk mitigation strategies. Work presented in [3] discusses risk mitigation based in future energy agreements. It had concluded that the use of energy commodities fails to increase portfolio returns in an efficient energy market with buy and hold behavior, just like retailer portfolios strategies. It also concludes that a buy and hold strategy is effective to decrease market exposure risk. The presented conclusions provide an idea of the hedging strategy deficiency in electricity markets. When energy retailers buy energy to hold it and use it in the future, they are fixing the future price and bought energy is probably also compromised to be sold to a fixed price too. Two energy bilateral negotiations used for market clearing can reduce opportunities to have extra returns, but essentially the market exposure in this transaction is zero.

At that point, in [22] the optimal design of bilateral agreements for an energy aggregator is explored. The proposed objective goal is to find a market clearing point by making use of distributed energy sources and filling grid agreements obligations in a planning horizon; fixing single energy generation agreements so just one fixed load agreement ensures solution robustness. The methodology used in this work considers a prediction horizon in the order of weeks. Each week with finite time slots, and an aggregator that has a set of generation agreements with a limited amount of request for each contract. On the demand side, it has a set of signed demand agreements or grid contracts to meet. The objective is to meet energy demand at the lowest cost. One-to-one assignations between generation agreements and load contracts is assumed to guarantee solution robustness. When one or several generation agreements are paired with demand requirements, assigned generation assets are not allowed to be assigned to other demand obligations until the specified demand is fully supplied. The end of each generation contract happens when there are no available movements left. Every week, available generation agreements are provided by an external factor called mobilization, and is used to simulate distributed generation resource availability. This scope aims to use a probability function to simulate random generators' availability, then make use of an optimization problem which solves a robust market clearing process by using expected generation sources to serve required energy at the lowest cost possible. A slack variable is used to estimate non-served energy, and solving the problem in a prediction horizon with stochastic programming, a short-medium term operation plan is solved. Finally, the methodology is stressed upon solving a long term horizon by implying high computational times. The mentioned work proposes a quite interesting idea: the use of several generation agreements with high uncertainties to supply load energy agreements. This study shows a new version of hedging strategy. Generation and demand discretization made with blocks presents an interesting approach reducing system complexity, allowing for the exploration of different properties and assumptions for each variable. The drawback in this methodology is the high computational cost implied, and the assumption of generation agreements with variable availability. This methodology focuses on short term planning lacking in integration with traditional generation plants and long term variables such as future expected demand failing in a proper detail level for long term planning.

In [23] short operation constraints are incorporated in long term generations plans, integrating technical and economic short term variables such as: start-up cost, ramp values, operation cost, fuel prices and $CO_2$ emissions, among others with long term variables related to generation expansion plan problem. Various authors make use of case studies using Coal, combined cicle gas turbine (CCGT), open cicle gas turbine (OCGT), and wind generation technologies to explore, by means of Monte Carlo simulations, and a set of generation scenarios. Scenarios are solved with two objective functions: minimum start-up cost and minimum operation cost. Some authors also solve the problem by including the generation dispatch, but computational costs are too high. Work just described is a planning tool which integrates short term and long term problems, different time scales models and the use of the Monte Carlo simulation to deal with a high computational burden problem. It presents a very nice idea of risk cover as the use of short term technical constrains in long term problems, creates robust solutions approaching the design to a worst case scenario.

Currently, many authors have been exploring the integration of short term and long term problems to include alternative sources and manage future uncertainties from the long term side. Long term markets are focused on infrastructure and long term energy agreements and investments. Having discussed a few references related to long term agreements, a short review of bottom up solutions is made next, focusing on long term construction plans, decisions related to investments in power plants, known as Generation Expansion Planning (GEP) that are often based on the Load Duration Curve (LDC). Linear optimization models have been already used for a long time to find the ideal mix of generation technologies meeting this demand. LDC based solutions describe the required installed generation capacity of each technology and their operating hours, in order to minimize the total cost, i.e. the investment and operational cost. Since traditional models do not include the variations of demand over time, they do not take into account the ramping and cycling capabilities of power plants. However, not including these technical constraints of power systems underestimates the flexibility needs of the system. This becomes increasingly relevant when facing a rising trend of renewable generation shares characterized by a variable output profile. Traditional approaches based on the LDC do not consider the potential value of flexibility provided by different generation technologies, and result in a sub-optimal solution. On the other hand, solutions that include these technical elements require high computational efforts. Secondly, traditional solutions do not take into account the uncertainty of the demand forecast, resulting in overcapacity or reliability issues regarding the installed capacity. As a consequence, they lead to sub-optimal investments associated with the power plant's long term use. The need to include technical constraints and uncertainty in the GEP requires the integration of new elements in the generation expansion problem. However, this increases the complexity of the GEP problem. The same goes for the use of scenarios that consider uncertainty but improve the ability to deal with long-term planning decisions, and provide robust results in the face of future trends in the power system.

The state-of-the-art in the generation investment problem shows different approaches, taking the integration of new variables and uncertainties into account. A first set of methods deal with the LDC model itself. A linear piecewise function is used to represent the LDC, and a residual LDC is used to integrate renewable sources in the part of the curve where most demand changes take place [24]. Exploring the LDC from Germany and Britain validates the relevance of the LDC methodology. The inclusion of technical improvements in the LDC methodology, such as ramp rates and the maximum on-time of a generating units, is suggested [25]. With a robust optimization that includes uncertainty of demand, the price of electricity and generation cost is proposed in [26]. A second set of tactics deal with the problem of technical integration constraints in the classical economic generation investment model, i.e. based on the time-series representation of the demand. The authors of [27] include several additional variables and constraints related with the power system to solve a single period problem. In [28] a relevant discussion about how dynamic constraints, such as ramping rates and start-up cost, are changing the optimal point of the classical generation investment solution is presented. The work stresses the need for methodologies able to make the solution in a prediction time horizon, also called multi-period solutions. A mixed solution proposed in [29] considers the integration of renewable generation in the GEP by means of net demand curves; to deal with prediction errors, an operating reserve constraint is imposed. The solution includes the ramp rate of the conventional technologies to cover the uncertainty of the wind generation power.

Finally, a set of detailed solutions make use of stochastic and time series based models to solve the GEP. A generation plan expansion methodology using a multi-period horizon solved by a bi-level problem is proposed in [30]. The problem maximizes the investment profits at the top level, and the second level deals with technical constraints such as: generation and transmission constraints and load flows. Penetration impact of renewable sources in the GEP is discussed in [31], optimizing a model that considers all the yearly investments, fixed and variable operational cost, reserve costs and ramping and start-up costs constraints. The problem deals with a new optimal point to balance the increasing renewable amount with reserves to meet the system reliability requirements. Time series and detailed solutions lead to the use of complex methodologies that imply a high computational cost. New methodologies must deal with a trade-off between the detailed level and the required time to solve the problem in a large time horizon. Detail is not always mandatory, planning exercises and scenarios analysis can use more time-efficient solutions with less technical and forecast required details.

Concluding this state-of-art section, short and long term variables and models integration is a promising strategy to face power system uncertainties. Authors are conscious of the big challenge related to forecast future alternative generation plants. Solving stochastic problems requires big computational efforts and there is still a chance of error, especially in long term horizons. Thus this, they are switching to create or integrate traditional generation technologies with alternative generations by means of technical variables design. Assuming worst case scenarios, and making designs assuming a maximum uncertain level while making the system reliable in no extreme operation cases. Nevertheless, integration of deterministic models could be a challenge too, especially if several time frames are involved. A common practice relies on splitting the problem in several parts and then integrate solutions obtained under this frame. The use of hierarchical structures has been used in several problems. An additional section focused in this methodology applied to power systems is included to explore the integration feasibility to portfolio risk management.

### 2.3.2. Hierarchical control in power systems

When the use of hierarchies or any distributed system are considered, it is necessary to establish a system partition, splitting the problem in a set of simple sub-problems that allows for the solution of each part with specific proper methodologies. In this case, solutions will be handled with control theory. Now, let's consider a common partition used to describe the power system taken from [19]. Here, the time frame is the selection parameter to produce the partition presented in table **2-1**. In this table, operation and management processes are grouped by time dynamics, organized from milliseconds to years. In relation to energy market dynamics: the financial operation and the dispatch have "very short term" dynamics. Generation plans that depend on demand and weather predictions are placed in the short term scale. Meanwhile, demand predictions associated with seasonal generation planning operate in medium term scale. Finally, the generation's expansion plans and demand growth are placed in the long term scale. Now, a short review of hierarchical structures applied in power system, most of which focus on control systems, is presented in order to explore the tool as an option to propose a new portfolio management methodology.

Control theory has been used widely in power systems problems [6]. It has a particular tool useful to hierarchical systems: hierarchical control [32]. However, the use of hierarchical control applied to management decisions structures is new. In [33] a hierarchical structure with Model predictive control (MPC) is proposed to solve optimal dispatch with a given generation portfolio. In [34], an energy distribution system with users that have bilateral communication is assumed. Each user can take energy from the grid or a renewable resource, and the load and generation of the renewable resources is stochastic. The objective is to reach the optimal usage schedule for all energy resources

| Time frame | Electricity systems issues | Power systems tools |
|---|---|---|
| $ms/s$ | Generator dynamics<br>Motor load dynamics | Transient stability management<br>Power-frequency regulation |
| min / 1 hour | Demand variations | |
| Very short term | Power interchanges<br>Economic operation<br>Frequency control | Economic dispatch<br>Generation control<br>Power flow<br>Security analysis<br>Fault analysis<br>Voltage stability analysis |
| h/days / 1 week<br>Short term | Weekly generation planning | Demand<br>Weather prediction<br>Unit commitment |
| weeks / months<br>Medium term | Seasonal generation planning | Demand prediction<br>Maintenance planning<br>Hydro planning<br>Fuel planning |
| years<br>Long term | Demand growth<br>Plant retirement<br>Investments opportunities<br>Hydrological cycles | Generation expansion plan<br>Maintenance<br>Scenario analysis<br>Production cost modelling |

**Table 2-1.**: Timescales in power systems management, planning and operation [19]

in the network, minimizing the cost of load supply. This paper also makes a review of the state-of-the-art related to the integrated management of the energy system. The strategies presented rely on real-time pricing and distributed generation based on load scheduling, and minimization of operation cost. Similarly, in [35] a hierarchical control structure applied to microgrids is presented, proposing three control levels or hierarchies for the coordination of a system equipped with distributed energy sources (DERs). The top level is in charge of handling the microgrid load. The second level aims to perform corrective actions over the frequency and voltage perturbations. The third level manages the connection between the microgrid and the interconnected system. In a general sense, this control system guarantees a cost-effective and reliable operation of the microgrid, and can work in coordination with the interconnected system or in island mode. The flexibility of the system also allows for a faster "black start" of the system, in case of microgrid isolation needs should the interconnected system become unstable. In relation to the link between power systems and the energy markets, each part of this system has different characteristics, and some models have been proposed to integrate the electricity market behavior with the operation of the system. The use of hierarchical structures to solve mixed time scales problems, most of them technical, can be used to integrate different financial models and technical constraints, leaving an open field of research to improve power systems problems in general.

Throughout this state-of-the-art, several proposals and methodologies to solve problems related with energy markets management were explored, as well as several mathematical tools involved in the problem's solution. Briefly, it is possible to state that the most common ones are: stochastic tools involving high computational cost and large solution times, computational intelligence involving sub optimal results, and single period and dynamic optimization where the use of quadratic forms and lineal models constrains are used to improved global optimal. When several time frames are involved by means of hierarchical structures, MPC theory is usually used to del with the problem, providing a solution method which integrates several dynamics with linear and no lineal models and, allows the inclusion of several constraints in to the problem. In this methodology, results had high dependency of the model's accuracy. Now, the literature review evidences a lack in management tools focused on the solution of an integrated and coordinated energy retailer portfolio. Considering an energy retailer that can participate in the generation market and the basic portfolio management theory bases, portfolio diversification helps to minimize the exposure to the particular risk of portfolio instruments and system uncertainties. Basically, risks associated with energy retailing tasks are: energy price exposure, availability risk and operational risks. Therefore, a diversification strategy advances to use a mix of energy sources that can be grouped in short, medium and long term assets to meet the energy retailer obligations and maximize the returns taking into account technical and financial constraints.

## 2.4. Proposal for retailing portfolio management strategy

The literature review presented in section 2.3 was used to explore management strategies utilized to solve energy retailing-like problems. In short, the need for new management strategies becomes evident when the energy supply-demand problem is considered in a future energy scenario; one with high renewable penetration and increasing uncertainties. Considering both the traditional and novel approaches reported, a lack in the integration of new market conditions in traditional management strategies is perceived. Early efforts were focused to tackle the problem with models and stochastic simulations. Now, research focused in the retailing problem is trying to reduce system uncertainties and allow the integration of new technologies by proposing robust designs. This new approach could help reduce future uncertainties in the power system and improve management problem.

### 2.4.1. Proposed portfolio diversification

Revisiting the energy retailing management problem described in section 2.2, management strategies make use of diversified portfolios to reduce the market risk implied in medium and long term operation by means of energy hedging. Including future and forward assets in the retailing portfolio ensures one will have energy in the future (medium and long term time) with a fixed price negotiated in the Over the Counter (OTC) market. But, at the same time, opportunities to get more returns are minimized [3] and, too big agreements expose retailers to liquidity and market risk as well. However, despite these problems energy agreements are used, and it is common to consider them like virtual generation plants with a defined amount of energy available, including operation constraints like: working hours, maximum amount per hour, among others, and a given start day. Exploring this idea led to the question: What happens if the energy retailer includes generation market participation alternatives in his portfolio? This approach could be used to reduce market exposure risk related to agreement hedging, as participation in the generation market allows one to have energy in the future with a known price and avoids the uncertainty related to bilateral price negotiation based on the underlying asset price. Assuming this, a wide set of integration options will be available to the energy retailer portfolio, thus increasing the relevance of a new management strategy to deal with the new portfolio.

The inclusion of generation plants can be considered as a diversification strategy by means of a particular version of goods transformation. Generation plants can be considered an intermediate good that is used to produce energy. Investments in generation plant construction, plus fixed cost and variable generation expenses, would be considered as the good's input price, and the output would be the energy produced, which could be seen as a produced necessity good. Besides, bearing in mind that there is a wide array of generation technologies, investments made in medium-term installation time plants, such as gas based technologies, represent an asset with a low initial investment cost and a medium-high generation cost to the portfolio. Medium-term assets provide, in technical operation terms, fast response to the front of fast load dynamics, such as regulated user consumption habits, and cover a needed backup in case renewable generation technologies are present in the generation scheme. On the other hand, bigger generation plants, such as hydro or coal, present a much higher installation cost and build time (long-term), but the operation costs are low or null. These kinds of plants are used to supply base load energy, and their flexibility to meet fast changes is compromised.

Later, taking into consideration the previously described additional medium and long terms assets, the energy retailer portfolio conformation is completed including short term assets. This thesis extends traditional portfolio management strategies by including short term assets in the portfolio, thus extending the functionality of the proposed management strategy with the following features: first, the introduction of an optimal market clearing strategy. The use of a dynamic optimization solved over a prediction time horizon, with market clearing strategy allows for the maximization of expected portfolio returns making use of the lowest cost energy sources to supply estimated power system demands. Secondly, an energy market clearing requires an instant and reliable energy source: the spot market. This asset is in charge of balancing the energy retailer's obligations. But while, the spot market is always available as an energy source, its prices are usually higher than those of energy agreements and energy produced by owned generations plants, making this asset only desirable for small, real-time hourly energy demand adjustments. However, including the spot market asset in the market clearing strategy increases the opportunity to get better retailer returns by buying cheaper energy (when available) instead of using owned generation assets. Finally, a short term portfolio introduces non-predictable alternative generation as an additional income. When available alternative energy can be sold immediately, replacing traditional generation sources, this operation increases retailer returns in a market clearing operation.

### 2.4.2. Proposed management strategy

Finally, after describing the basics of the financial instruments used to diversify the retailer portfolio and how they are clustered in sub portfolios by time, it is necessary to discuss the integration of their individual solutions. Grouping portfolio assets by time dynamics increases the optimization problem flexibility, allowing one to use particular models and deal with particular dynamics and uncertainties. In contrast, the results of each solution are different too. Especially in relation to the obtained time frames. As an example: the use of generation plants requires one to analyze data with a yearly resolution, whereas a market clearing operation makes use of data with hourly or daily resolutions. Despite this, both problems are part of a bigger one, and share information and variables. It is here where a coordination function is required. Solving technical and financial problems in each sub system and exchanging only useful and required information between subsystems provides a global integrated and coordinated solution. We present now the first approach to the described integration, published in [7], in order to explain integration and interactions of the described systems as part of the proposed energy retailer management strategy figure **2-4**, the time variables: $T_l$,$T_r$, $N_{p_l}$, $N_{p_r}$ and $N_{P_s}$ will we detailed in section 5.

Long and medium term optimization problems, from now on simply called long term portfolio or long term problem, are the first portfolio optimization solved here; considering as input the historical energy load data the generation expansion plan problem (GEP) is solved. The solution for GEP considers a set of generation technologies where fixed and variable costs of each generation technology are used as decision variables to minimize the installation and operation cost required to supply the expected energy demand represented by the system load duration curve. The problem solution provides the required installed capacity for each technology and the expected operation in a year as well. A modified GEP version is proposed in this work, including the generation ramp velocity into the problem; with this, the solution includes a maximum load change rate for the designed installed capacity into the problem. Finally, the installed capacities, expected generation, and ramp velocities for a year are provided for the remaining portfolios as required, as given information.

Afterwards, long term data is brought to the coordinator problem. Here, the financial function that represents the full energy retailing portfolio cash flow considers four issues:

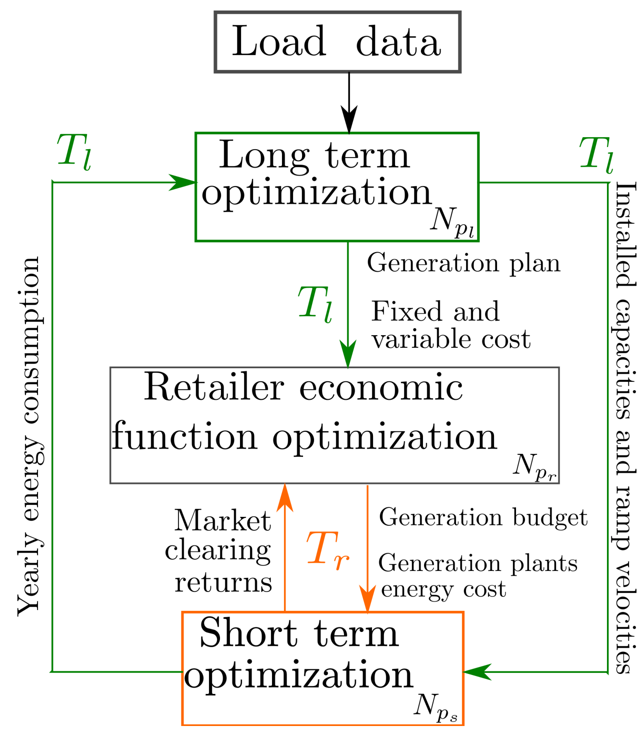


**Figure 2-4**.: Proposed management strategy and data flow

First, with the data provided from the long term problem and the financial values of generations plants considered, the expected incomes and payments are estimated. To do this, it is necessary to define energy prices that will be used to sell energy to regulated and non-regulated customers, and assuming that the expected generation schedule from the long term problem is the energy that will be sold, future incomes are estimated. In the same way, the generation schedule is used to estimate the production cost for each generation technology. Finally, fixed costs related to operation and maintenance (O&M) and payments to capacity construction cost are calculated with the installed capacity value.

Second, take advantage of robust design made in the long term portfolio. Flexibility included with installed capacity and with ramp velocities is used to include alternative generation in the generation plan. Assume a minimum daily production for a given installed capacity that doesn't compromise system stability. Expected incomes and fixed expenses are calculated analogously to the procedure made with traditional generations plants.

Third, a financial component is included in the model. The first asset is a risk-free asset that allows one to store cash with an expected return rate. The second asset included is a loan function that provides the possibility for making loans, in case it is needed. Last, traditional energy forwards agreements are also included. Their negotiation is not the subject of this thesis, but are included manually into the problem providing a certain amount of energy with a fixed price for a given date. Forwards cost payments are also included in the model.

The fourth component is related to short term returns. This term objective is the validation of the assumed expected returns calculated in the portfolio, acting as a system sensor. Expected generation cost obtained from the long term schedule are calculated and sent as an available generation budget for the short term portfolio. There, in principle, according to the design made in the long term portfolio, the market clearing process could be achieved with the installed capacity available, and the assigned generation budget is enough to cover this operation cost. Now, in market clearing optimization, all available generation technologies, renewable sources and forward agreements, including the spot market, are used to meet the real energy demand at the lowest cost. Due to load, spot price and renewable uncertainties, returns obtained from market clearing operations are different from the ones expected when considering the long term problem. Then, by updating initial expected returns with market clearing values, energy retailer profits are obtained.

With the cash flow obtained from the interactions between the elements previously described, energy retailer function maximizes retailer returns, balancing payments of generation technologies and energy agreements. Here, the management strategy could be modified by a portfolio manager, taking into account that frequent payments are key items in portfolio performance: High payments reduce loan and financial fees, decreasing available cash, and extending payments over time increases related fees, but allows for high cash availability. A good management strategy would pay an initial investment as soon as possible, increasing future incomes before the generation plan's life span is over. Solving the problem in a prediction horizon allows a portfolio manager to explore different scenarios and configurations; therefore, it is necessary to extend the proposed strategy as a dynamic optimization.

Considering the challenges of solving a dynamic portfolio with several time frames and models, the use of dynamics system theory becomes relevant. Taking advantage of the time clustering presented in table **2-1**, each portfolio can make use of specific prediction models that enables their optimization problem in a prediction horizon. This approach is widely used, as shown in [36, 37, 32, 38, 26], where hierarchical dynamic structures are solved by means of Model predictive control theory (MPC). MPC theory allows one to solve dynamic constrained problems using the receding horizon principle which, given a prediction horizon, calculates based on the plant model forecast $\hat{y}(k+N_p)$ a set of vectors for the future control actions $u(k+N_p)$ and the future system states $x(k+N_p)$ solving the optimization problem in the future.
In summary, integrating the facts presented previously in this chapter, a general formulation for solving the hierarchical energy retailer management strategy was proposed. The management strategy makes use of MPC to solve three portfolio optimizations, which together form a set of assets used to minimize the risk of the energy retailer task by using generation technologies as diversification assets. The problem is coordinated by an economic function that integrates all the

portfolios models, a distributed structure allows for easy use in each portfolio particular model, in order to represent several assets including new smart grid technologies and to include particular forecast techniques to calculate future portfolio actions.

## 2.5. Energy retailer portfolio with alternative generation technologies model

Now that the management strategy is explained, the model used to represent the described energy retailer cash flow $R^r(k)$ is presented in equation 2-1 for a given $k$ time, where: The free risk interest rate $r_1(k+1)$ is applied to the available cash $R^r(k)$. Expected returns from medium and long term generation investments are represented as $R^l(k+1)$, and $R^a(k+1)$ are alternative generation technologies profits, cost of $N_a$ forward energy agreements is represented with $\sum_{a=1}^{N_a} C_a^{fw}(k+1)$, $v(k)$ are the transfers made between the loan function $L(k+1)$ and the retailer and, $R^s(k+1)$ are the short term returns

$$\begin{aligned} R^r(k+1) &= R^r(k)r_1(k+1) + R^l(k+1) + R^a(k+1) - \sum_{a=1}^{N_a} C_a^{fw}(k+1) + v(k+1) \\ L(k+1) &= L(k)r_2(k+1) + v(k+1) \end{aligned} \tag{2-1}$$

Now, in order to explain all the terms in presented model, let's first define some global variables common to all portfolios: Generation technologies considered in the problem are represented with $i = 1...N_t$; energy forward agreements are indexed as $a = 1...N_a$, discretization of load values is made with $N_b$ blocks, where $j = 1...N_b$ refers to each block section (Details are presented in section 3.1).

### 2.5.1. Medium and long term financial model

Medium and long term variable returns $R^l(k+1)$ include the following terms: yearly fixed cost of generation technologies built $C_i^f$, installed capacity cost $C_i^0$ with a compound interest function at $r_3$ loan rate and $n_c$ compounding frequency. The cost of the availability of $N_t$ generation technologies is represented with two variables, the sum of installed capacity cost $X_i(k+1)$ which has a fixed operation and maintenance $C_i^f$, and incomes related with energy production $y_{ij}(k)$ sold to costumers with regulated $C^r$ and non-regulated $C^{nr}$ prices.

$$\begin{aligned} R^l(k+1) = &\sum_{i=1}^{N_t} y_{i3}(k+1)C^{nr}(k+1) - \sum_{i=1}^{N_t} y_{i3}(k+1)C_i^g(k+1) + \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} y_{ij}(k+1)C_{ij}^r(k+1) \\ &- \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} y_{ij}(k+1)C_i^g(k+1) - \sum_{i=1}^{N_t} X_i(k+1)C_i^f(k+1) - \sum_{i=1}^{N_t} C_i^0(k+1)\left(1+\frac{r_3(k+1)}{n_c}\right)^{n_ck+1} \end{aligned}$$

(2-2)

Medium and long term generation investment returns $R^l(k+1)$ are presented considering three energy demand levels: $N_b = 3$ to represent total demand of the energy retailer in one year, each $j$ block should get its required energy $y_{ij}$ from $i = 1 \ldots N_t$ generation technologies, according to the solution given by the long term portfolio. The first two levels $b = 1,2$ correspond to peak and medium energy demand. Energy supplied in these levels is considered sold at regulated user price $C^r(k+1)$ In the same way, energy sold in the third block $b = 3$ is assumed to be sold to non-regulated customers with a $C^{nr}(k+1)$ price. Note that all $N_t$ generation technologies have the same generation cost $C_i^g(k+1)$.

Related to energy prices, these values are relative to the energy retailer economic strategy or country regulation and it is out of the scope of this work to model these variables. Thus this, the strategy allows to import as given data, or to make use of economic functions to establish regulated and no regulated energy sale prices. Then, if none of these options are available, this work proposes generic expressions that could be used to calculate the retailing prices. Regulated energy price could be calculated taking into account expected generation, desired returns or, in this case a simple approach is made with the mean value of available generation technologies cost $C_i^g(k)$ plus a spread $\Delta C_{ij}^r$, defined by the energy retailer. Proposed spread assignation model makes possible to get different returns according to the demand level where the energy is sold and technology used. This expression can also be extended as base to estimate no regulated prices. On the other hand, non regulated energy price also could be assumed with a fixed price result of external politics or negotiations. General expressions are presented in equations 2-4 and 2-3 and as said they are not mandatory.

$$C^r(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^r(k) \tag{2-3}$$

$$C^{nr}(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^{nr}(k) \tag{2-4}$$

The last term from long term results used in the energy retailer portfolio is generation plant construction cost $C_i^0(k+1)$, a compound interest $r_3$ applied to the cost of the $N_t$ generation plants. This term is extremely relevant because it represents the cost paid for the ability of produce energy with a fixed price (plus other fixed values). These payments are usually used in sensibility financial analysis as "Weighted Average Cost of Capital" (WACC) or "Internal Rate of Return" (IRR) to determine expected returns and project feasibility, which are not a research subject in this work. In this dissertation, compound interest function will be used as an estimation function to measure the impact payments in the cash flow. Also it is possible to consider annualized cost to spread the construction cost over the plan life span.

### 2.5.2. Alternative generation economic model

The alternative generation plant returns $R^a(k)$ representation is analogous to traditional generation plants discussed before; the difference is that alternative plants are not considered in long term operation planning due to their generation uncertainties, but their financial costs are included in the retailer cash flow in order to cover their installation and operation costs.

$$\begin{aligned}R^a(k+1) = {} & E^{pv}(k+1)C^r_{pv}(k+1) - C^0_{pv}(k)\left(1+\frac{r_4(k)}{n_c}\right)^{n_c k} + E^w(k+1)C^r_w(k+1) \\ & - C^0_w(k)\left(1+\frac{r_3(k)}{n_c}\right)^{n_c k} - X_{pv}(k+1)C^f_{pv} - X_w(k+1)C^f_w\end{aligned} \tag{2-5}$$

Alternative generation plants have different assumptions to estimate their expected returns $R^a(k+1)$. It is a fact that the challenge is in forecasting alternative generation sources i.e: wind and sun, however based on historical data, it is possible to define an average production that could be assumed as a daily energy production. Regarding retail prices, instead of using non-regulated prices, the proposed model is provided with extra flexibility, allowing one to fix a different cost to alternative energy produced.

### 2.5.3. Short term economic model

Lastly, short term returns are a balance variable resulting from market clearing operations that use the previously described generation plants from the short term portfolio. This implies two important facts: First, a slack variable in charge of financial corrections due to system uncertainties is represented with $v(k+1)$ acting as bank loans with an associated $r_2(k+1)$ interest rate. This variable compensates feasible differences between expected and real returns, avoiding insolvency states. Second, the presented retailing model does not include an explicit spot market asset as a variable used to perform market clearing. The proposed management strategy assumes that the energy $\sum_{i=1}^{N_t}\sum_{j=1}^{N_b} y_{ij}(k)$ will be fully provided by the generation plants and forward energy agreements. The expected generation budget $B^s(k+1)$ is provided by the energy retailer optimization and is given information for the short term portfolio.

$$B^s(k+1) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_b} y_{ij}(k+1)C^g_i \tag{2-6}$$

Later, when the market clearing process has been made, $R^s(k+1)$ will be provided by the short term portfolio optimization discussed in section 4 where equation 4-23 introduces the model used to calculate these returns.

### 2.5.4. Full retailer models integration

Now, with all model terms explained, the final discussion is: how to deal with time differences between models? $R^l(k+1)$ is updated with yearly information. However, the GEP problem solved in section 3 considers an hourly time resolution to propose a robust generation matrix. A designed generation scheme could meet maximum system load along one year. In other words, by making use of the extreme hourly demand level as design reference, in theory, the installed capacity is able to supply continuously the system peak load for each hour in the year. This fact is used to approach a daily generation budget according to an optimal schedule obtained in the LDC problem. This robust budget allows one to cover, in financial terms, a full traditional generation scheme, then, alternative technologies' contributions represent extra generation incomes to the problem. As mentioned in alternative model explanation, an average daily alternative generation is assumed, but, those incomes are not considered in the generation budget, assuming a basic zero generation cost, and expected alternative profits are just considered in market clearing process, avoiding speculation in management strategy. Then, the time resolution available to estimate a generation budget is given between one hour and a year. On the other hand, the short term portfolio manages time scales between hours and weeks. Considering generation budget flexibility explained beforehand, it is possible to balance the expected generation budget with short term portfolio resolution and prediction horizon. Now, with the explained facts it is possible to propose the use of a scale factor called $Tr$ to balance time differences between long and short variables in retailer model described as follows:

$$\begin{aligned}
&R^r(k+1) = R^r(k)r_1(k+1) + R^l(k+1) + R^a(k+1) - \sum_{a=1}^{N_a} C_a^{fw}(k+1) + v(k+1) \\
&L(k+1) = L(k)r_2(k+1) + v(k+1)
\end{aligned} \tag{2-7}$$

Where:

$$\begin{aligned}
R^l(k+1) &= \sum_{i=1}^{N_t} \frac{y_{i3}(k+1)}{T_r} C^{nr}(k+1) - \sum_{i=1}^{N_t} \frac{y_{i3}(k+1)}{T_r} C_i^g(k+1) + \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} \frac{y_{ij}(k+1)}{T_r} C_{ij}^r(k+1) \\
&\quad - \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} \frac{y_{ij}(k+1)}{T_r} C_i^g(k+1) - \sum_{i=1}^{N_t} X_i(k+1)\frac{C_i^f(k+1)}{T_r} - \sum_{i=1}^{N_t} C_i^0(k+1)\left(1+\frac{r_3(k+1)}{n_c}\right)^{n_c k+1} \\
C^{nr}(k) &= \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^{nr}(k) \\
C^{r}(k) &= \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^{r}(k)
\end{aligned}$$

$$\begin{aligned}
R^a(k+1) &= E^{pv}(k+1)C_{pv}^r(k+1) - C_{pv}^0(k)\left(1+\frac{r_3(k)}{n_c}\right)^{n_c k} + E^w(k+1)C_w^r(k+1) - X_{pv}(k+1)C_{pv}^f \\
&\quad - X_w(k+1)C_w^f - C_w^0(k)\left(1+\frac{r_3(k)}{n_c}\right)^{n_c k}
\end{aligned}$$

$$
\begin{aligned}
R^r(k+1) &\geq 0 \\
L(k+1) &\geq 0 \\
\sum_{i=1}^{N_t} C_i^0(k+1) &\geq 0 \\
C_{pv}^0(k) &\geq 0 \\
C_w^0(k) &\geq 0
\end{aligned}
$$

In short, the energy retailer cash flow model has fixed and variable costs related to short and term variables. Proper use of a scale factor allows one to adjust and match retailer model time resolution variables. Then, by modeling fixed variable and installation cost of generation technologies, a robust generation budget is used to assign financial resources to be managed in a market clearing operation. The integration of a robust generation expansion plan which includes ramping constrains allows one to provide energy, including some alternative generation. Finally, Market clearing optimization makes use of all assets available: generation technologies, alternative generation, forward agreements and spot market to provide operation returns and update the cash flow.

The next step is managing the retailer cash flow described. To do this it is important to identify which variables can be manipulated. Considering that the investment decisions are solved in other portfolio and the return came from a different function as well, management strategy must fulfill the following rules: first, to provide the expected budget needed for generation and market clearing operations. Second: to guarantee a fixed operation cost from traditional and alternative generation technologies. Third: to manage payments related to installed capacity construction; this parameter is subject to manipulation in accordance with particular retailer management conditions. The expected time used to pay generation investments significantly changes the management cash flow. Lastly, the retailer function manages loan operations used to cover cash shortages and investments opportunities. So, taking into account these objectives, the next step is to propose a dynamic optimization model to solve the cash flow problem meeting all the requirements described before.

## 2.6. Retailer model optimization

As discussed in last section, it is necessary to maximize the energy retailer profit represented by $R^r(k+1)$ in equation 2-7. Considering manipulable variables, this section proposes an objective function to manage retailer cash flow by using optimization constraints to meet all requirements involved. The idea is to illustrate a proposed methodology flexibility by integrating short, medium and long term assets. This means that other objective functions can be proposed.
Considering generation installed capacity cost as a variable where the amount to be paid is flexible, those payments are chosen as a manipulated variable to regulate retailer cash flow. Remaining variables such as: O& M, generation budget, energy prices are not flexible. The equation 2-8 propose

a financial objective function where $C_i^0(k), C_{pv}^0(k), C_w^0(k), v(k)$ are used as arguments. All of them, except the energy agreements that are assumed to be paid immediately, have been modified with compound interest rate (CIR). According to proper financial functions, the use of CIR penalizes the time used to pay construction investment obligations.

$$
\begin{aligned}
&\max_{C_i^0(k),C_{pv}^0(k),C_w^0(k),v(k)} R^r(k)r_1(k) - \sum_{i=1}^{N_t} C_i^0(k+1)\left(1+\frac{r_3(k+1)}{n_c}\right)^{n_c k} - C_{pv}^0(k+1)\left(1+\frac{r_4(k+1)}{n_c}\right)^{n_c k} \\
&-C_w^0(k+1)\left(1+\frac{r_4(k+1)}{n_c}\right)^{n_c k} - \sum_{i=1}^{N_a} C_a^{fw}(k+1) + v(k+1) + \sum_{i=1}^{N_t} \frac{y_{i3}(k+1)}{T_r} C^{nr}(k+1) \\
&-\sum_{i=1}^{N_t} \frac{y_{i3}(k+1)}{T_r} C_i^g(k+1) + \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} \frac{y_{ij}(k+1)}{T_r} C_{ij}^r(k+1) - \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} \frac{y_{ij}(k+1)}{T_r} C_i^g(k+1) \\
&-\sum_{i=1}^{N_t} X_i(k+1)\frac{C_i^f(k+1)}{T_r} + E^{pv}(k+1)C_{pv}^r(k+1) + E^w(k+1)C_w^r(k+1) - X_{pv}(k+1)C_{pv}^f \\
&-X_w(k+1)C_w^f
\end{aligned}
\tag{2-8}
$$

Subject to:

$$L(k+1) = L(k)r_2(k+1) + v(k+1)$$

$$C^{nr}(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^{nr}(k)$$

$$C^r(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \Delta C^r(k)$$

$$C_{pv}^r(k+1) = C_{pv}^r(0)$$

$$C_w^r(k+1) = C_w^r(0)$$

$$B^s(k+1) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_b} \frac{y_{ij}}{T_r}(k+1)C_i^g$$

$$R^l(k+1) \geq 0$$

$$L(k+1) \geq 0$$

$$1h \leq T_r \leq 8760h$$

The presented model accurately maximizes the cash flow available by minimizing loses related to generation construction rates for one year measured in hours $8760[h]$ . A trivial solution immediately pays all the generation investments avoiding time penalties. Considering that a trivial solution is an ideal case, the optimization problem should be solved in a time horizon. A time ahead solution allows one to consider reasonable payments, improving the management strategy to real world conditions. Now, as a final step, the proposed management methodology should be extended with a dynamic optimization methodology.

## 2.7. Balancing energy retailer investments with model predictive control

In order to create a management and planning strategy, the optimization problem must be solved in a $N_{p_r}$ time ahead horizon. As a dynamic system, the actions taken over by the system variables will have an impact on the future evolution of retailer cash flow. The objective now is to propose a dynamic optimal management strategy. The proposed solution must take into account future values and bring a set of optimal solutions $u_r(k)$ for each time, which guarantees optimal sets along the prediction horizon. To do this, a space state model representation of equation 2-8 is used. $u_r(k)$ has a set of $P$ variables used to represent the control actions over their corresponding states in $x_r(k)$, interpreted as financial actions. The optimization problem is solved by means of optimal control theory based on the receding horizon strategy. Now, let's consider a system described by a linear discrete time model:

$$\begin{aligned} x_r(k+1) &= A_r x_r(k) + B_r u_r(k) \\ y_r(k) &= C_r x_r(k) + D_r d_r(k) \end{aligned} \tag{2-9}$$

where $x_r \in \mathbb{R}^{n_{x_r}}$ is the system states, $y_r(k) \in \mathbb{R}^{n_{y_r}}$ is the system output and $u_r(k) \in \mathbb{R}^{n_{u_r}}$ is the current control vector. Using equation 2-7, the state space representation of the problem is written as follows:

$$x_r(k) = \begin{bmatrix} C_1^0(k) \\ \vdots \\ C_{N_t}^0(k) \\ C_{pv}^0(k) \\ C_w^0(k) \\ C_1^{fw}(k) \\ \vdots \\ C_{N_a}^0(k) \\ L(k) \\ R^r(k) \end{bmatrix} \qquad u_r(k) = \begin{bmatrix} P_1^0(k) \\ \vdots \\ P_{N_t}^0(k) \\ P_{pv}^0(k) \\ P_w^0(k) \\ P_1^{fw}(k) \\ \vdots \\ P_{N_a}^0(k) \\ v(k) \\ 0 \end{bmatrix} \tag{2-10}$$

$$A_r(k) = \begin{bmatrix} I_{Nt} & 0 & 0 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 1 & 0 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 0 & 1 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 0 & 0 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 0 & 0 & 0_{Na} & r_2 & 0 \\ -1_{Nt} & -1 & -1 & -1_{Na} & 0 & r_1 \end{bmatrix} \qquad B_r = \begin{bmatrix} -I_{Nt} & 0 & 0 & 0_{Na} & 0 & 0 \\ 0_{Nt} & -1 & 0 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 0 & -1 & 0_{Na} & 0 & 0 \\ 0_{Nt} & 0 & 0 & -1_{Na} & 0 & 0 \\ 0_{Nt} & 0 & 0 & 0_{Na} & 1 & 0 \\ 0_{Nt} & 0 & 0 & 0_{Na} & 1 & 0 \end{bmatrix}$$

$$C_r(k) = \left[ \underbrace{-\left(1+\frac{r_3(k)}{n_c}\right)^{n_c k}}_{N_t} \quad -\left(1+\tfrac{r_4(k)}{n_c}\right)^{n_c k} \quad -\left(1+\tfrac{r_4(k)}{n_c}\right)^{n_c k} \underbrace{-\left(1+\frac{r_2(k)}{n_c}\right)^{n_c k}}_{N_a} \quad -1 \quad r_1(k) \right]$$

$$d_r(k) = \left[ \underbrace{C^{nr}(k) - C_i^g(k)}_{N_t} \quad \underbrace{C^r(k) - C_i^g(k)}_{i\in N_t; j\in 1\ldots N_b-1} \quad \underbrace{C_i^f(k)/T_r}_{N_t} \quad C_{pv}^r(k) \quad C_w^r(k) \quad -C_{pv}^f(k) \quad -C_w^f(k) \right]^T$$

$$D_r(k) = \left[ \underbrace{y_{i3}(k)}_{N_t} \quad \underbrace{y_{ij}(k)}_{i\in N_t; j\in 1\ldots N_b-1} \quad \underbrace{X_i(k)}_{N_t} \quad E^{pv}(k) \quad E^{w}(k) \quad X_{pv}(k) \quad X_w(k) \right]$$

The state space model presented in equation 2-9 splits will be used to solve the dynamic optimization problem. At the $k-th$ time step, the system output $y_r(k)$ is composed by two terms: free response given by $D_{r(k)}$ and $d_r(k)$ which represents non-manipulable incomes and the cost of the system. And the remaining term is the forced system response. Now, defining a new optimization problem which considers the dynamic model along a $N_{P_r}$ prediction horizon. The optimal control actions $\tilde{U}_k^r = \{u_r(k|k), ..., u_r(k+N_{p_r}-1|k)\}$ used to manage the retailer portfolio are obtained. Taking into account the forced dynamic response cost represented by $C_r$ and $x_r$ variables, all represented dynamics involved in a forced system response will be considered to proposed the economic objective function. In addition, an optional weight matrix $Q^r$ is used to penalize changes in the control variables (if desired). This could be used to implement technical or financially real constraints such a: penalization for big changes in the control actions to help to avoid unfeasible or infinite solutions. Then, the problem to be solved in the projection horizon is described as follows: Then, by extending the dynamic system in the prediction horizon, a new set of variables is obtained. This representation is useful for solving the full problem in one step. And it is widely used, specially when a problem could become be unstable or unbounded, as is the case where $C_r(k)$ could grow infinitely. Thus this, let at time step $k$, let $x_{k_r} = [x_r^T(k), \ldots, x_r^T(k+N_{p_r})]^T$ and $u_{k_r} = [u_r^T(k), \ldots, u_r^T(k+N_{p_r})]^T$ are the state trajectory and the control sequences, with $N_{p_r}$ the retailer prediction horizon and $J_{econ}(x_{k_r}, u_{k_r})$ the economic stage cost. The system is subject to hard constraints on state $x_r(k) \in \mathbb{X}_r$, output $y_r(k) \in \mathbb{Y}_r$ and input $u_r(k) \in \mathbb{U}_r$ for all $k \geq 0$, where $\mathbb{X}_r \subset \mathbb{R}^{n_{x_r}}$, $\mathbb{Y}_r \subset \mathbb{R}^{n_{y_r}}$, $\mathbb{U}_r \subset \mathbb{R}^{n_{u_r}}$ are closed sets. In order to calculate the optimal control solution $u_{k_r}$ for the energy retailer the cost function will be based on the state space output $y_r(k) = C_r x_r(k)$ described in equation 2-9 as $\tilde{C}_r(k) = [C_r, \ldots, C_r(k+N_{p_r})]^T$, and the economic MPC formulation is given:

$$\tilde{A}^r = \left[ \; A_r(k) \quad \ldots \quad A_r(k+N_{p_r}) \; \right] \qquad \tilde{B}^r = \left[ \; B_r(k) \quad \ldots \quad B_r(k+N_{p_r}) \; \right] \tag{2-11}$$

$$\tilde{X}_k^r = \left[ \; x_k^r(k) \quad \ldots \quad x_k^r(k+N_{p_r}) \; \right] \qquad \tilde{U}_k^r = \left[ \; u_k^r(k) \quad \ldots \quad u_k^r(k+N_{p_r}) \; \right] \tag{2-12}$$

$$\tilde{C^r} = \left[\begin{array}{ccc} C_k^r(k) & \dots & C_k^r(k+N_{p_r}) \end{array}\right] \qquad \tilde{D_k^r} = \left[\begin{array}{ccc} D_k^r(k) & \dots & Du_k^r(k+N_{p_r}) \end{array}\right] \tag{2-13}$$

$$\tilde{Q^r} = \left[\begin{array}{ccc} Q^r & \dots & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & Q^r \end{array}\right] \qquad \tilde{d_k^r} = \left[\begin{array}{ccc} d_k^r(k) & \dots & d_k^r(k+N_{p_r}) \end{array}\right] \tag{2-14}$$

Finally, with the augmented system, the dynamic optimization problem can be solved for a prediction horizon with following formulation.

$$\max_{\tilde{U_k^r}} \tilde{C^r}\tilde{X_k^r} + \tilde{U_k^r}^T \tilde{Q^r}\tilde{U}_k$$

Subject to system constrains extended along the predicition horizon

$$\begin{aligned}
&x_r(k+1) = A_r x_r(k) + B_r u_r(k) \\
&L(k+1) = L(k) r_2(k+1) + v(k+1)\ \forall k = 0, \dots N_p \\
&C^{nr}(k+1) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} y_{ij}(k+1) C_i^g(k+1) + \Delta C_{ij}^r \\
&C_{ij}^r(k+1) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} y_{ij}(k+1) C_i^g(k+1) + \Delta C_{ij}^r \\
&C_{pv}^r(k+1) = C_{pv}^r(0) \\
&C_w^r(k+1) = C_w^r(0) \\
&B^s(k+1) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_b} \frac{y_{ij}}{T_r}(k+1) C_i^g \\
&R^l(k+1) \geq 0 \\
&L(k+1) \geq 0 \\
&1 \leq T_r \leq 8760 \\
&x_r(k) \in \mathbb{X}_r, \ \ k = 0, \dots, N_{p_r} \\
&u_r(k) \in \mathbb{U}_r, \ \ k = 0, \dots, N_{p_r}
\end{aligned} \tag{2-15}$$

In short, this chapter discussed energy retailing management objectives and strategies used. Then, based on the future new power system scenarios and the presented state-of-art of strategies used was identified that traditional strategies relies on energy forward agreements to reduce portfolio risk. In trade, this kind of strategy is not always effective to increase portfolio returns. Furthermore, it can be dangerous in some cases, as it creates other risks. To face this, a new management strategy based on generation investments. Hedging future energy with generation plants allows to reduce future energy price risk and increase expected profits for energy retailers. Also considering the generation ramp rate of the generation matrix, the use of alternative generation plants is considered. Then, a short portfolio is used to estimate the market clearing process. A budget based on the expected generation cost of generation technologies available is used to establish a generation budget that is used in the market clearing process to balance power generation between traditional and alternative generation plants, some energy agreements and the spot market. By doing this, retailer returns are maximized. All this process is coordinated by energy retailer cash flow functions in charge of cash flow management, including fixed and variable cost of the retailer portfolio. Finally, the optimization function is solved by means of model predictive control in a prediction time horizon, providing a planning tool to be used in portfolio management. Now, the following chapter explains the solution of the generation investment problem and market clearing process to finally integrate all solutions in a case study.

# 3. Medium and long term portfolio problems

The main objective of medium and long term portfolios in the energy retailer operation is to minimize the operational and financial risk related to energy markets. The energy retailer has the option to buy energy from the spot market or to buy it through energy agreements. Additionally, if regulation allows it, it is possible to produce one's own energy by investing in generation plants with the proper technical and financial assumptions. As mentioned before, the objective is to reduce the energy market's risk to exposure. The spot market asset in the long term is not desirable as the uncertainties related to energy price and availability are too high to be considered. Energy agreements commonly signed in the OTC market are attached to previous negotiations between generators and energy retailers. Once signed, energy agreements can be seen as virtual generation plants which offer a certain amount of energy for a limited amount of time at an established price. Generation plants can be seen as a variation of energy agreements, where the energy price is determined by fixed and variable generation costs, and not by a bilateral negotiation. Then, generation plants produce a limited amount of energy with a price related to the technology used. Using generation plants instead of energy agreements provides a flexibility in terms of energy dispatch. The energy retailer can choose according to the price and the load level which plant to use. Furthermore, at a certain time, the short term portfolio can choose according the spot price, if it is better to supply the energy from the spot market or not. The described approach makes the problem analog to the generation expansion plan problem, where based on the system load duration curve (LDC) of the system, the generation mix is optimized using installed capacity and operation cost, plus fixed values, to provide energy at the lowest price. This problem has been studied since 1982, and, as mentioned in section 2.3, is now subject of new research aiming to integrate alternative generation into the solution. Now, this chapter presents a proposal for the GEP problem and its integration into the management strategy discussed in this work.

## 3.1. Load duration curve discretization to estimate future generation investments

The generation expansion plan problem provides optimal investments decisions based on system load time series, expressed as the Load Duration Curve (LDC). LDC is a continuous function $D(\alpha_n)$ with $0 \leq \alpha_n \leq 8760$ hours that represents the amount of time a certain electricity demand is requested to the power system. With a set of generation technologies, several combinations of installed capacities can be used to meet the LDC electricity demand. The solution procedure begins with the LDC discretization (detailed explanations of LDC discretization are presented in [39]). The objective, as shown in figure **3-1**, is to find the minimal cost combination to supply energy using the installed capacity and energy produced as decision variables.

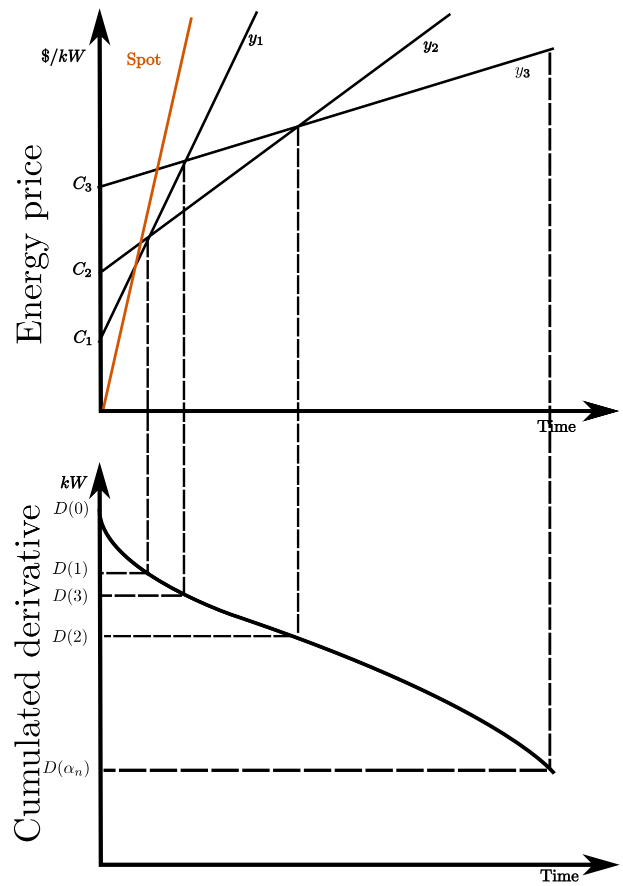


**Figure 3-1**.: Generation expansion problem

Several solutions consider a discrete LDC representation to solve the problem, as shown in the state-of-art. In this work, the proposed block discretization is based on [39] and [40]. Considering the area below, the $D(\alpha_n)$ curve is approached with the sum of several $b_j$ blocks where the discretization parameter is based on temporal decomposition. In figure **3-2** a,b and c, the graphics illustrate the use of a time axis with $\alpha_n$ values as variables to minimize discretization errors $\varepsilon_j$. By minimizing discretization errors, the resulting sets $\theta_j$ are the width that corresponds to the optimal time duration of the $b_j$ blocks for one year. Then, the height of the $b_j$ are the $D(\alpha_n)$ function values represent then maximum required power (installed capacity) for each block.

Then, $\theta_j$ and $D(\alpha_n)$ are used to define the approximation of $D(\alpha_n)$ as a discrete function, considering $n$ a finite number $n \in \mathbb{R}^1$ and $n \geq 1$ will have an error associated $\varepsilon$ and can be expressed

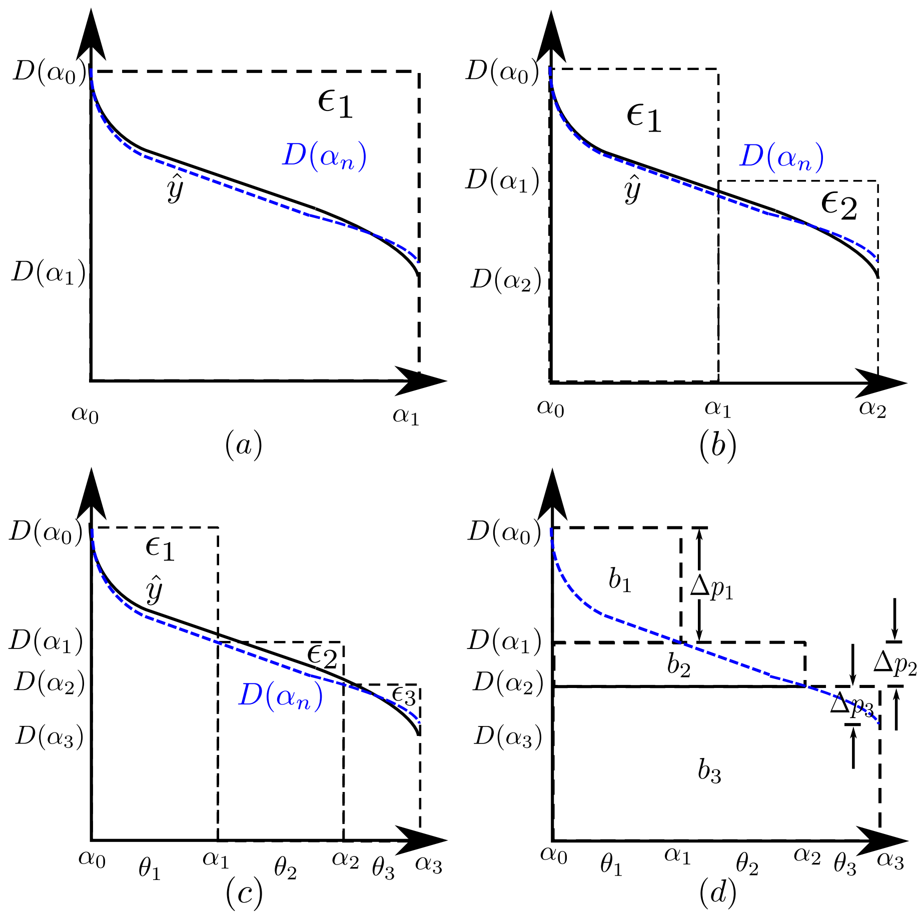


**Figure 3-2**.: LDC discretization problem

as:

$$\varepsilon = \int_0^{8760} D(\alpha_n) d\alpha_n - \sum_{n=1}^{\alpha_n} \theta_n D_{\alpha_n - 1} \tag{3-1}$$

If $\int_0^{\alpha_n} D(\alpha_n) d\alpha_n$ is piecewise approximated with rectangles considering $\theta_j = \alpha_n - \alpha_{n-1}$ result preserves the LDC decreasing characteristic. Hence, it is possible to say that:

$$\theta_{\alpha_n} D(\alpha_{n-1}) \geq \theta_{\alpha_n} \frac{D(\alpha_{n-1}) - D(\alpha_n)}{2} \tag{3-2}$$

Now, the described approximation the LDC block discretization will always be greater than the LDC function for a finite number of blocks. Providing a confidence interval to generate a maximum amount of energy offers a robust solution in term of installed capacity. In order to reduce the associated error minimization and generation capacity oversize, a trapezoid LDC approximation for the energy blocks is used (see figure **3-3**). Finally, the optimization problem is presented in equation 3-3

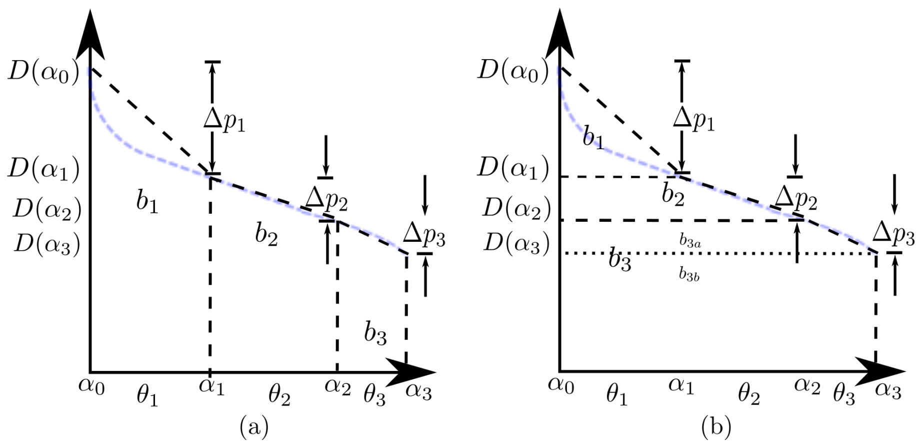


**Figure 3-3**.: LDC discretization problem improvement

$$\min_{\alpha_n} \left[ \sum_{n=1}^{N} (\alpha_n - \alpha_{n-1}) D(\alpha_{n-1}) - \sum_{n=1}^{N} \left( \frac{D(\alpha_{n-1}) - D(\alpha_n)}{2} \right) (\alpha_n - \alpha_{n-1}) \right] \tag{3-3}$$

Subject to

$$0 \leq \alpha_n \leq 8760$$
$$D'(\alpha_n) \leq 0$$

From now on, optimal values that minimize the LDC discretization error, stated simply the optimal blocks, will be defined as:

$$\begin{aligned} \theta_j &= \alpha_n - \alpha_{n-1} \\ b_j &= \theta_j D(\theta_j) \end{aligned} \tag{3-4}$$

To improve illustrative simplicity, trapezoid areas will be used in this work as rectangles representing the energy of discretized LDC. Thenceforth, for optimal discrete LDC each LDC block exhibits the following characteristics: block $b_3$ has the lowest demand uncertainty and the lesser approximation error. From a financial and operative point of view, this block represents non-regulated users whose consumption is attached to forward energy agreements. This block is usually supplied with base load generation technologies. Note from Fig **3-3** that the $b_3$ block has a trapezoid $b_{3a}$ part, and a fixed energy block $b_{3b}$ is usually known as base load in power systems. Block $b_2$ represents more variable energy consumption, mostly comprised by small factories and the smaller non-regulated users and residential sectors. Volatility of this block is significantly higher than block $b_3$ and it is this variability that mostly correlates to regulated user patterns. In addition, $b_2$ block's energy consumption is usually generated through technologies with affordable prices for big amounts of energy. But it should also be flexible with a fast response to the load variations.

Finally, the $b_1$ demand block represents system demand peaks. These peaks' duration hardly last more than one hour and their appearances during the day are very few; these facts create a market opportunity to deal with them, allowing one to cover them with energy agreements or demand response strategies. At the same time, it implies a big operation challenge for generators and system operators stressing the power system to its production limits. Finally, figure **3-4** represents in the short discretization proposed including $\Delta p$ values discussed in next section.

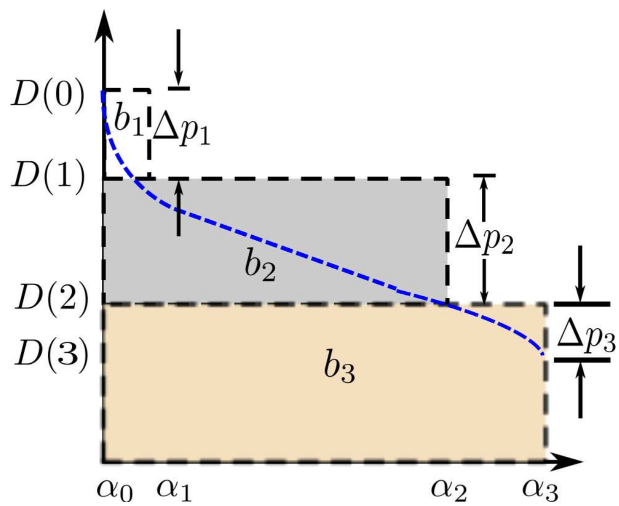


**Figure 3-4**.: Discretized LDC graphic explanation

## 3.2. Ramping velocity constraint in generation investments planning

The LDC discretization proposed in section 3.1 could be used to analyze each block data separately. In order to explore this, considering discretized blocks as clusters to group dynamics of energy presented in the LDC, this information can be used to improve the LDC problem. Recently, smart grid technology penetration has increased system dynamics. Faster and bigger changes to the generation and load time series have been evidenced. This fact is not new on a smaller scale and had been tackled, compensating these changes with generation technologies and their ramping velocity. Due to this, it's common to use terms like "fast and slow generation technologies" to refer to them. Consequently, by exploring the time series dynamics and generation ramp velocities relationship, this work focuses on a general methodology to improve the LDC problem, including technical constraints into the optimization problem. By doing this, it would be possible to design optimal generation solutions able to meet specific load change requirements. One possible application of this methodology leads to the safe use of alternative generation plants. Covering alternative generation plants with fast generation plants allows the system to back up their uncertainties for short times while a bigger plant compensates the power balance.

The hypothesis is: Considering a $N_t$ set of generation technologies, it is possible to mix them taking into account the ramp velocities in an economic diversification approach in order to meet load changes. Including this technical constraint in the GEP creates a new optimal design that will meet operational constraints at the lowest cost. Now, consider that every load change $\Delta p$ requires a change in the operational point of one or several power plants to produce the required energy compensation $\Delta y$. It is possible to establish that the ideal market clearing operation is $\Delta p = \Delta y$ for each $t$. And, considering a power generation set with $N_t$ generation technologies available, it is possible to meet the operation changes in the system with a mix of the capacities of each technology represented as a weighted sum, where $\lambda_i$ is the participation of the $i-th$ technology in the power change and $V_i$ the ramp rate of each technology:

$$\Delta p = \sum_{i=1}^{N_t} \lambda_i V_i y_i \tag{3-5}$$

With the weighted generation portfolio approach formulated in equation 3-5, it is possible to extend the diversification approach for each $b_j$ block including ramp velocity constraint in the whole LDC and GEP. This work will use the load time series analysis described in section 3.3 to find the $\Delta p_j$ values for each $N_p$ demand level. These values will be used as the minimum ramping value that the solution must guarantee (see equation 3-6) to meet the technical design parameter imposed.

$$\Delta p_j \leq \sum_{i=1}^{N_t} \sum_{j=1}^{N_b} \lambda_{ij} V_i \tag{3-6}$$

## 3.3. Methodology to determine ramping values in generation expansion problem

In order to identify the $\Delta_p$ value in each demand level proposed, the methodology calculates the time ahead load time series derivative. Then, used LDC time series is matched with each demand level obtained in section 3.1, (see figure **3-5**).
Derivatives of each block are shown in figure **3-6**. Finally the $\Delta p_j$ values are obtained from the maximum derivative value for each block and presented in table **3-1**. A comparison between the identified and the maximum $\Delta p_j$ values for each demand level is shown in table **3-1**. The maximum $\Delta p_j$ values are the biggest change possible defined by the $b_j$ block size.
The obtained $\Delta p_j$ values presented in table **3-1** evidences that ramping results are highly dependent on LDC discretization. However, considering that LDC is commonly split into base, medium and peak loads, recent works such as [29] focus on the medium section of the LDC to integrate fast and renewable and non-renewable technologies as a complement in this region. The presented analysis

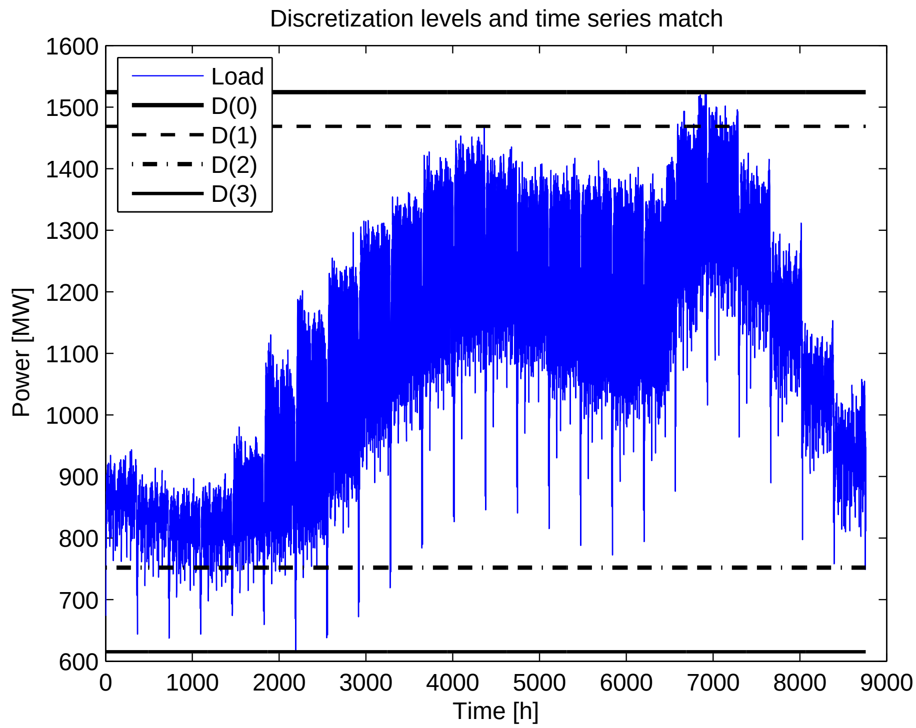


**Figure 3-5**.: Discretization levels and time series match for energy load from EPM retailing company - 2013

| | Max $\Delta p_j$ [MW/h] | Derivative $\Delta p_j$ [MW/h] |
|---|---|---|
| Block 1 | 62 | 53 |
| Block 2 | 716 | 422 |
| Block 3 | 136 | 136 |

**Table 3-1**.: $\Delta p_j$ values for each block

results are aligned with other works identifying $b_2$ as the most variable LDC region.

Now that the derivatives for each block are identified, a comparison between the load derivatives with some generation technologies' ramp velocities is presented in figure **3-7**. The figure includes the percent of occurrences of load peaks exceeding ramp velocity, presented in section 3.4.1, in one year. It is important to note that the methodology used for this comparison considers hourly change values. Therefore, it was necessary to scale each technology ramp value $V_i$ from minutes to hours; so the comparison made contrasts hourly changes against the maximum possible compensation for each technology. Then, approximately 91.7% of hourly changes could be covered with Coal generation. 8.04% could be fulfilled with CCGT velocity. Finally, 0.2% exceeds COAL and CCGT capabilities, and OCGT is the remaining technology considered in the set that could meet these changes. Note that including OCGT provides extra flexibility to the demand of the system

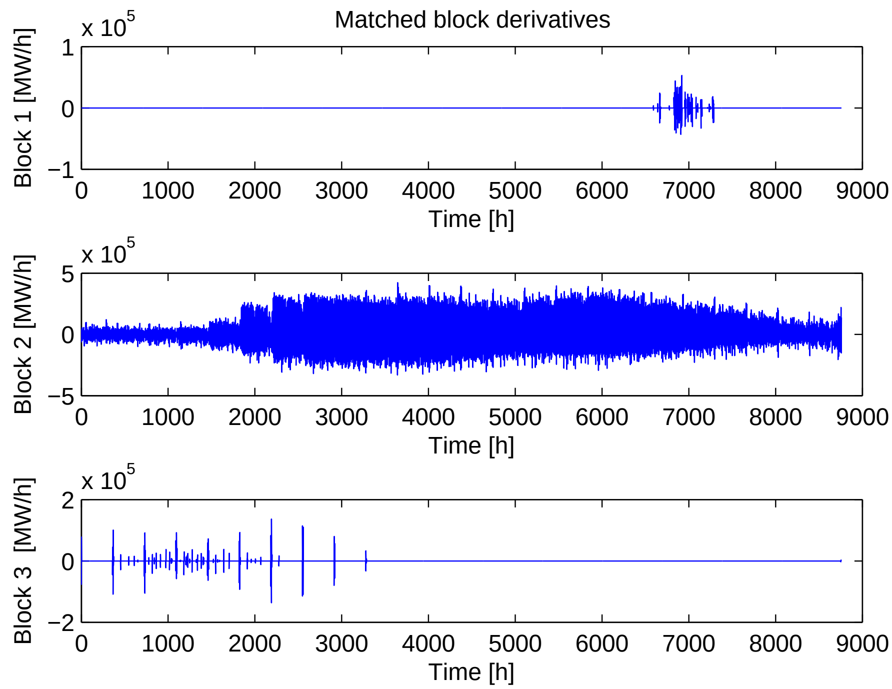


**Figure 3-6.**: Matched block derivatives

changes.
In short, a comparison between load changes and generation ramp velocities gives us an idea of a generation mix that includes system flexibility. Now the challenge is to integrate this results in the GEP solution.

## 3.4. Generation expansion problem with ramping constrained model formulation

With the $\Delta p_j$ values for each demand block, the next step is to find the optimal combination of generation technologies to supply at the lowest cost taking into consideration ramping constraints. The equation (3-6) allows one to diversify generation technologies considering ramp velocities by means of $\lambda_{ij}$ values. In order to meet energy and flexibility criteria, each demand level of discretized LDC will integrate velocity constraints. This is made by balancing the generation mix of each block combining expected energy required with $y_{ij}$ with $\lambda_{ij}$ values. The $\sum_{i=1}^{Nt}\sum_{j=1}^{Nb} y_{ij}\lambda_{ij}\theta_j = b_j$ equality guarantees the required energy in each block. The dynamic constraint $\sum_{i=1}^{Nt}\sum_{j=1}^{Nb} \lambda_{ij}V_i \leq \Delta p_j$ puts the desired operative level for the ramping combination in each block. Finally, considering $0 \leq y_{ij} \leq x_i\lambda_{ij}$ the operation of each plant and the installed capacity are also restricted by $\lambda_{ij}$ variables. This constraint, joined with $\sum_{i=1}^{Nt}\sum_{j=1}^{Nb} y_{ij} \leq x_i$, extends the $\lambda_{ij}$ impact to the installed capacity variable. Now, in order to compare the proposed and referenced

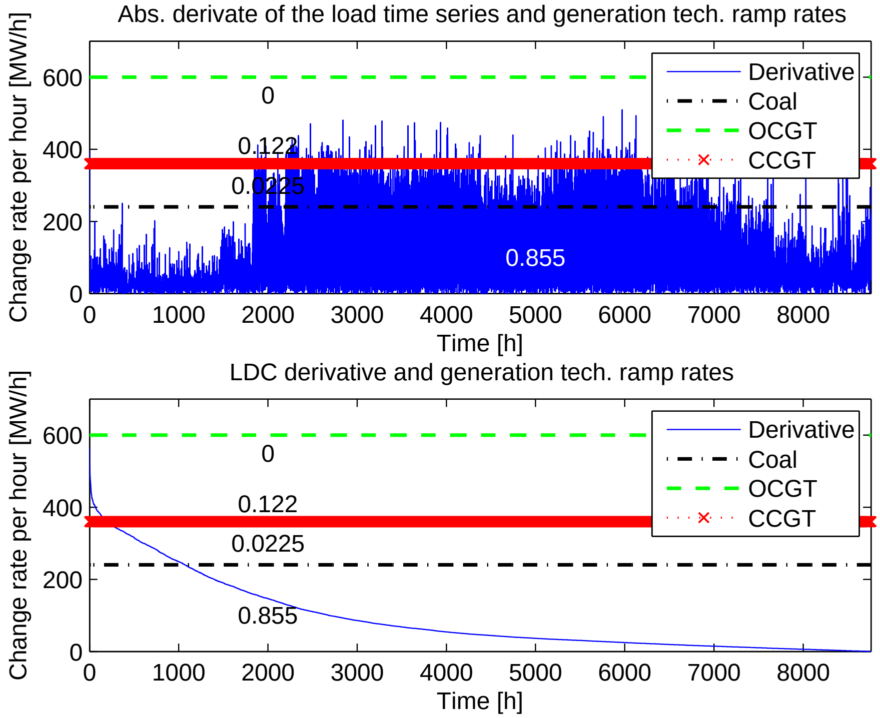


**Figure 3-7.**: Derivative and ramp velocities comparison

approach, reference for used variables is presented in table **3-2**, and classic and dynamic formulations are presented in the equation (3-9), as follows:

| Variable | Name | Unit |
|---|---|---|
| $i = 1 \ldots Nt$ | Generation technologies | |
| $j = 1 \ldots Nb$ | Discretized blocks | |
| $c_i$ | Annualized installation cost | $\left[\frac{\$}{kW}\right]$ |
| $f_i$ | Operation cost | $\left[\frac{\$}{MW}\right]$ |
| $x_i$ | Installed capacity | $[kW]$ |
| $y_{ij}$ | Technology use | $[MW]$ |
| $\theta_j$ | Block duration | $[h]$ |
| $b_j$ | Maximum required energy | $[MWh]$ |
| $\Delta p_j$ | Maximum power change | $\left[\frac{MW}{h}\right]$ |
| $\lambda_{ij}$ | Velocity weight | $[\%]$ |

**Table 3-2.**: Variables description of the load duration curve optimization problem

Lets define common variables for each problem as follows:

$$x_l = \begin{bmatrix} x_1 & \dots & x_i & y_{11} & \dots & y_{1j} & \dots & y_{ij} & \lambda_{ij} & \dots & \lambda_{1j} & \dots & \lambda_{ij} \end{bmatrix}^T \tag{3-7}$$

$x_l$ represents the system variables: installed capacity, use of each technology and the weights of the dynamic solution for each technology.

$$C_l = \begin{bmatrix} c_1 & \dots & c_i & f_1\theta_1 & \dots & f_1\theta_j & \dots & f_i\theta_j & 0_{ij} \end{bmatrix} \tag{3-8}$$

$C_l$ represents the solution cost for one year. The $c_i$ values represent the annualized installation capacity and fixed operation cost for each generation technology, $f_i$ represents the sum of the operation and maintenance (O&M) cost and the fuel cost for each technology. The use of the annualized costs shares the installed capacity price over the life span of each technology. Note that the cost of $\lambda_{ij}$ values is zero. In order to compare the classic and the ramping constrained models, the same cost function is used. Then, the models used to solve the GEP are presented:

$$\begin{array}{ll}
\text{Economic solution} & \text{Ramping constrained solution} \\
\min\limits_{x_i,y_{ij}} C_l x_l & \min\limits_{x_i,y_{ij}} C_l x_l \\
\text{Subject to:} & \text{Subject to:} \\
\sum\limits_{i=1}^{Nt}\sum\limits_{j=1}^{Nb} y_{ij} \le x_i & \sum\limits_{i=1}^{Nt}\sum\limits_{j=1}^{Nb} y_{ij} \le x_i \\
\sum\limits_{i=1}^{Nt}\sum\limits_{j=1}^{Nb} y_{ij}\theta_j = b_j & \sum\limits_{i=1}^{Nt}\sum\limits_{j=1}^{Nb} y_{ij}\lambda_{ij}\theta_j = b_j \\
0 \le x_i \le \infty & \sum\limits_{i=1}^{Nt}\sum\limits_{j=1}^{Nb} \lambda_{ij}V_i \ge \Delta p_j \\
0 \le y_{ij} \le \infty & 0 \le y_{ij} \le x_i\lambda_{ij} \\
 & 0 \le \lambda_{ij} \le 1
\end{array} \tag{3-9}$$

Classic economic solution and the proposed ramping constrained solution are compared in equation 3-9. Note that when $\lambda_{ij} = 1$ leads to the classic formulation, this particular solution appears when all generation technologies are fast enough to meet $\Delta p_j$ requirements.

### 3.4.1. Case study

In order to compare presented models, an application case with four scenarios is proposed based on data used in section 3.3. The data represents 2013 load data from one of the biggest energy retailers from Colombia. The data is composed by regulated and non-regulated users, as renewable generation technologies are not mature in the market, nor is demand response or similar strategies.

Generation technologies used in the problem, presented in table **3-3** were selected to form a competitive set of technologies in terms of cost and ramping rates: a slow base load technology and two fast technologies are used. Big installed capacity prices imply low generation cost and a slow ramp rate, whereas fast generation technologies had smaller installed capacity cost with higher operation cost and ramp velocities.Next technical values, presented in **3-3**, are taken from [31] and [41].

| Gen. Tech. | Capital Cost $\left[\frac{\$}{kW}\right]$ | Fixed Cost $\left[\frac{\$}{kW}\right]$ | Variable Cost $\left[\frac{\$}{MWh}\right]$ | Life Span $[years]$ | Ramp Rate $\left[\frac{MW}{min}\right]$ |
|---|---|---|---|---|---|
| Coal | 1700 | 34 | 5 | 40 | 4 |
| OCGT | 486 | 12 | 15 | 20 | 10 |
| CCGT | 855 | 21 | 10 | 30 | 6 |

**Table 3-3**.: Generation technologies cost and operational variables used in the problem

Thenceforth, test scenarios based on the 2013 load data shown in figure **3-8** and three additional artificial scenarios are created. It is importante to mention that each called scenario represents an energy demand condition, and they are considered as a sequence along the time horizon. The first scenario is taken from the demand time series presented in figure **3-5**, and the demand levels obtained from the discretization presented in section 3.1. The $\Delta_p$ values of the first scenario correspond to the values presented in table **3-1**. This scenario will be used as reference for following proposed scenarios, with the objective being to simulate particular or extreme conditions to stress the proposed solution.

The second scenario presents a 10% growth in all blocks for $b_j$ and $\Delta_p$ values. Assuming a positive development in the country, this scenario reflects a stable economy where regulated and non-regulated users have increased their energy consumption, raising as well the uncertainties and demand peaks for each in the LDC. Usually this growth is estimated based on the country's Gross Domestic Product (GDP) and related economic variables.

The third scenario assumes an additional 10% increase in block 1 and a 30% reduction in block 2, pushing the hypothetical case of high load peaks and uncertainties in the operation. This scenario could be the product of high penetration of distributed PV or wind generation in regulated costumers, reducing their consumption throughout the day (in block 2), and shifting their uncertainties to peak demands, assuming high concentration of the alternative generation in particular regions with similar weather conditions.

Finally, a fourth scenario simulates a 10% growth in block 3's load. Keeping previous values in blocks one and two, the simulated increment in block 3 assumes a non-regulated user expansion.

This could be the most optimistic and demanding scenario, as high renewable penetration increases system uncertainties and non-regulated user consumption requires a solid firm generation.

The described scenarios are used to represent hypothetical situations on the LDC. They don't necessarily take place every year. However, these scenarios are useful to push extreme situations on a design strategy, allowing one to look several years ahead in the generation expansion planning problem.

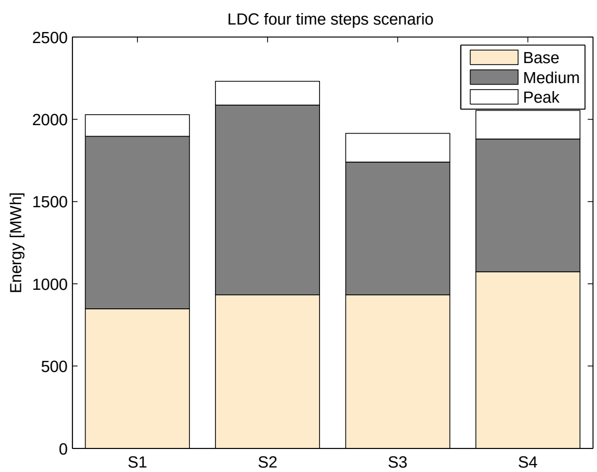


**Figure 3-8**.: Proposed changes in the LDC values. Each step is an independent energy requirement along a time sequence

## 3.4.2. Economic and ramping constrained comparison

The presented results will compare a traditional economical LDC solution that lacks of ramping constraints and the ramping constrained LDC methodology described in section 3.1. Making use of the LDC hourly time resolution and matching the generation ramp velocity units to LDC time frame, a robust solution which provides the optimal economic combination of generation technologies to meet a yearly energy demand with a low computational demand is obtained.
Solving for the same LDC scenarios equations presented in 3-9, installed capacities for each solution are presented in figure **3-9**
Yearly use of each technology per block are presented in figures **3-10** and **3-13** for classic and ramping constrained solutions respectively. Starting with scenario 1 (S1) results, traditional model without ramping constraints and the proposed ramping constrained model provides the same solution for installed capacity and use: a base load technology operating in $b_2$ and $b_3$ energy blocks, which has the higher energy demand. An OCGT generation plant is the choice for $b_1$ block, providing the energy with a higher cost but the lowest install capacity cost. In this solution, the same technology mix meets the ramping requirements. Then, in scenario number two (S2), the classic

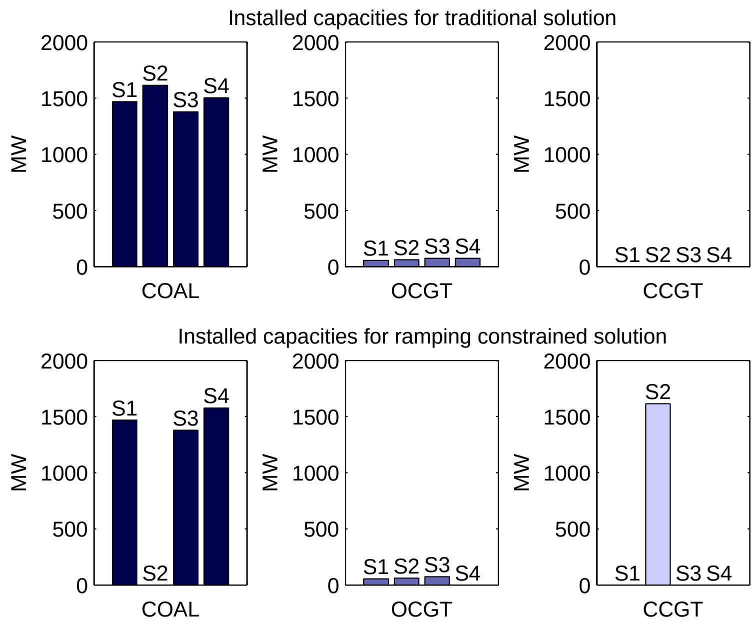


**Figure 3-9**.: Traditional and ramping constrained installed capacities for each scenario

solution increases the installed capacity proportionally to the power increase required in the scenario. The lack of ramping constraints make the solution blind to the dynamic changes of demand. In contrast, a noticeable change in the generation mix is made by the ramping constrained solution in scenario two (S2) where the demand increment is supplied by using a mix between OCGT and CCGT, where CCGT is used to replace base technology instead of Coal (see figure **3-10**) S2 column for each technology; this dramatic change it is not desired in real operation and will be addressed in next sections. This change increases the solution's operative cost but represents the lowest possible cost to meet the ramping requirements. With this result, a trade-off between capacity and system response flexibility has been demonstrated. Subsequently, in scenario three, a small increment in both solutions in the OCGT technology covers peak increment induced in block 1 when energy required in block 2 was reduced; this suggests that the simulated load shift of scenario 3 could be managed by means of fast generation technologies. Finally, in the fourth scenario, the classic solution compensates base block $b_3$ increment by increasing Coal installed capacity as base generation technology, while the ramping constraint methodology decides that it is better to increase Coal installed capacity covering power required in all $b_j$ blocks. This scenario suggests an interesting result covering all system demand with Coal, showing again a tradeoff between installed capacity and system flexibility.

From previous results, the proposed solution is very sensitive to increments in $\Delta_p$ values. GEP solutions could be dramatically different between classic and proposed models. Therefore, considering that in real applications strong changes in installed capacity are not desirable, the next step is to stabilize the ramping constrained model solutions. This can be made, analogously to real operation, considering previously installed capacities in each solution. Establishing this consid-

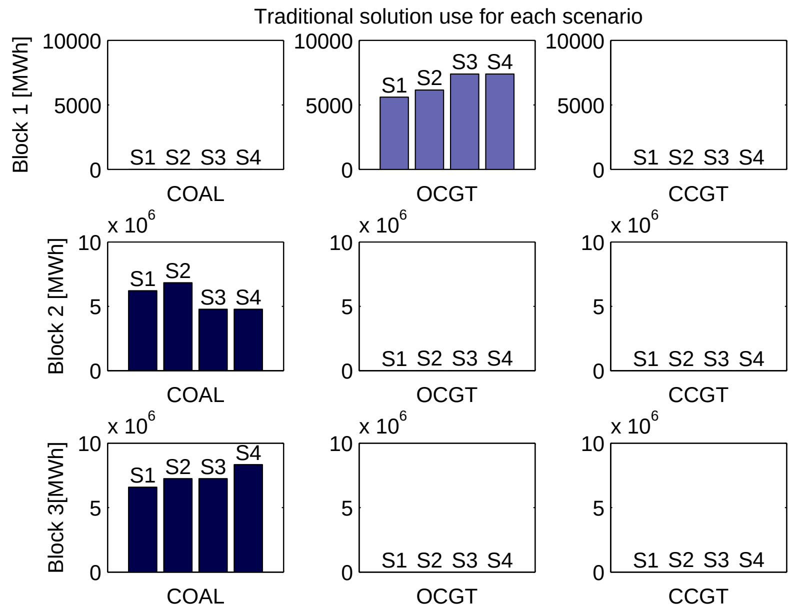


**Figure 3-10**.: Traditional solution use for each scenario

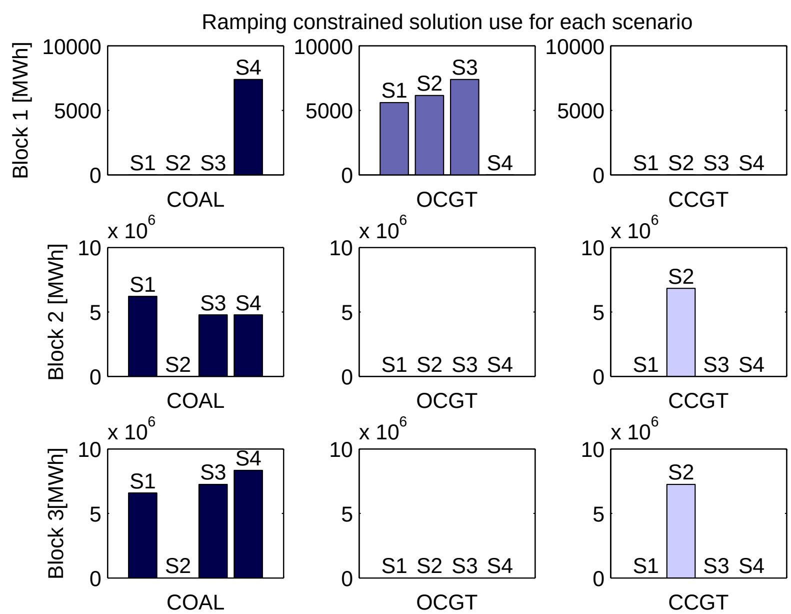


**Figure 3-11**.: Ramping constrained solution use for each scenario

eration, the obtained solutions could restrict negative installed capacity changes and avoids false economic results, such as: ignoring long term planning fixed maintenance and operation cost of generations plants that could not be avoided. Nevertheless, if the problem solution decides that a specific generation technology will not be used in the operation, the generation variable could be used to discard the technology keeping the installed capacity considered in the problem. In order to deal with aforementioned problem, it is necessary to solve the GEP in a prediction horizon that allows one to use previous system states as the initial condition.

## 3.5. Planning generation investements with Model predictive control

The solution for a generation investment plan in a prediction time window is increasingly relevant as mentioned in [28]. The inclusion of variables such as: renewable sources, demand growth and new power system driving variables make it necessary to deal with power system future scenarios. In section 3.4.2 the need for a solution to a proposed modification of the GEP plan in a plan horizon considering previous state values was mentioned. Now to tackle these problems, the MPC is considered a well-known tool to solve constrained linear and non-linear problems that is flexible and can handle this emerging problems. To create an optimal generation planning tool, this work implements an MPC controller using the receding horizon strategy to solve the ramping constrained model. An MPC-based solution calculates the optimum values for the GEP along an estimated or forecasted demand values. Using the model proposed in equation (3-9) as an economical objective function, and including the proper constraints, the optimum solution considers the time ahead data of the system. The MPC solution allows one to significantly improve the optimization results in planning terms. Optimal solutions now consider the previous state as the initial condition and at the same time optimizes the future values according to the scenarios provided. To do this, let's consider a system described by a linear invariant discrete time model:

$$\begin{aligned} x_l(k+1) &= A_l x_l(k) + B_l u_l(k) \\ y_l(k) &= C_l x_l(k) + D_l u_l(k) \end{aligned} \tag{3-10}$$

where $x_l(k) \in \mathbb{R}^{n_{x_l}}$ is the system states, $y_l(k) \in \mathbb{R}^{n_{y_l}}$ is the system output and $u_l(k) \in \mathbb{R}^{n_{u_l}}$ is the current control vector. Using equation 3-6 the state space representation of the problem for $i = 1 \dots N_t$ generation technologies and a LDC discretized in $j = 1 \dots N_b$ blocks can be written as follows:

$$x_l(k) = \begin{bmatrix} x_1 & \dots & x_i & y_{11} & \dots & y_{ij} & \lambda_{11} & \dots & \lambda_{ij} \end{bmatrix}^T \tag{3-11}$$

As mentioned, infrastructure investments had a natural condition for the $x_i$ variables: they cannot decrease. Negative changes in the installed capacity would mean a "destruction" or aging of the plant. This, in real operation, implies a plant shut down or decrements in plant efficiency. In this work, negative values are not considered; plant aging is minimized, considering the maintenance cost in the fixed operation cost. However, the aging parameter can be easily included in the space state model.

$$u_l(k) = \begin{bmatrix} u_{x1} & \dots & u_{xi} & u_{y11} & \dots & u_{yij} & u_{\lambda 11} & \dots & u_{\lambda ij} \end{bmatrix}^T \tag{3-12}$$

The $u_l(k)$ vector represents control actions taken to modify $x_i$ variables. $u_{xi}$ are the decisions taken to increase installed capacity. $u_{yij}$ the expected use of generation technologies and $u_{\lambda ij}$ the weights of generation technologies according to ramp velocities. The interactions between $x_l(k)$ and $u_l(k)$ variables are described for the $A_l$ and $B_l$ matrixes as follows:

$$A_l = \begin{bmatrix} 1 & 0 & 0 & ... & 0 \\ 0 & \ddots & 0 & ... & 0 \\ 0 & 0 & 1_i & ... & 0 \\ 0 & 0 & 0 & ... & 0 \end{bmatrix} \tag{3-13}$$

$A_l$ represents the states evolution. Thus, the installed capacities are the only variables considered persistent in the system (integration variables). The installed capacity at step $(k+1)$ depends only on the previous state $(k)$ and the $u(k+1)$ control actions explicit in the $B_l$ matrix.

$$B_l = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3-14}$$

The $B_l$ matrix indicates the relationship between the control actions and the variables. In this case, there is only the direct influence of each control variable over its corresponding state.

$$C_l = \begin{bmatrix} c_1 & ... & c_i & f_1\theta_1 & ... & f_1\theta_j & ... & f_i\theta_j & 0_{ij} \end{bmatrix} \tag{3-15}$$

Vector $C_l$ is the same as described in equation 3-8. The use of the same cost vector in all optimization cost functions allows one to directly compare the results of the methodologies exposed. The relationships related to the constraints are explicit in the MPC as hard constraints. Changes in the model output as a consequence of the control actions are not considered, therefore $D = 0$. Now, with the dynamic state space system written, the traditional economic MPC problem is defined as follows:

$$\min_{u_{k_l}} J_{ecol}(x_{k_l}, u_{k_l})$$

subject to:

$$\begin{aligned} & x_l(k+1) = A_l x_l(k) + B_l u_l(k) \\ & y_l(k) = C_l x_l(k) + D_l ul(k) \\ & x_l(k) \in \mathbb{X}_l, \ \ k = 0, \ldots, N_{p_l} \\ & u_l(k) \in \mathbb{U}_l, \ \ k = 0, \ldots, N_{p_l} \end{aligned} \tag{3-16}$$

At time step $k$, let $x_{k_l} = [x_l^T(k), \ldots, x_l^T(k+N_{p_l})]^T$ and $u_{k_l} = [u_l^T(k), \ldots, u_l^T(k+N_{p_l})]^T$ are the state trajectory and the control sequences, with $N_{p_l}$ the long term prediction horizon and $J_{ecol}(x_{k_l}, u_{k_l})$

the economic stage cost. The system is subject to hard constraints on state $x_l(k) \in \mathbb{X}_l$, output $y_l(k) \in \mathbb{Y}_l$ and input $u_l(k) \in \mathbb{U}_l$ for all $k \geq 0$, where $\mathbb{X}_l \subset \mathbb{R}^{n_{x_l}}$, $\mathbb{Y}_l \subset \mathbb{R}^{n_{y_l}}$, $\mathbb{U}_l \subset \mathbb{R}^{n_{u_l}}$ are closed sets. The objective functions of equation 3-9 where clearly a linear states combinations; using the MPC methodology, great flexibility in the objective function is available. In order to calculate the optimal control solution $u_{k_l}$ the cost function will be based on the state space output $y_l(k) = C_l x_l(k)$ described in equation 3-10 as $\tilde{C}_l(k) = [C_l(k), \ldots, C_l(k+N_p)]^T$, and the economic MPC formulation is given:

$$
\begin{aligned}
&\min_{u_{k_l}} \sum_{n=0}^{N_{p_l}} \tilde{C}_l(k+n) x_{k_l}(k+n) \\
&\text{subject to:} \\
&x_l(k+1) = A_l x_l(k) + B_l u_l(k) \\
&y_l(k) = C_l x_l(k) + D_l u_l(k) \\
&\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij}(k+n) \leq x_i(k+n) \\
&\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij}(k+n) \lambda_{ij}(k+n) \theta_j = b_j(k+n) \\
&\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} \lambda_{ij}(k+n) V_i \geq \Delta p_j(k+n) \\
&0 \leq y_{ij}(k+n) \leq x_i(k+n) \lambda_{ij}(k+n) \\
&0 \leq \lambda_{ij}(k+n) \leq 1
\end{aligned}
\tag{3-17}
$$

### 3.5.1. Model predictive controller results

Making use of the described dynamic solution, generation investment planning tool results are presented. As designed in the $A(k)$ matrix, the MPC should keep the installed capacity between scenarios and increase the values if needed. In order to compare solutions obtained with the ramping constrained model and MPC solutions, installed capacity results of both solutions are presented in figure **3-9**. First scenario (S1) has the same installed capacity for all the solutions (including the classic approach). Then, considering previous installed capacities and, according to dynamics imposed (energy demand and dynamics are increased) with proposed scenarios, the MPC solution manages the installed capacities as follows: In scenario two (S2), imposed load increment is supplied with a generation mix that effectively combines Coal, OCGT and CCGT. A small increment in COAL and OCGT installed capacities is applied, and CCGT install capacity appears in the optimum mix. Compared with Coal installed capacity, OCGT and CCGT installed values suggest that they will be used to compensate imposed load changes $\Delta p_j$ rather than be used as base generation technologies. Hence, the MPC solution effectively balances previous installed capacities and their ramp velocities with new requirements meeting imposed conditions keeping installed capacities investments bounded. Scenario three and four require less energy than scenario 2, so an installed capacity increment is not expected, as these scenarios are designed to stress system flexibility and their effects in the GEP problem can be seen in the expected use of each technology.

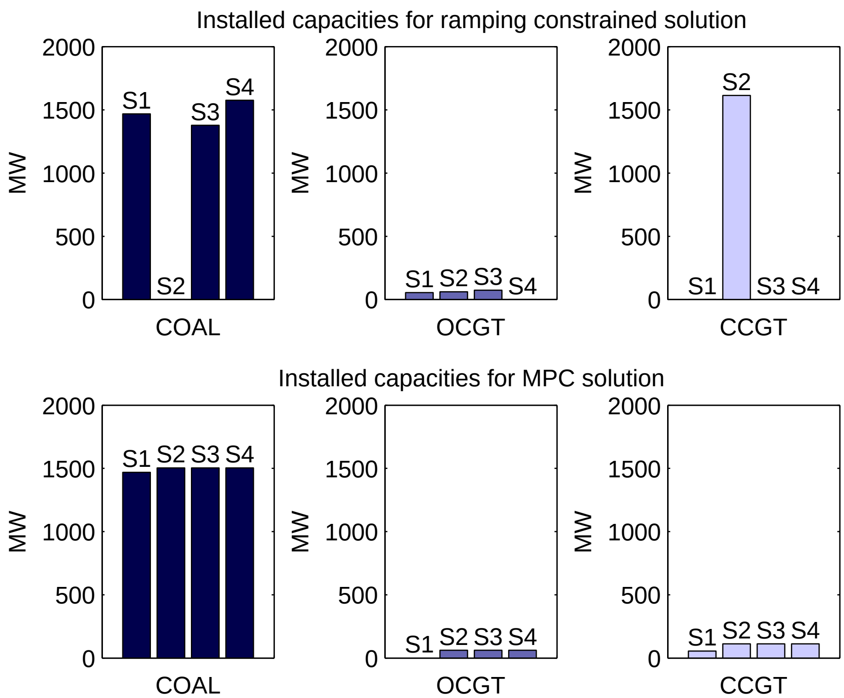


**Figure 3-12**.: MPC solution install capacity for each scenario

Then, with the MPC results from figure **3-12** previous installed capacity values $x_i$ are considered in following interactions. When a previous installed capacity is already built, the optimization has the choice to turn off a particular technology, making its generation $y_{ij} = 0$, and pay the fixed O&M cost and which they are not eligible. Thus, these results will be more focused in figure **3-13**, which presents the use of the above mentioned installed capacities.

The MPC expected use in first scenario (S1) makes use of available technologies: Coal and OCGT to supply energy demanded. Then, the second scenario (S2), due to an imposed increment, decreases Coal generation in block three and at the same time introduces CCGT; this change balances block three's required energy using Coal as base generation and CCGT to cover the load changes increment. This result determines the effectiveness of diversification strategy in the generation mix. Then, blocks one and two present just an increment in energy generation with available technologies used in previous scenarios pointing out that used technologies are still able to manage load changes present in this scenario.

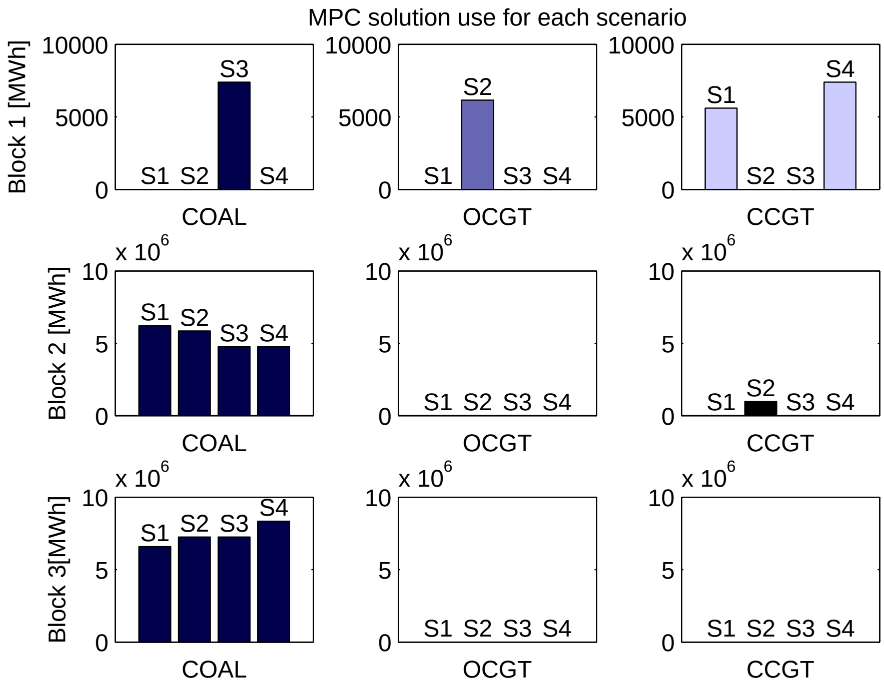


**Figure 3-13.**: MPC solution use for each scenario

The third scenario (S3) presents an interesting solution for required energy, highlighting utility of the diversification strategy between blocks. An imposed load shift from block two to block one enabled MPC to take advantage of released energy to balance the new operation point with recently released resources. Note how Coal energy production for block 1 in S3 is bigger that OCGT energy produced in S2, while energy in block two decreases from S2 to S3. This solution meets the block one ramping constraint and energy demanded with coal. The use of Coal in all blocks improves the generation cost while the ramping constraint condition guarantees safe system operation.

The fourth scenario (S4), where the solution is stressed increasing load and dynamics in block three, is managed by the MPC by switching all the Coal installed capacity to supply energy in block two and three while CCGT is used to replace Coal energy in block one. Again, ramping constraint allows for safe supply of energy in two blocks with Coal as the cheapest solution available; then, block 1 is fully supplied with CCGT as the following cheaper technology able to manage the expected load changes.

In short, this chapter explored the GEP methodology. Using the load time series derivative combined with LDC discretization, a technical constraint which combines available energy technologies to meet a minimal system flexibility was added to traditional GEP formulation. Then, using MPC theory to solve proposed GEP with ramping constraints, a generation expansion plan and use tool was obtained. This tool considers previous installed capacities and solves the GEP problem adding additional installed capacity if required, and minimizes the operation cost while meets a technical robust design. Introduction of flexibility metrics in generation design opens the opportunity of safe integration of alternative generation. Considering that their lack of reliability as firm energy generators could be seen as load changes in the load time series and the design operation constraints imposed could bring safe operation values for a certain amount of alternative generation installed. This methodology relies on expected scenarios provided. These scenarios could be made with expected assumptions or expert knowledge, but could also be made with models or load prediction procedures. In any case, scenario design could be made off-line and provided to this methodology represented as $N_b$ energy blocks with $\Delta p_j$ maximum change.

### 3.5.2. Chapter brief and conclusions

This chapter discussed the traditional solution based on the load duration curve used to optimize the generation plants mix that supplies the costumers required energy. The traditional static model, used to find the minimal operation cost based on the plant's economic costs optimization, is improved including a technical constraint related to the ramp velocity of the generation plants. This constraint, avoids to under estimation of the generation mix flexibility in front of the load changes presented in the daily operation. Afterwards, the new proposed model is dynamically solved by means of a model predictive controller. The proposed dynamic solution finds a new optimal solution of the generation expansion. problem. The new solution minimizes the installation and operation cost along a prediction horizon and, at the same time, meets the imposed ramping technical constraint. The new proposed solution makes evidenced that the installed capacities values of the generation plants are more stable along the time and, the economic operation is achieved by changing the operation times of the available plants. The dynamic solution in addition to the technical constraint included made a contribution in the state of art of generation planning problem published in the paper [42].

# 4. Short term portfolio problem

The short term portfolio is on charge of a critical part of the energy retailer operation: the market clearing process. Short term portfolio must manage all the retailer's energy sources in order to meet energy agreements signed with no regulated costumers and the volatile regulated users demand.

In a typical situation, energy retailer would have several energy sources available to choose including the spot market. Thus this, short term portfolio is composed by: Spot market, considered as immediate energy source with a variable cost; energy agreements, which offer a rigid amount of energy spread over certain time to a fixed price and the are used to reduce retailer risk exposure produced by spot market price volatility. Finally, this work also considers as asset in the short term portfolio, the option to have own generation plants. These plants are modeled as energy agreements signed by the energy trader with itself. This assumption presents an advantage such as energy agreements has a deterministic or known future price. Generation agreements cost is based in the construction, maintenance and plants operation. Mentioned assets are included in a short term management strategy in order to improve the risk exposure and to increases expected returns.

## 4.1. Short term portfolio scheme

Short term energy retailer objective is to meet the energy obligations signed with the costumers at the lowest cost. Load and price forecast have been used to meet this task trying to anticipate required energy and generation prices to increase returns of the market clearing process thus this, a good management strategy highly depends of the accuracy of available information. Management strategy should choose according to the expected load the optimal generation set to be used in order meet the forecasted load with a minimal cost. A decision making scheme presented in figure **4-1** and, detailed in [43] will be used to solve the portfolio problem.
Load and spot price series will be forecasted with a Holt-Winters model. The exponential smoothing family where the Holt-Winters model belongs has been widely used to forecast seasonal time series, such as, load and partially the spot price information and it has been selected to forecast the interest variables in this work. It is remarkable that is not such as good tool for long term forecasting and this thesis will use only in the short term portfolio considering that this work is not focused in the forecast problem. Furthermore, considering assumptions made in the retailer portfolio design, obtained forecast predictions allows to use a MPC to optimize the short term portfolio doing the market clearing process. Now, each part of the decision making scheme will be explained.

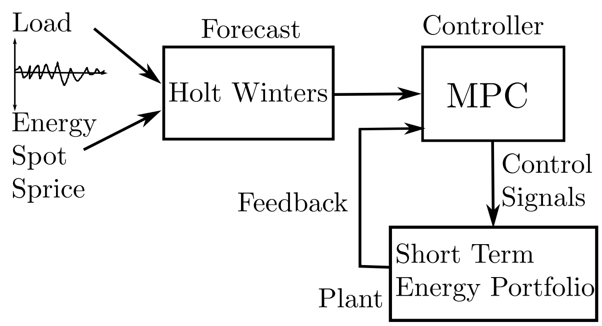


**Figure 4-1**.: Decision-making scheme for short-term energy portfolio based on Holt Winters estimator and MPC

## 4.2. Short term variables forecast

A wide selection of models can be used to forecast the load and spot price series. It is out of this thesis scope to focus in the short term forecast problem. In order to solve the short term forecast problem, in [44] a review of exponential smoothing methods is presented. The author also writes the model in state space form. Load and spot price estimation with a Holt Winters model as mentioned in [45] after 50 year still being used in energy forecast problems. This model as estimator is particularly simple and efficient to predict seasonal time series. Some recent applications validates the use of this estimator, see: [46, 47, 48].
Finally, there are about fifteen Holt winter models available, the procedure to choose the most adequate model and his respective description is presented in following sections, where the load forecast model is presented in section 4.2.1 and spot price forecast problem is discussed in section 4.2.2

### 4.2.1. Short term load model

Considering that costumers behavior load time series has seasonal patterns in order to model the time series with the Holt Winters model it is necessary to identify the seasonal period. George Box and Gwilym Jenkins proposed in 1976 the auto correlation function used to identify no-randomness in time series or data. Making use of the load derivative to obtain the auto correlation function of the time series presented in figure **5-10** , presented in figure **4-2**, seasonal patterns can be identified by means of the significant lags.
By inspection, the load time series seasonality is obtained. As expected, each seven samples strong correlations are found and the seasonal value corresponds to the week values period. The partial correlation function is usually used to estimate an ARIMA or other auto regressive models order and it is presented in figure **4-3**. Due to the use of the Holt Winters model to represent the analyzed time series the auto correlation function information is not used.
A Holt winters model with additive trend and additive seasonal components presented in equation

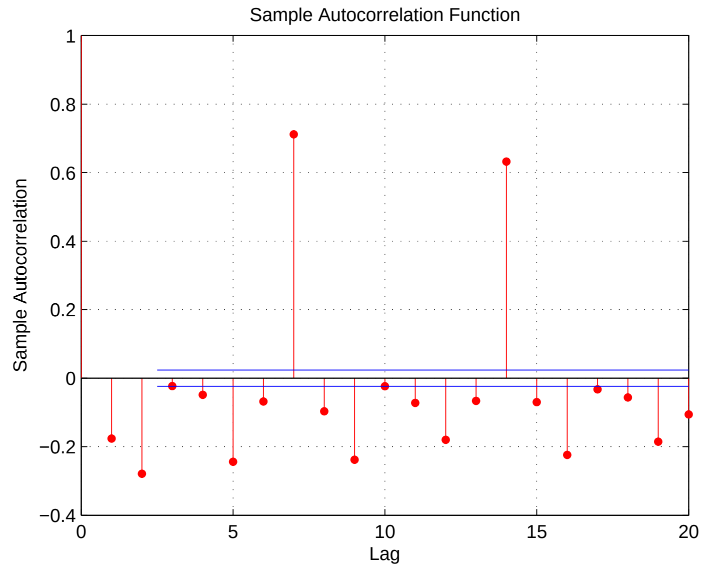


**Figure 4-2.**: Retailer load time series auto correlation function from figure **5-10**

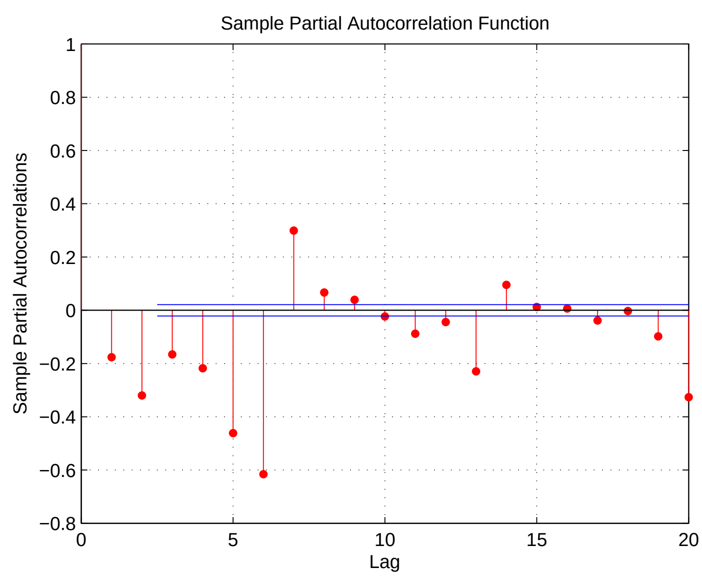


**Figure 4-3.**: Retailer load time series partial correlation function from figure **5-10**

4-1 will be used to model the short term load. The seasonal component identified will be represented with the $T_h^l$ variable. Additionally, in this model $\mu_h^l(k)$ represents the series level. $\beta_h^l(k)$ the slope and $S_h^l(k)$ the seasonal component. $\alpha_h^l$,$\beta_h^l$ and $\gamma_h^l$ are model parameters that can be assigned by heuristics, least squares estimation or other optimization methodologies.

$$\hat{y}_h^l(k) = \mu_h^l(k) + b_h^l(k) + S_h^l(k) \tag{4-1}$$

where:
$\mu_h^l(k) = \alpha_h^l(y_l(k) - S_h^l(k - T_h^l)) + (1 - \alpha_h^l)(\mu_h^l(k-1) + b_h^l(k-1))$
$b_h^l(k) = \beta_h^l(\mu_h^l(k) - \mu_h^l(k-1)) + (1 - \beta_h^l)b_h^l(k-1)$
$S_h^l(k) = \gamma_h^l y_h^l(k) - \mu_h^l(k)) + (1 - \gamma_h^l)S_h^l(k - T_h^l)$

## 4.2.2. Short term load forecast

Now, in order to propose a short term load prediction model, equation 4-1 will be transformed in to the state space model representation. In [44] add [49] a full description of the state space framework with Holt Winters models applied to forecast problems is discussed. Regarding to the model parameters $\alpha_h^l = 0$ will make a fixed level model, $\beta_h^l = 0$ a fixed trend model and $S_h^l = 0$ will make the seasonal variation fix.

$$\begin{aligned} x_h^l(k+1) &= A_h^l x_h^l(k) + B_h^l u_h^l(k) \\ y_h^l(k) &= C_h^l x_h^l(k) + D_h^l u_h^l(k) \end{aligned} \tag{4-2}$$

This representation $x(k)$ contains the Holt Winter states which are the level, slope and seasonal components. Additionally, in order to make the appropriate forecast formulation, the seasonal lags also are included as system states. This is required due to the model dependence of previous data.

$$x_h^l(k) = \begin{bmatrix} \mu_h^l(k) & b_h^l(k) & S_h^l(k - T_l + 1) & S_h^l(k - T_l + 2) & \cdots & S_h^l(k) \end{bmatrix}^T \tag{4-3}$$

$$A_h^l = \begin{bmatrix} 1-\alpha_h^l & 1-\alpha_h^l & -\alpha_h^l & 0 & \cdots & 0 \\ -\alpha_h^l\beta_h^l & 1+\alpha_h^l\beta_h^l & -\alpha_h^l\beta_h^l & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \cdots & 1 \\ -\gamma_h^l(1-\alpha_h^l) & -\gamma_h^l(1-\alpha_h^l) & (\gamma_h^l\alpha_h^l + (1-\gamma_h^l)) & 0 & \cdots & 0 \end{bmatrix} \tag{4-4}$$

$$B_h^l = \begin{bmatrix} \alpha_h^l & \alpha_h^l\beta_h^l & 0 & \cdots & 0 & \gamma_h^l - \gamma_h^l\alpha_h^l \end{bmatrix}^T \tag{4-5}$$

$$\hat{y}_h^l(k) = \mu_h^l(k) + b_h^l(k) + S_h^l(k - T_l + 1) \tag{4-6}$$

$$C_h^l = \begin{bmatrix} 1 & 1 & 1 & 0 & \cdots & 0 \end{bmatrix} \tag{4-7}$$

$$D = \begin{bmatrix} 0 \end{bmatrix} \tag{4-8}$$

### 4.2.3. Short term spot price model

Energy price volatility is one of the most biggest challenges in the energy portfolio forecast task, several works and techniques had been used to tackle this problem. This work makes use of Holt Winters model as forecast technique, relaying in GEP design presented in section 3 and the hedging strategy based in generation plants described in 2.4 , in theory, spot market is not necessary to perform the market clearing process and this forecast will be used only to take advantage of spot market opportunities. Applying the same process described in section 4.2.1 to the spot price time series derivative, the auto correlation function is presented in figure **4-4**. It is difficult to identify a specific model for this item series, only one lag in the 13th position give us a seasonality notion, and considering that it is a daily resolution time series, there is not a direct relationship to be establish with the lag number. Furthermore, partial correlation test presented in figure **4-5** is not useful to extract extra information about model composition. Thus this, model used is the additive trend with no seasonality Holt Winters.

$$\hat{y}_h^s(k) = \mu_h^s(k) + h_h^s b_h^s(k) \tag{4-9}$$

where:
$\mu_h^s(k) = \alpha_h^s y_h^s(k) + (1-\alpha_h^s)(\mu_h^s(k-1) + b_h^s(k-1))$
$b_h^s(k) = \beta_h^s(\mu_h^s(k) - \mu_h^s(k-1)) + (1-\beta_s)b_h^s(k-1)$

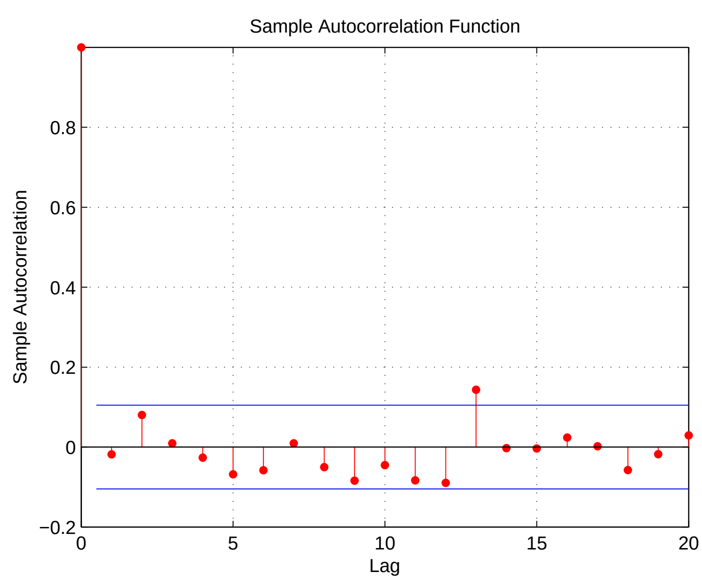


**Figure 4-4**.: Spot price auto correlation function from figure **5-10**

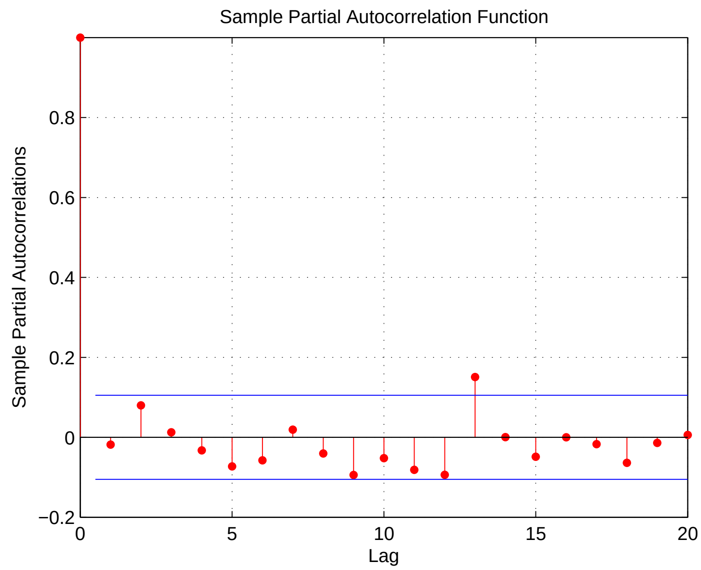


**Figure 4-5**.: Spot price partial correlation function from figure **5-10**

### 4.2.4. Short term spot price forecast

$$x_h^s(k) = \begin{bmatrix} \mu_h^s(k) & b_h^s(k) \end{bmatrix}^T \tag{4-10}$$

$$A_h^s = \begin{bmatrix} 1-\beta_h^s & \beta_h^s & -\beta_h^s \\ 1-\alpha_h^s & 0 & 1-\alpha_h^s \end{bmatrix} \tag{4-11}$$

$$B_h^s = \begin{bmatrix} \alpha_h^s & \alpha_h^s\beta_h^s & 0 & \cdots & 0 & \gamma_h^s - \gamma_h^s\alpha_h^s \end{bmatrix}^T \tag{4-12}$$

$$\hat{y}_h^s(k) = \mu_h^s(k) + b_h^s(k) + S_h^s(k - T_l + 1) \tag{4-13}$$

$$C_h^s = \begin{bmatrix} 1 & 1 & 1 & 0 & \cdots & 0 \end{bmatrix} \tag{4-14}$$

$$D_h^s = \begin{bmatrix} 0 \end{bmatrix} \tag{4-15}$$

Shortly, load and spot price forecast models where presented. Forecasting mentioned variables by means of Holt-Winters provides a low computational cost methodology that is reliable in short prediction horizons. The use of Holt-Winters models requires a model parameters tuning which in most applications is made by heuristics or empiric approaches. Then, model adjustment and prediction horizons are discussed in section 5 where, all the models are integrated and time resolutions and other variables are defined to explore the study case proposed in this work.

## 4.3. Short term portfolio assets models

In order to conform a short term energy portfolio with hedging strategy to be managed a diversification with energy assets was considered in section 2.4. To do this, it is necessary to model all the assets that will be used in the portfolio. These assets are composed by: the spot market, future energy agreements, generation plants modeled as energy agreements and last, alternative generation plants. The idea is to represent mentioned assets with models that makes them able to be managed by a dynamic optimization strategy. Now a brief description of the assets used is presented.

### 4.3.1. Spot market model

It is the main instrument used to balance the real time demand supply. The pool market puts the energy clear price, usually bye means of a bid made between generators. Then, energy is offered to clients that can participate in this market such as energy retailers. Additionally, energy spot markets can offer services that provides flexibility to their clients, they are presented in three basics groups:

- Day ahead: The energy generation of the next day is traded. Commonly, a bid system is used to establish the energy price. Each hour is traded separately.

- Day of: Transactions made in this market covers the remaining days hours. Each hour is traded separately.

- Hour ahead: This market only trades the energy generation for the next hour.

- Real time or Ex-post: It is a reconciliation market on charge of clear the predictions deviations of the previous markets.

In this work, the spot market will be used as a real time market, on charge of the correction of the predictions made in the energy retailer management strategy. The Holt Winters model presented in section 4.2 is used as model for the energy spot price $P^s$. The financial instrument is represent as the product of the traded energy and the spot price:

$$C^s(k) = P^s(k)E^s(k) \tag{4-16}$$

Where $C^s(k)$ is the energy traded cost in the $k$ time, $P^s(k)$ is the energy spot price and $E^s(k)$ is the energy used to balance the energy retailer portfolio. It is clear that the spot market model exposes to the energy retailer to the high price volatility. However, it is secure energy source with the necessary market liquidity to buy and sell energy if needed.

### 4.3.2. Futures and energy forward agreements

Forward and future agreements are basically financial assets that represents the delivery of goods or services in the future. Buying future energy is a common technique used to relieve the exposure to the price volatility of the energy spot market and, at the same time, brings to the buyer the guarantee of the energy supply in the future.

In power markets, forwards and futures represents the future delivery of the signed energy, as financial instruments they are complex instruments and the agreement requires some specific conditions described in this section.

Now, a brief description of the basic aspect of forwards and futures is presented. The main difference between futures and forwards is the standardization degree of each one. Futures are well defined standard agreements traded in a regulated market, and forwards are not standard future agreement traded in the Over The Counter (OTC) markets. Agreements standardization implies market liquidity making the futures easy to trade in a regulated market. Meanwhile, forwards are signed by two parts with specific values discussed by the parts in the OTC market. The forward flexibility makes them the most preferred agreements in power markets, offering to the buyer to supply specifics energy requirements. However, futures and forwards has similar descriptions sharing the same basic features:

- Delivery information: Total amount, delivery frequency (day/hour), among others

- Delivery price or the price formula to the cost calculation

- Delivery duration: Time period in which the energy will be delivered

- Delivery location and Expiration day

Finally, a remarkable difference between futures and forwards is the settle time. Futures needs to be settled every day forcing to the have a cash flow available to receive or pay the returns or losses associated to the price volatility.

This thesis focuses in a planning tool methodology, in this order, forwards agreements are the most suitable tool to hedging an energy portfolio. The non standardized agreements allows to design flexible portfolios, and the flexible settle time provides a time window to balance the portfolio returns specially in long time scenarios simulations. Taking this into account, forward agreements will be used to provide energy to the portfolio, assuming that the negotiation in the OTC market was performed by an external negotiation process. To use the forwards agreements in the proposed solution, the following fields are used to describe each assets.

### Name

The name is based in the Future Contracts international code: Futures contracts codes have five characters. The first two characters identify the contract type, the third character identifies the month and the last two characters identify the year. The months are represented as presented in table **4-1**.

| | |
|---|---|
| January = F | July = N |
| February = G | August = Q |
| March = H | September = |
| April = J | October = V |
| May = K | November = X |
| June = M | December = Z |

**Table 4-1**.: Months names for future contracts

Example: *FWF13* is a Forward agreement with exercise date: January 2013.

### Amount

Amount represents the energy available of the asset given in $kWh$ or $MWh$. This value, decreases each time that the retailer sells energy from the asset.

Example: the *FWF13* has 10 MW available to be sold starting on January 2013

### Exercise price

Exercise price *exprice* is the economic cost that the energy retailer must pay to the generator for each kWh of the asset. This price is previously negotiated between the generator and the energy retailer.

Example: *FWF13* pays 140 $/kWh

### Expiration date

In the *call* type of the forward agreements the buyer (energy retailer) has the option to execute or not the agreement, the final date to take the decision is the expiration date *dataexp*. If the buyer decide to not execute the agreement must pay a fee to the generator. This thesis only consider the execution option.

Example: *FWF13* has the expiration date 01/01/2013

#### Duration

This value indicate how many days the agreement remains active. The agreement can also end if the Amount of available energy becomes zero.

Example: The duration of *FWF13* is 30 days, in this case in January 31 the agreements ends.

#### Active

This binary value indicates depending on the current date if the forward agreement is active. This fact involves that the agreement was executed. The current day must be greater that the expiration date and lower than the date corresponding to the end of contract (Duration).

Finally, forward agreement model used to integrate the asset in the management problem is represented as the result of a previous negotiation. As example the structure used to model forwards data in the portfolio is presented in table **4-2**:

| Asset | Name | Amount $[MWh]$ | Price USD | Expiration | Duration | Active |
|---|---|---|---|---|---|---|
| 1 | FWF131 | 5 | 390 | 01/01/2013 | 30 | • |
| 2 | FWF132 | 3 | 140 | 01/01/2013 | 30 | • |
| 3 | FWV13 | 7 | 190 | 01/10/2013 | 15 | • |
| 4 | FWF13 | 8 | 165 | 01/01/2013 | 365 | • |
| 5 | FWK13 | 3 | 140 | 31/05/2013 | 280 | • |
| 6 | FWU13 | 2 | 190 | 30/09/2013 | 60 | • |

**Table 4-2**.: Energy forward agreements examples

Then, it is necessary to propose a function to represent $N_a$ forward agreements evolution. Fixed values as dates, price $C_a^f$, name are just given information and the amount $E_a^f$ changes depends of the use of the used energy represented by $U_a^f$ in the $k$, the relationship is described as follows:

$$E_a^f(k+1) = E_a^f(k) - U_a^f(k) \tag{4-17}$$

subject to:

$$U_a^f(k) \geq 0$$
$$E_a^f(k+1) \geq 0$$

### 4.3.3. Installed capacity investments as forward agreements

In the long term, load and energy spot price forecast presents a lot of uncertainties that makes accurate forecast a hard task to do. Considering this, short term operations as economic dispatch are hard to include in long planning scenarios. To face this, methodologies as the generation expansion problem (GEP) presented in section 3.1 propose robust generation schemes that should be able to meet the required energy in the future. Additionally, anticipates the required power increments, allowing to start the generation plants construction before the power is required. This section explains how to include the GEP solutions as energy agreements in order to manage short and long term variables in the short term energy portfolio.

Main objective of forward agreements is to provide energy in the future with a known cost. Agreements have two relevant values considered in this section: total energy amount and energy price. These values also are available when a generation plant is described: first, installed capacity is the amount of energy that could be generated similar to the forward amount. Second, fixed and variables cost plus, desired returns could represent the energy production price similar to the agreement exercise price. Then, assuming an energy retailer position, the use of generation plants investments as energy agreements, requires some assumptions related with the regulation framework and some economic decisions:

- Region regulation allows energy retailers to participate in the generation market.
- Generation market regulation allows to commit all the generation plant power as needed.
- Transmission constrains and cost are not considered in the problem.
- Only active power generation service is considered.
- The agreement expiration day corresponds to the date when it is assumed that the generation plant begins to produce energy.

Assuming that the presented assumptions are met, the energy retailer company can invest in the construction of his own generation plants and sign his own forward agreements avoiding the negotiation process. Consequently, it is necessary to discuss the financial strategy to support the generation plant construction. It is known, that it is possible to finance investments by means of shares or stocks. In this thesis the plant full cost will be assumed by the energy retailer. Construction cost of generations plants highly depends on the installed capacity which is optimized by the GEP algorithm. Modeling the construction price with the Net Present Value (NPV) and payments with compound interest formula makes possible to estimate at any time the generation cost in the future, this becomes increasing relevant in planning problems, allowing to take decisions related to investments and payments. Now, some examples of generation plants seen as energy agreements are presented in table **4-3**. Here, the name refers to the generation technology used. amount is the installed capacity; price is the generation prices including generation profit; expiration is the date when the plant is operative, and duration is the plant life span. Active is the same binary variable used to indicate if plant is active or not.
Now, in order to integrate the energy forward agreements to the dynamic problem equation 4-18 represented the dynamic model of $i$ generation plants. Energy delivered by the generation plant

| Asset | Name | Amount | Gen. Price | Expiration | Duration | Active |
|---|---|---|---|---|---|---|
| 1 | Coal | 5 | 390 | 01/01/2013 | 30 | • |
| 2 | OCGT | 3 | 140 | 01/01/2013 | 30 | • |
| 3 | OCGT | 7 | 190 | 01/10/2013 | 15 | • |
| 4 | Coal | 8 | 165 | 01/01/2013 | 365 | • |
| 5 | OCGT | 3 | 140 | 31/05/2013 | 280 | • |
| 6 | CCGT | 2 | 190 | 30/09/2013 | 60 | • |

**Table 4-3**.: Generation based Energy forward agreements examples

are represented by the energy $E_i^g$ supplied by the $i-th$ generation technology and depends of the expected consumption $U_i^g$ and the installed capacity $X_i$ and ramp velocities $V_i$ of each generation technology.

$$E_i^g(k+1) = E_i^g(k) + U_i^g(k) \tag{4-18}$$

subject to:

$$U_i^g(k) \leq V_i$$
$$E_i^g(k) \leq X_i$$

### 4.3.4. Wind power generation

Now, to include wind generated electricity $E^{wt}$in the short term model, several assumptions are made: First, all the energy produced is given to the system; storage is not included. The data series of an average wind profile are given. This wind profile is assumed for all wind turbines. Also it is assumed that the wind turbines are distributed across the region, this allows to consider a minimum mean energy production. Finally, assuming that all turbines have the same technical parameters and they are equipped with a maximum power tracking controller, the ideal model that describes total power production of wind turbines is presented in equation 4-19.

$$E^{wt}(k,V_w) = \begin{cases} 0 & V(k) \leq V_{\underline{c}} \vee V_w(k) \geq V_{\overline{c}} \\ P_{wr}\frac{V_w^3(k)-V_c}{V_r^2-V_c^2} & V_{\underline{c}} \leq V_w(k) \leq V_r \\ P_r & V_r \leq V_w(k) \leq V_{\underline{c}} \end{cases} \tag{4-19}$$

Where, $V_{\underline{c}}$ is cut-in wind speed, $V_{\overline{c}}$ is the cut-off wind speed, $V_r$ is the rated wind speed and $V_w(k)$ is the wind speed at time $k$

### 4.3.5. Photovoltaic power

Photovoltaic energy (PV) generation also has similar assumption that the wind turbine power production model. Radiation $G(k)$ data is given and a minimum radiation level per day could be assumed. Conversion efficiency is taken into account with $f_{pv}$ value. $G_0$ is the radiation at standard operational conditions. Then PV energy $E^{pv}$ is estimated with the ideal model presented in equation 4-20 as follows:

$$E^{pv}(k,G) = P_{pv}\left(\frac{G(k)}{G_0}\right) f_{pv} \tag{4-20}$$

## 4.4. Short term portfolio model

The short term portfolio used (based on [50]) is on charge of balance the energy required by the costumers with the energy available in the portfolio assets. Energy balance must supply the regulated $E^r$ and no regulated energy $E^{nr}$ at $k$ time using the following sources: spot market $E^s$, the energy available in $a$ forward agreements $E_a^f$, the own $i$ generation plants $E_i$ and finally, renewable generation are included with wind power $E^{wt}$ and photo-voltaic sources $E^{pv}$. Relationship used to described this is presented in equation 4-21 as follows

$$E^r + E^{nr} = E^s + \sum_a E_a^f + \sum_i E_i^g + E^{wt} + E^{pv} \tag{4-21}$$

Above energy balance mix two different kinds of users and five different energy sources. In order to propose a management strategy able to optimize the energy retailer returns and meet the load in a planning horizon, a dynamic portfolio model based on the energy balance shown in equation 4-21 is proposed, integrating the assets models proposed in section 4.3 the energy balance can be expressed as:

$$E^r(k) + E^{nr}(k) = E^s(k) + \sum_a E_a^f(k) + \sum_i E_i^g(k) + E^{wt}(k,V) + E^{pv}(k,G) \tag{4-22}$$

subject to:

$$E_a^f(k) \geq 0$$
$$E_i^g \geq 0$$

This model will be used to solve the market clearing problem. Composed by deterministic variables such as: forward agreements $E_a^f$, generation plants $\sum_i E_i^g$ and, stochastic variables like: the spot market $E^s$, alternative sources $E^{wt}$, $E^{pv}$ and user consumption $E^r + E^{nr}$. Solving the energy balance in real time is an important challenge in retailer operation. In this order, diversification strategy proposed in section 2.4 to solve management problem, relies in the use of the generation plants and forward agreements, they are used to reduce financial and operation risk or this operation. In order to integrate economic and financial conditions in this strategy and share information with the retailer economic function an economic constraint is included as follows:

$$P^s(k)E^s(k) + \sum_a E_a^f(k)C_a^f + \sum_i E_i^g(k)C_i^g(k) \leq B_s(k) \tag{4-23}$$

Generation budget $B_s(k)$ given in $[\$/T_r]$ is assigned in the retailer economic function and, is used as boundary restricting the amount of cash available to use in market clearing operations. According to strategy description, generation budget is assigned with an amount enough to guarantee all the economic resources such that $B_s(k) = \sum_i E_i^g(k)C_i^g(k)$. This is a robust assumption that allows to pay the production of all the expected demand estimated in the GEP problem with own generation plants. The use of signed forward agreements as energy source requires a different treatment: their acquisition was made in an off line negotiation so, in this work, according to agreement duration a depreciation expression is used in the estimate agreement's price, such that when the agreement is about to expire the energy price is getting closer to zero. Then, extra returns are obtained in the market clearing process switching to cheaper sources if conditions are favorable and making use of energy produced by alternative generation plants.

Last, as said before $B_{s(k)}$ values came from an economic retailer function providing a generation budget for each time. This means that every time step, generation budget is modified due to incomes and expenses related to the market clearing process. Then, these differences will produce the market clearing returns and must be calculated and updated to the retailer economic function. Given this, after the market clearing process, this expected generation budget must be compared with real expenses made in energy generation. In order to provide $R^s(k)$ returns to the energy retailer function described in section 2.5.3, short term return function first is described by means of **dummy variables**. The objective to understand interactions and times required to communicate the retailer and short term portfolios:

$$\begin{aligned} R^r(k+1) = R^r(k) - [G_B(k+1) - G_E(k+1)] + [G_C(k) - G_R(k)] + \\ [(G_B(k) - G_C(k)) - (G_E(k) - G_R(k))] \end{aligned} \tag{4-24}$$

Where $R^r(k+1)$ are the retailer returns obtained form the market clearing. $G_B(k+1)$ is the expected generation budget assigned in the retailer coordination function. $G_E(k+1)$ corresponds to the expected energy sales, also assigned in the retailer function. Both variables, $G_B(k+1)$ and $G_E(k+1)$ are calculated along all retailer prediction horizon, assuming the worst operation case designed in the long term portfolio. Then, $G_C(k)$ and $G_E(k)$ are the generation cost and the energy sales associated to market clearing process.
Values obtained after market clearing process should be compared with the robust value providing following information:

- Returns obtained from the optimization problem, taking into account all generation assets available, including alternative generation to meet at the minimum cost required energy.

- Balance of the economic differences between expected robust generation budget and expected robust energy produced against real generation cost and real energy sold

Now, replacing in equation 4-24 the real variables used in the models of the retailer (equation 2-7 and short term portfolio (equation 4-22). Equation 4-25 is the representation to the update dynamics that settles the balancing process between the short term portfolio and the retailer economic level.

$$
\begin{aligned}
R^r(k+1) = R^r(k) - &\left[B_s(k+1) - \left(\sum_{i=1}^{N_t} \frac{y_{i3}(k+1)}{T_r} C^{nr}(k+1) + \sum_{i=1}^{N_t}\sum_{j=1}^{N_b-1} \frac{y_{ij}(k+1)}{T_r} C^r_{ij}(k+1)\right)\right] \\
&+ \left[\left(E^s(k) + \sum_a E^f_a(k) + \sum_i E^g_i(k) + E^{wt}(k,V) + E^{pv}(k,G)\right)\right. \\
&- \left.\left(P^s(k)E^s(k) + \sum_a E^f_a(k)C^f_a + \sum_i E^g_i(k)C^g_i(k)\right)\right]
\end{aligned}
\tag{4-25}
$$

## 4.5. Short term model optimization

Model used to market clearing presented in equation 4-22 and equation 4-23 that puts an economic constraint are used to propose an optimization that maximizes the return and meet the retailer energy agreements balancing the portfolio assets. Taking into account the cost of the respective energy assets described in section 4.3 the optimization problem can be written as:

$$
\max_{U^s(k),U^f_a(k),U^g_i(k)} -C^s(k)E^s(k) - E^f_a(k)P^f_a - E^g_i(k)P^g_i(k) \tag{4-26}
$$

subject to:

$$
\begin{aligned}
& E^r(k)+E^{nr}(k)=E^s(k)+\sum_a E_a^f(k)+\sum_i E_i^g(k)+E^{wt}(k,V)+E^{pv}(k,G) \\
& P^s(k)E^s(k)+\sum_i E_i^g(k)C_i^g(k)\leq B_s(k) \\
& E_a^f(k+1)=E_a^f(k)-U_a^f(k) \\
& E_i^g(k+1)=E_i^g(k)+U_i^g(k) \\
& E^s(k)=U^s(k) \\
& 0\leq E_i^g(k)\leq X_i \\
& U_i^g(k)\leq V_iT_s \\
& E^{wt}(k,V)=\begin{cases} 0 & V(k)\leq V_{\underline{c}} \vee V(k)\geq V_{\overline{c}} \\ P_{wr}\frac{V^2(k)-V_c}{V_r^2-V_c^2} & V_{\underline{c}}\leq V(k)\leq V_r \\ P_r & V_r\leq V(k)\leq V_{\underline{c}} \end{cases} \\
& E^{pv}(k,G)=P_{pv}\left(\frac{G(k)}{G_0}\right)f_{pv} \\
& E_a^f(k)\geq 0 \\
& U^s(k)\geq 0 \\
& U_a^f(k)\geq 0 \\
& U_i^g(k)\geq 0
\end{aligned}
$$

Using the energy balance presented in equation 4-22 as constraint in the objective function, it is proposed to balance the portfolio in a $k$ time, minimizing the supply cost paid for the energy retailer to meet his energy supply obligations. Introducing $U_i^g(k)$, $U_a^f(k)$, $U^s(k)$ as control variables used to change the energy required to their respective assets $E_i^g(k)$, $E_a^f(k)$, $E^s(k)$ ,it is possible to include particular constraints to the required energy changes. Including the relationship $U_i(k)\leq V_i$ the optimization solutions meets the ramp constraint for each $i$ generation technology. This requirement mixes a technical design parameter in an economic problem. Also, it is possible to include similar conditions to the spot market purchases $U^s(k)$ and the use of energy agreements $U_a^f(k)$. The linear problem involved is easy to solve in terms of the mathematical procedure. The given cost function will supply the required energy at the lowest cost, but it is already known that the load and price volatility are too high and time ahead decisions are vital in the short term portfolio. Wind generated power $E^{wt}(k)$ and photo-voltaic power $E^{pv}(k)$ depends of natural cycles, and it is assumed that the energy produced is included in the balance every time they are available. The challenge in this problem is how to solve it in future $k$ times ahead, considering high uncertainties and including the risk management strategies proposed in this thesis.

## 4.6. Short term economic model predictive control

With the optimization problem described in section 4.5 and, the need to solve the problem in a prediction horizon in order to update with the market clearing returns the retailer cash flow presented in equation 4-25. A time ahead view of the system is used to propose a management strategy, that balance the short long term variables to meet technical and economic objectives. Solutions presented in sections 2 and 3 are integrated in the short term portfolio optimization presented in section 4.5. Now with the required future information, the short term portfolio from equation 4-22 is presented as a dynamic system in the state space form.

$$\begin{aligned} x_s(k+1) &= A_s x_s(k) + B_s u_s(k) \\ y_s(k) &= C_s x_s(k) + D_s S_s(k) \end{aligned} \tag{4-27}$$

where $x_s(k) \in \mathbb{R}^{n_{xs}}$ is the system states, $y_s(k) \in \mathbb{R}^{n_{ys}}$ is the system output and $u_s(k) \in \mathbb{R}^{n_{us}}$ is the current control actions vector such as:

$$x_s(k) = \left[\begin{array}{ccc} E^s(k) & E_i^g(k) & E_a^f(k) \end{array}\right]^T \tag{4-28}$$

$$u_s(k) = \left[\begin{array}{ccc} U^s(k) & U_i^g(k) & U_a^f(k) \end{array}\right]^T \tag{4-29}$$

$$A_s = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \ddots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1_i & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1_a \end{bmatrix} \tag{4-30}$$

$A_s$ matrix provides the $x_s(k) \in$ states dynamics. Generation based agreements takes into account previous energy values $E_i^g(k)$ to estimate the $i-th$ generation plant operation point in future decisions. These changes applied with the $U_i^g(k)$ control signal must be checked to not exceed the generation installed capacity $X_i$ of each plant. Equally, energy obtained from the forwards agreement $E_a^f(k)$ must be consider to calculate the future use given by $U_a^f(k)$ and avoid to use more energy than it is available. Last, spot market energy state $E^s(k)$ is considered as an ideal market independent from previous states providing any amount of energy at any time.

$$B_s = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1_i & 0 \\ 0 & 0 & -1_a \end{bmatrix} \tag{4-31}$$

$B_s$ matrix represents how the control actions $u_s(k)$ modifies the $x_s(k)$ states. Moreover, considering the fact that all the forward agreements and the generation plants could not be active at the same time, binary time dependent variables are required in the problem.
Resulting vector is

$$\phi_a(k)\begin{cases} 1 & \text{date } a = 1,...,N_a \\ 0 & \text{Otherwise} \end{cases} \tag{4-32}$$

Analogously for

$$\phi_i(k)\begin{cases} 1 & \text{date } i = 1,...,N_t \\ 0 & \text{Otherwise} \end{cases} \tag{4-33}$$

Now a selection matrix is created

$$B_s^*(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \phi_i & 0 \\ 0 & 0 & -\phi_a \end{bmatrix} \tag{4-34}$$

$$C_s(k) = \begin{bmatrix} C^s(k) & C_a^f(k) & C_i^g(k) \end{bmatrix} \tag{4-35}$$

Cost associated to energy production are included in $C_s(k)$ matrix. Here, the spot price $C^s(k)$ is generated by the Holt-Winters model and the $C_i^g(k)$ comes from the energy retailer optimization in the top level. Energy agreements $C_a^f$ has a previous negotiated price and are assumed fixed. Considering renewable energy as not dispatchable and the expected costumers energy consumption as external variables, expected returns produced for these variables are included as perturbations in the model output as follows:

$$D_s(k) = \begin{bmatrix} C^{wt}(k) & C^{pv}(k) & C^r(k) & C^{nr}(k) \end{bmatrix} \tag{4-36}$$

$D_s(k)$ vector are the energy sale price. An important assumption has to be made in order to split regulated and no regulated energy sales. The association is made classifying energy produced by the generation forward agreements that were assigned to work in the $b_3$ block.

$$S_s(k) = \begin{bmatrix} E^{wt}(k) & E^{pv}(k) & E^r(k) & E^{nr}(k) \end{bmatrix} \tag{4-37}$$

Last, $S_s(k)$ represents all the energy used in the market clearing process. Now, lets consider the standard MPC formulation which solves the optimization problem in the short prediction horizon $N_{p_s}$. At time step $k$, let $x_{k_s} = [x_s^T(k),\ldots,x_s^T(k+N_{p_s})]^T$ and $u_{k_s} = [u_s^T(k),\ldots,u_s^T(k+N_{p_s})]^T$ are the state trajectory and the control sequences, with $N_{p_s}$ the short term prediction horizon and $J_{ecos}(x_{k_s}, u_{k_s})$ the economic stage cost. The system is subject to hard constraints on state $x_s(k) \in \mathbb{X}_s$, output $y_s(k) \in \mathbb{Y}_s$ and input $u_s(k) \in \mathbb{U}_s$ for all $k \geq 0$, where $\mathbb{X}_s \subset \mathbb{R}^{n_{x_s}}$, $\mathbb{Y}_s \subset \mathbb{R}^{n_{y_s}}$, $\mathbb{U}_s \subset \mathbb{R}^{n_{u_s}}$ are closed sets. In order to calculate the optimal control solution $u_{k_s}$ the cost function will be based on the state space output $y_s(k) = C_s x_s(k)$ described in equation 4-27 as $\tilde{C}_s(k) = [C_s(k), \ldots, C_s(k+N_{p_s})]^T$ extending the market clearing cost along the prediction horizon, and the economic short term MPC formulation is given:

$$\min_{u_{k_s}} J_{ecos}(x_{k_s}, u_{k_s})$$

subject to:

$$\begin{aligned}
&x_s(k+1) = A_s x_l(k) + B_s u_s(k) \\
&y_s(k) = C_s x_s(k) + D_s us(k) \\
&x_s(k) \in \mathbb{X}_s, \;\; k = 0, \ldots, N_{p_s} \\
&u_s(k) \in \mathbb{U}_s, \;\; k = 0, \ldots, N_{p_s}
\end{aligned} \tag{4-38}$$

Where, replacing all respective models is obtained:

$$\min_{u_{k_s}} \sum_{n=0}^{N_{ps}} \tilde{C}_s(k+n) x_{k_s}(k+n)$$

subject to:

$$\begin{aligned}
&x_s(k+1) = A_s x(k) + B_s u_s(k) \\
&y_s(k) = C_s(k) x_s(k) + D_s(k) S_s(k) \\
&E^r(k+n) + E^{nr}(k+n) = E^s(k+n) + \sum_a E^f_{a+n}(k) + \sum_i E^g_i(k+n) + \\
&E^{wt}(k+n, V) + E^{pv}(k+n, G) \\
&P^s(k+n) E^s(k+n) + \sum_i E^g_i(k+n) C^g_i(k+n) \leq B_s(k+n) \\
&E^f_a(k+n+1) = E^f_a(k+n) - U^f_a(k+n) \\
&E^g_i(k+n+1) = E^g_i(k+n) + U^g_i(k+n) \\
&E^s(k+n) = U^s(k+n) \\
&0 \leq E^g_i(k+n) \leq X_i(k+n) \\
&U^g_i(k+n) \leq V_i
\end{aligned} \tag{4-39}$$

$$E^{wt}(k+n, V) = \begin{cases} 0 & V(k+n) \leq V_{\underline{c}} \vee V(k+n) \geq V_{\overline{c}} \\ P_{wr} \frac{V^2(k+n) - V_c}{V_r^2 - V_c^2} & V_{\underline{c}} \leq V(k+n) \leq V_r \\ P_r & V_r \leq V(k+n) \leq V_{\underline{c}} \end{cases}$$

$$E^{pv}(k+n, G) = P_{pv} \left( \frac{G(k+n)}{G_0} \right) f_{pv}$$

With the proper logical economic constraints

$$\begin{aligned} &E_a^f(k+n) \geq 0 \\ &U^s(k+n) \geq 0 \\ &U_a^f(k+n) \geq 0 \\ &U_i^g(k+n) \geq 0 \end{aligned} \tag{4-40}$$

### 4.6.1. Chapter brief and conclusions

This chapter presented the model and optimization of the energy retailer short term portfolio. Mentioned portfolio is represented by an economic cost function that takes into account all the energy sources available and minimizes the operation cost while meets the energy balance of the demanded energy (market clearing). This application is based in [43] and [51] where the use of MPC and Holt Winters models where discussed. Now, in this dissertation, this chapter modeled several energy sources such as: the spot market, forward energy agreements, photo-voltaic and wind generation and last, a contribution made integrates the solution of the generation expansion plan, solved in section 3 as energy agreements.

The integration of the generation plants in the market clearing process is achieved by means of an hierarchical structure that re-samples some values in order to fit the time differences between the economic and technical variables. At the end, the expected returns from the GEP solution are compared and updated with the returns obtained from the market clearing process. This novelty allows to create a planning tool for energy investment dealing with medium, long and short term variables updating the expected cash flow of the investor in a prediction horizon.

# 5. Hierarchical integration and results

This chapter presents the integration and solution of the management strategy proposed as hierarchical structure. In order to explore the performance of this tool solution this chapter is presented as follows: First, the used scenario is described. Here, used data, technical and economic variables of each portfolio and time scales assumed in the hierarchies are presented. Second, considering one year data, the solution given by the proposed GEP problem described in section 3 is explored. This section shortly discusses technical and economic implications of the GEP solution. Third, generation mix costs and expected returns obtained in the GEP are included in the energy retailer economic function, presented in equation 2-15, and the first iteration of the retailer economic optimization is presented. This section explores the performance and economic assumptions made in the energy retailing economic function. Then, using these first results, economic and technical variables required to integrate to the hierarchy and solution of the short term function are discussed. Fourth, an approximation to energy market clearing operation is solved in the sort term portfolio, represented in equation 4-39. Using variables assigned in the retailer optimization, market clearing operation illustrates how the dynamic management strategy reduces operation cost improving system performance. Last, the assumed real operation returns are compared with expected returns obtained form the GEP problem. Then the problem is solved interactively for one year data and, the performance of the proposed hierarchical structure is discussed.

## 5.1. Simulation information and assumptions made

The case study case presented in section 3.5 , where the year 2013 load data was used to solve the GEP problem with ramping constrains, brought the following generation mix presented in table **5-1** , corresponds to the first scenario (S1):

| Technology | Installed cap. $MW$ | Ramp vel. $MW/h$ | Install. cost USD Millions | F&O cost USD/year Millions | Variable cost USD/$MWh$ |
|---|---|---|---|---|---|
| Coal | 1469 | 240 | 2496 | 49 | 5 |
| CCGT | 55 | 360 | 47.4 | 1.17 | 10 |
| Total | 1524 | | 2543 | 50.17 | |

**Table 5-1**.: Optimal generation mix for the first load scenario

The presented generation mix is modeled as energy agreements in table **5-3**, where all the short term portfolio assets are presented. With obtained generation mix, specifically considering the installed capacities, was possible to estimate the cost associated to the operation of each generation technology. Assuming worst case solution, that is the one obtained from the GEP, obtained values will be used in the retailer function to calculate respective incomes and expenses. Then, these values are used to define a robust expected cash flow used as reference to operate in the retailer function and short term levels.

### 5.1.1. Time frames used in the hierarchy integration

In order to achieve the integration of all the retailer portfolio components it is necessary to compensate portfolios time differences. Table **5-2** presents the time resolution and prediction horizons for each portfolio. This table has the required information to scale, with proper assumptions, each variable to the required time resolution discussed in section 2 and revisited in this section. The base calculation time resolution for all the problem is the monthly one, used in the retailer function. The idea is to scale yearly time resolution variables to months. And short term results are solved in a prediction horizon, that allows to update monthly obtained results to the retailer function.

| Portfolio | Time resolution | Variable | Prediction horizon | Variable |
|---|---|---|---|---|
| Long | 1 year | $T_l$ | 4 years | $N_{p_l}$ |
| Retailer | 1 month | $T_r$ | 12 months | $N_{p_r}$ |
| Short | 1 day | $T_s$ | 1 month | $N_{p_s}$ |

**Table 5-2**.: Time resolutions used in the hierarchy

### 5.1.2. Forward and generation agreements used

Afterwards, energy agreements and generation plants modeled as agreements too, are presented in table **5-3** they will be used in the study case as energy assets used to diversify the retailer portfolio. Energy agreements are assumed as result of a simulated negotiation and their respective amounts and times are settled to explore how the proposed methodology behaves with this kind of asset. It is remarkable that this work is not focused in this kind of financial instrument, but it is capable to include them and also other financial instruments available.

Now, a highlight must be made to discuss the energy price of conventional generation technologies. Usually, as presented in table **3-3**, economic values for the generation and fixed costs are described individually. Moreover, in this work, energy retailer model considers a separated term for generation and fixed cost, but at the same time they are included in the same economic balance. It is expected that returns obtained from energy retailing are sufficient to pay: installed capacity, fixed and variables cost. So, in order to avoid possible feasibility problems, it is assumed that fixed and variable cost can be included in the generation technology price and paid by the retailer returns, or can be included in the energy sale prices and charged directly to clients. In this case, fixed and variable cost had been charged in generation and energy sales prices, shifting the payment to clients but at the same time, taking them into account in the retailer cash flow.

| Asset | Name | Amount MW | Price USD | Expiration $\$/kW$ | Duration - Life span |
|---|---|---|---|---|---|
| 1 | FWF131 | 8 | 0.139 | 01/01/2013 | 30 days |
| 2 | FWF132 | 8 | 0.107 | 01/01/2013 | 30 days |
| 3 | FWV13 | 8 | 0.092 | 01/10/2013 | 180 days |
| 1 | Coal S1 | 1468 | 0.036 | 01/01/2013 | 40 years |
| 2 | OCGT S1 | 8 | 0.076 | 01/01/2013 | 20 years |
| 3 | CCGT S1 | 55 | 0.053 | 01/10/2013 | 30 years |

**Table 5-3.**: Energy forward and generation agreements used in year 2013 example

Agreements costs are assumed as the product of the amount and the exercise price. The starting date value of each agreements are established arbitrary to stress the solution performance and illustrate their effect in the retailer cash flow. Figure **5-1** shows in red color when each forward agreements will be available in the problem. It is remarkable that if available energy of each agreements becomes zero before the active period ends, the energy agreement becomes as inactive. This implies that forward active combination will change for each time sample. Finally, in order to con-

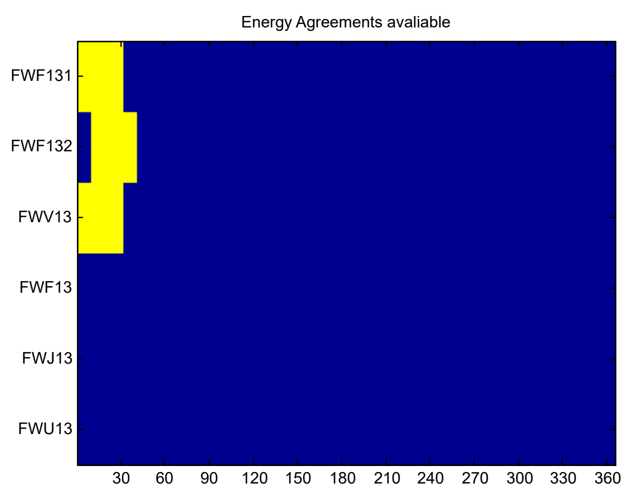


**Figure 5-1.**: Availability of energy agreements in 2013 year

sider the life span limit of each forward, an exponential decay factor was applied to the forward price such as $C_{N_a}(k) = C^0_{N_a} e^{-k/d_a}$, where $d_a \in N_a$ is the duration of each forward agreement; this assumption puts an economic dynamic that forces the strategy to try to use the energy available before expires according to the life span of the agreement. This effect is presented in figure **5-2** where only agreements duration are considered to illustrate how price changes until their agreements expires.

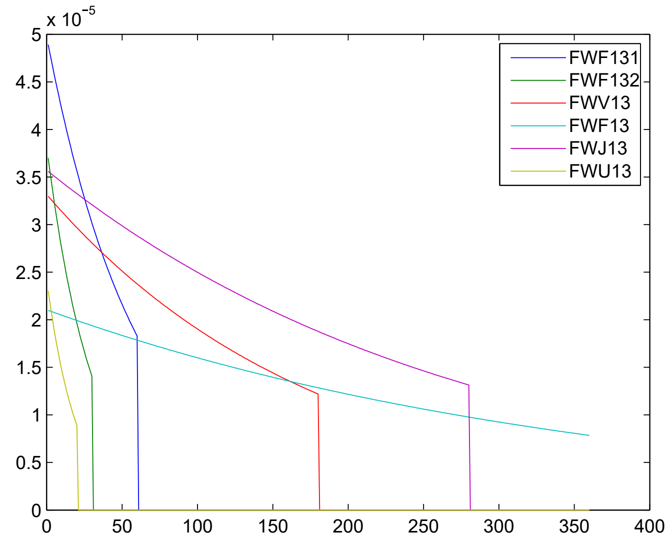


**Figure 5-2**.: Forward energy prices decay applied

Regarding to the availability of generation plants, result presented in figure **5-3** assume that the time lapse between the GEP solution and the construction time has been met. If the GEP solution increases the installed capacity amount incoming scenarios, additional agreements with the new extra installed capacity are included.

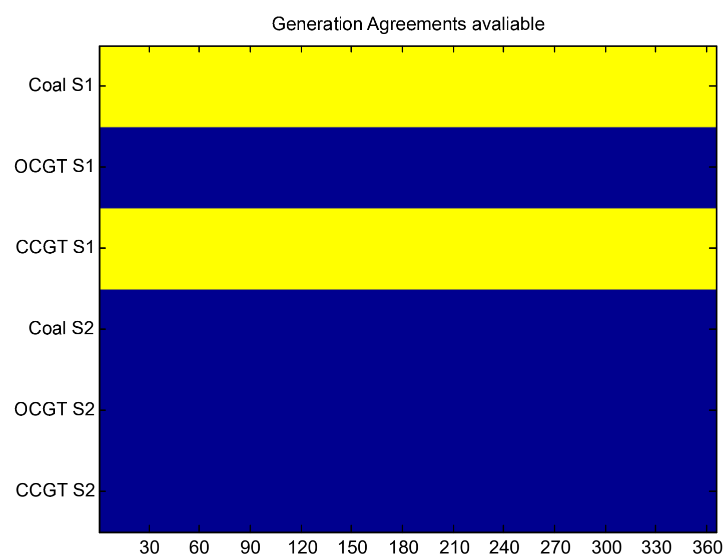


**Figure 5-3**.: Availability of generation plants year 2013

### 5.1.3. Alternative generation included in the solution

As mentioned in previous sections, this work makes use of the technical ramping constrain included in the GEP to consider the use of alternative generation plants in the generation mix. The idea is to include an alternative installed capacity that meets the imposed $\Delta P$ values in the GEP design. Assuming alternative generation as a perturbation from the generation system perspective, and it is possible to say that the generation mix could compensate the alternative plants energy variations. Now with the ideal generation models described in section 4.3 and using parameters present in table **5-4**, economic and technical variables used in this work are presented as follows: First, the cost per unit of alternative generation plants is presented. Second, the installed capacity costs is presented. Last, time series used as input are explored to use them to present the expected alternative energy generation data.

| Technology | Variable | Value |
|---|---|---|
| Wind | $V_{\underline{c}}$ | 2.5 $m/s$ |
| | $V_{\overline{c}}$ | 25 $m/s$ |
| | $V_r$ | 10 $m/s$ |
| | $P_{wr}$ | 30 kW |
| PV | $f_{pv}$ | 0.8 |
| | $G_0$ | 1000 $W/m^2$ |
| | $P_{pv}$ | 1 kW |

**Table 5-4**.: Alternative generation plants parameters

The parameters corresponds to a single generation unit of each type. Now, the economic cost of each alternative generation technology are presented in table **5-5**. Then, this cost and installed capacity are linearly scaled to increase the alternative installed capacity.

| Technology | Installed capacity cost | O& M |
|---|---|---|
| Wind turbine (30$kW$) | 2800 USD | 560 USD/year |
| Solar panel (1$kW$) | 5832 USD | 1166 USD/year |

**Table 5-5**.: Alternative generation costs per unit

Finally, scaling the installed capacity with three wind turbines and two hundred solar panels as a total amount of 290 $kW$ of alternative installed capacity is considered with an expected life span of 20 years. Costs related to considered installed capacity are presented in table **5-6**. Later, some additional cases of generation capacity are explored when the financial cost and the solution risk measurements are presented.

Now, time series used to simulate the alternative generation are described. Wind profile was pro-

| Technology | Installed capacity | O& M |
|---|---|---|
| Wind turbine (90$kW$) | USD | 1680 USD/year |
| PV (200$kW$) | USD | 233200 USD/year |

**Table 5-6**.: Alternative generation installed capacity costs

vide by the *Instituto de Hidrología Meteorología y Estudios Ambientales*[1] and irradiance data by the *Cenicafe* institution [2]. In order to match the short term time resolution, a resolution of 24 hours had been used to calcualte the mean daily mean value. Obtaining the results presented in figure **5-4**.

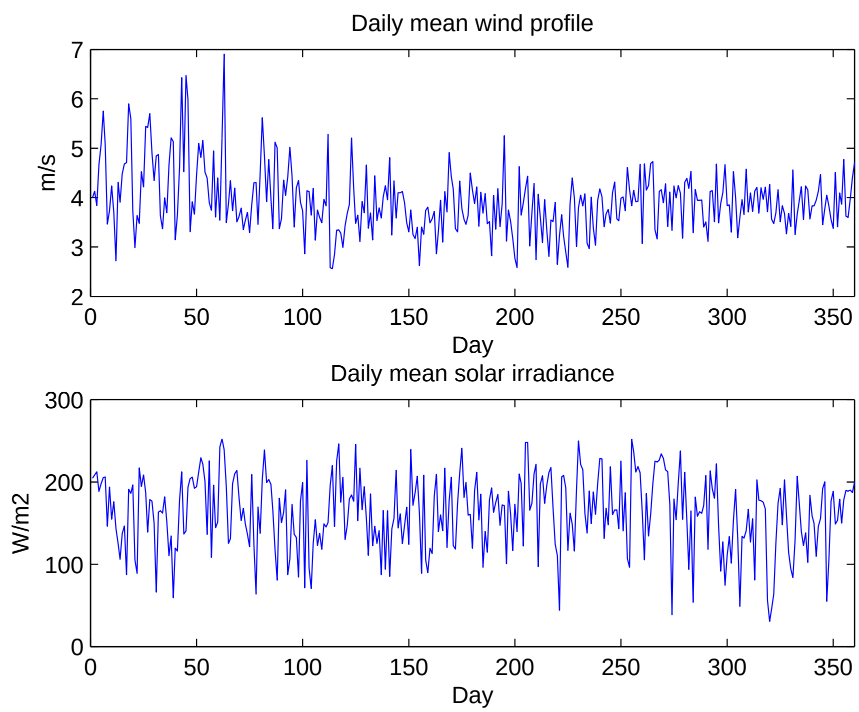


**Figure 5-4**.: Solar irradiance a wind velocity profile used. Data from: Instituto de Hidrología Meteorología y Estudios Ambientales and Cenicafe

Then, with the boxplot presented in figure **5-5** it is observed that both series have symmetric observations $Q_1 \approx Q_3$, and the quartiles size suggest an acceptable dispersion. So, the median values of the presented time series could be used to approach a mean daily alternative generation. Alternative generation plants cost were presented in table **5-6**, where installed capacity and fixed cost were taken into account. Even considering that, it is possible to assume a minimum energy generation with the mean values per day of the data series. Energy produced with alternative

[1]Datos estadísticos meteorológicos de temperatura del aire y velocidad de viento en la superficie en el municipio de Unguía-Chocó." Bogotá D.C., 2016.

[2]"Datos históricos agroclimáticos del municipio de Cañasgordas - Antioquia." Medellín, 2015.

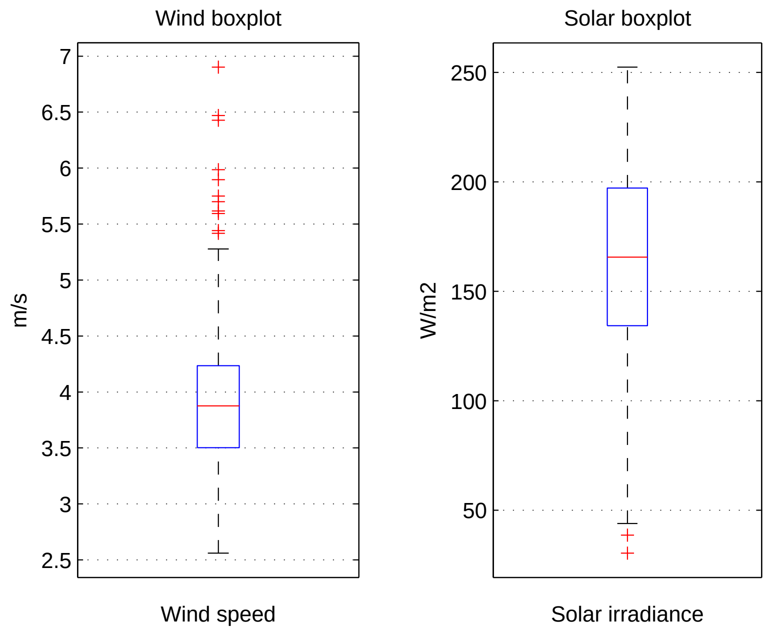


**Figure 5-5**.: Box plot of daily average values of wind and solar irradiance

generation is only taken into account in the short term portfolio, and returns obtained are updated in the data reconciliation described in equation 4-25, where alternative energy substitutes some generation technology and this energy is assumed to be sold to regulated users. Last, expected generation with alternative generation plants is presented in figures **5-6** and **5-7**

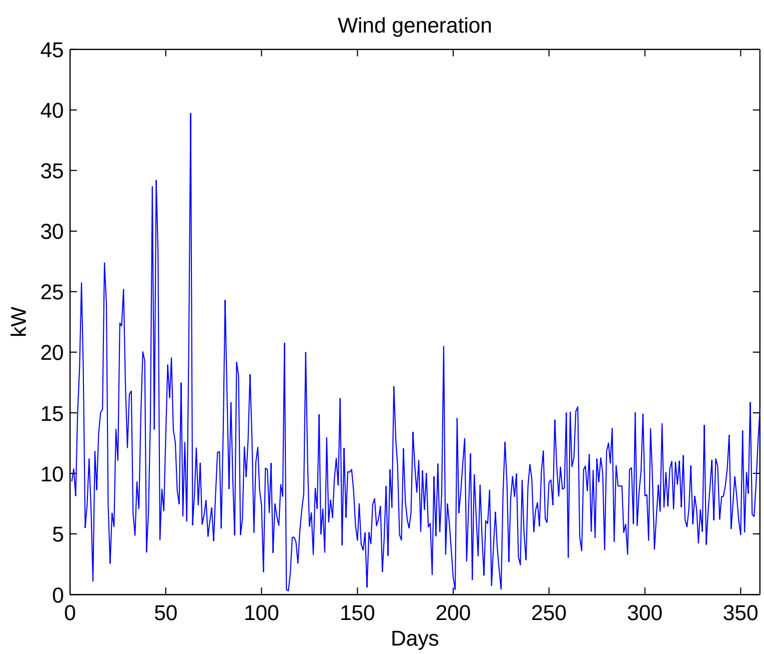


**Figure 5-6**.: Energy produced with wind a set of turbines

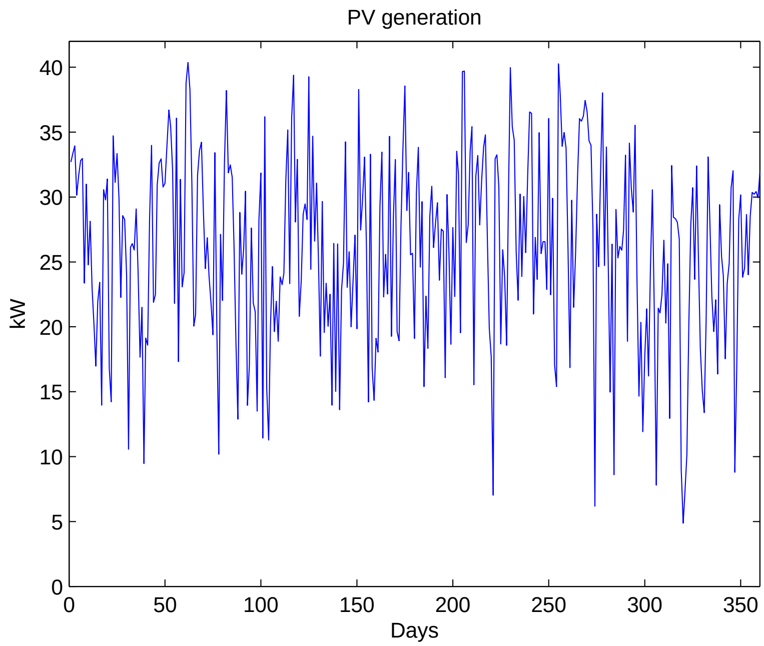


**Figure 5-7**.: Energy produced with a set of PV panels

Alternative generation figures evidences that production is lower that installed capacity. This can be attributed to several causes. First, using daily mean values as input, data dispersion is reduced erasing peak production times (positive and negative). Second: intrinsic uncertainties associated to natural sources, as example wind profile and generation figures (Figures **5-4** and **5-6**, evidences higher production in the first quarter of the year. In any case, robust design made with the GEP guarantee energy required by the system, and meets the generation variance presented, without compromising system reliability. Economic cost of alternative generation plants are covered in the retailer optimization function, where alternative and classic generation returns are combined in the cash flow the probability of default payments.

## 5.1.4. Economic analysis of generation assets costs

In last section, installed capacity and other costs of the generation technologies were described. It's a fact that investments in generations plants implies very high initial costs, and a motivation to make these investments is to get cheaper generation cost and reduction of liquidity and market risk exposure. Then, the trade-off between the risk exposure and negotiation reductions against higher investments should be reviewed. Exploring mentioned relationship, this work proposed a methodology that relies in these investments to optimize the cash flow of a retailer company. Balancing long term investments with short term returns is the strategy proposed to maximize retailer incomes in long term prediction horizon. Before presenting the solution to this strategy an exploration of the initial cost values is made. This exploration aims to establish proportions between costs and incomes of the generation technologies providing a context to frame the expected performance of solution proposed.

Now, tables **5-1**, **5-3** and **5-6** present the cost of the available energy assets. These cost must be paid once and is important to remember that they came from following facts developed in this thesis: Traditional installed capacity was optimized in the long term portfolio. This allowed to introduce a given amount of alternative generation. Forward energy agreements were considered to stress short term solution performance and alternative generation cost were included taking advantage of GEP design made. These costs are used in retailer portfolio as part of the optimization objective function. The optimization problem aims to minimize interests rate looses related to payments of these investments. This fact makes retailer cash flow and problem feasibility highly sensible to how the strategy decides the value of these payments. The most common methodology used to deal with these payments is the annualization of the installed capacity cost along the generation plant's life span. Spreading the cost along the life span, with a given interest rate, a set of regular payments is obtained. These payments are much reasonable in financial terms, but in exchange reduces the retailer profits due to the financial taxes incurred. Then, considering installation cost and life span of each technology, annualized costs are calculated and briefed in table **5-7** where the cost of interests paid along life span are also shown.

| Technology | Capacity | Life span | Total cost | Interest rate | Annualized cost | Interest |
|---|---|---|---|---|---|---|
| Coal | 1469 $MW$ | 40 years | 2.49$e$9 | 3% | 6.37$e$7 | 5.15$e$7 |
| CCGT | 55 $MW$ | 30 years | 0.04$e$9 | 3% | 0.16$e$7 | 7$e$5 |
| Wind turbines | 90 $kW$ | 20 years | 5.6$e$5 | 2% | 3.42$e$4 | 1.17$e$5 |
| PV | 200 $kW$ | 20 years | 5.2$e$5 | 2% | 3.20$e$4 | 1.24$e$5 |

**Table 5-7**.: Brief of full and annualized installed capacity costs for first scenario

Now, after that installation cost were discussed, each generation plant has fixed operation and maintenance (O&M) cost implied. This cost are not eligible and should be paid regularly along the life span. These cost depends on the installed capacity amount and they are presented in table **5-8**.

| Technology | F&O cost |
|---|---|
| Coal | 49$e$6 USD/year |
| CCGT | 1.17$e$6 USD/year |
| Wind turbines | 1680 USD/year |
| PV | 233200 USD/year |
| Total | 50.4$e$6 USD/year |

**Table 5-8**.: Operation and maintenance (O&M) cost

In short, this section discussed financial assumptions and implications related to the costs of including generation plants in the retailer portfolio. As seen, with the use of these assets, there are not great uncertainties in the long term calculations of their cost, with the exception of the energy agreements included, whose negotiations are not include in this work's scope. On the other hand, high initial investments are required and it is necessary to cover them. The used of annualized payments relaxes the problem but also increases the installed capacity costs. Next, the exploration of the incomes related to energy sales and their production cost as the way to produce returns in proposed management strategy.

### 5.1.5. Prices and load estimation

Regarding to the estimation of demand and prices related to energy retailing operation (sale and purchase), they are discussed in this order: first regulated and non regulated energy prices estimation is presented. Second, spot energy price and load estimation used is shown.

Complexity behind calculations of energy sell prices are too high and this value is critical in the energy retailer operation and in any trade considered. Operation returns depends of the energy sale prices and even can lead to unfeasible or undesired operation conditions in the system. Specially, when the retailing returns depend of high energy volumes and earns in each $kW$ sold are too small. Aiming for generality in the solution, energy prices will be based in the operation and fixed costs plus an imposed spread. This creates a direct relationship between solution's design and operation and the economic spreads and, at the same time, avoids possible speculation or overestimation. Regulation laws and government considerations can be included as additional cost or fees without problem. Therefore, this example will consider an approach to the marginal energy cost establishing the price based on: an average energy cost plus, an approximated fixed cost per kilowatt plus an spread. Expressions used for regulated and non regulated energy prices are presented in equations : 5-1 and 5-2.

$$C^r(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \sum_{i=1}^{N_t} \frac{C_i^f(k)}{\sum_{j=1}^{N_b} b_j} + \Delta C^r(k) \tag{5-1}$$

$$C^{nr}(k) = \sum_{i=1}^{N_t} \frac{C_i^g(k)}{N_t} + \sum_{i=1}^{N_t} \frac{C_i^f(k)}{\sum_{j=1}^{N_b} b_j} + \Delta C^{nr}(k) \tag{5-2}$$

with $Nt = 3$, all traditional generation technologies are included in the cost, bringing generality to the imposed price. Fixed cost are calculated with the expected energy used in the GEP design assuming the robust design case. Then, spread values are assigned with a low margin cost such that $\Delta C^r(k) = 0.2$ USD and $\Delta C^{nr}(k) = 0.1$ USD which compared with mean energy price and prices obtained are presented in table **5-9**.
Briefly, comparing obtained energy prices with average prices around the world (which can vary significantly) in several online sources was obtained that prices go from 3 to 41 USD cents. Hence,

| $C^r$ USD/kWh | $C^{nr}$ USD/kWh |
|---|---|
| 0.2140 | 0.1140 |

**Table 5-9.**: Regulated and no regulated energy sale prices

estimated prices are very close to marginal costs and could be increased without any speculation. More over, this methodology only considers some technical and operational cost, also several taxes and hidden cost are missing that could lead to price increments. As additional analysis, calculated prices will be compared with real retailer regulated and no regulated prices. Comparison is made making use of sell price series that corresponds to the retailer where the load series were obtained, presented in figures **5-9** and **5-8**. Retailer prices compared corresponds to a generation mix basically composed by Hydro power plants. The prices evidence very low generation costs. As conclusion, it is evident that, it is possible to produce energy with sell prices even lower that prices used in this case. It is remarkable that hydro generation was not included in the GEP problem, by two facts: to provide more competition between generation technologies prices in the GEP solution. Second, to provide a more global context since high hydro installed capacities are not available in all countries. Finally, variables assumed to estimate energy prices produce a reasonable and conservative sell price compared with world energy sell prices.

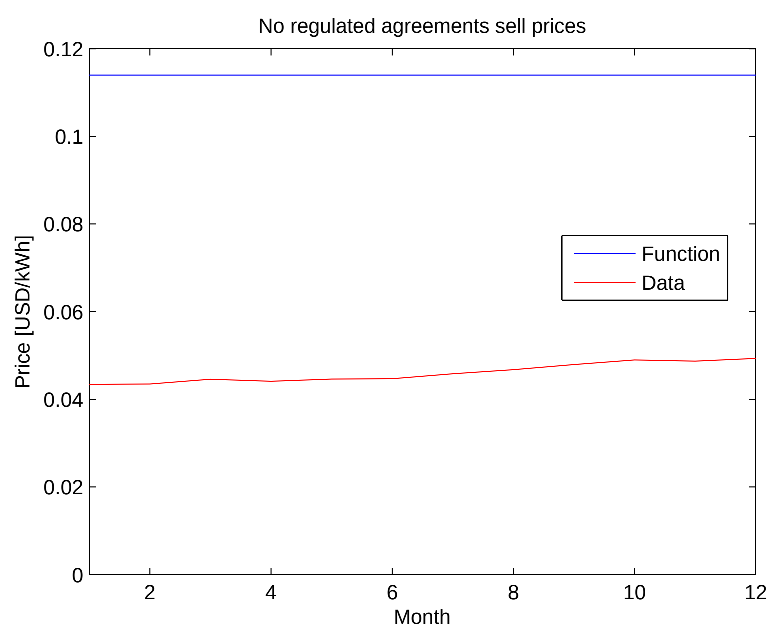


**Figure 5-8.**: No regulated agreements sell price model and mean retailing price in Colombia

Now, load and spot price estimation were discussed in section 4.2.1 and 4.2.2. Considering a time resolution of one day established in this section, short term portfolio needs a forecast of one day head and formulation made for the Holt-Winters model performs efficiently, assuming that every

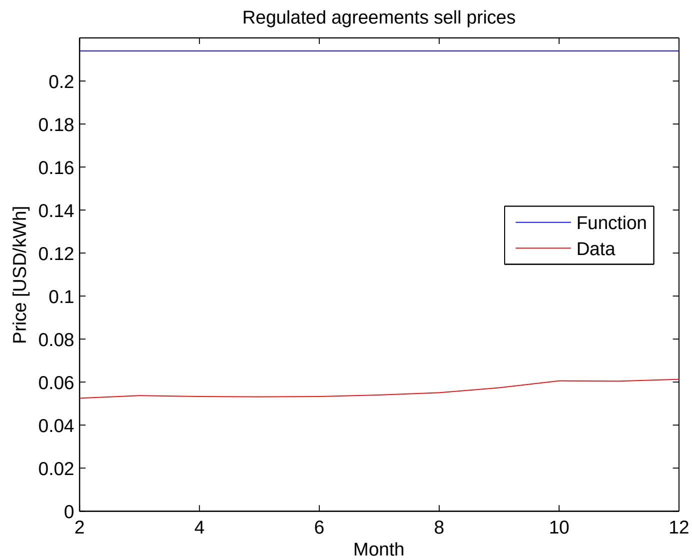


**Figure 5-9**.: Regulated agreements sell price model and mean retailing price in Colombia

time step historical information is updated. Then obtained results are evidenced in figure **5-10** and the RMSE are presented in Table **5-10**.

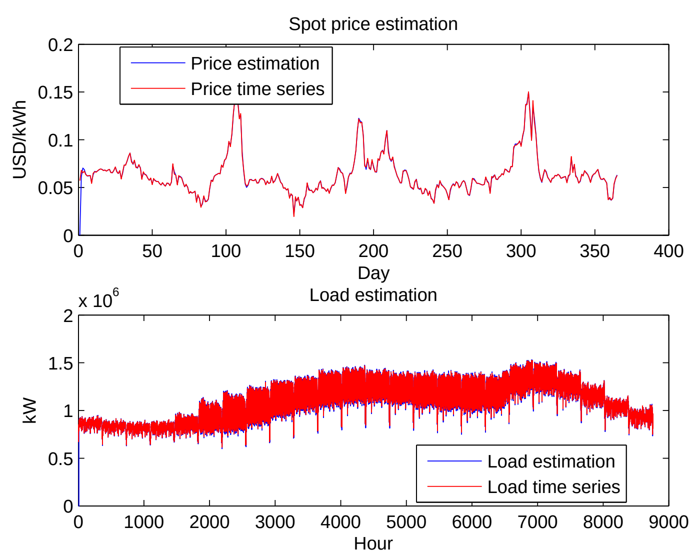


**Figure 5-10**.: Spot price and load estimation of the EPM retailer time series by mean of Holt Winters models

In this point, where spot market price and load forecast are presented,it is important to discuss some pros and cons of the proposed methodology. First, one day time frame used in the short term portfolio implies the use of daily mean values, erasing extreme conditions in the time series. Of course this is a rough approximation, but the next detail level is the solution of the economic dispatch problem, which is not included in this methodology's scope.

| Variable | RMSE estimation |
|---|---|
| Energy price | 0.003 USD/kWh |
| Load (No regulated) | 13 kW |
| Load Regulated | 10 kW |
| Total load | 23 kW |

**Table 5-10**.: Holt-Winters models RMSE one time step ahead estimation errors

Second, having defined the scope and, according to the proposed methodology, daily time frame used provides a detailed solution used to update the expected returns assumed in the retailer optimization problem. Assigned generation budget was calculated assuming a feasible robust scenario, then,it is expected that daily operation on charge of short term optimization provides better returns and, at the end of the month (that corresponds to the prediction horizon assigned) an improvement in the cash flow should be evident.
Then, the use of better forecast techniques in the load and spot price data should be focused in the medium and long term time in order to design the generation mix and consequently to have more accurate cash flow predictions. Finally, errors in the short term estimation are covered in economic and technical terms, installed capacity is able to meet the worst case scenario while generation budget also can pay this generation. Besides, the spot market is available as last resource in case of an extraordinary success. At the end, long term design and cash flow relies in the robust design, focusing the attention in how to deal with incomes and expenses at the retailer level. These iterations are presented in next sections.

## 5.2. Integration of the management strategy for one year.

Now, with the expected generations cost, energy sale prices and models required to solve the market clearing process. Based on figure **5-11** where system iterations are explained. Performance and results of the proposed strategy are presented.
Starting with the installed capacity cost provided by the GEP solution for the first scenario, presented in table **5-7** and , using them as initial condition $X_r(k)$ in $k = 1$ assuming that there is not previous loan and providing an starting cash condition of US$20 million. Cash initial condition is a critical condition in the problem initialization. It is necessary to guarantee problem feasibility and, considering fixed cost and generation budget as initial values US$10 million is the starting point that avoids loans in first iteration, then next dynamics are too complex to be predicted in the system. Assigned values were chosen on purpose because they provide a feasible starting point and at the same time stresses the system performance in front of loans management.

Solution for the energy retailer model presented in equation 2-15 which in short minimizes the looses related to the installed capacity payments due to interest rates is presented in figure **5-12**,

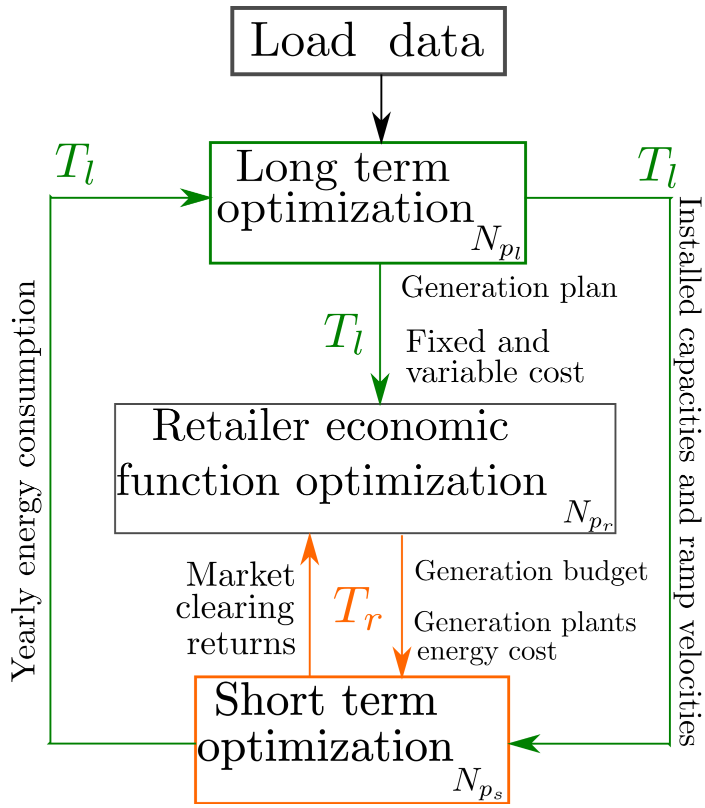


**Figure 5-11**.: Hierarchical structure data flow

| Variable | Value [USD Millions] | Description |
|---|---|---|
| $C_1^0(k)$ | 63.71 | Anual Coal installed capacity cost |
| $C_2^0(k)$ | 0 | Anual OCGT installed capacity cost |
| $C_3^0(k)$ | 0.016 | Anual CCGT installed capacity cost |
| $C_{pv}^0(k)$ | 0.03440 | Anual Wind installed capacity cost |
| $C_w^0(k)$ | 0.03220 | Anual PV installed capacity cost |
| $C_1^{fw}(k)$ | 1.111 | FWF13 installed capacity cost |
| $C_2^{fw}(k)$ | 0.857 | FWF13 installed capacity cost |
| $C_3^{fw}(k)$ | 0.743 | FWF13 installed capacity cost |
| $L(k)$ | 0 | Loans |
| $R^r(k)$ | 20 | Avaliable cash |

where the annualized debt amount of used assets is shown.

As seen took about 8 months to pay the biggest debt, in figure **5-13** decisions are presented. Payments amount are controlled by the MPC which allow to put particular constraints over the control actions, in this case debt payments. This property of the MPC methodology is extremely useful in financial problems allowing to model financial concentration as financial limitations or to impose arbitrary constrains by the retailing company. Also, it is common to use this kind of restrictions to

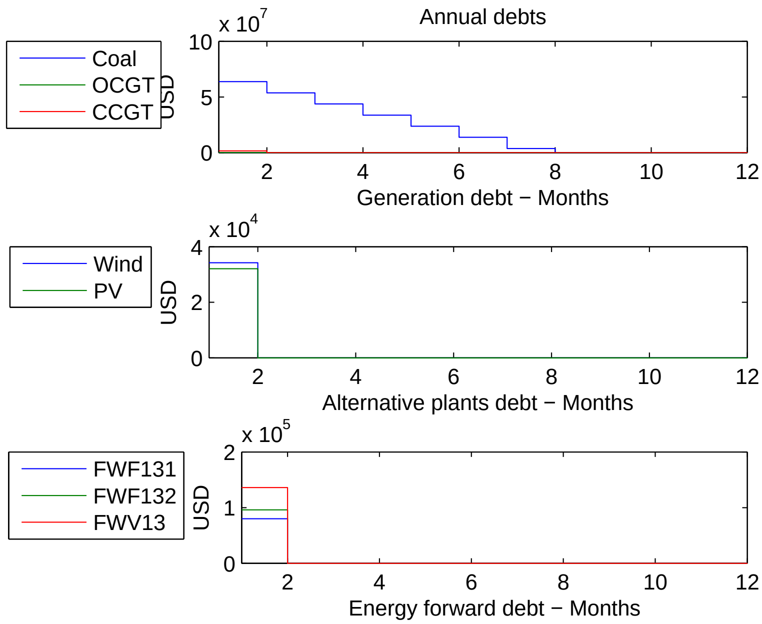


**Figure 5-12.**: Retailer debt for scenario 1

avoid unrealistic solutions. In this case payments related with generation technologies are limited to US$10 million per month. Loans and debt are discussed later.

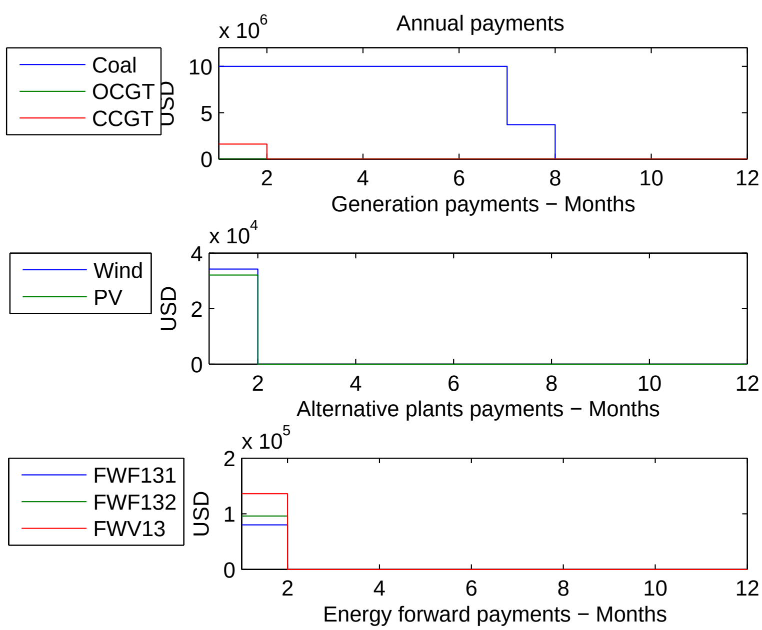


**Figure 5-13.**: Retailer payments for scenario 1

Having optimized the installed capacity debts and their associated payments in the retailer economic function by means of the proposed MPC, debts dynamics evidenced a priority to pay first the smaller ones according to optimization constraints and budget available in the cash flow. Consequently, it is necessary then to explore two economic related variables left: cash flow and loans. These variables are the last values to be explored in the retailer function due to their interactions with the short term portfolio.

Now to board the retailer cash flow it is necessary to understand his values depends of incomes and expenses of the energy retailing operation. Starting with the retailing operation costs where fixed and variable cost are explored. In section 3 generation mix design was obtained solving the GEP problem. GEP solution provided installed capacities and their yearly optimal expected operation plan, presented in figure **3-13**. This optimal design was made based in an hourly time resolution considering maximum energy values and their variations. Therefore, the design can be considered as a robust solution. Now, making use of the GEP design as operation reference, yearly operation values are used to estimate variable incomes and expenses related to energy production and they are presented in table **5-11** as follows:

| Technology | Block | Energy MWh | Gen. Price $\$/MWh$ | Sell price $\$/MWh$ | Gen. Cost $\$/kWh$ | Sales \$ | Returns \$ |
|---|---|---|---|---|---|---|---|
| Coal | $b_1$ | 0 | 5 | 214 | 0 | 0 | 0 |
| | $b_2$ | 6.20e6 | 5 | 214 | 3.10e7 | 1.32e9 | 1.29e9 |
| | $b_3$ | 6.58e6 | 5 | 114 | 3.29e7 | 0.75e9 | 0.71e9 |
| CCGT | $b_1$ | 0.56e4 | 10 | 214 | 0.56e5 | 0.12e7 | 0.11e7 |
| | $b_2$ | 0 | 10 | 214 | 0 | 0 | 0 |
| | $b_3$ | 0 | 10 | 114 | 0 | 0 | 0 |

**Table 5-11**.: Yearly expected generation cost and energy sales per block

These yearly values has been calculated with the following assumptions: Energy sale prices that have a higher impact in the expected returns were estimated fixed and variable costs. Regarding to expect demand, it is important to highlight that $b_j$ values discussed in section 3.1 are the result of the LDC discretization and, each $b_j$ block has been defined as the product of the energy demand level and his time duration. This product avoids to over estimate the expected generation values, bounding the expected generation according to the demand level where the generation agreement was calculated instead of the expected generation with the installed capacity and the 8760 year's hours.

Last, before continuing to the short term solution details, it is necessary to consider that yearly fixed and variable cost exceeds the short term time resolution. Therefore, the assumption made to meet this task is the linear escalation of the yearly time frame used to monthly values and with the use of the $b_j$ energy blocks the energy proportion is preserved and the result is presented in table **5-12**.

Now, after having obtained yearly operation returns and scale them, a monthly expected generation

| Technology | Block | Energy MWh | Gen. Price $\$/MWh$ | Sell price $\$/MWh$ | Gen. Cost $\$/kWh$ | Sales \$ | Returns \$ |
|---|---|---|---|---|---|---|---|
| Coal | $b_1$ | 0 | 5 | 214 | 0 | 0 | 0 |
| | $b_2$ | 5.10e5 | 5 | 214 | 2.58e6 | 1.1e8 | 1.04e8 |
| | $b_3$ | 5.41e5 | 5 | 114 | 2.74e6 | 6.25e8 | 0.59e8 |
| CCGT | $b_1$ | 4.60e3 | 10 | 214 | 0.50e5 | 0.10e6 | 0.10e6 |
| | $b_2$ | 0 | 10 | 214 | 0 | 0 | 0 |
| | $b_3$ | 0 | 10 | 114 | 0 | 0 | 0 |

**Table 5-12**.: Monthly expected generation cost and energy sales per block

budget $B_s(k)$ that corresponds to the sum of generation cost of table **5-12** is obtained and assigned to the short term portfolio as economic constraint. This is the last step in the hierarchy integration. Now, solving the optimization formulated in 4-39 considering Holt winters models used to load and spot price time ahead estimation and, alternative generation time series are used to solve the market clearing problem allocated in the short term portfolio.

## 5.2.1. Short term portfolio solution

With obtained GEP design, the variables escalation and robust costs estimation made in the retailer function, the management strategy can proceed to solve the short term portfolio. This section will make use of all energy assets designed along this work focused in the market clearing task. The objective here is to meet the energy required by costumers at the lowest price. This operation is constrained by the generation budget. Now, solving the optimization described in 4-39 produces the control actions presented in figure **5-14** and the system states presented in **5-15**. Decisions represents changes in the use of the generations assets. These actions are constrained by ramp velocities in the generations assets and specified maximum changes in the generation agreements. Spot market as an ideal generation source is assumed to be able to supply demanded energy at any time. System states are the energy required to each asset, in case of the generation technologies limited by installed capacity and in energy agreements, limits are given by the remaining energy available. It is important to remember that every day alternative generation is included in the energy balance, considering that the installed capacity is low compared with the total load. Alternative generation is not shown in the plots for simplicity.
Now, in order to illustrate the controller performance, only 75 days are shown making use of figures **5-14** and **5-15**. First, all artificial generation agreements are active with their respective expiration dates and every day their prices decay. Controller makes use of the time ahead predictions and extracts energy of the lower price agreements or the agreement closer to expire. In Figure **5-15** shows how controller stops are used of the forward *FWV13*, considering expiration days minimizing loses related to unused energy. On purpose, agreements experiment times where established in closer dates in order to proceed with analysis of iteration between spot market and generation

plants, as the main assets considered in this solution.

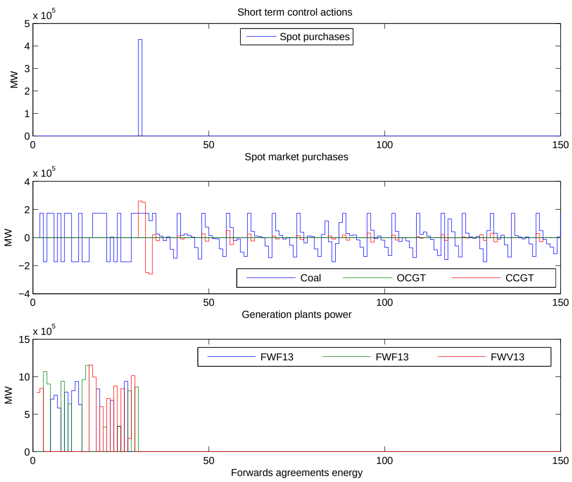


**Figure 5-14**.: Short term portfolio control

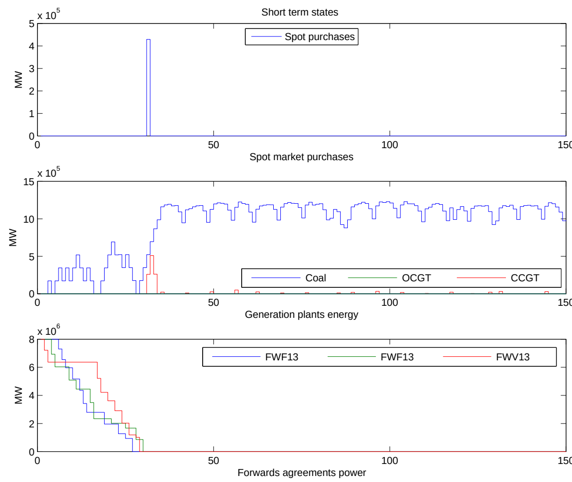


**Figure 5-15**.: Short term portfolio states

Then, with the end of the energy agreements, demand should be supplied making use of the spot market, generation plants and the alternative generation. Due to the availability of the energy agreements, coal plant was producing energy at levels below his installed capacity. Now that the required energy increases, the system controller decides to increase the generated energy in the coal plant keeping the increments constrained by the ramp velocity. The ramp constraint avoids that coal plants reaches the demanded power instantly and, considering this delay the system makes use of the spot market and the CCGT plant to complete the dispatch. Last, when coal plant is working as base technology (supplying most of the required energy), the generation control system is able to meet the demand and his changes with the occasional use of CCGT and, in other times not shown in the plot, using spot market when prices are low. This operation result in a minimal operation cost and meets the demand requirements increasing the retailer returns that will explored next.

The returns, as explained in section 2, are updated every $T_r$ time, they are obtained in market clearing operation and calculated with equation 4-24. Now, revisiting the returns problem with a more detailed description of the implied vales. The first task is to understand the dynamics presented in the update function referenced, let´s explore comparisons between expected and market clearing variables.

First, generation budget $GB(k)$ and real operation cost $GC(k)$ are presented in figure **5-16**. Considering the high difference between the robust budget and generation cost values, an additional plot is required to see the details of the generation cost values and it is presented in figure **5-17**. Here, the monthly robust budget assigned, as expected, is higher that market clearing generation cost. The influence in the first month of the energy agreements is evidenced decreasing the generation cost value, then the fluctuation in the cost around the mean value is shown. These changes are consequence of iterations with the spot market and the occasional dispatch of the CCGT plant.

Persistent use of the base generation technology to supply system's real energy demand puts a low mean operation cost in the solution.

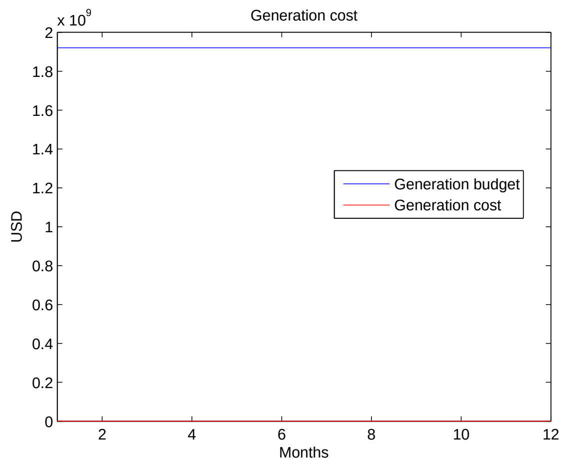


**Figure 5-16**.: Energy retailer generations cost comparison

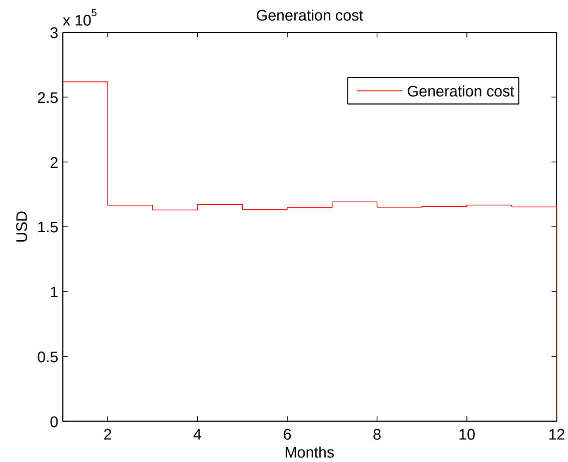


**Figure 5-17**.: Energy retailer generation cost for one year

Then, analogously energy sales are presented in figures **5-18** and **5-19** representing robust operation $GE(k)$ that assumes full load all the month and real retailer sales $GR(k)$. Equally, the real sales are lower that the robust estimated. As seen, absolute variations on energy sale are not too high and the small changes presented are attributed to load increments, considering that sell prices are fixed along the year.

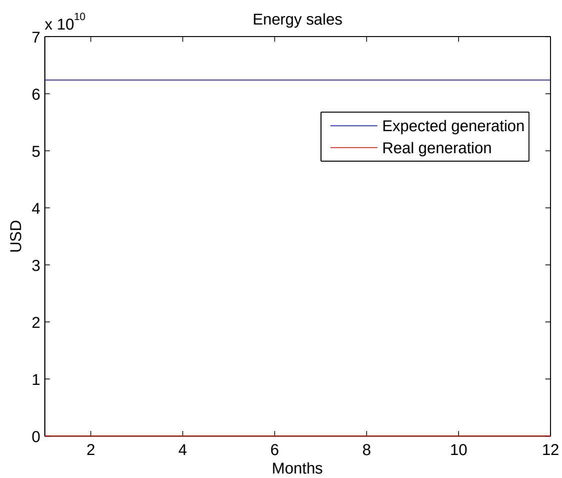


**Figure 5-18**.: Energy retailer sales comparison

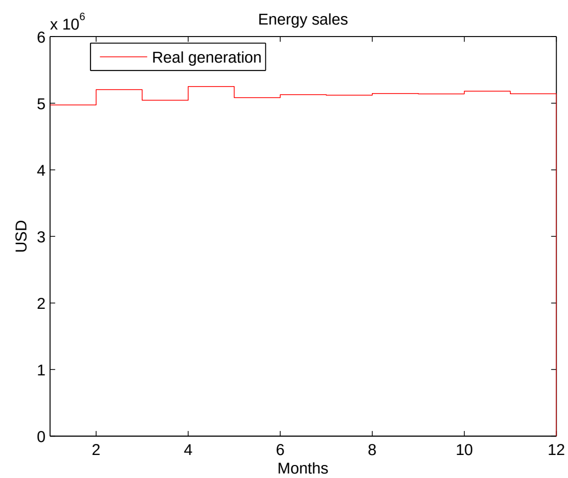


**Figure 5-19**.: Energy retailer operation sales for one year

Now, with calculating the short term returns with the presented financial variables related to the short term portfolio, the returns obtained are presented in figure **5-20**.

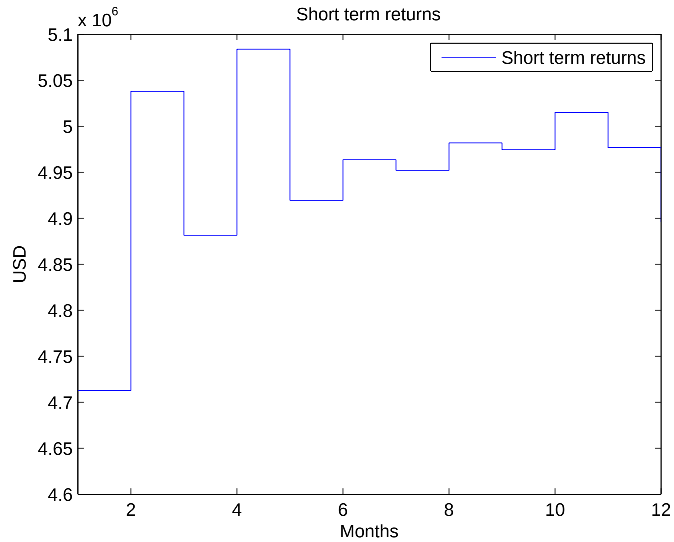


**Figure 5-20**.: Energy retailer obtained short term returns for one year

Finally, making use of the short term return variable, it is possible to calculate the energy retailer cash flow update values described in 4-24. Figure **5-21** shows the update equation evolution. Dynamics of the cash flow are determined by the payments of the generation technologies, short term returns (all of them already discussed), fixed and maintenance cost (F&M) and loans with his respective payments presented in figure

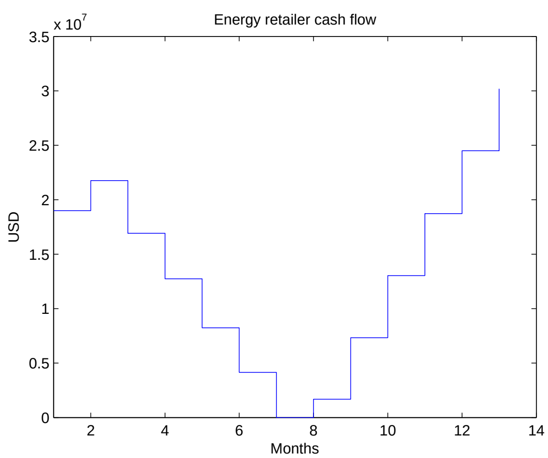


**Figure 5-21**.: Yearly energy retailer cash flow

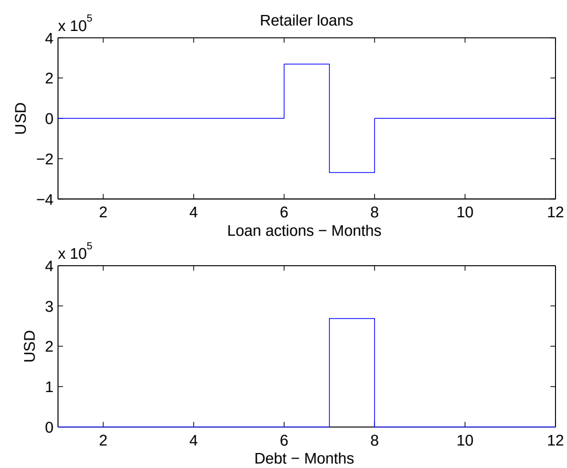


**Figure 5-22**.: Yearly energy retailer loans and payments

The energy retailer cash flow with the help of the loan option, that can be seen as a slack variable, evidences the effect of annualized payments of installed capacities. Until 8 month, short term returns produced in the market clearing operation are used to pay installed capacities cost plus not eligible costs. Later, savings in the cash flow begin to increase. As mentioned, initial cash condition was assigned to stress the loan option; in the month 7 the retailer cash flow is zero and the MPC decides to ask for a load that is paid the next month with returns obtained of the retailing operation. Then, retailer cash flow begins to achieve savings overcoming and even surpassing, or recovering initial capital condition. The positive cash flow obtained is sensible company management or strategy rules such as the energy sell prices, the imposed values in this example are conservative but, it is possible to obtain higher returns while keeping the prices close to to real operation values.

Now, the full integration of the hierarchical portfolio management strategy has been made. Next step is to explore the retailer cash flow values, which are at last the most significance value in the strategy, and as planning tool, is the consequence of all assumptions made.

## 5.3. Management strategy performance test

Now that the operation and performance of the management strategy has been shown, it is mandatory to provide a metric related to system reliability. Considering that this solution could be used as a planning tool in energy retailing management where the objective is to maximize the the retailer returns, the cash flow is the main variable that involves all the variables of the systems involved in the problem, the uncertainties of this variable,well know as risk, could be used to tackle the objective of this section.

According to [52] VaR, it is not the most proper risk measurement to evaluate risk in long holding periods in a given portfolio, such as power plants investments. Thus this, Cash flow at Risk (CFaR) also known as Earnings-at-Risk (EaR) is the methodology used. According to the author of the book used EaR definition is: "The considered random variable is the earnings of a company until a specified date. For energy companies this includes spot price revenues generated by the assets less all production costs plus all related trading and hedging transactions". EaR is the difference between the expected earnings and the earnings corresponding to the given confidence level". Thus this, EaR will be used with two purposes: First, identify the solvency risk of proposed strategy. Second, to analyze the impact of renewable energy, as variable with high uncertainties, in the generation mix and consequently in the retailer cash flow.

Now, assumptions and considerations made to perform the EaR analysis are listed, then, scenarios used are described and EaR results are presented. First consideration to be discussed is the reference used to compare the results. Even though all the generation mix design is based in the modified GEP strategy proposed, the mentioned design is not useful for a EaR analysis. The use of LDC in the GEP design overrides influence of load changes assuming a single combination of energy blocks along the year. This implies that GEP or also named robust design only could be used to calculate the expected cash flow returns with: expected energy sales, annualized installed

capacity, fixed and variable operation costs of the system in the robust scenario, naturally this value is highly over estimated: US$61,481 millions which in fact is a value not realistic and either useful for a risk analysis. Next, the presented case analyzed in this section will be used as reference in the EaR analysis. Briefly, this design was made with very conservative assumptions: low energy sales prices, low initial conditions for the cash variable, and low renewable energy installed capacity with low wind profiles and sun radiation. Also, energy agreements are removed all this in order to test a very conservative scenario avoiding speculation in the energy retailer cash flow.
Last, two scenarios are tested, keeping the GEP installed capacities fixed, two increments in the wind turbines and PV technologies are made. Fixing the capacities in the limits of the GEP design system reliability is ensured in fornt of the uncertaintites of the PV and wind generation. Also, capacity increments were selected to be range of the financial feasibility, meaning installed capacities provides feasible economic solutions with the same amount of cash available and the same energy sales prices used in the study case. Now, based on [53] and [52] EaR expressions presented in 5-3 and 5-4 could be used to calculate the risk of the cash flow. Making use of 5-3 with a 95% confidence with table **5-13** resumes values used to analyze risk in the proposed scenarios.

$$EaR_{\alpha} = \mathbb{E}(R^r) - [\mathbb{E}(R^r) - q_{\alpha}R^r] \tag{5-3}$$

$$EaR_{\alpha} = \frac{\mathbb{E}(R^r)}{[\mathbb{E}(R^r) - q_{\alpha}R^r]} \tag{5-4}$$

| Traditional generation 1524 MW | 90 kW Wind 3000 kW PV | 1500 kW Wind 1500 kW PV | 30 MW Wind 10 MW PV |
|---|---|---|---|
| Mean | \$9.925.510 | \$9.927.889 | \$9.947.486 |
| Variance | \$22.828.318.230 | \$22.823.896.368 | \$22.794.287.783 |
| EaR | \$33.785 | \$33.782 | \$33.760 |

**Table 5-13**.: EaR analysis for energy retailer cash flow in test scenarios

Alternative installed capacity increments are low compared to the traditional generation amount due to financial constraints imposed to the system where, big values of alternative generation will implicate to have greater cash initial conditions or would force the controller to borrow more money, as explained before. However, it is observed small improvements in mean and variance values as well for the yearly cash flow values. The explanation is: zero generation cost of alternative plants impacts directly generation cost increasing expect returns. At the same time, considering that alternative generation is used as perturbation in the generation system, all energy supplied with alternative generation represents a load decrease that is reflected in less variations in the power required to the traditional generation plants. In consequence, EaR decreases with the alternative generation increment. This fact also could be explained from the economic theory point of view:

diversification.

Having all the energy production attached to a few generation plants, directly transmits load variance to the generation cost and energy sales. Situation could be worse if generation plants depends of high volatile fuels. Final remark is to question if alternative generation should increase the EaR considering their stochastic nature. In this case, the answer is No. Proposed GEP design provides reliability in front of alternative generation uncertainties and short term portfolio results evidenced that CCGT plant is used frequently for several possible reasons. One of them is cover fast changes along the day due to the alternative generation operation. Additionally, as mentioned before, alternative generation is considered with low production time series making the energy production relatively low avoiding possible over estimation in the savings due to free cost energy. Last, considering all results presented and comparison of EaR values with mean returns and variances, it is possible to say that proposed management strategy provides in cases with zero and increasing alternative generation plants, an expected low risk cash flow providing as planning tool a solid scenario test tool to analyze or to mange energy retailing operation including generation plants as assets.

In short, this chapter explained with an application case the integration of all the hierarchical structure proposed to mange the energy retailer portfolio. The technical and economic integration of the GEP with alternative generation by means of the retailer economic function was successfully made. The integration of several time frames increased the time resolution in the economic analysis, allowing to calculate daily operation returns and to integrate and compare them with the traditional yearly values obtained in the classic GEP solutions. This detailed approach extended the planning capacities to the daily time resolutions providing a methodology to estimate with the expected returns of the market clearing operation with alternative generation.

Then, the impact of the integration of alternative or non conventional generation in the classic GEP generation matrix was evidenced in the risk analysis made to the strategy. This impact has two main causes. First, the cost increments due to the high installation cost of alternative generations compensated with the almost zero generation cost of then. Second, the energy supplied with alternative generation reduces the use of traditional generation plants decreasing the variance of the conventional operation cost and, directly decreasing the cash flow variance. All this changes where measured with the EaR risk measure. The test scenario constrained the amount of alternative generation but the methodology is flexible as planning tool and scenario analysis allowing to energy retailers to consider several designs in long term scenarios analysis.

# 6. Conclusions

A management tool for energy markets focused in retailing companies was developed in this PhD dissertation. The proposed management strategy integrates short, medium and long term energy assets by means of an hierarchical structure to conform an energy retailer portfolio. The management strategy maximizes the retailer returns in a prediction horizon while minimizes risk exposure avoiding the use of future energy agreements as hedging instruments.

The main contribution of this work is the integration of short medium and long term models related with power markets. Making use of traditional generation plants, alternative generation technologies and an approach to market clearing operations, the energy retailer cash flow is maximized and at the same time, the use of generation assets minimizes the risks exposure implied by the use of forward energy agreements. In chapter 2, the solution of the energy retailing problem in emerging power markets was discussed. The identified lacks in the retailers management strategies were used to propose a management strategy based on an hedging strategy. The hedging strategy is based in the optimal economic and technical integration of several power plants in the retailer portfolio. The proposed optimization problem includes as variables in the retailer economic function: market clearing returns, fixed and variable costs, and installed capacity investments of all generation technologies, plus financial loans. Solving the dynamic optimization, by means of model predictive control theory, the future expected cash flow is obtained allowing to plan and to explore different operation conditions and scenarios with this management tool.

Regarding to the solution of this thesis several side contributions were found. The most relevant ones related to optimal investment portfolio management with hierarchical control for energy markets are:

- A modified version of the generation expansion problem (GEP) extended as a dynamic optimization problem and solved with MPC. With this contribution an optimal dynamic generation plan is obtained, the plan includes ramp velocities of generation technologies and load dynamics in the design. In chapter 3 this contribution is developed as follows: First, a comparison with traditional GEP is made evaluating traditional and proposed solutions in four scenarios separately. As result, the influence of load dynamics in the GEP is used to show an economic compromise between the system dynamic response and the solution cost for each scenario. Second, a MPC controller is used to solve the proposed GEP problem considering at the same time all the scenarios, this approach creates a GEP planning tool which provides an integrated expansion plan, which considers previous installed capacities and future system states minimizing losses in operation and installed capacities costs with a computational time in order of seconds.

- Modified GEP design provides robust operation conditions in term of installed capacity and load changes. This fact is used to include alternative generation plants in the mix without compromising system reliability. Also, GEP design is used to establish, in addition to the installed capacity cost, fixed and variable cost related to generation plants. These costs, plus alternative generation plants costs, are used to estimate the annualized payments that are assumed when generation plants are owned and operated.

- Generation plants designed with the GEP are considered in the management strategy as energy agreements where the execution price is no subject of negotiation. This reduces financial risk attached to a unknown price negotiation. Even more, any function or desired profit could be included in the estimation of the execution prices. This leads to obtain pseudo energy agreements with known future price, available energy and financial constrains, these constraints are obtained with the ramp velocities of the GEP and the are used to limit the maximum changes per time unit in the use of the agreement.

- The use of the hierarchical structure coordinated by the energy retailer economic function, successfully integrates at technical and economic levels, medium and long term investments related to installed capacity investments, with the short term portfolio which is on charge of market clearing. With this, energy sale returns are calculated based on load estimation. The obtained returns in the market clearing operation, that includes renewable technologies, are used to pay generation plants cost and create savings, if possible, with the obtained retailer cash flow.

- Proposed management strategy has a high generality level allowing to use a wide selection of models in each component of the retailer portfolio. The independence between portfolios allows to take into account different dynamics and models that could be different in terms of time and complexity. Furthermore, is possible to establish arbitrary load profiles and energy sales prices, this could be used to analyze profit changes in different market scenarios measured with a expected returns risk metric.

## 6.1. Solution utility

The Presented management strategy is designed to analyze cash flows of retailing companies, taking into account technical and economic variables. The strategy is able to hedge future energy with generations plants and avoids the use of energy agreements. Its principal feature is the ability to easily integrate different models, related with the power markets, which have different dynamics and complexity.

In general, the methodology allows to include a wide selection of models or variables that should be part of one portfolio selected according to its time frame. The models or variables included must meet the required data amount or allow a forecast in a time window and should be possible to share technical and economic results with the other layers. Thus, according to power systems expected evolution in the short - medium future models like generation technologies, ancillary services, demand respond, energy storage could be added in the energy retailer portfolio plus several forecast techniques. Then, once the models of interest are included in the hierarchical structure, the management strategy could be used to make analysis of the technical and economic system performance under different scenarios.

## 6.2. Future work

As general methodology, future work of this dissertation could be focused in several research lines: modeling, forecast, risk management, technical design and economic analysis. Nevertheless, along the development of this work some immediate contributions related with some strong assumptions made are proposed:

First, in order to increase the short term portfolio detail level, it is proposed to include start up and shut down times of the generation plants in the market clearing operation. To do this, it is necessary to work in the short term model with an hourly time resolution. It is a fact that long term simulations with hourly time frames demand a huge computational effort and resources. Now, considering hierarchical structure proprieties, the proposal is to explore the feasibility of splitting the 8760 hours required to solve at least one year in smaller time frames, this time escalation could be done similarly to the time escalation made in this work assuming worst case as scenario in the prediction horizon and then comparing them with real values obtained.

Second, it is recommended to explore the integration of renewable sources and other smart grid technologies in the traditional generation system. Actually alternative technologies have been positioned in the generation matrices in the world even and they are included in the countries energy road-maps. It is pertinent to continue researching in this integration considering new technologies and government policies.

Last, regarding to the financial field: In order to increase model detail in long term simulation cases, the inclusion of transaction costs and variable interest rates in the economic function is suggested. Also, considering the retailer cash flow behavior identified along the development of the study case. It is suggested to study the proposal of an optimization problem that allows the retailer to find a combination to get specific returns for a given time mixing: energy sales prices, annualized costs, fixed and maintenance cost and short term returns.

# A. Standart model predictive control theory

This chapter explains the basics of the Model predictive control (MPC) methodology. This methodology was used to solve the dynamic optimization problems discussed in this dissertation. As a planning methodology, this thesis proposed the solution of several management problems that requires data prediction and to take future actions based on this data. Furthermore, the input data used is highly dynamic and, decisions made based in this data are susceptible to prediction errors and uncertainties. Thus this, it is necessary to solve the process interactively and efficiently allowing to compensate the mentioned failures along the prediction horizon.

In order to deal with mentioned problems, MPC methodology provides a suitable solution allowing to efficiently solve a dynamic optimization problem in a prediction horizon including constraints. The publication "A Brief Overview Of Model Predictive Control" [54] presents a general methodology review, where three remarkable characteristics of MPC are listed as follows:

- Explicit use of a model to predict the process output along a future time horizon.
- Calculation of a control sequence to optimize a performance index.
- A receding horizon strategy, so that at each instant the horizon is moved towards the future, which involves the application of the first control signal of the sequence calculated at each step.

Based on these characteristics it is possible to establish a direct relationship between the MPC and the portfolio managment problem (see [43]). The idea is to use a prediction model for the relevant variables, in this case, energy market variables, such as: energy demand and energy spot price, among others. Then, with prediction model an dynamic optimization problem is solved. Solving the dynamic optimization with MPC methodology allows to choose between several objective functions or even a combination of them. This fact provides some important highlights about the MPC methodology:

- Allows to include constraints into the problem.
- With the use of state space models it is possible to split the controlled and control variables in the optimization problem . Consequently, it is possible to impose specific constraints to the mentioned variables.

- The ability to use several types of objective functions allows to make use of mathematical formulations with interesting properties such as convexity. This fact provides the opportunity of solve the optimization problem with advanced optimization methods improving stability and efficiency in to the problem.

- Can deal with multivariable, (MIMO) multi-input multi-output processes.

- A disadvantage is that MPC requires: **an appropriate process model.**

Last, the optimization problem is solved interactively making use of the receding horizon strategy (presented in the flowing part of this chapter). These interactions allows to update the forecast models and fix errors caused by uncertainties, exogenous variables among others.

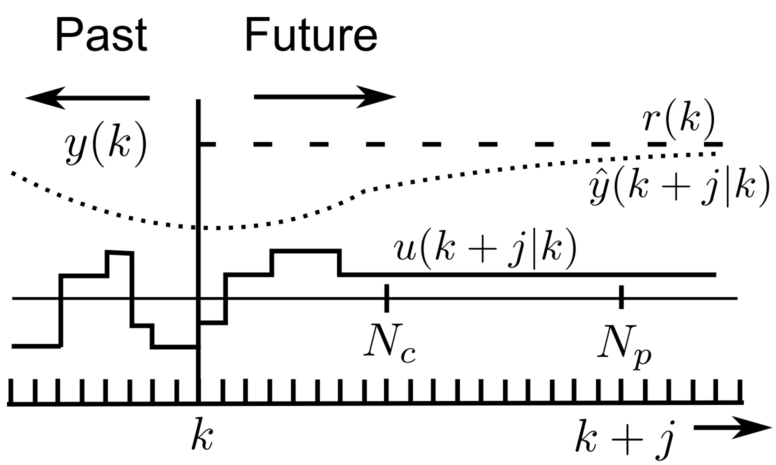


**Figure A-1**.: Receding horizon strategy

First, in order to illustrate the MPC operation lets consider figure **A-1** where predicted outputs $\hat{y}(k+j|k), j=1,2,...,N_p$ along a prediction horizon $N_p$ are calculated for each instant of time $k$ using the process model. The predicted outputs depend on both the past values and initial conditions of the model $y(k)$ and the applied control actions $u(k+j|k)$ in previous times $k=0..N-1$. The sequence of future control signals is computed to optimize a performance criterion, often to minimize the error between a reference trajectory or index $r(k)$ and the predicted process output $\hat{y}$. Then, current control signal $u(k)$ is transmitted to the process. At the next sampling instant $y(k+1)$ is measured and the process is repeated.

# A.1. Description of the elements of the model predictive control

## A.1.1. Prediction model

The prediction model, can be linear or nonlinear, normally the MPC works with linear models. As a main base of the prediction for the MPC, the model can be written in a discrete state space equations, a general form of a state space is defined as:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \tag{A-1}$$

where $x(k)$ are the states of the system, the $A$ matrix describes the states evolution, $B$ establishs the relationship between the inputs and the state, $u(k)$ the inputs of the system, $y(k)$ the output of the system, $C$ is the relations between the states and the output and $D(k)$ a direct relation between the inputs and the outputs sometimes called the feedtrhough term.

## A.1.2. Performance index

Also called cost criterion, penalizes the reference tracking errors and the amplitude of control actions used to minimize the function.

$$J(u(k), e(k)) = \sum_{t=1}^{N_p} e(k+j)^T e(k+j) + \sum_{t=1}^{N_c} u(k+j)^T u(k+j) \tag{A-2}$$

A more general cost criterion will be used. This formulation, includes $Q$ and $R$ matrices that allows to weight the states and control values respectively. This matrices are assumed to be symmetric positive definite.

$$J(u(k), e(k)) = \sum_{t=1}^{N_p} e(k+j)^T Q e(k+j) + \sum_{t=1}^{N_c} u^T(k+j) R u(k+j) \tag{A-3}$$

where $e(k+j) = \hat{y}(k) - r(k)$, $N_p$ is the prediction horizon and $N_c$ is the control horizon, $u(k+j)$ denotes the control input $u$ at time step $k+j$, $e(k+j)$ denotes the error value $e$ at time step $k+j$.

## A.1.3. MPC formulation

Given the prediction model by the equation A-1:

$x(k+1) = Ax(k) + Bu(k)$

$y(k) = Cx(k)$

a typical formulation for the MPC problem is proposed as follows:

$$J(\hat{u}(k), \hat{e}(k)) = \sum_{t=1}^{Np} e^T(k+t|k)Qe(k+t) + \sum_{t=1}^{Nu} u^T(k+t)Ru(k+t|k) \tag{A-4}$$

If the prediction model is linear the substitution of the equation A-1 in A-4 gives to the cost function the form:

$$J(\hat{u}(k)) = \hat{u}^T(k)H\hat{u}(k) + 2f\hat{u}(k) \tag{A-5}$$

$$H = \hat{B}^T\hat{Q}\hat{B} + \hat{R} \tag{A-6}$$

$$f = (x(k)^T\hat{A}^T - \hat{y}^T)\hat{Q}\hat{B} \tag{A-7}$$

where $\hat{u}(k) = \begin{bmatrix} u^T(k) & u^T(k+1) & \dots & u^T(N_p-1) \end{bmatrix}^T$, $u(k+t) = u(k+N_c)$, $\forall N_c \leq t \leq N_p$, $\hat{Q}$ and $\hat{R}$ are block diagonal matrices with the adequate dimensions, being $Q$ and $R$ the blocks of $\hat{Q}$ and $\hat{R}$ respectively, and

$$\hat{B} = \begin{bmatrix} CB & 0 & \dots & 0 \\ CAB & CB & \dots & 0 \\ \vdots & & \ddots & 0 \\ CA^{N_p-1}B & & \dots & CB \end{bmatrix} \tag{A-8}$$

$$\hat{A} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{N_p} \end{bmatrix} \tag{A-9}$$

$$\hat{Q} = \begin{bmatrix} Q & 0 & \dots & 0 \\ 0 & \ddots & \dots & \\ \vdots & & \ddots & 0 \\ 0 & & \dots & Q \end{bmatrix} \tag{A-10}$$

$$\hat{R} = \begin{bmatrix} R & 0 & \dots & 0 \\ 0 & \ddots & \dots & \\ \vdots & & \ddots & 0 \\ 0 & & \dots & R \end{bmatrix} \tag{A-11}$$

where the objective is to: $\min_{u(k)} \quad J(u(k))$

### A.1.4. Constraints

In real applications, the processes have constraints related to the application of each problem, industrial processes have limits given by: temperature, operation limits and physical restrictions, in financial systems, the constraints can be related to the transactions cost, amount of stocks that can be negotiated. The MPC is a strong technique thanks to the constraints handling capabilities. If the problem does not have constraints, it has a explicit least squares solution.
Normally, the constraints are applied to the states, input or output signals, along all the time $k$

$$\begin{aligned} u_{min} &\leq u(k) \leq u_{max} \\ y_{min} &\leq y(k) \leq y_{max} \\ x_{min} &\leq x(k) \leq x_{max} \\ \Delta u_{min} &\leq \Delta u_(k) \leq \Delta u_{max} \end{aligned} \tag{A-12}$$

The constraints must be met. This is made by forcing to the control inputs to be modified to guarantee the constraints conditions. There also exist the equality constraints, normally used to keep the control signal constant beyond certain time. For instance:

$$\begin{aligned} \Delta u(k+t|t) &= 0 \\ t &\geq N_c \end{aligned} \tag{A-13}$$

Regarding about the time duration of the problem, in order to obtain a problem with an amount of data or size tractable, it is used a control horizon. In other words, the full problem is not solved in a single step, as shown in the receding horizon strategy. When the input signal is calculated, it is assumed to be constant beyond a certain moment in the future. This horizon is called “control horizon” denoted by $N_c$ and the formulation is:

$$u(k+t|t) = u(k+N_c-1|k)\,\text{for}\,t \geq N_c \tag{A-14}$$

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