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Departamento de Engenharia Electrotécnica

Algorithms and Methodologies for Decision Support in Energy Efficiency on Buildings

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Orientador: *Professor Doutor Rui Neves da Silva*

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Abstract

Faculdade de Ciências e Tecnologia
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Mestre em Engenharia Electrotécnica e de Computadores

by João Tiago Vieira de Sousa Virote

Buildings worldwide account for approximately 40 percent of the global energy consumption and the resulting carbon footprint significantly exceeds those of all transportation combined. However, large and attractive opportunities to reduce energy use in buildings exist today. To reach ambitious energy efficiency goals, the building sector must undergo through technological innovation, informed customer choices, and smart business decisions.

Existing building simulation tools provide users with key building performance indicators, such as energy use and demand. However, these tools do not deal with activities performed by building occupants and with the resulting utilization of spaces. At best, they rely on assumptions referring to human behavior. As a result, energy prediction often does not represent the real building utilization. Therefore, it is assumed that user behavior is one of the most important input parameter influencing the results of building performance simulations.

A methodology for constructing an energy consumption model that reflects the human behavior dynamics and occupancy patterns within a building is presented. This research will provide a possible methodology for the pillars of future work in modeling the building usage under real patterns of utilization. A simulator has been developed from a model where both human behavior and building have been incorporated. Simulations have been performed to test different behavioral situations where the developed models and algorithms have been applied for prediction purposes. The proposed methodologies focus on the applicability of a rule-based expert system to support the simulator and stochastic modeling. The building's occupant behavior is modeled with a hidden Markov model and the building's spaces are described as Markov chains.

Universidade Nova de Lisboa

Sumário

Faculdade de Ciências e Tecnologia
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Mestre em Engenharia Electrotécnica e de Computadores

por João Tiago Vieira de Sousa Virote

Os edifícios em todo o mundo são responsáveis por, aproximadamente, 40 por cento do consumo energético global e emissões de gases de efeito de estufa, resultando numa contribuição significativamente superior à de todo o sector de transportes. Com o intuito de reduzir estas contribuições, os edifícios existentes têm de ser submetidos a uma inovação tecnológica e os projetos de investimentos em eficiência energética têm de ser assegurados.

As ferramentas existentes de simulação da performance de edifícios podem fornecer indicadores de desempenho, tais como o uso e procura de energia. No entanto, estas ferramentas não analisam o comportamento dos ocupantes do edifício e a sua utilização dos espaços. Frequentemente estas baseiam-se em pressupostos referentes ao comportamento dos ocupantes, que podem muitas vezes diferir da realidade e como resultado, a previsão do consumo energético não representa a real utilização do edifício. Assim, o comportamento do ocupante é um dos paramentos que mais influencia os resultados dos simuladores.

São apresentadas metodologias para a construção de um modelo de consumo energético que reflita o comportamento dos ocupantes, dinâmica e ocupação de espaços do edifício. Nesta dissertação foi desenvolvido um simulador a partir de um modelo onde o comportamento do ocupante e do edifício foram incorporados. Foram realizadas diferentes simulações representativas de diferentes cenários comportamentais e ocupacionais, onde os modelos e algoritmos desenvolvidos foram aplicados para fins de previsão e análise de potenciais oportunidades de investimento. As metodologias propostas incidem na aplicação de um sistema inteligente baseado em regras para suportar o simulador, assim como em modelação

estocástica. Mais especificamente, o comportamento dos ocupantes é modelado com modelos de Markov, e os espaços do edifício são descritos como cadeias de Markov.

List of Acronyms

BEC	–	Building Energy Consumption
BS	–	Building Sector
ECM	–	Energy Consumption Model
EIA	–	Energy Information Administration
GHG	–	Greenhouse Gas
HMM	–	Hidden Markov Model
ICT	–	Information and Communication Technology
IEA	–	International Energy Agency
LCA	–	Life Cycle Analysis
LCC	–	Life Cycle Cost
MC	–	Markov Chain
WBCSD	–	World Business Council for Sustainable Development

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1

Introduction

This chapter presents a macroscopic overview of the problem under analysis and introduces the themes that concern this dissertation. The document layout appears at the end followed by a brief resume of each one of the document chapters.

1.1 Introduction

The building sector plays an important role as it accounts for a significant percentage of the global energy consumption and greenhouse gas emissions. In order to reduce the global energy consumption and environmental impacts, the building sector is fundamental. Energy use in buildings is closely connected to their operational and space utilization characteristics as a result of the behavior of their occupants. These occupants' behaviors are often based on assumptions rather than based on measured observations and resulting predicting models. Therefore, current simulation tools must be provided with models that reliably predict the energy consumption of a specific building. This becomes an important factor when using these tools for supporting retrofitting projects in energy efficiency on buildings.

In the current research project, a modeling methodology is proposed for capturing occupancy patterns and to predict the building's energy consumption. Additionally, a prototype was developed for supporting such models and methodologies.

This first chapter provides an introductory discussion of the research performed in this dissertation.

1.2 Motivation

Energy currently represents a major challenge, first because of the impact of greenhouse gas emissions (GHG) on global warming and second because of the threat the fossil fuels future shortage poses on energy-dependent economies.

Every day, the construction sector builds or renovates thousands of places where people work, live, spend their leisure time or rest. People in general spend about 90% or more of their time indoors (EPA's Green Building Workgroup, 2009). Today, the building sector (BS) is fully aware its huge responsibility being the highest energy consumer and main contributor of GHG emissions. The building sector (residential, commercial, offices), representing about 40-45% of today's total energy consumption, offers the largest single significant potential for cost effective energy savings (WBCSD, 2009)[1].

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[1] © 1997-2010 World Business Council for Sustainable Development (WBCSD).

[2] 2010 ICT project: Energy consumption prediction with building usage measurements for software-

Energy is needed to provide essential services in any society, services that can be expressed as: light, comfort, power and mobility. It is this demand for services that drives the increasing supply in the energy system. The services can however be provided by technologies that uses less or more energy and different types of energy for the same output of services.

Furthermore, accurate simulation tools to evaluate the expected impact of new systems and solutions in the energy use in buildings are still a bottleneck. At present the energy use in buildings with equal building and systems characteristics can differ by a factor of four, primarily due to user behavior. Different conditions lead to different solutions for buildings. However, some basic principles for better energy efficiency can be adapted and disseminated to end users and policy makers alike (Ad-hoc Industrial Advisory Group, 2010).

In a context of meeting ambitious targets for improving energy independence and for fighting against climate change, the long-term goals are surely towards *low energy*, *passive* and *energy positive buildings*, which require new knowledge and technologies to overcome current limitations. Nevertheless, a number of research challenges needs to be addressed for a sustainable strategy for energy efficient buildings. Consequently, today's research is crucial. This dissertation was motivated by the research objectives of the EnPROVE[2] project (EnPROVE, 2010), which focus the energy consumption within building sector. The ultimate goal is to provide a decision making tool in order to sustain retrofitting projects in existing buildings for a reduction in the building's energy consumption (BEC). This achievement would be obtained through better energy efficiency, savings, storage or generation. The application is based on the installation of energy efficient technologies, taking into account the occupant's behavior within the building, which reflects as the building's use.

1.3 Research Statement

The outcome of buildings retrofitting projects usually is unpredictable due to the uncertainty surrounding the occupant's behavior. Therefore, it is crucial to take into account the interaction between the occupants and the building. As a result, it is important to capture the building's usage patterns in to order to construct an energy consumption model that reliably predicts its energy consumption and analyze potential energy saving areas. This dissertation

[2] 2010 ICT project: Energy consumption prediction with building usage measurements for software-based decision support. http://www.enprove.eu

explores the applicability of stochastic models to represent the space occupancy and the occupant's behavior. Moreover, it explores the representation of the interaction between the building and occupants through rules. How can stochastic models be used to model the space occupancy patterns and occupant's behavior in order to predict the building's energy consumption and its waste?

1.4 Scope and Proposed Approach

The purpose of this project is to develop a methodology to construct an energy consumption model that reflects the human behavior dynamics and occupancy patterns within a building. This research will provide a possible methodology for the foundations of future work and methodologies. The current approach will focus on the space occupancy patterns and usage of the lighting system. ***FIGURE 1-1*** illustrates the macroscopic approach to the developed methodology.

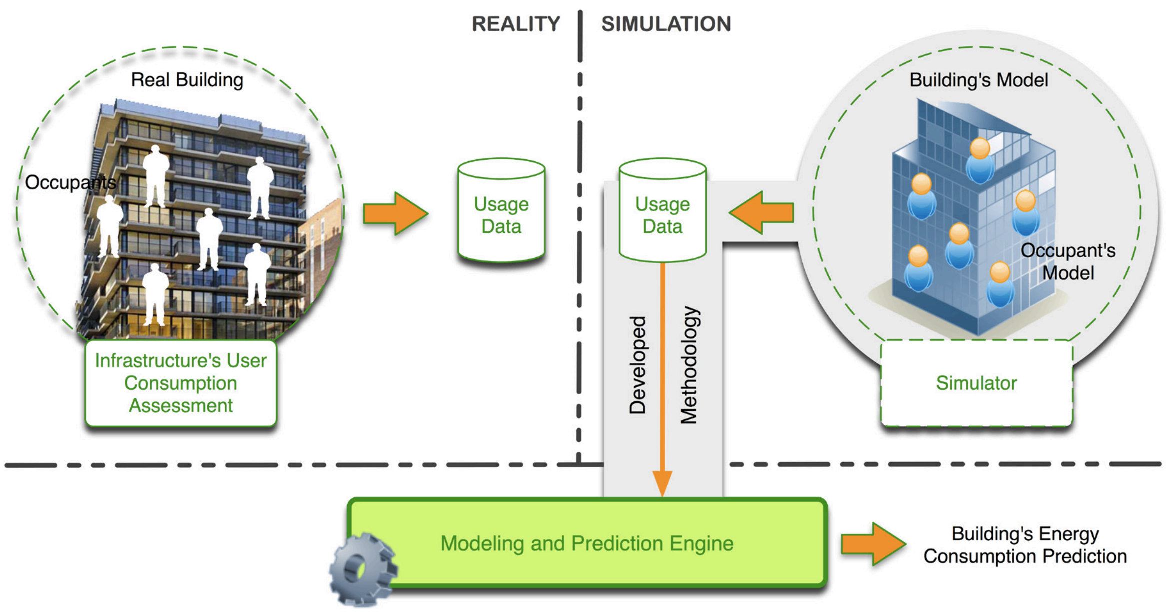

FIGURE 1-1: Macroscopic representation of the developed methodology

The work is divided into four parts. First, a simulator has been developed from a model where both human behavior and building have been incorporated. Second, simulations have been performed to test different behavioral situations. Third, the developed models and algorithms have been applied for prediction purposes, and fourth, the results of different simulations have been presented and discussed.

The developed prototype is programed in Java platform. The consistency of the simulator output cannot be verified but serves as support for the discussions and conclusions about the applicability of the proposed methodologies. The results of the simulations were not compared to measured real-life data or results from other simulators. Instead, comparisons are made between results from different starting values within the simulator. Although, the focus is on modeling and prediction methodologies for buildings energy consumption, the simulator was a collateral work for producing data and validating the models.

The proposed methodologies will focus on the applicability of a rule-based expert system to support the simulator and algorithms. Moreover, the building's occupant behavior will be modeled with a hidden Markov model and the building will be described through a composition of Markov chains.

1.5 Original Contributions

A large number of studies, which are addressed in chapter 3, have been conducted in recent decades to understand how building occupants interact with building environmental systems and how to simulate the building performance and environment. The core tools in the building energy field are the whole-building energy simulation programs that provide users with key building performance indicators, such as energy use, demand and costs. In addition, most current building simulation programs do not deal with activities performed by building occupants and with the resulting utilization of space. At best, these tools rely on assumptions referring to occupant behavior. This research provides a methodology for modeling the building spaces under different occupancy patterns. These models intend to represent the building with the purpose of predicting scenarios for potential energy savings. Furthermore, the developed models can be extended in order to account for specific energy saving areas. Finally, a special feature of this research is the development of a software prototype that supports the proposed models and methods. Additionally, an innovative characteristic of the developed prototype is that it integrates a state of the art computer science framework based on a rule-based expert system.

1.6 Outline

This dissertation is structured as follows:

- *Chapter 1* – The motivation for this dissertation is introduced. Moreover, the thesis is formulated along with original contributions.

- *Chapter 2* – A brief introduction on energy usage in the World and the problem within the building sector is addressed. Additionally, this chapter identifies the building sector as a potential sector to achieve a substantial decrease in energy demand.

- *Chapter 3* – The focus of this chapter is to perform a background analysis on the related work in this area of building simulation. Finally, the proposed methodology is addressed.

- *Chapter 4* – Stochastic modeling is introduced along with some models.

- *Chapter 5* – In this chapter the proposed methodology is presented and the system architecture is described.

- *Chapter 6* – This chapter presents the simulation results and its analysis.

- *Chapter 7* – In this last chapter, the dissertation conclusions are made along with some prospects about future work.

2

World Energy Scenario and Energy in Building Sector

This chapter presents and examines the world energy scenario and current patterns of energy consumption. Moreover, the building sector is highlighted as an important sector to achieve a potential decrease in energy demand. Furthermore, energy efficiency along with associated problems is addressed. The information presented forms the background for the energy scenario.

2.1 Introduction

Sustainability, or "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (United Nations, 1987), is not a new concept. The idea of sustainability is based on the fundamental fact that earth is a closed system with finite resources, which cannot support continuously high rates of human growth and consumption (Borowske, 2007), as illustrated in ***FIGURE 2-1***.

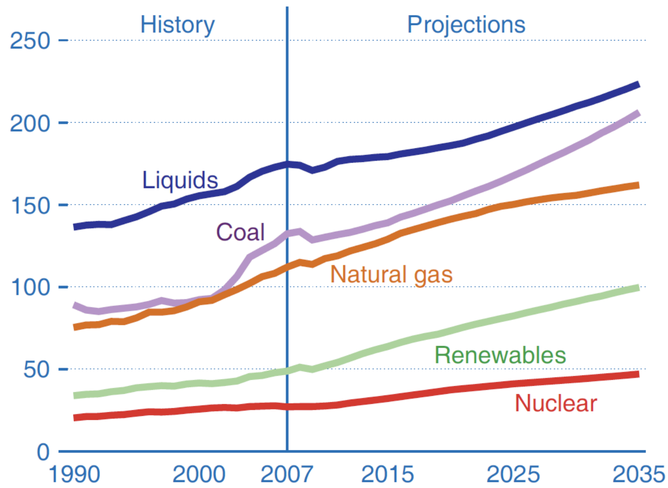

FIGURE 2-1: World marketed energy use by fuel type, 1990-2035 (quadrillion Btu[3]*)* **(EIA, 2010)**

Analyzing the intersection between energy and issues of climate change requires the adoption of a long-term perspective. Energy infrastructure takes time to build and has a useful life that measured in decades. New energy technologies take time to develop and even longer to reach their maximum market share. Increasing concentration of GHG as a result of human activities affects ecosystems and global climate over a long period (IEA, 2003).

According to the International Energy Agency (EIA): "*Scenarios are a tool for helping us to take a long view in a world of great uncertainty (…) Scenario planning is about making choices today with an understanding of how they might turn out*". The most common scenario is the reference scenario of the forecasting type, which assumes the continuation of historical trends into the future. Although this represents strong assumptions, these scenarios represent the basis for energy predictions. This type of scenario is often referred as a *business-as-usual scenario* or *reference scenario*. A usual tool in long-term scenario analysis is the application

[3] 1 quadrillion Btu = 1 Quad = 10^{15} Btu = 1.055 EJ

of mathematical and statistical models. An interesting taxonomy for energy scenarios can be found (IEA, 2003).

2.2 World Energy Scenario: Brief Overview

Globally, the production and use of energy accounts for 50–60% of emissions of GHG to the atmosphere, as a result, energy and environment are closely inter-related. The key challenge facing society at large is depicted in ***FIGURE 2-2***, where the average energy consumption per capita is illustrated for selected nations of the world.

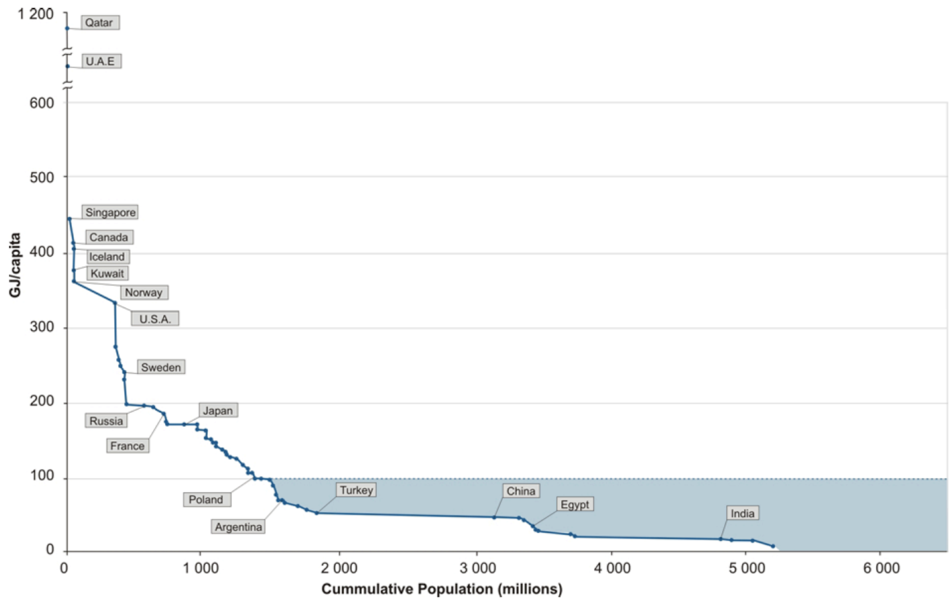

FIGURE 2-2: Annual energy per capita as a function of World's cumulative population **(WEC, 2007)**

In ***FIGURE 2-2*** the shaded area corresponds to 500 EJ/year[4], and shows everyone below Poland today achieving this same per capita energy use, it should be noted that, approximately, one thousand million people have no record of energy use to date.

One of the biggest challenges for the future will be to reduce poverty and raise living standards around the world. An important factor in achieving this goal will be to continue meeting the world's energy needs safely, reliably and affordably, even as population and economic growth pushes global demand higher by almost 35% compared to 2005, as depicted in ***FIGURE 2-3***. *Where will this energy come from*? *How will it be used*? *What will it cost*? *What are the ancillary impacts*?

[4] 1 EJ = 10^{18} J = 10^9 GJ = 24 Mtoe (Million tones of oil equivalent) = 0.948 MBtu

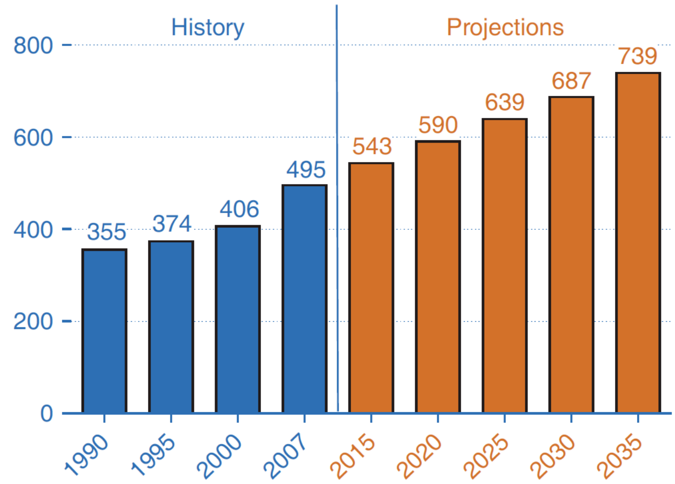

FIGURE 2-3: World market energy consumption, 1990-2035 (quadrillion Btu) **(EIA, 2010)**

Besides the predicted evolution of the energy demand, ***FIGURE 2-4*** shows an increase in expected energy prices. Basically, the problem is that, not only the world's energy consumption expected to duplicate, but also its cost will increase in the long-term.

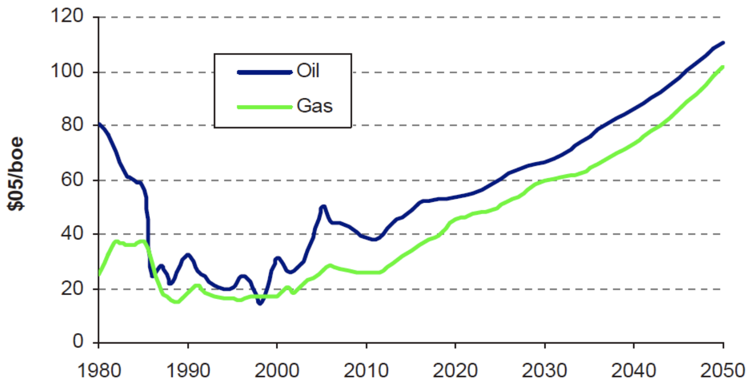

FIGURE 2-4: Prices of oil and gas from the reference scenario **(WETO, 2006)**

After outlining the world energy scenario, a few aspects can be questioned. *How is the world's energy consumption distributed*? *What sector consumes the most*? The answer to these questions is illustrated in ***FIGURE 2-5*** where is possible to verify that the building sector consumes approximately 40% of the world's energy.

As result of this scenario, there are two approaches: either an increase in the energy supply; or through a decrease in the demand. The first approach is not completely viable, because it would exacerbate the environmental issue and increase the dependence on risk-prone fossil fuel energy sources and carbon dioxide (CO_2) emissions. However, it is also important to account with the renewable energy sources for supporting this energy demand, however, accordingly to EIA, the role of renewable energy accounts for, approximately, 7% of the total energy generation. The second approach is to aim for widespread energy efficiency: enhanced environmental protection, reduced costs for energy services and other financial benefits (EIA, 2010). This issue is further addressed in the following sub-section.

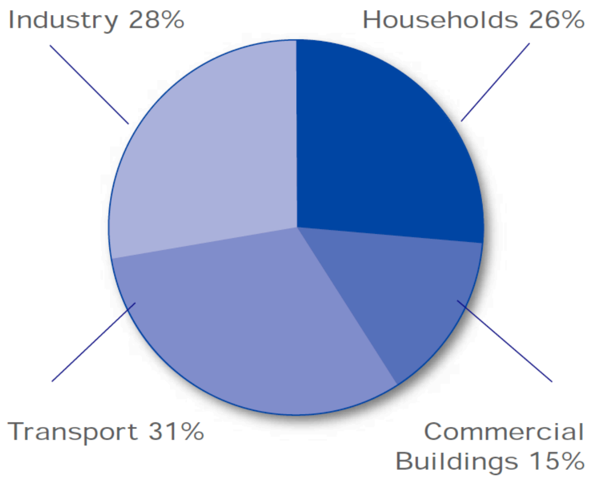

FIGURE 2-5: World's energy by sector in Mtoe **(GreenBuildung plus-Project, 2010)**

2.3 Energy Efficiency: Business or Energy Resource?

Today the concept of energy efficiency has evolved extensively and addresses several more aspects such as, economy, sustainability of resources, environmental impact, security and the reliability of energy systems. From an energy point of view, energy efficiency can be considered an energy resource. By decreasing energy demand, the existing energy supply will support further needs. Energy efficiency is a term widely used, often with different meanings in public policy making. A clear distinction between energy efficiency and energy conservation is that the first refers to adoption of a specific technology that reduces the overall energy consumption without changing the relevant behavior, while the second implies merely a change in consumer's behavior (Oikonomu et al, 2009).

Consumer behavior and lifestyle choices are strongly related to the concept of the rational use of energy, the end-use energy saving and the end-use energy efficiency. Energy savings and energy efficiency refer to two microeconomic situations, which deserve to be differentiated. Energy efficiency concerns the technical ratio between the quantity of primary or final energy consumed and the maximum quantity of energy services obtainable (heating, lighting, cooling, mobility, and others). End-use energy saving addresses the reduction of final energy consumption, through improved energy efficiency or behavioral change (Hertwich, 2005). Regarding to the economic perspective, investments in energy efficiency deliver a significant advantage to society. These investments result in direct, tangible, cost savings, in addition to the long-term benefits of a better environment, delivered via the energy savings and carbon dioxide emission savings. This benefits the investors, home or business owner, via lowered energy bills, and the society at large via lower energy import costs.

Could energy efficiency have a more central role in the economical life than just being a redeemer for wasteful use? The need for energy conservation and management systems is substantial. The cost of building new power generation and distribution systems are enormous and riddled with environmental problems. Add to those obstacles the continued problem of oil and gas supply, and the need for doing more with less becomes transparently clear.

Summarizing, energy efficiency provides solutions as it is cheaper to avoid the use of a kWh of energy than to build new plants or reinforce infrastructure to provide that same kWh. Consequently, energy efficiency means more useful kWhs and less need for increased generating capacity. This means moving towards optimum energy supply at minimum cost. Even though energy efficiency may reduce the energy demand, it is also important to account for the human factor and its impact in the energy consumption. *How does human behavior affect energy efficiency*? This effect is referred to as Jevons Paradox and is introduced in the next sub-section.

2.3.1 Introduction to Jevons Paradox and Energy Efficiency

Many energy efficiency investments do not reduce energy consumption by the amount predicted by simple engineering models. *Does an increase in energy efficiency always lead to a reduction in energy consumption*? Such improvements make energy services cheaper, so consumption of these services increases. For example, since energy-efficient lamps consume less energy, consumers may choose to leave the lights on for more time, even in periods of absence, thereby off-setting some of the energy savings achieved, if any. This is termed the *directed rebound effect*. Even if consumption of energy services remains unchanged, there are reasons why energy savings across the economy may be less than simple calculations suggest. Similarly, any reductions in energy demand will translate into lower energy prices, which encourage increased energy consumption. These mechanisms are collectively known as *indirect rebound effects*. The sum of direct and indirect rebound effects represents the economy-wide *rebound effect*. These are normally expressed as a percentage of the expected energy savings from an energy efficient improvement, so a rebound effect of 20% means that only 80% of the expected energy savings are achieved (UKERC, 2007). Generally, the losses in expected energy savings are associated with gains in equipment service, such as hours of utilization, and increase in comfort.

Regarding to the magnitude of the effects, these can be described as a *weak rebound effect* (efficiency measures are not as effective as expected), a *strong rebound effect* (most of the expected savings do not materialize), and a *backfire effect* (the efficiency measures lead to increase energy demand) (Hertwich, 2005). In (Alcott, 2005) relevant literature is addressed along with Jevons' theoretical arguments.

Direct rebound effects for household's energy services in OECD[5] countries are likely to be less than 30%. However, they could be larger for producers and potentially larger in developing countries. Measured direct rebound effects due to building retrofits are presented in ***TABLE 2-1***. The evidence for indirect rebound effects is poor, but nevertheless it is suggested that they may be significant.

TABLE 2-1: Measured direct rebound effects after building retrofits **(Murray, 2009)**

Building	Initial energy consumption (Kwh/m^{2}yr)	Calculated energy consumption after retrofitting (Kwh/m^{2}yr)	Actual energy consumption after retrofitting (Kwh/m^{2}yr)	Calculated savings (%)	Actual savings (%)	Rebound share (%)
1	203	144	168	29	17	41
2	218	161	176	26	19	27
3	185	132	147	29	20	29
4	218	167	198	24	9	61
5	193	127	150	34	23	34
6	169	108	122	36	28	22
7	168	116	115	31	31	0
8	148	91	97	39	35	11
9	239	140	172	41	28	32
10	179	134	144	25	20	23
11	159	117	141	26	11	57
Average	**189**	**129**	**148**	**32**	**22**	**30**

[5] Organization for Economic Co-operation and Development is an international economic organization of 33 countries.

Finally, energy efficiency is tied to energy use and demand, and as a result, it must somehow be separated from other factors that affect demand, especially structural, weather, and behavioral factors.

The following section, introduces the building sector as the biggest contributor for the world's energy consumption and climate changes. Furthermore, the concepts of sustainability, energy efficiency and behavior will be considered together. Finally, the building sector is identified as one potential sector for decreasing energy consumption in order to achieve sustainability goals.

2.4 Buildings Sector: A Hidden Culprit

With so much attention given to transportation emissions, other sectors are neglected. The ***FIGURE 2-6*** is only an illustration of the energy consumption in building sector by the lighting systems. This sector is the single largest contributor to energy consumption and global warming. In order to clarify this misconception, this section points out some aspects of the building sector. While cars have had to meet increasingly strict fuel efficiency standards, buildings for the most part have been spared. Surprisingly little attention has been paid to ensuring energy efficiency in buildings despite the tremendous impact buildings have on costs and on the environment. However, that oversight is beginning to be addressed. A combination of higher energy prices, skyrocketing demand for electricity and deepening environmental concerns has pushed to a tipping point the concept of energy efficiency in buildings.

FIGURE 2-6: Illustration of the energy consumption by the lighting systems in the building sector

Energy efficiency in buildings is important from both an economic and environmental point of view. The technology exists for substantial energy savings in the building sector but the potential for such savings has still to be fully exploited. To achieve efficiency and sustainability goals building designers require effective design tools for analyzing and understanding the complex behavior of the building's energy use. The following diagram, ***FIGURE 2-7***, depicts the three fundamentals pillars for energy efficient buildings – economy, environment and social.

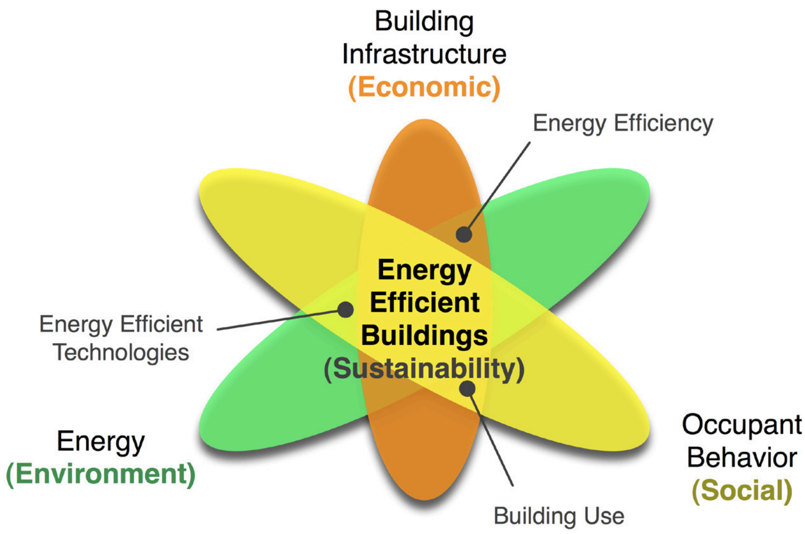

FIGURE 2-7: Three fundamentals pillars for energy efficient buildings and sustainability

The following sub-sections will address the various aspects of buildings, such as, the building life cycle cost (LCC), building energy consumption by sector and human effect on building site energy. Moreover, energy efficiency and measures to achieve it are also addressed.

2.4.1 Energy Consumption and Economic Perspective

With high-energy prices likely for the foreseeable future, the world may have little choice but to make a concerted effort to use energy in buildings more efficiently.

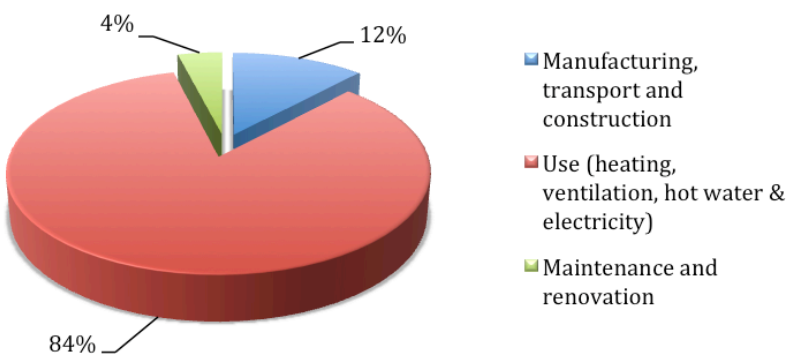

FIGURE 2-8: Building's life cycle energy use, adapted from **(al, 2009)**

A study by WBCSD of the whole life cycle of buildings shows that the most important part of the total energy consumption occurs during the operation phase of a building. ***FIGURE 2-8*** indicates that more than 80% of the energy consumption can be spent on the operational phase (WBCSD, 2007). Nevertheless, other phases like construction, production, renovation or demolition should not be ignored as they can also provide some opportunities for energy savings. As illustrated in ***FIGURE 2-9*** and ***FIGURE 2-10*** the energy consumption is different in commercial and residential buildings, but still is mainly focused on heating, cooling and air conditioning systems, as well as the lighting systems.

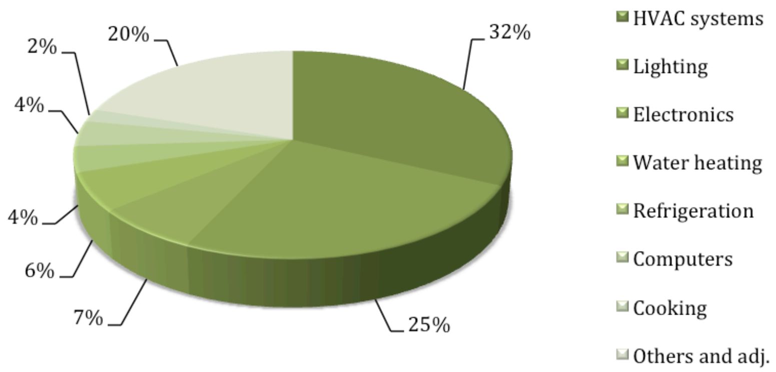

FIGURE 2-9: Energy use in commercial buildings, adapted from **(Ad-hoc Industrial Advisory Group, 2010)**

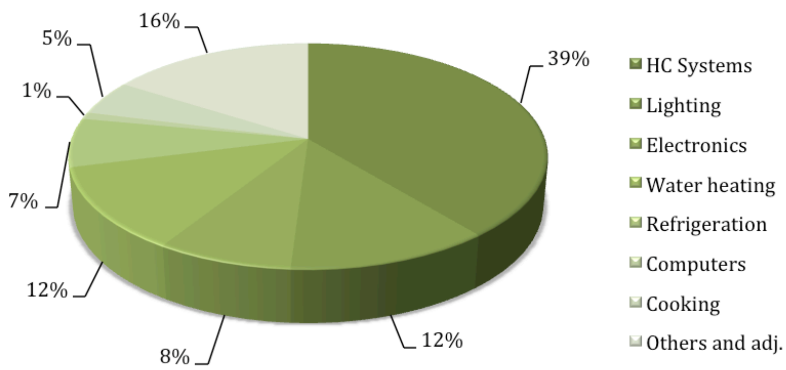

FIGURE 2-10: Energy use in residential buildings, adapted from **(Ad-hoc Industrial Advisory Group, 2010)**

Options for improving energy efficiency depend significantly on the kind of structure in question. For new buildings, design is a key driver of energy performance, with developers the key decision-makers affecting a building's design and efficiency. For existing buildings, how a property is operated and how its occupants use the space are the key determining factors for energy consumption. Notwithstanding their different perspectives, developers who mandate energy-efficient designs, building operators who employ effective management practices and educated, energy-conscious tenants can significantly reduce energy consumption of buildings by working together toward a common objective.

As illustrated in ***FIGURE 2-11***, for new buildings, cases have shown that energy savings of 20 to 70% are possible through energy-conscious design. For existing buildings, operators are using energy management as a service differentiator and routinely reducing energy consumption by 10 to 30%; commercial business occupants are using energy management in buildings they lease to improve their cost structure and are able to achieve 5 to 25% savings in energy consumption; and owners through building upgrading and renovation have shown 15 to 35% energy savings is possible. In sum, the efforts by all stakeholders are capable of 25 to 50% of energy savings for existing buildings. Economics are powerful, promising quick paybacks on investments for building developers and their tenants. The economic case is equally strong for governments, which are building power plants in an attempt to keep up with surging demand from new buildings and their often-inefficient air-conditioning, windows and lighting (Hong et al., 2007).

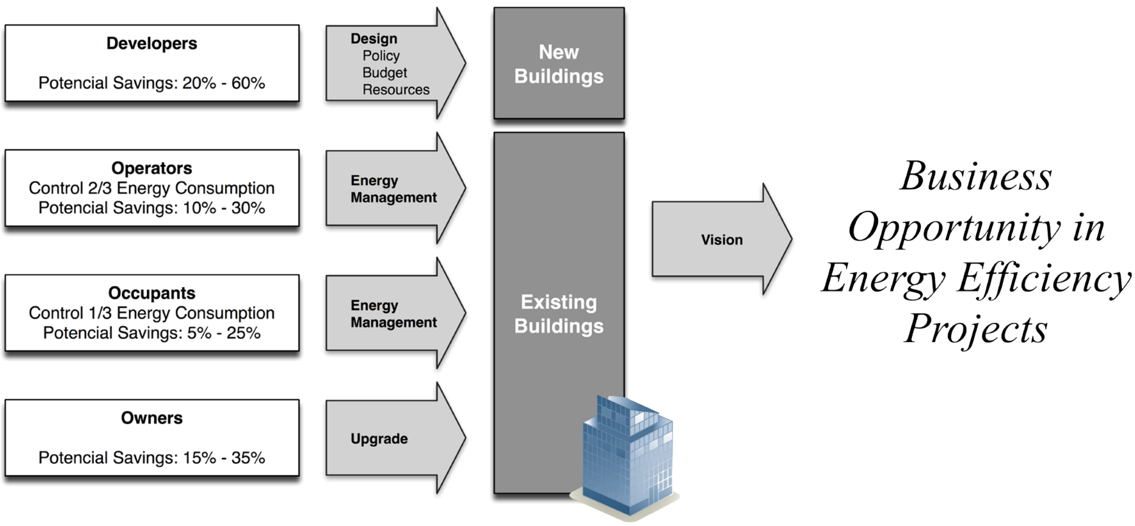

FIGURE 2-11: Key influences on building energy consumption, adapted from **(Hong et al., 2007)**

Finally, besides the economic approach and how society can benefit from reduced energy consumption, it has also to be taken into account the environmental perspective, as explored in the next sub-section.

2.4.2 Environment Perspective

With an increase in the energy demand for industry, transportation and the building sector, depicted in ***FIGURE 2-12***, it is crucial to evaluate how this demand does, and will probably continue to, influence the natural resources and the environment of the planet as illustrated in ***FIGURE 2-13***.

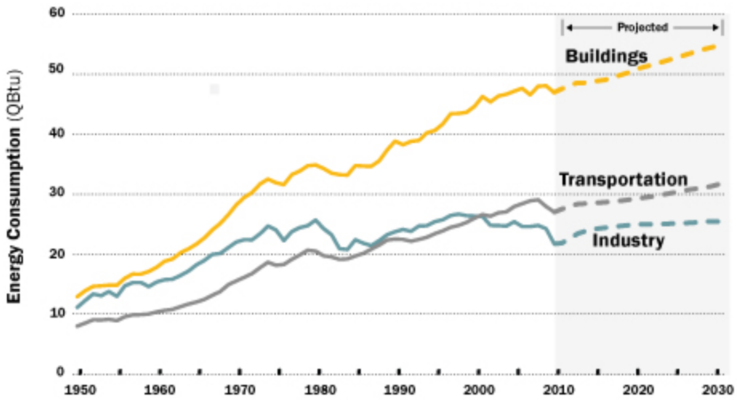

FIGURE 2-12: Energy consumption by sector, EIA data source **(Architecture 2030, 2010)**

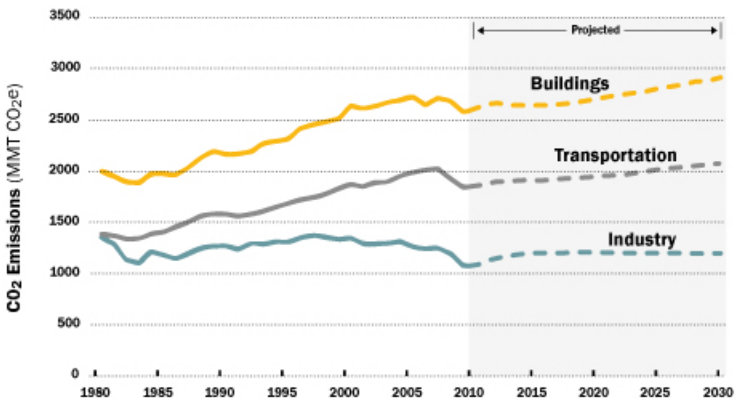

FIGURE 2-13: CO_2 emissions by sector, EIA data source **(Architecture 2030, 2010)**

Accordingly to the above graphics, the building sector consumes more energy than any other sector. Due to the fact that this energy is produced from burning fossil fuels, this sector is the largest responsible for GHG emissions. A contentious and valuable study about the environment can be found in (Hansen et al, 2008).

The challenges the building sector faces are too complex to be solved by a single action. Looking only at the integration of renewable energy in the build environment will not in itself be sufficient to decrease energy dependence. In a similar way, retrofitting buildings one by one will never solve climate change problems. These are some of the reasons why there is the need to adopt a holistic approach, considering technological aspects and technology integration as well as the user as the key for successful impact. In ***FIGURE 2-14*** a longer-term strategy to achieve sustainability in the building sector is shown.

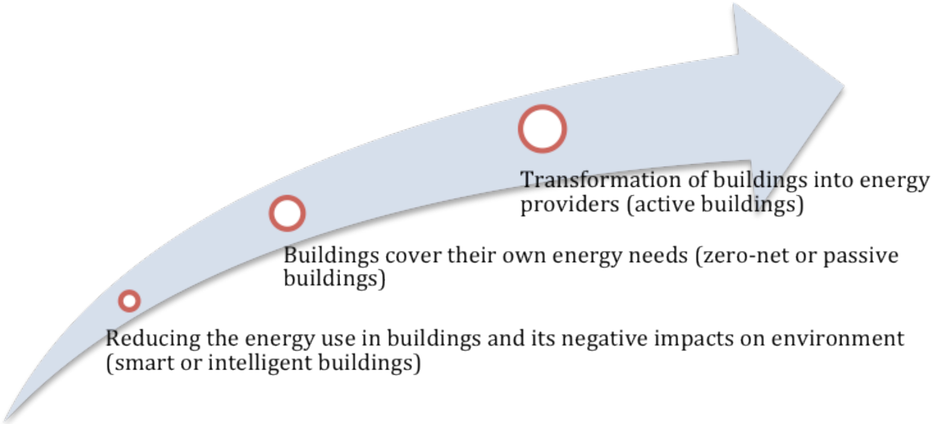

FIGURE 2-14: Energy efficiency longer-term strategy to reduce the energy use of buildings and its impacts on environment, adapted from **(Ad-hoc Industrial Advisory Group, 2010)**

Accordingly to the ***FIGURE 2-14***, the short-term goal is to reduce building's energy demand through technological innovation. Moreover, this technological innovation when considering renewable technologies, such as micro energy generation through solar, wind or thermal resources can, in middle term perspective, achieve buildings with zero net energy consumption. As an ultimate goal, and from a long-term perspective, buildings could not only provide for their own energy use, but they also could behave as distributed energy providers, contributing to a smart energy grid (European Commission, 2007) (Microsoft, 2009).

2.4.3 Building 's Use and Occupant Behavior

Over the past years, the evolution of modern energy and technology has enabled people in developed countries to achieve a lifestyle in which access to energy, at home, at work and on the road, is largely taken for granted. In many of these places, the challenge today is to continue meeting these existing needs. Gaining access to energy represents hope and opportunity. It means improved transportation, increased commerce, expanded industry and greater access to health care and other social services.

Generalizations about human and economic systems often fail because these systems are adaptable in ways that physical systems are not. Policy choices affect how the future unfolds, and parameters that embody historical behavior are bound to lead us astray whenever a forecast relies on those parameters to project far into the future. Assuming that human behavior is immutable will inevitably lead to errors in forecasting the future, no matter which kind of modeling is performed. A comprehensive study towards rational use of energy is performed in (Fandel & Zuleeg, 2008). Relationships between cause and effect for individuals and human institutions are dependent on the institutional, social, and economic context. Furthermore, these relationships change over time. Energy has important symbolic and behavioral aspects that can have as much impact on consumption as energy efficient equipment. For instance, lifestyle or habits may actually increase energy consumption. User behavior is influenced by economic, social and psychological factors that influence both buying of new equipment and the use of energy. In addition, the rebound effect limits potential energy savings, as introduced above.

Accordingly to WBCSD wasteful behavior can add 33% to a building's designed energy consumption while conservation behavior can save the same amount, ***FIGURE 2-15***. Wasteful behavior uses twice the energy as the minimum that can be achieved. There as two separate aspects of energy behavior: acquiring efficient equipment and using energy efficiently (Oikonomu et al, 2009). The transition to using efficiently is difficult because it involves the unpredictable human behavior along with a widespread change in habits, for example, turning off appliances when not in use.

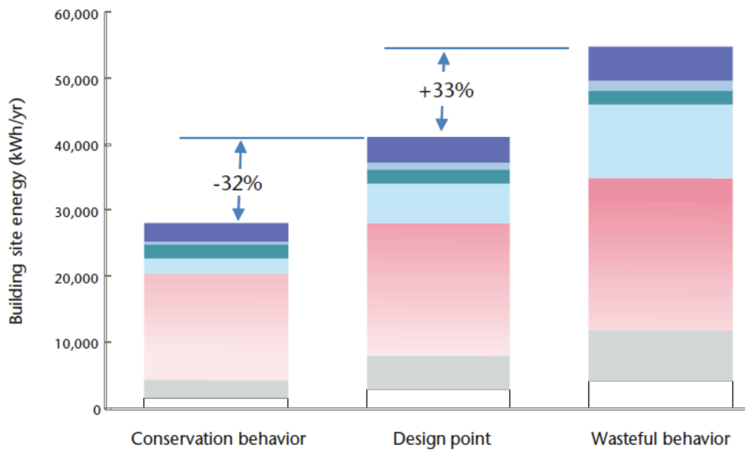

FIGURE 2-15: The impact of user behavior on residential site energy consumption **(WBCSD, 2009)**

The balance between technical solutions for energy efficiency and human actions for energy efficiency needs to be weighted system by system. This energy efficient behavior can become almost automatic when trends in lifestyle, energy efficient technologies and behaviors coincide. This emphasizes the importance of lifestyles and behavior in energy consumption. Misunderstandings and wrong conceptions about indoor comfort and energy use are common. Most office users are not even aware of the fact they can affect the energy use. The behavior of building occupants need to be taken into account, as it is responsible for almost half the outcome of planned energy reduction.

Summarizing, building occupants are a valuable source of information on building performance and for achieving efficiency goals it must be taken into account when investing in retrofitting projects. The following section will introduce the concepts of energy efficient technologies as a tool to account for human behavior in order to achieve energy efficiency.

2.4.4 Energy Efficient Technologies

Accordingly to Midden the interaction between human beings and technology regardless of the conservation of natural resources, can be divide into four technology roles: (1) as intermediary; (2) as amplifier; (3) as determinant, and (4) as promoter of environmentally significant behavior (Midden et al, 2007). Furthermore, (Midden et al, 2008) promotes energy efficient technologies to achieve sustainable consumer behavior.

"*It is common for technology to be introduced to reduce cost, while it's greatest value turns out to be the added value capabilities that it brings*" (BPA, 2006).

Intelligent building technologies (IBT) or *energy efficient technologies (EET)* seek to improve the building's environment and functionality for occupants/tenants while controlling costs. The ability to measure the use of specific building resources enables individual users to be billed for the resources they consume. The owner/operator wants to provide this functionality while reducing individual costs. Such reduction is possible. An effective energy management system, for example, provides lowest cost energy, avoids waste of energy by managing occupied space, and makes efficient use of staff through centralized control and integrating information from different systems.

While some energy efficient technologies may have the potential to reduce the energy intensity of economic activity, they also must be considered within the context of any potential reduction of the rebound effect. Technology can help to raise awareness of energy waste and reduce the level of waste (Ockwell, 2008). Decision-makers are often unaware of their energy consumption, and technology can provide useful information to trigger action so long as it is used appropriately and not as a substitute for substantial energy saving measures, ***FIGURE 2-16***. Energy efficient technologies exist and are cost-effective. The building sector in particular presents one of the biggest opportunities for cost-effective energy consumption reduction.

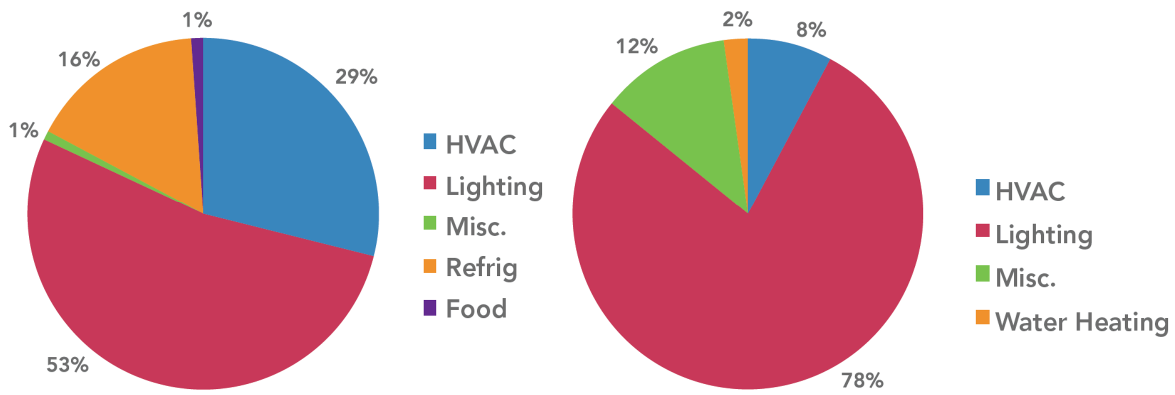

FIGURE 2-16: Electricity Savings by End-use (Market Potential). Left: Commercial sector; Right: Residential sector **(CalCEF Innovations, 2010)**

Despite this proven cost-effective opportunity to reduce energy consumption, a large portion of the potential for energy efficiency in the existing residential building sector remains untapped. Numerous barriers are responsible for this persistent energy efficiency gap. Market barriers include, for example, difficulty in accessing capital and the presence of information asymmetries. Financial barriers are also decisive in inhibiting progress towards more energy efficient buildings. Such barriers encapsulate a wide range of issues, including the initial cost barrier, risk exposure, discount factor issues, and the inadequacy of traditional financing mechanisms for energy efficiency projects. Although the initial cost of energy efficient technologies can be higher than their less efficient counterparts, the majority of these technologies make economic sense when analyzed on a lifecycle cost basis (IEA, 2008).

3

Building Simulation and Behavior Modeling

This chapter describes the previous work on building simulation and human behavior modeling. Furthermore, the approach adopted will be addressed and related to other previous work.

3.1 Introduction

A large number of studies have been conducted in the past decades to understand how building occupants interact with building environmental systems and how to simulate the building performance and environment. This is usually referred as *building simulation* or *building performance simulation* in the literature. Building simulation is, therefore, a "master" expression for a whole research area regarding the building's life cycle and all its aspects. The core tools in the building energy field are the whole-building energy simulation programs that provide users with key building performance indicators, such as energy use and demand, temperature, humidity, and costs. In addition, most current building simulation programs do not deal with activities performed by building occupants and with the resulting utilization of space and movement through spaces. At best, these tools rely on assumptions referring to human behavior (Robinson, 2006).

This section will provide an overview on previous work related to the concepts presented in chapter 2, such as building operation, human behavior, energy efficiency and decision support. Furthermore, a bridge to the proposed methodology is build. Due to the diversity of studies and the inherent complexity of this area it will be divided in three major subjects: building performance simulation, user behavior in whole building simulation and behavioral modeling.

3.2 Building Performance Simulation

A number of approaches have been proposed to simulate the energy consumption of a building. In (Crawley et al, 2005) a comparison of twenty major building energy simulation programs is performed. These programs are: BLAST, BSim, DeST, DOE-2, ECOTECT, Energy-10, Energy Express, Ener-Win, EnergyPlus, eQUEST, ESP-r, IDA ICE, IES<VE>, HAP, HEED, PowerDomus, SUNREL, Tas, TRACE and TRNSYS. From these, EnergyPlus is considered to be the state of the art with regard to building energy simulation software and is used widely by simulation experts and beginners alike. The reason for this is that EnergyPlus is based on the most popular features and capabilities of BLAST and DOE-2, and because it is just a calculation engine without any graphical user interface. An example is the

DesignBuilder[6], which is acknowledged as the most comprehensive interface to EnergyPlus. Therefore, connectivity and extensibility are some directives in the development process. This ensures broad participation in program enhancement and facilitates third party interfaces and module development (Crawley et al, 2001) (ENERGYPLUS™, 2010). In (Hoes et al, 2008) building performance simulation has become an accepted method of assessment during the building design process. Furthermore, due to an increasing complexity of building design and higher demand for performance requirements on sustainability, use of building simulations will become inevitable.

The results of Mahdavi suggest that user interactions are difficult to predict at the level of an individual person (Mahdavi et al, 2009). However, general control related behavioral trends and patterns for groups of building occupants could be extracted from long-term observational data. As this data is the outcome of actual long-term observations and high-resolution measurements in a building, they are more representative than most currently applied simulation assumptions. In this way, patterns obtained for one building cannot be transported to other different building, because the occupancy models would be different. Therefore, it is assumed that user behavior is one of the most important parameter influencing the results of building performance simulations. Unreliable assumptions regarding user behavior may have large implications for such assessments. Moreover, this effect will become crucial when the design under investigation contains improved passive and active energy efficiency measures.

3.3 Energy and User Behavior in Building Simulation

In this section some recent and interesting research regarding some abstract concepts presented in chapter 2 are summarized. Here, an overview of the life cycle energy analysis of buildings in (Ramesh et al, 2010), which studies the total energy use during the life cycle, are desirable to identify phases of largest energy use and to develop strategies for its reduction. The study performed in (Oikonomu et al, 2009) departs from microeconomic theory and attempt to unveil some parameters that should be taken into account by planners when designing policies for energy efficiency improvement. It takes into account the rebound effect. A methodology to perform parametric studies in order to design low energy buildings is addressed in (Chlela et al, 2010). This methodology consists of developing meta-models, which evaluates the energy demand and the final building energy consumption. The research

[6] Visit http://www.designbuilder.co.uk

in (Andrews & Krogmann, 2009) investigates factors explaining the adoption of energy efficient technologies. This study shows that numerous technologies have penetrated the commercial building sector, but only a few have become dominant. Moreover, energy efficient technologies were thought to be unlikely to diffuse very rapidly. The application of artificial neuronal networks (ANN) for predicting energy savings from retrofitting projects is conducted in (Yalcintas, 2008). The impact of occupant behavior on building energy use was measured through energy audits in (Masoso & Grobler, 2010). They concluded that more than 50% of the energy used was consumed during non-working hours. A recent work on modeling activities of office occupants for accurate building evaluation and simulation is addressed in (Tabak & Vries, 2010). Finally, another application of ANN regarding energy prediction in buildings is addressed in (Holcomb et al, 2009) and a comparison between detailed model simulation and ANN is performed in (Neto & Fiorelli, 2008).

As referred to in the previous section, in current building performance simulation tools user behavior generally is mimicked in a very rigid way. In recent years, some models have been developed to include the interaction of the user behavior in building simulation. Models for the simulation of occupant's interactions with windows have been addressed in the following works: the Humphreys algorithm for window opening was derived from analysis of extensive survey data and it was implemented in the ESP-r software (Rijal et al, 2007). More work related to windows usage can be found in (Herkel et al, 2008), (Haldi & Robinson, 2009). In (Borgeson & Brager, 2008) a methodology for predicting occupant window control is presented. Reinhart developed LIGHTSWITCH 2002 using a dynamic stochastic algorithm (Reinhart, 2004). Based on an occupancy model and a dynamic daylight simulation application, it predicted manual lighting and blind control actions providing the basis for the calculation of annual energy demand for electrical lighting. In another work (Page et al, 2007) (Page et al, 2008), hypothesized that the probability of occupancy at a given time step depends only on the states of occupancy at the previous step. In this way, he proposed the applicability of Markov chains towards occupancy prediction. As a continuation of the work by Reinhart and Nicol in (Nicol, 2001), Bourgeois attempted to bridge the gap between energy simulation and empirically based information on occupant behavior via a module called SHOCC (Sub-Hourly Occupancy Control), that was also integrated in ESP-r application (Bourgeois et al, 2006). Moreover, the SHOCC module is applied in (Hoes et al, 2008). However, this module requires several assumptions with respect to the occupation degree and the behavior of users. That is, when the number of occupants is relatively high and they operate with less strict time schemes for individual occupants the predictions are less reliable. For these, and more complex situations, another module can be used. This module is USSU (User Simulation of Space Utilization) in (Tabak, 2009).

3.4 Behavioral Modeling

The study of human behavior has been the focus of many fields of research. Behavior is an extensively investigated problem in business process modeling, cognitive modeling, distributed artificial intelligence, computational organizational theory and educational psychology (Guang-Zhong Yang, 2009). The main challenge is related to the modeling of complex human behavior using realistic yet adaptable models. One of the most popular models is that of a hidden Markov model (HMM), which is a stochastic model, assuming a system to be a Markov process with unknown parameters. This subject is addressed in chapter 4. The HMM is composed of hidden and observable states and aims to model a sequence or a time series by learning probable models of state transitions and observations. Due to their ability to model spatial-temporal information in a natural way, a significant amount of work in the area of behavior recognition is based on HMMs. For example, probabilistic user behavioral models are applied for modeling web users in (Pavlov et al, 2003). A survey in behavior modeling is properly performed in (Guang-Zhong Yang, 2009). Because little is known about user activities in buildings, several experiments observe motions of real users with cameras and other means of locating people (Tabak, 2009). In other experiments user activities regarding light control have been monitored, providing useful statistics to improve lighting control (Mahdavi et al, 2009). Although such experiments provide realistic user patterns, it is not easy to extract the reasons for activities and thus derive abstract dynamic models. In (Zimmermann, 2007) agent models are addressed as suitable for behavior modeling, and multiple-agents simulation studies are performed. These systems were also successfully applied in (Zeiler et al, 2006) (Sharma et al, 2008). More literature about agent taxonomy is in (Wooldridge & Jennings, 1994) (Franklin et al, 1996) (Fonseca, 2001).

The study performed in (Borgeson & Brager, 2008) classifies human behavior as not deterministic, but aggregate tendencies are recognizable in the data collected. Models based on the probability of observed phenomena like window opening or closing are best suited for capturing such behavior. Stochastic modeling can take several forms. Some can be simple functions that produce the probability of an action given a set of environmental conditions as inputs, while others like Markov chains and survival analysis can use the current state or other time varying factors to influence the outcome.

3.5 Approach

The proposed methodology tackles the aforementioned building performance simulation tools' weaknesses. The gravity center of this study is the prediction of the building energy consumption as a result of the occupant behavior. The focus will be the space occupancy patterns due to the interactions with the lighting system, because they represent one of the most consuming sectors within a building and also they represents the biggest energy saving opportunity as introduced in chapter 2. Consequently, it is crucial to have information about the building user actions. This can be achieved through the installation of a sensorial network that would register these events over time and space in a real building under regular usage patterns (Silva et al, 2005). Moreover, capturing occupant activities and behavior through sensors, video and audio is addressed in the following works: (Silva et al, 2005) (Yuan et al, 2006) (Guo & Miao, 2007) (Brdickka et al, 2009) (Huang et al, 2009). Usually, the objective is to learn situations, identify specific occupants, and recognize ongoing activities and human behavior. An interesting work based on this last aspect is carried out in (Wada & Matsuyama, 2000).

This type of processes, generally occur during relatively large time periods, which is a limiting factor for simulations purposes. Furthermore, this information from a real building is not available. So to overcome this limitation, it is necessary to recur to simulation methods. It is important to take note of the concepts introduced in previous section of building simulation so there no confusion with building simulation tools definition. The simulator has two proposes. Firstly, it is a means of generating data according to different usage and occupant behavior. Secondly, it provides a way for validating the obtained models and the proposed modeling methodology. Finally, these models and methodology could be integrated in a building simulation tool for more reliable predictions of a building's energy consumption (such as ESP-r or EnergyPlus) (Page et al, 2008).

How to build the simulator? How to represent the occupants? How to model the occupant behavior? Furthermore, *how to model the building usage patterns for energy predictions?*

In order to answer the research questions, a tool was developed that included the methodologies depicted in ***FIGURE 3-1***.

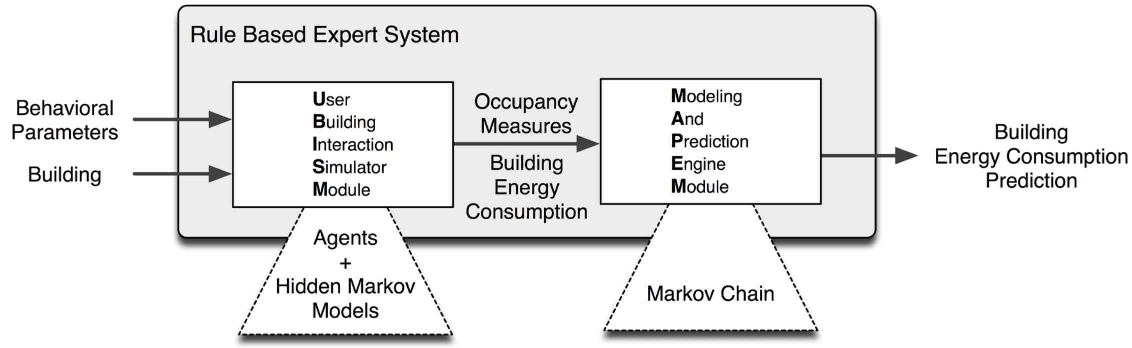

FIGURE 3-1: Conceptual diagram of the proposed methodology

There are many ways to deal with uncertainty. One, and perhaps the simplest, approach is to replace each uncertain quantity either by its average, its median, or by some critical value, and then proceed with a deterministic approach, but often this leads to poor results (Stedinger, 2005).

The occupants will be modeled through a multi-agent system. Agents have become an important concept both in artificial intelligence and computer science. The implemented agents enjoy some common properties, such as, *autonomy*, *reactivity* and *pro-activeness*. Summarizing, agents are not more than a self-contained, concurrently executing software process, which exhibits the properties listed above (Jennings, 1995) (Graesser, 1997).

As described in the behavior modeling section, HMM are popular tools in this field, because of their power of modeling statistical patterns evolving over time. Standard HMM and assume stationary state transition distribution, keeping the model structure and parameters constant over time. In this context, user behavior is defined as the presence of people in the building along with their actions that influence the indoor environment. These models will be used as generators. Keeping in mind that human behavior is extremely complex and because it is characterized by a strong stochastic nature the model aims to produce a representative pattern of observations. The objective is not to try to create a universal model of user behavior. User behavior is defined in a huge feature space, with many aspects still unexplored or not understood. The approach is to define domain specific models, starting with limited scenarios for simulation applications, and model as many features as necessary for each scenario.

A mathematic model based on chains will be applied to predict the building spaces' state, aiming to provide an energy consumption model. In order to support these models and methodologies, an expert system is used to provide information and decision support to building developers and potential users on the adoption and application of specific energy efficient technologies. Unique mechanisms for simulation and knowledge representation developed for the system allow the simulation of decision-making models while maintaining system edibility. This expert system is supported via rule reasoning, which is denominated rule-based expert system. Because interactions can be commonly described by rules, the application of a rule system becomes automatic.

The next chapter will describe and mathematically fundament the modeling process using stochastic models, referred as *stochastic modeling*.

4

Stochastic Modeling

This chapter introduces the basic concepts and definitions used in analysis involving probability and statistics. Furthermore, some stochastic models are clarified. These concepts and models are used throughout this chapter and later chapters in the document.

4.1 Introduction

The basic concept in *probability theory*[7] is that of the *random variable* $X(t)$. By definition, the value of a random variable cannot be predicted with certainty. For example, $X(t)$ could be one's location at time t, where t is the future. For an introduction to probability concepts see (Snell, 1997).

A *random experiment* is a physical situation whose outcome cannot be predicted until it is observed. A *sample space* or *state space* Ω is a set of possible outcomes of a random experiment. For example, a random experiment could be the tossing of a coin once up in the air, in this way, the state space would be either *head* or *tail*. As a result of this definitions, a random variable X is defined as a function from the sample space to the real number: $X: \Omega \rightarrow \mathbb{R}$. That is, a random variable assigns a real number to every possible outcome of a random experiment. The use of the word *state* conforms to the usual idea of the state of a system.

A collection of random variables whose values change through time according to probabilistic laws is called a *stochastic process* (Goodman, 1998) (Faris, 2001) (Igusa, 2006) (Fewster, 2010), as illustrated in ***FIGURE 4-1***.

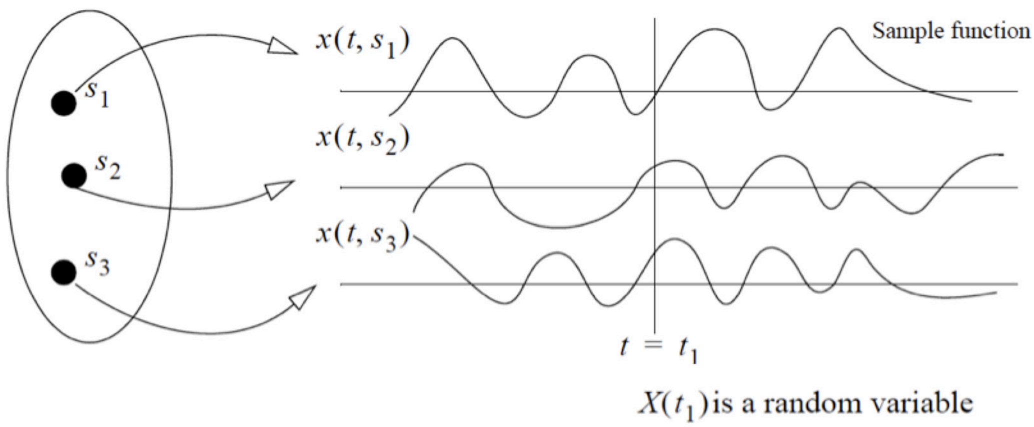

FIGURE 4-1: Representation of a stochastic process and relation to random variables **(Veeraraghavan, 2004)**

[7] It is the branch of mathematics concerned with analysis of random phenomena. A good overview on fundamentals of applied probability theory is (Drake, 1967)

In this way, a stochastic process X is a family of random variables $\{X(t)|t \in T\}$ defined on a given probability space, indexed by the time variable t, where t varies over an index set T. Just as a random variable assigns a number to each outcome s in a state space S, a stochastic process assigns a *sample function* $x(t,s)$ to each outcome s. A sample function $x(t,s)$ is the time function associated with outcome s of an experiment. The ensemble of a stochastic process is the set of all possible time functions that can result from an experiment.

Accordingly with the *state space* S and the index set T, the stochastic processes are categorized differently. If the set T is finite or countable, $T = \{0,1,2,3 \dots\}$, then it is a *discrete-time process*. On the other hand, if T is not finite or countable, $T = [0, \infty[$, then it is a *continuous-time process*. Regarding the state space, if S it is finite or countable then is a *discrete state space* otherwise is a *continuous state space* (Watkins, 2007).

The current study will be concerned exclusively with **Markov processes**, which are a type of stochastic process. What makes Markov processes important is that they not only model many phenomena of interest, but also their lack of memory makes it possible to predict how these models may behave, and to compute probabilities and expected values which quantify that behavior. The characteristic property of this type of processes is that it retains no memory of where it has been in the past. This means that only the current state of the process can influence where it goes next. A suitable example of such phenomena is the *random walk*[8] (Faris, 2001), illustrated in ***FIGURE 4-2***.

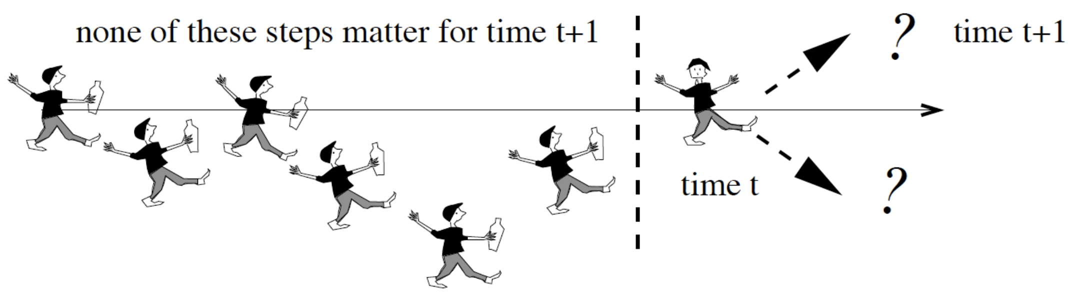

FIGURE 4-2: Example of a Markov process: The simple random walk **(Fewster, 2010)**

The current study will be concerned exclusively with the case where the Markov process assumes only a finite or countable set of states, usually referred as **Markov chain (MC)**.

[8] Random walk is a standard example of a stochastic process and is described in almost every literature regarding stochastic processes or probability theory

The next section gives an introduction to these models focusing on those characteristics that are needed for the modeling and analysis of problems.

4.2 Markov Chains

This section gives a brief introduction to discrete time and discrete state space Markov processes. Interested readers can consult the book (Ross, 2000). Often, the term *Markov chain* is applied to refer a Markov process with discrete state space (Norris, 1997). Furthermore, the Markov chain usually implies a discrete time set, however, some authors, uses the term *discrete-time Markov chains* (Gallager, 2009) to differ them from the continuous time case, *continuous-time Markov chains*.

4.2.1 Specifying a Markov Chain

Markov chains can be considered as a variant of *finite state machines*[9] in a way that they have similar representations and are based on the same principle of a state sequence that evolves as time passes, hence the model's name "chain". The main difference resides in the concepts of the state transitions. They are often represented as *digraphs* (Bang-Jensen et al, 2010) in which the nodes represent the *states* of the process and the *edges* represent the *transition probabilities* between the states. ***FIGURE 4-3*** depicts two examples of Markov chains.

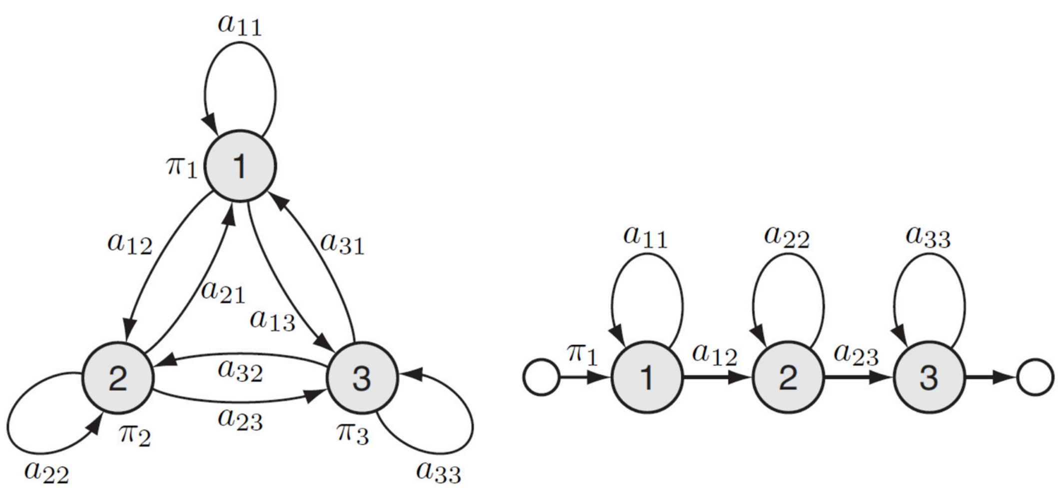

FIGURE 4-3: A 3-state Markov chain digraph structure examples. Left: ergodic[10] model. Right: left-to-right model

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[9] This variant is know as *probabilistic finite state machine* (Vidal, 2005a; Vidal, 2005b)

[10] *Ergodic* structure means that all nodes are interconnected

A MC is a time-indexed stochastic process with the *Markov property* **(4.1)**. Having the Markov property means that given the present state, future states are independent of the past states and only depend on the current state.

$$P\{X_{n+1} = j \mid X_n = i,\, X_{n-1} = i_{n-1}, \dots,\, X_0 = i_0\} = P\{X_{n+1} = j \mid X_n = i\} = p_{ij} \quad (4.1)$$

Distribution of X_{n+1} depends on X_n but whatever happened before time n does not count

The probability p_{ij} **(4.1)** is called *one-step transition probability* because it represents the probability that the process will make a transition to state i given that currently the process is in state j in one-step or transition.

A Markov chain having a set of *states* $S = \{s_1, s_2, \dots, s_M\}$ is called *finite-state Markov chain*. The process starts in one of these states and moves successively from one state to another. Each move is called a step. If the chain is currently in state $X_i \in S$, then it moves to state $X_j \in S$ at the next step with a probability p_{ij}. The state X_n has an arbitrary probability distribution, and the initial state is defined through the vector $\boldsymbol{\pi}$ **(4.2)**, which is required for a full probabilistic description of the process, but is not needed for most of the results.

$$\boldsymbol{\pi} = \begin{bmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_M \end{bmatrix} = \begin{bmatrix} P(X_0 = s_1) \\ P(X_0 = s_2) \\ \vdots \\ P(X_0 = s_M) \end{bmatrix} \quad \text{and} \quad \mathbf{X}_n = \begin{bmatrix} P(X_n = s_1) \\ P(X_n = s_2) \\ \vdots \\ P(X_n = s_M) \end{bmatrix} \quad (4.2)$$

For the following consideration it is assumed that the chain is *time-homogeneous* **(4.3)**. This means that transition probabilities between states are constant over time, and these are called *homogeneous Markov chains*.

$$p_{ij} = P\{X_{n+1} = j \mid X_n = i\} = P\{X_n = j \mid X_{n-1} = i\} \quad \forall_{t \in T}, \forall_{i,j \in S} \quad (4.3)$$

4.2.2 Transition Matrix

For a homogeneous Markov chain the transition probabilities can be noted in a time independent *stochastic matrix* **P** **(4.4)**. The matrix **P** is called *transition matrix* and is a $|S|\times|S|$ matrix.

$$\mathbf{P} = (p_{ij}), \qquad p_{ij} \geq 0, \forall_{i,j\in S} \ \mathit{and} \sum\nolimits_{j\in S} p_{ij} = 1 \ : \ i \in S \tag{4.4}$$

How can this transition matrix be interpreted? ***FIGURE 4-4*** graphically depicts how this matrix should be constructed.

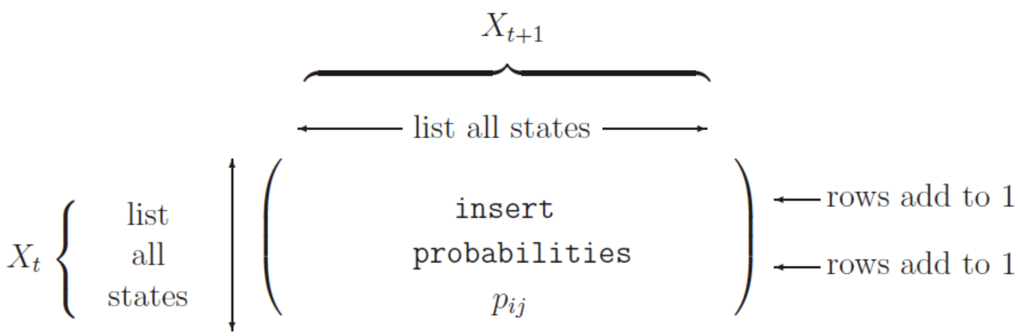

FIGURE 4-4: Interpretation of the Markov chain's transition matrix

How can one construct the transition matrix? One obvious assumption of the MC is that the states of the system are observable. So, given an observed data sequence $\mathbf{X}_N = \{X_1, X_2, \dots, X_n\}$, one can find the transition frequency $\mathcal{F}_{jk}$ of the states in the sequence by counting the number of transitions from state j to state k in one step. Then one constructs the transition matrix for the sequence $\mathbf{X}_N$ as follows (Ching, 2005):

$$\boldsymbol{\mathcal{F}} = \begin{bmatrix} f_{11} & \cdots & f_{1m} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mm} \end{bmatrix} \tag{4.5}$$

From $\mathcal{F}$, one can get the estimates for P as follows:

$$\mathbf{P} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mn} \end{bmatrix} \tag{4.6}$$

Where:

$$\mathrm{P}_{jk} = \begin{cases} \dfrac{\mathcal{F}_{jk}}{\sum_{j=1}^{m} \mathcal{F}_{jk}}, & \displaystyle\sum_{j=1}^{m} \mathcal{F}_{jk} > 0 \\ 0, & \displaystyle\sum_{j=1}^{m} \mathcal{F}_{jk} = 0 \end{cases} \tag{4.7}$$

4.2.3 Transient Distribution Analysis

This section will provide the tools and concepts for analyzing the dynamics of such processes, that is, what happens to P_N after n-steps. The next section will deal with the case when $\lim_{N\to\infty} P_N$.

As shown is previous section, the transition matrix is obtained through the observed state sequence. However, after constructed the model, multiple state sequences are possible although some sequences are more probable then others. These possible sequences are called *path*. How can one calculate the probability of a path? Starting with a state sequence $\mathbf{X} = \{\mathrm{X}_0, \dots, \mathrm{X}_n\}$ illustrated in ***FIGURE 4-5***.

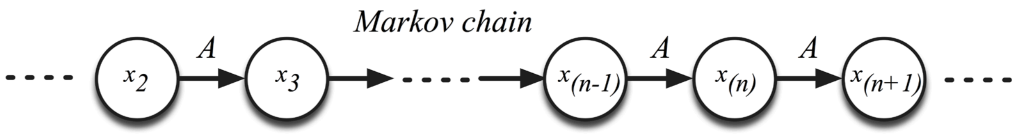

FIGURE 4-5: A state sequence from a Markov chain

It follows that the joint distribution of the random variables is well defined, and can be calculated as:

$$\begin{aligned} P\{\mathrm{X}_0, \dots, \mathrm{X}_n\} &= P\{X_0\}P\{X_1|X_0\} \cdots P\{X_n|X_0, \dots, X_{n-1}\} \\ &= P\{X_0\} \prod_{n=1}^{N} P\{\mathrm{X}_n|\mathrm{X}_{n-1}\} \end{aligned} \tag{4.8}$$

For a general stochastic sequence $\mathbf{X}$, one must compute $P_N\{x, y\}$ by summing over all paths of length n starting at x and ending in y:

$$P_N\{x,y\} = \sum_{x_1,\dots,x_{n-1}} P\{X_1 = x_1, \dots, X_{n-1} = x_{n-1}, X_n = y \mid X_0 = x\} \tag{4.9}$$

Equation **(4.9)** can be interpreted such that for a general stochastic sequence $\mathbf{X}_\mathrm{N}$ the sequence probability is calculated by summing over all paths of length N, starting in one state x and ending at y. Furthermore, for a MC one can write equation **(4.8)** in a more generic form and add it to equation **(4.9)** for a generic and compact form, as follows:

$$P\{X_1 = x_1, \dots, X_{N-1} = x_{N-1}, X_N = y \mid X_0 = x\} = P(x_1|x) \dots P(y|x_{N-1}) \tag{4.10}$$

$$P_N\{x,y\} = P\{x\} \sum_{x_1,\dots,x_{N-1}} \prod_{n=1}^{N} P\{\mathrm{x_n}|\mathrm{x_{n-1}}\} \tag{4.11}$$

In equation **(4.11)** $x_0 = x$ and $x_n = y$. This can be related to the transition matrix, where $P_N\{i,j\}$ is the (i,j)th entry of the matrix $\boldsymbol{P}^n$.

Using the one-step matrix $\boldsymbol{P}$ it is possible to write the n-step transition matrix $\boldsymbol{P}^n$. This matrix is defined to be the probability that a process in state i will be in state j after n additional transitions. The next point will analyze the existence of a limiting distribution for X_n, as $n \to \infty$ with is referred as *stationary distribution*. Such distribution is called stationary for the following reason **(4.12)**.

$$\lim_{n\to\infty} \boldsymbol{P}^n \to \boldsymbol{\Pi} \tag{4.12}$$

Where $\boldsymbol{\Pi}$ is an invariant/constant marginal distribution, independent of time. In other words, $\boldsymbol{P}$ will converge to a constant distribution.

4.2.4 Convergence to the Stationary Distribution

How does a Markov chain ϕ behave after a long time n has elapsed? The sequence $\{X_1, X_2, X_3 \dots\} : n \in \mathbb{N}$ cannot, in generally, converge to some particular state s since it enjoys the inherent random fluctuation, which is specified by the transition matrix. However, the distribution of X might converge to a *steady state* distribution. For advanced characteristics in convergence of stochastic process see (Pollard, 1984). This means that, once a MC has reached a distribution $\boldsymbol{\Pi}$, it will stay there. An example is illustrated next, in ***FIGURE 4-6***.

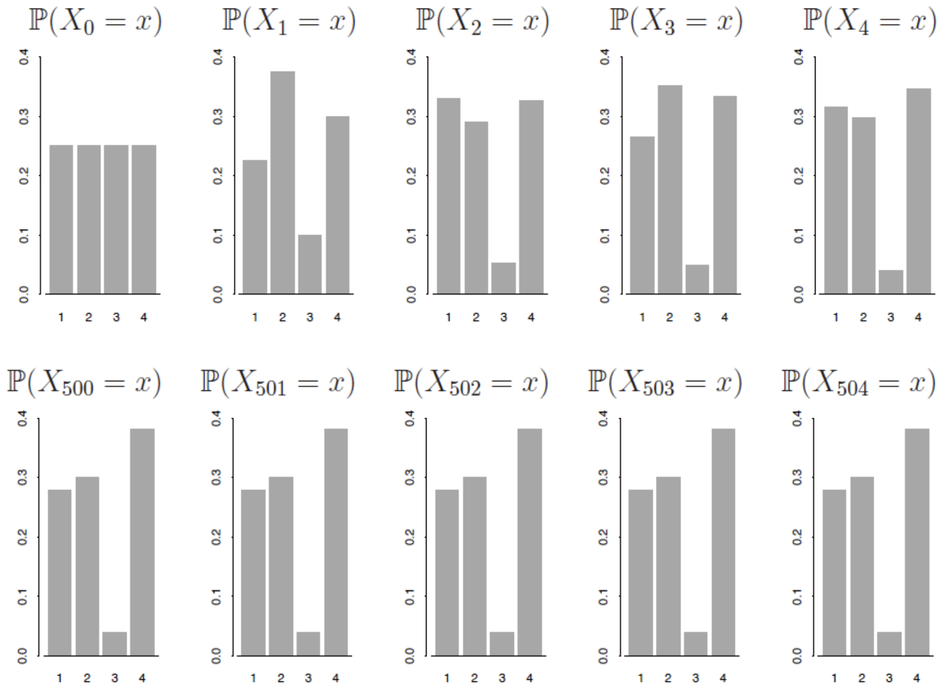

FIGURE 4-6: Marginal distributions of a MC with 4 states over a few steps **(Fewster, 2010)**

The ***FIGURE 4-7*** illustrates the evolution of the states probabilities distribution for the same MC used in the ***FIGURE 4-6***.

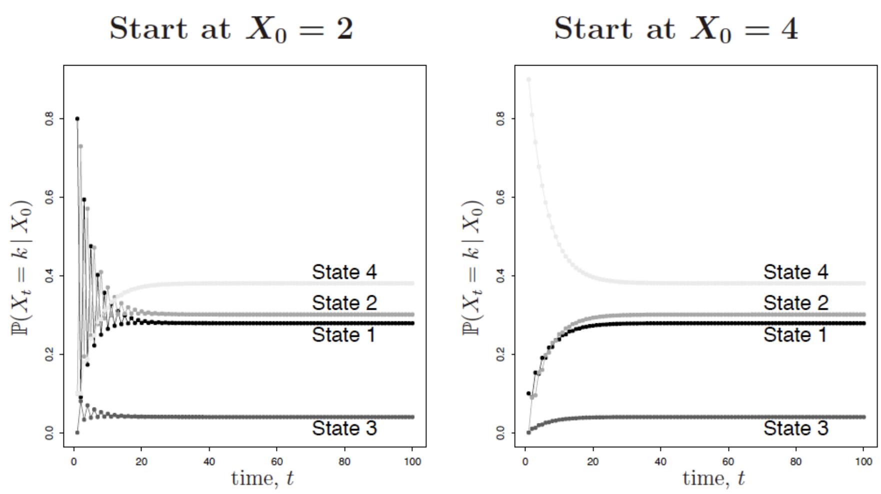

FIGURE 4-7: States probability distribution of a Markov chain over 100 steps **(Fewster, 2010)**

This equilibrium distribution $\mathbf{\Pi}$ for $\boldsymbol{P}$ is a probabilistic vector, referred as *steady-state vector*, which satisfies the following conditions:

1. $\mathbf{\Pi}\boldsymbol{P} = \mathbf{\Pi}$;
2. $\sum_{i=1}^{N} \pi_i = 1$
3. $\pi_i \geq 0 \; for \; all \; i.$

A convenient way of dealing with the nth power of a matrix is to find the eigenvalues and eigenvectors of the matrix (Gallager, 2009). To find the equilibrium vector, notice that $\mathbf{X}\boldsymbol{P} = \mathbf{X} = \boldsymbol{I}\mathbf{X}$, one can solve the equation $(\boldsymbol{P} - \boldsymbol{I})\mathbf{X} = \mathbf{0} \Leftrightarrow \boldsymbol{R}\mathbf{X} = \mathbf{0}$. In this case, $\mathbf{X}$ is the null space basis of $\boldsymbol{R}$. Finally, $\boldsymbol{\Pi}$ can be obtained by normalizing $\boldsymbol{R}$ **(4.14)**.

$$\boldsymbol{\Pi} = \frac{\mathbf{X}}{||\mathbf{X}||} \tag{4.13}$$

4.3 Hidden Markov Models

The hidden Markov models can be considered as the simplest dynamic Bayesian network (Murphy, 2002). The *Kalman filter*[11] is a well-known example (Welch & Bishop, 2006). HMM is a stochastic process in which the system being modeled is assumed to be a Markov chain with unknown parameters due to the fact that the system states are not observable. In this section the concept of Markov models is extended in order to include the case where the observations are a probabilistic function of the state. The resulting model, HMM, is a doubly embedded stochastic process with an underlying stochastic process that is not observable, however it can only be observed through another set of stochastic process that produce the observations sequence. A hidden Markov processes taxonomy is evaluated in (Ephraim, 2002)

4.3.1 Definition

Let $\phi = (S, P, \pi)$ be a first order homogeneous MC, as it was introduced before. Now it is assumed that the states of the MC cannot be directly observed, which means that s_n is hidden. Instead of that it is assumed that in every point in time the system emits some symbol v with a certain probability, as depicted in ***FIGURE 4-9***. This property can be considered as an additional stochastic process involved. The emitted symbol v can be observed, and thus v_n is visible. The probability for such an emission at time n depends only upon the underlying state s at that time, so it can be denoted as the traditional probability $P\{v_n|s_n\}$. Comparing with MC, in a HMM there is no one-to-one correspondence between the hidden states and the observable symbols. Therefore, it is no longer possible to tell what hidden state the model was

[11] A revealing introduction to some of the concepts of Kalman filtering (Maybeck, 1979)

in just by looking at the observation symbol. With these properties a HMM is introduced as a 5-tuple function:

$$\lambda = (S, P, \pi, \Sigma, \delta) \tag{4.14}$$

An HMM is usually characterized by the following parameters (Rabiner, 1989) and (Ching, 2005):

- N, The number of hidden states in the model. Although the states are hidden, for many practical applications there is often some physical significance attached to the states. The individual states are denoted as:

$$S = \{s_1, s_2, \dots, s_N\} \tag{4.15}$$

  When the state at time t assumes a specific value, it is referred as q_t, where Q is the sequence of the hidden states.

- M, The number of distinct observations symbols per hidden state. The observation symbol corresponds to the physical output signal of the system being modeled. The individual symbols are denoted as:

$$V = \{v_1, v_2, \dots, v_M\} \tag{4.16}$$

  When the symbol at time t assumes a specific value, it is referred as o_t, where O is the sequence of the observed symbols.

- The state transition probability distribution $[A]_{ij} = \{a_{ij}\}$ where

$$a_{ij} = P\{Q_{n+1} = s_j \middle| Q_n = s_i\}, \qquad 1 \le i, j \le N \tag{4.17}$$

  And,

$$\sum_{j=1}^{N} a_{ij} = 1, \qquad 1 \le i \le N \tag{4.18}$$

- The observation symbol probability distribution in the hidden state j, $[B]_{jk} = \{b_j(v_k)\}$ where

$$b_j(v_k) = P\{O_n = v_k | Q_n = s_j\}, \qquad 1 \le j \le N\,, \qquad 1 \le k \le M \tag{4.19}$$

And,

$$\sum_{k=1}^{M} b_j(v_k) = 1, \qquad 1 \le j \le N \tag{4.20}$$

- The initial state distribution $\boldsymbol{\pi} = \{\pi_i\}$, where

$$\pi_i = P\{Q_1 = s_i\} \tag{4.21}$$

Given the appropriate values of N, M, A, B and π, the HMM can be used as a generator to give an observation sequence:

$$\mathcal{O} = \{O_1, O_2, O_3, \dots, O_T\} \tag{4.22}$$

Where T is the number of observations in the sequence. For simplicity, the following compact notation is used to indicate the complete parameter set of the HMM:

$$\lambda = (A, B, \pi) \tag{4.23}$$

The ***FIGURE 4-8*** illustrates examples of typical HMM structures, where the previous parameter set is depicted.

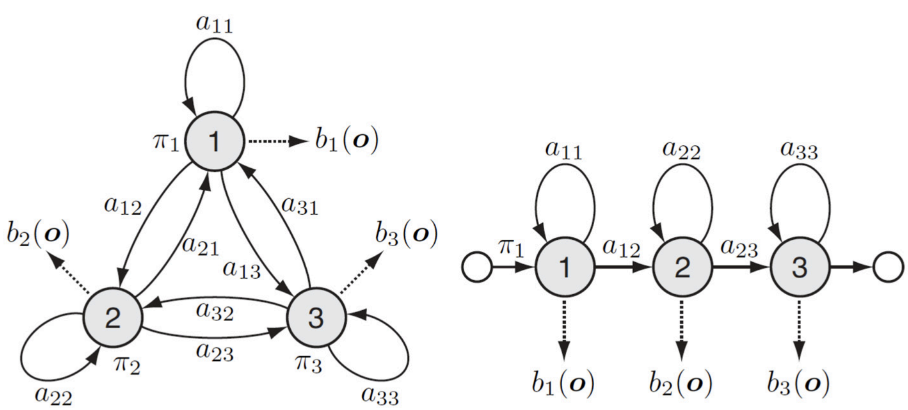

FIGURE 4-8: A 3-state HMM structure examples. Left: ergodic model. Right: left-to-right model

The ***FIGURE 4-9*** depicts a sequence of hidden and observable states of a HMM that could be the outcome of either one of the models illustrated in ***FIGURE 4-8***.

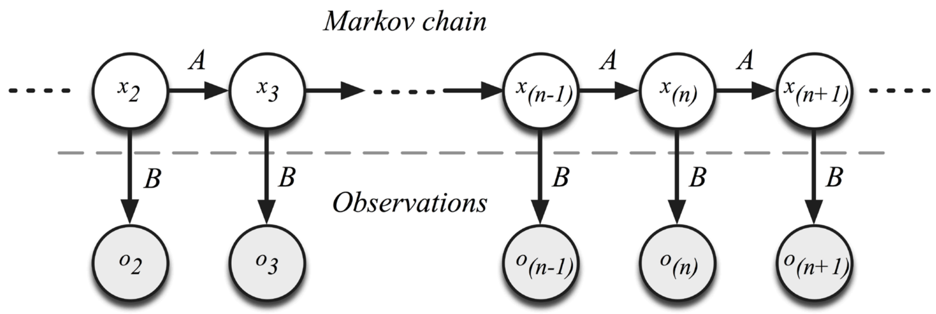

FIGURE 4-9: A sequence of hidden and observable states from a hidden Markov model

Consider a generic state sequence **(4.24)** and corresponding observations **(4.25)** with length four:

$$X = \{x_0, x_1, x_2, x_3\} \tag{4.24}$$

$$\mathcal{O} = \{o_0, o_1, o_2, o_3\} \tag{4.25}$$

Then π_{x_0} is the probability of starting in state x_0. Also, $b_{x_0}(o_0)$ is the probability of initially observing o_0 and a_{x_0,x_1} is the probability o transiting from state x_0 to state x_1. Continuing, the probability of the state sequence X is given by:

$$P(X) = \pi_{x_0} b_{x_0}(o_0) a_{x_0,x_1} b_{x_1}(o_1) a_{x_1,x_2} b_{x_2}(o_2) a_{x_2,x_3} b_{x_3}(o_3) \tag{4.26}$$

4.3.2 Three Fundamental Problems for Hidden Markov Models

There are three fundamental problems for HMM to be applied to various areas, these problems are the following:

A. Problem 1 – The *evaluation* problem

Given one or many HMMs λ (that is, a set of $\{A, B, \pi\}$ triples) describing different systems and a observation sequence $\mathcal{O} = \{o_1, o_2, o_3, \dots, o_T\}$, what is the probability that the observations are generated by the model, that is, what is the $P\{\mathcal{O}|\lambda\}$? Which HMM most probably generated the given observation sequence?

B. Problem 2 – The *decoding* problem

Given a model λ and a sequence of observations $O = \{o_1, o_2, o_3, \dots, o_T\}$, what is the most likely hidden states sequences in the model that produced the observations? In many cases one could be interested in the hidden states of the model since they represent something of value that is not directly observable.

C. Problem 3 – The *learning* problem

Given a model λ and a sequence of observations $O = \{o_1, o_2, o_3, \dots, o_T\}$, how should one adjust the model parameters $\{A, B, \pi\}$ in order to maximize $P\{O|\lambda\}$? This can be viewed as training the model to best fit the observed data. Also, this problem, and by far the hardest, is to take a sequence of observations (from a known set), known to represent a set of hidden states, and fit the most probable HMM.

4.3.3 Three Fundamental Algorithms

In this section, some HMM properties will be described along with the common solutions for the problems enumerated previously.

A. Problem 1 – The *evaluation problem* solution

As described before, the evaluation problem concerns about discovering the probability of an observation sequence $O = \{o_1, o_2, o_3, \dots, o_T\}$ given the model $\lambda = \{A, B, \pi\}$. The most straightforward way of doing this is through enumerating every possible state sequence of length T, the length of the observation sequence. Consider one such fixed state sequence:

$$Q = \{q_1, \dots, q_T\} \tag{4.27}$$

Where q_1 is the initial state. This can be simply calculated by multiplying the output probabilities for each state, that is:

$$P(O|Q,\lambda) = \prod_{t=1}^{T} (Po_t|q_t, \lambda) = \prod_{t=1}^{T} b_{q_t}(t_t) \tag{4.28}$$

$$= b_{q_1}(o_1) b_{q_2}(o_2) \dots b_{q_T}(o_T) \tag{4.29}$$

Furthermore, the probability of such a state sequence **(4.27)**, can be calculated by multiplying the state transition probabilities successively. It can be written as:

$$P(Q|\lambda) = \prod_{t=1}^{T} a_{q_{t-1},q_t} = \pi_{q_1} \prod_{t=2}^{T} a_{q_{t-1},q_t} = a_{q_1,q_2} a_{q_2,q_3} \dots a_{q_{T-1},q_T} \tag{4.30}$$

The equation **(4.28)** represents the probability of one specific state sequence that produced the desired observations $\mathcal{O}$. Using Bayes theorem, the joint probability of $\mathcal{O}$ and Q knowing the model λ, can simply be written as:

$$P(\mathcal{O}, Q|\lambda) = P(\mathcal{O}|Q, \lambda) P(Q, \lambda) \tag{4.31}$$

Merging equations **(4.28)** and **(4.30)** with equation **(4.32)** results:

$$P(Q|\lambda) = \prod_{t=1}^{T} a_{q_{t-1},q_t} \prod_{t=1}^{T} b_{q_t}(t_t) = \prod_{t=1}^{T} \left(a_{q_{t-1},q_t} b_{q_t}(t_t) \right) \tag{4.32}$$

Hence, the probability of the observation sequence $\mathcal{O}$ given λ is calculated by using marginalization of state sequences Q, that is, summing $P(\mathcal{O}, Q|\lambda)$ over all possible state sequence Q. This can be written as:

$$P(Q|\lambda) = \sum_{all\ Q} \prod_{t=1}^{T} \left(a_{q_{t-1},q_t} b_{q_t}(t_t) \right) \tag{4.33}$$

To resume, all the previous equations just say that the probability of a observation sequence $\mathcal{O}$ given a complete parameterized model λ can be directly evaluated by considering all the possible state combinations that could produce that specific $\mathcal{O}$. From (Petkovic, 2001) the direct definition of equation **(4.33)** calculation involves in the order of $2TN^T$ calculations, which is generally unfeasible. The strength of the HMM approach derives largely from the fact that there exists an efficient algorithm to achieve the same result. To find $P(\mathcal{O}|\lambda)$ the so-called ***forward algorithm***, also known as the ***forward-backward Algorithm***, is applied. This algorithm is based on a *trellis* or *lattice* structure, which is a representation of possible hidden states due to a given observation over time. This structure is represented by a particular model in ***FIGURE 4-10*** and in a generic way in ***FIGURE 4-11***.

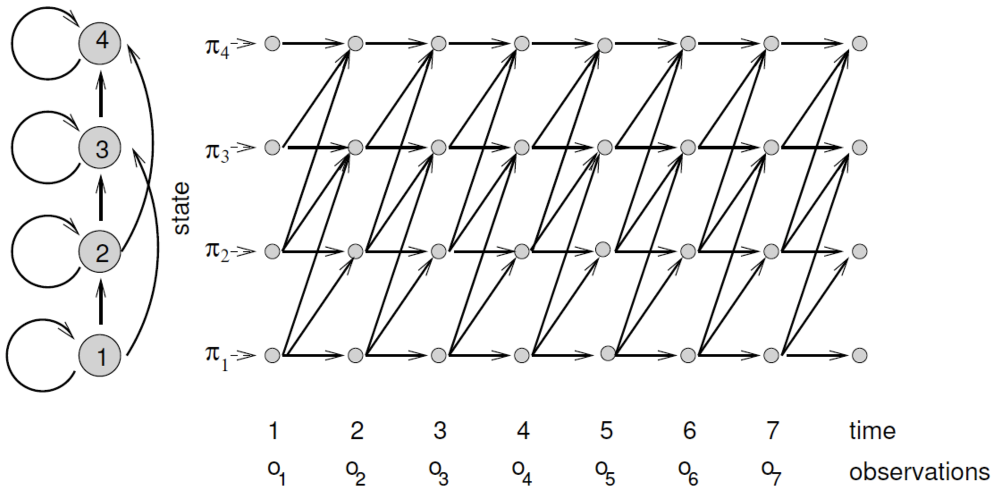

FIGURE 4-10: Example of a HMM with 4 states and possible states transition over time. Hidden states lattice or trellis representation

How is a trellis structure read? Basically, a trellis structure is like a map of a HMM. It expresses for which state it is possible to transit given the current observation and the state. For example, in ***FIGURE 4-11***, given the first observation o_1, the model can be in any state of the first column, accordingly to the probabilities π_i. Consequently, given the second observation o_2, the model can transit to any state of the second column, accordingly to the current state in the first one.

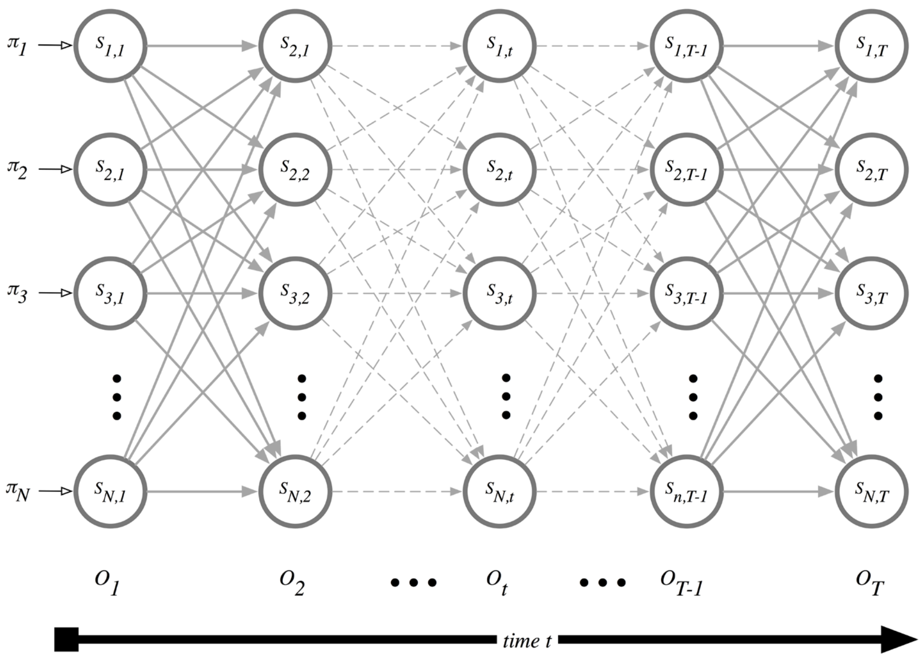

FIGURE 4-11: Generic representation of a lattice structure

In this algorithm an additional variable is defined, the *forward probability* $\alpha_t(i)$, defined in equation **(4.34)**, as the partial observation sequence $o_1, o_2, \dots, o_t$, until time t and state S_i at time t, given the model λ. Similarly, the *backward probability* $\beta_t(i)$, defined in equation **(4.36)** can be deduced, as the probability of the partial observation sequence from $t+1$ to the end, given state S_i at time t and the model λ. However, for this algorithm only the forward variable is need. The both variables will be helpful in solving the learning problem.

$$\alpha_t(i) = P\left(o_{1,}o_2, \dots, o_t, q_t = S_i | \, \lambda\right) \tag{4.34}$$

$$\beta_t(i) = P\left(o_{t+1,}o_{t+2}, \dots, T, q_t = S_i | \, \lambda\right) \tag{4.35}$$

The key result is that $\alpha_t(i)$ and $\beta_t(i)$ can be computed inductively as follows:

1) *Initialization:*

$$\alpha_1(i) = \pi_i b_i(o_1), \qquad 1 \le i \le N \tag{4.36}$$

$$\beta_T(i) = 1, \qquad 1 \le i \le N \tag{4.37}$$

2) *Induction:*

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(j) a_{ji}\right] b_i(o_{t+1}), \quad t = 1, \dots, T-1\,, \qquad 1 \le j \le N \tag{4.38}$$

$$\beta_t(i) = \sum_{j=1}^{N} a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)\ , \qquad t = T-1, \dots, 1\,, \qquad 1 \le i \le N \tag{4.39}$$

Finally, the last step gives the desired calculation of $P(\mathcal{O}|\lambda)$ as the sum of the terminal forward probabilities $\alpha_T(i)$. This is the case since, by definition,

$$\alpha_T(i) = P\left(o_{1,}o_2, \dots, o_T, q_T = S_i | \, \lambda\right) \tag{4.40}$$

3) *Termination:*

$$P(\mathcal{O}|\lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{4.41}$$

$$P(O|\lambda) = \sum_{i=1}^{N} \pi_i \beta_1(i) \tag{4.42}$$

To resume, the forward probability calculation is based upon the lattice structure. The key is that since there are only N states (nodes at each time slot in the lattice), all the possible state sequences will remerge into these N nodes, regardless of the observation sequence length. The calculation of $P(O|\lambda)$ through the sum **(4.41)** or **(4.42)** is polynomial of order TN^2.

B. Problem 2 – The *decoding* problem solution

Unlike the previous problem for which an exact solution can be given, there are several possible ways of solving this decoding problem, namely finding the "optimal" state sequence associated with a given observation sequence. This optimal state sequence can be tricky due to the definition of optimal or the most likely state sequence. The most widely used criterion is to find the single best state sequence (path), in order to maximize $P(Q|O,\lambda)$ which is equivalent to maximizing $P(Q,O|\lambda)$. In order to solve this problem, an algorithm similar to the dynamic programming (S. Dasgupta, 2006) is applied, commonly known as ***Viterbi Algorithm*** (Ryan, 1993). The state sequence that maximizes the likelihood function is called *Viterbi path*. In this method, the whole state sequence with the maximum likelihood is found, that is:

$$Q^* = \arg\max_Q \{P(Q|O,\lambda)\} = \arg\max_Q \left\{\frac{P(Q,O|\lambda)}{P(O)}\right\} = \arg\max_Q \{P(Q,O|\lambda)\} \tag{4.43}$$

This algorithm starts with the definition of the quantity $\delta_t(i)$ as:

$$\delta_t(i) = \max_{q_1 q_2,\dots,q_{t-1}} \{P(q_1 q_2, \dots, q_{t-1} = S_i, o_1 o_2 \dots o_t|\lambda)\} \tag{4.44}$$

That is, $\delta_t(i)$ is the best score (highest probability) along a single path, at time t, which accounts for the first t observations and ends in state S_i. This $\delta_t(i)'s$ are called Viterbi variables, and by induction:

$$\delta_{t+1}(j) = \left[\max_i \delta_t(i) a_{ij}\right] b_j(o_{t+1}), \qquad 1 \le t \le T-1\,, \qquad 1 \le i \le N \tag{4.45}$$

To retrieve the state sequence, one must keep track of the argument, which maximized equation **(4.60)**, for each t and j. This is achieved through the array $\psi_t(j)$. In this way, the Viterbi path can be found by recursion as:

1) *Initialization:*

$$\delta_1(i) = \pi_i b_i(o_1), \qquad 1 \leq i \leq N \tag{4.46}$$

$$\psi_1(i) = 1 \tag{4.47}$$

2) *Recursion:*

$$\delta_t(j) = \max_{1 \leq i \leq N} \left[\delta_{t-1}(i) a_{ij} \right] b_j(o_t), \qquad 2 \leq t \leq T, \qquad 1 \leq j \leq N \tag{4.48}$$

$$\psi_t(j) = \arg\max_{1 \leq i \leq N} \left[\delta_{t-1}(i) a_{ij} \right], \qquad 2 \leq t \leq T, \qquad 1 \leq j \leq N \tag{4.49}$$

3) *Termination:*

$$P^* = \max_{1 \leq i \leq N} [\, \delta_T(i)] \tag{4.50}$$

$$q_T^* = \arg\max_{1 \leq i \leq N} [\, \delta_T(i)] \tag{4.51}$$

4) *Path backtracking:*

$$q_t^* = \psi_{t+1}(q_{t+1}^*), \qquad t = T-1, T-2, \dots, 1 \tag{4.52}$$

To resume, Viterbi algorithm is similar in implementation to the forward-backward algorithm. The major difference is the maximization in equation **(4.45)** over previous states, which is used in place of the summing in forward-backward algorithm. It also should be clear that the trellis structure efficiently implements the computations of the Viterbi algorithm. An example of the Viterbi path is depicted in ***FIGURE 4-12***.

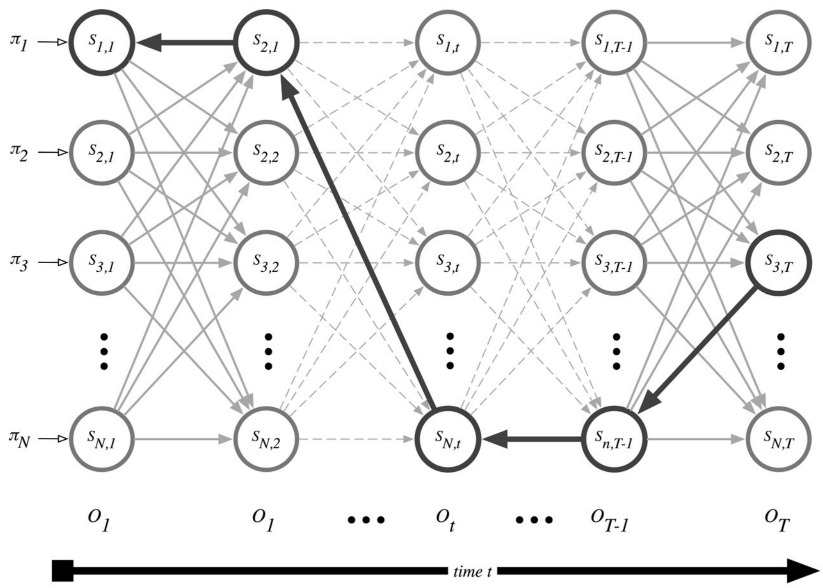

FIGURE 4-12: Viterbi path example in a HMM lattice structure

C. Problem 3 – The *learning* problem solution

There is no known way to analytically solve the model parameter set which satisfies a certain optimization criteria such as maximum likelihood as follows,

$$\lambda^* = \arg\max_{\lambda}\{P(\mathcal{O}|\lambda)\} = \arg\max_{\lambda}\left\{\sum_{all\ Q} P(\mathcal{O}, Q|\lambda)\right\} \tag{4.53}$$

In a Markov chain, the states are not hidden and there is a one-to-one correspondence between the states and observations. So, to estimate the λ parameters it is enough just to calculate the appropriate frequencies from the observed sequence of outputs. These frequencies constitute sufficient statistics for the underlying distributions. Since this learning problem is an optimization problem from incomplete data, including the hidden variable Q, it is difficult to determine λ^* which globally maximizes likelihood $P(\mathcal{O}|\lambda)$ for a given observation sequence $\mathcal{O}$ in a close form. However, a model parameter set λ, which locally maximizes $P(\mathcal{O}|\lambda)$ can be obtained using an iterative procedure such as the expectation-maximization algorithm (Bilmes, 1998) (Borman, 2004). This conducts the optimization of the complete dataset. This optimization algorithm is often referred to as the ***Baum-Welch algorithm***.

Using an initial parameter instantiation λ, the Baum-Welch algorithm iteratively re-estimates the parameters $\{A, B, \pi\}$ while improving the probability $P(\mathcal{O}|\lambda^*)$, such that $P(\mathcal{O}|\lambda^*) \geq P(\mathcal{O}|\lambda)$. This algorithm is divided into two steps.

The E-Step computes the forward and backward probabilities for a given model λ.
The M-Step re-estimates the model parameters λ^*.

In order to describe this procedure (iterative update and improvement) of HMM parameters, first is defined $\xi_t(i,j)$, the joint probability of being in state S_i at time t and state S_j at time $t+1$, given the model and the observation sequence **(4.54)**.

$$\xi_t(i,j) = P\left(q_t = S_i, q_{t+1} = S_j | \mathcal{O}, \lambda\right) \tag{4.54}$$

The sequence of events leading to the conditions required by equation **(4.54)** is illustrated in ***FIGURE 4-13***.

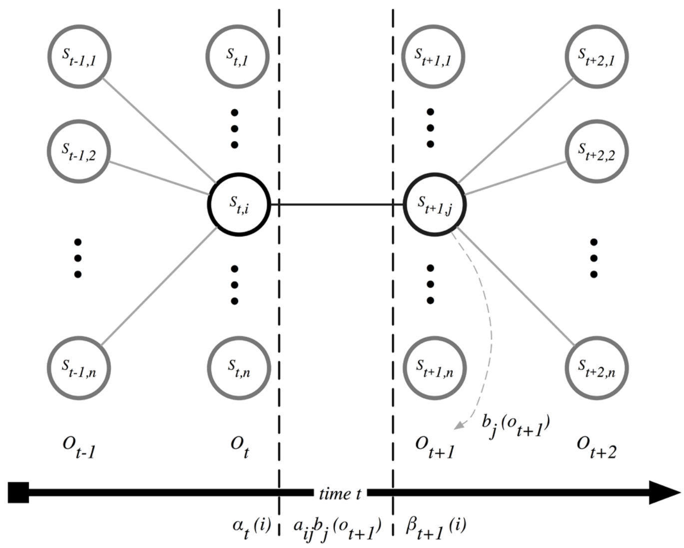

FIGURE 4-13: Illustration of the forward and backward probability variables

Moreover, applying the Bayes' theorem to equation **(4.54)**, it can be rewritten as:

$$\xi_t(i,j) = \frac{P\left(q_t = S_i, q_{t+1} = S_j, \mathcal{O}|\lambda\right)}{P(\mathcal{O}|\lambda)} \tag{4.55}$$

$$= \frac{\alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{P(\mathcal{O}|\lambda)} = \frac{\alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)} \tag{4.56}$$

Now, $\gamma_t(i)$ variable must be created in order to define the probability of being in state S_i at time t, given the observation sequence O, and the model λ. This is considered the posteriori variable:

$$\gamma_t(i) = P(q_t = S_i|O,\lambda) = \frac{P(q_t = S_i, O|\lambda)}{P(O|\lambda)} \tag{4.57}$$

Applying the forward and backward variables from equations **(4.34)** and **(4.35)** to the equation **(4.56)**, this can be expressed as:

$$\xi_t(i,j) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\beta_t(i)} \tag{4.58}$$

From equation **(4.58)** it is observable the relationship between $\xi_t(i,j)$ and $\gamma_t(i)$, which is given by:

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j), \qquad 1 \le i \le N, \qquad 1 \le t \le M \tag{4.59}$$

Now it is possible to describe the Baum-Welch algorithm learning process. Assuming a starting model λ, the $\alpha's, \beta's, \xi's\ and\ \gamma's$, are calculated by the recursion in the previous equations. From a time perspective, these two new variables can be interpreted as the expected number of transitions, that is:

$$\sum_{t=1}^{T-1} \gamma_t(i) = Expected\ number\ of\ transitions\ from\ state\ S_i \tag{4.60}$$

$$\sum_{t=1}^{T-1} \xi_t(i,j) = Expected\ number\ of\ transitions\ from\ state\ S_i\ to\ state\ S_j \tag{4.61}$$

The final step is to update the HMM parameters accordingly to equations **(4.62)** **(4.63)** **(4.64)**, known as re-estimation formulas:

$$\pi^* = \gamma_1(i), \qquad 1 \le i \le N \tag{4.62}$$

$$a_{ij}^{*} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}, \qquad 1 \le i \le N\,, \qquad 1 \le j \le M \tag{4.63}$$

$$\beta_j^{*}(k) = \frac{\sum_{t-1,o_t=v_k}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}, \qquad 1 \le i \le N, \qquad 1 \le k \le M \tag{4.64}$$

The new estimate model is defined as $\lambda^{*} = \{A^{*}, B^{*}, \pi^{*}\}$.

5

Implementation

The models in previous chapters are combined in order to achieve the proposed goals. As a result, this chapter presents the system top-level architecture as well as a macro and microscopic analysis of each module separately. Furthermore, the developed methodologies and algorithms are illustrated and specified.

5.1 Introduction

In chapter 2 the building thematic was introduced and identified as the sector that most contributes for the degradation of the planet. Moreover, was also described as a potential sector where substantial reductions either in energy demand as in carbon footprint could be achieved. Finally, building occupants were considered an added value in building performance and a dominant factor to be considered in retrofitting projects. Next in chapter 3, previous work regarding building performance and human behavior were presented. Additionally, the starting point of this research was specified. Chapter 4 mathematically supports the proposed models to be applied in the specific problem of modeling the spaces and the building occupants behavior. In this context, this chapter concerns the proposed implementation. The overall system architecture is depicted followed by a description of each module separately. Furthermore, the methodologies and algorithms developed are described.

5.2 Proposed System Architecture: Macroscopic Approach

The top-level architecture is illustrated in ***FIGURE 5-1***, and it is decoupled in four different modules, represented as gray boxes.

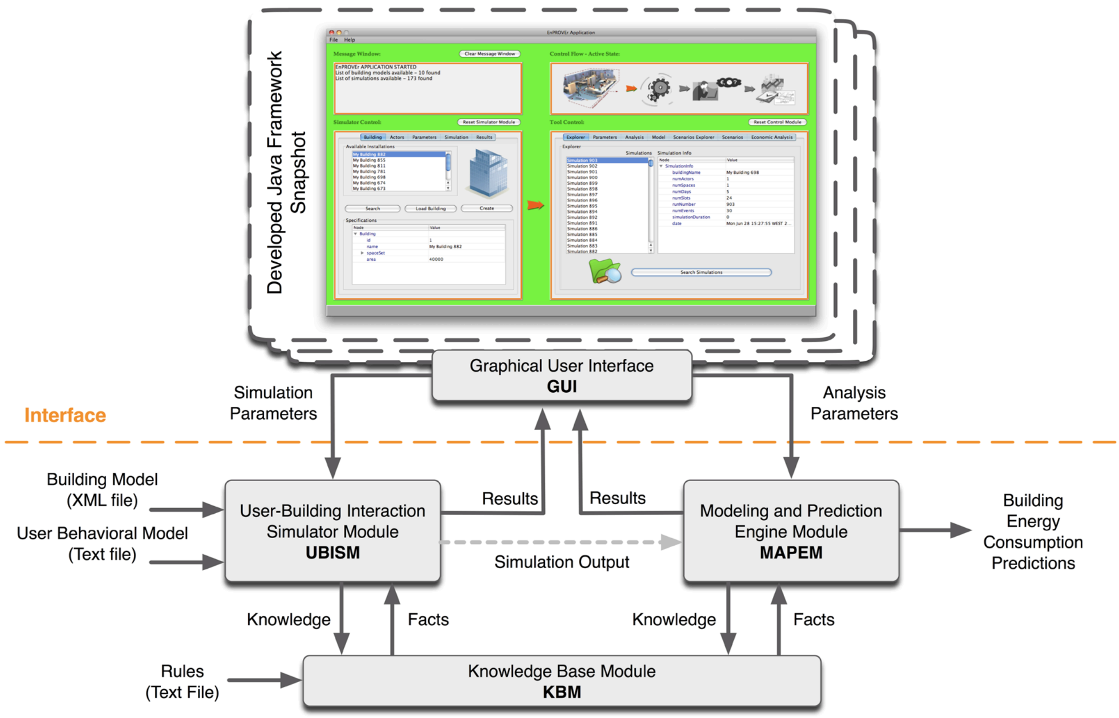

FIGURE 5-1: Top-level framework architecture

As represented in ***FIGURE 5-1***, the GUI module is just a gateway for the system core and does not execute any algorithm or functional operations. From this point of view, the framework is divided in three functional modules, the *user-building interaction simulation module* (UBISM), *the modeling and prediction engine module* (MAPEM) and the *knowledge base module* (KBM). These will be fully described in the following sections.

5.2.1 User-Building Interaction Simulation Module

The UBISM can be decomposed in a block structure as illustrated in ***FIGURE 5-2***. This module inputs are: building model, user behavior model and simulation parameters. The building model is based on a XML file, which is parsed and decomposed as facts into the knowledge base. The users are simulated through agents and theirs behaviors are modeled with a hidden Markov model where its parameters are in a text file. The reason for this is to facilitate the alteration of simulation conditions just by editing a text file and not to compile the program each time. Finally, the simulation parameters determine how the simulation will run, which in turn will affect the building usage patterns.

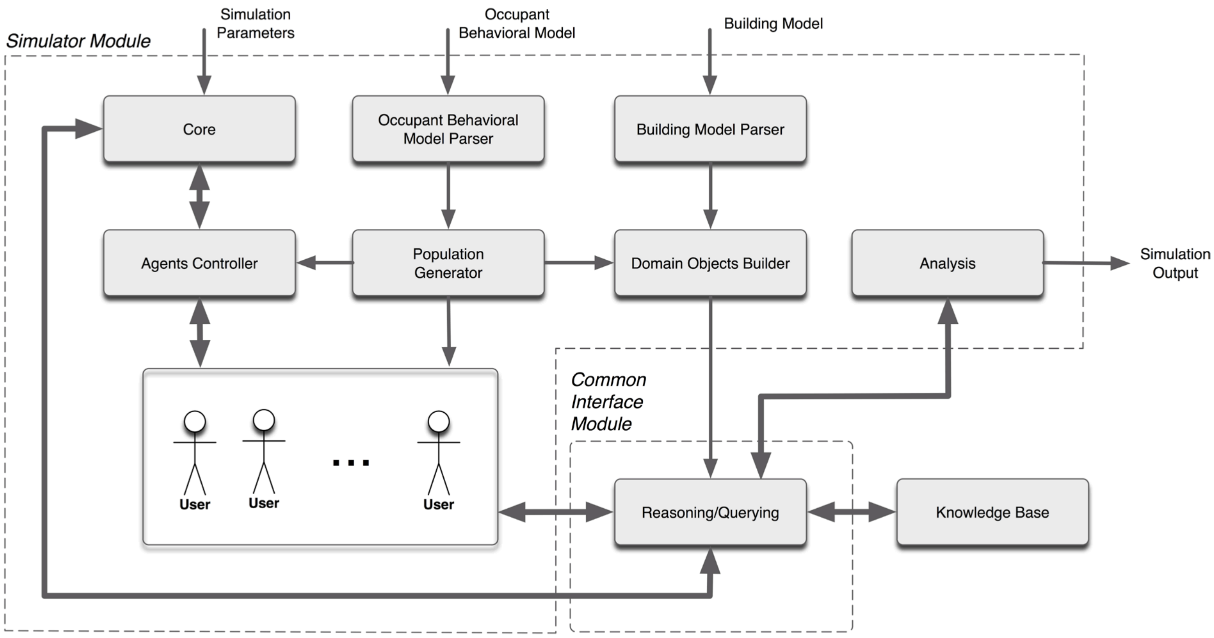

FIGURE 5-2: Microscopic architecture of the UBISM

What does this module do exactly? And how? As illustrated, this module can be decoupled into a few sub-models with well-defined objectives, as summarized in ***FIGURE 5-2***. Each user is represented as an agent and its behavior is modeled through an HMM. This model is represented as a text file for easy modification and validation. Consequently, a module for parsing this file is necessary and it is represented as the "*Occupant Behavioral Model Parser"* module. Furthermore, the simulation could contain one or more users, so one needs to create each agent and incorporate the HMM into it. The module "*Population generator*" encapsulates these operations. Still concerning with the agents, an important issue is the management and controlling of these agents. This is achieved through the module "*Agents Controller*". The building is described through a XML file. As a result, the module "*Building Module Parser*" is responsible for parsing this file. The "*Simulation Controller*" deals with the simulation parameters. The "*Domain Objects Builder*" transforms the domain objects into knowledge, by accessing the "*Reasoning/Querying*" module in order to insert the objects into the knowledge base as facts. Finally, the "*Analysis*" module performs the assessment of the simulation output, such as the building energy consumption and data.

5.2.2 Modeling and Prediction Engine Module

The MAPEM is depicted in the ***FIGURE 5-3***.

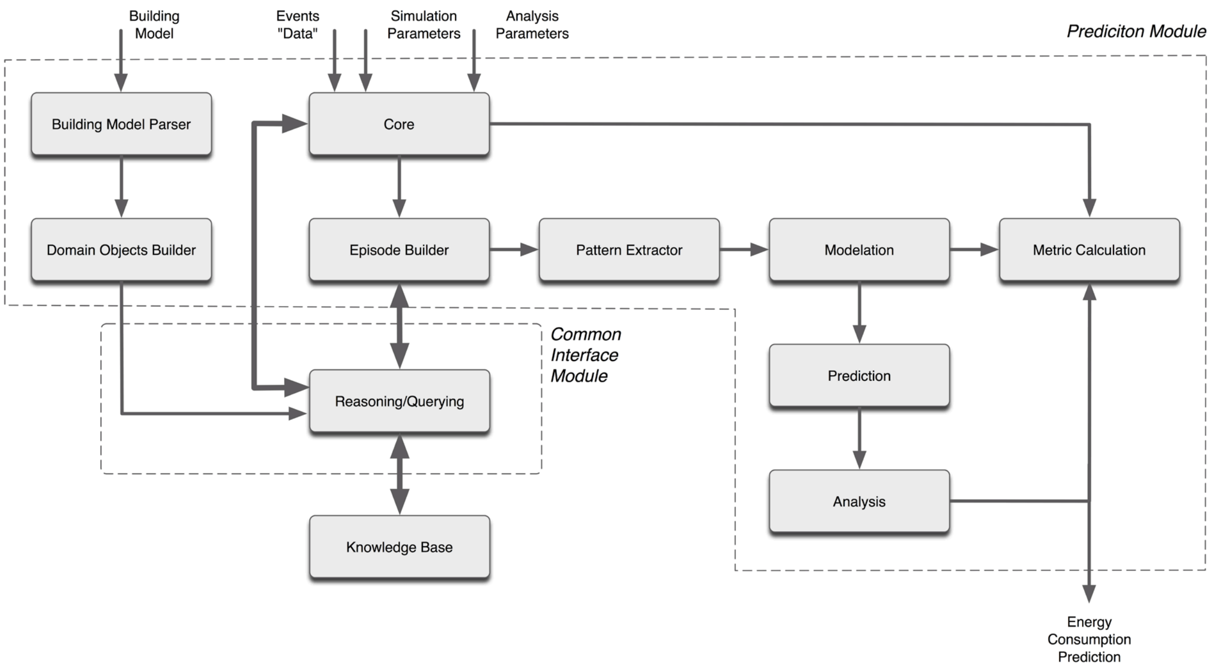

FIGURE 5-3: Microscopic architecture of the MAPEM

This block is responsible for miming the data provided the UBISM, build the energy consumption model for the building and predict its energy consumption. Similar to the previous module, the building module is also needed in this module. The file containing the model is parser in the "*Domain Objects Builder*" module and then, through the "*Domain Objects Builder*" is transformed into knowledge and inserted into the knowledge base as facts. This module also has as input the simulation parameters for proper analysis of the simulated data. In addition, the analysis parameters as input are needed for manipulation of some variables of the produced models. The develop methodology for data analysis is performed in the "*Episode Builder*" module. The module "*Pattern Extractor*" creates a cluster of information for each space of the building in order to construct the energy consumption model for that space. This is performed in the "*Modelation*" module. Each energy consumption model is one Markov chain. Finally, the obtain models are simulated in the "*Prediction*" module and the output analysis is performed by the "*Analysis*" module. The model quality and other metrics are calculated in the "*Metric Calculation*" module.

5.2.3 Knowledge Base Module

The KBM module is depicted in ***FIGURE 5-4***.

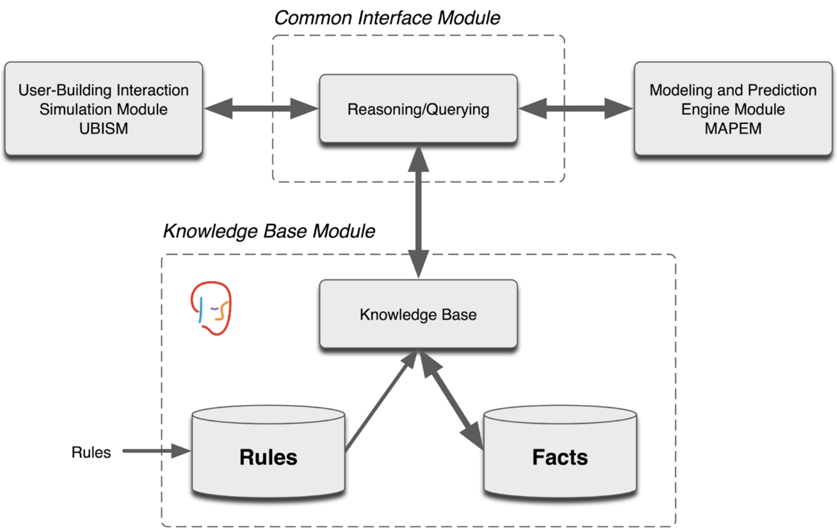

FIGURE 5-4: Microscopic architecture of the KBM

This module is implemented with Drools (JBoss Community, 2010) and is responsible for the inference process and framework runtime support. The motivation for Drools is because it provides out of the box a unified platform for rules, workflow and event processing. The traditional approach is to fallow a process oriented or rule oriented. The problem starts exactly there. *What is the best approach in a specific problem?* With this platform, it is possible to use either one of them or a combination. Furthermore, this platform is well supported, which facilitates its utilization. Alternatively, more rule systems exists, such as

CLIPS (CLIPS Expert System Group, 2009), Jess (Sandia, 2008) or Oracle Business Rules (Oracle, 2010), however, compared with Drools, they provide an inferior level of services integration, such as event processing, that in our problem is extremely helpful due to the nature of the simulator and the methodology applied in the module *episode builder* of the MAPEM. *How does Drools works?* A block structure is illustrated in ***FIGURE 5-5***.

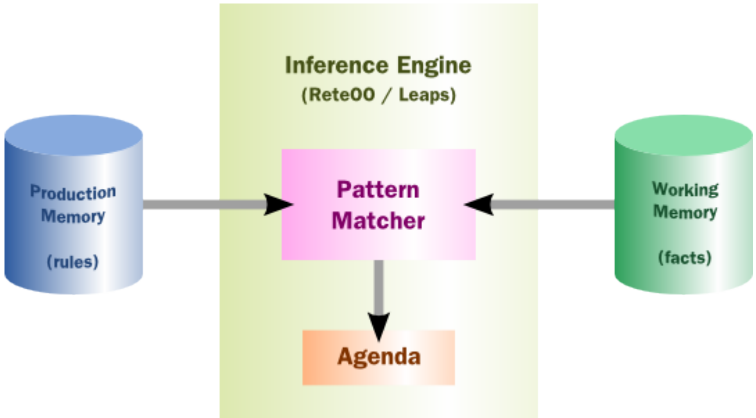

FIGURE 5-5: Drools inference scheme **(JBoss Community, 2010)**

This module consists of two repositories and two sub-models. In this way, there is one repository for the *rules* and another for the *facts*. The "*Knowledge Base*" module is responsible for managing both the rules and facts. The "*Reasoning/Querying*" module permits two different accesses to the knowledge base. The reasoning operation is responsible for running the rules against the facts. The querying operation is responsible for executing queries to the knowledge base, so new or existing facts could be retrieved. The rules can be added, removed or modified at any time of the program. Accordingly to these rules, new facts could be produced and old ones can be interpreted differently. Finally, this module is responsible for the *intelligence* of the framework, as it permits a gateway for the *logic* and *information* interpretation without compiling the code.

This section has introduced the proposed system architecture along with a description of each module following by a brief description. The next section will address the methodology and algorithms implemented for performing the described functions.

5.3 Algorithms and Methodologies

In the previous section the top-layer architecture was presented. The principal modules have been identified and described along with an overview of each module. This section will demystify how each module works, by introducing the main algorithms and developed methodologies.

5.3.1 Simulation Methodology

The simulation objective is to produce *data*, representing the building usage measurements. The data is a collection of *events*, as a result of the occupant actions, that has some effect in the space where that action occurred, as illustrated in ***FIGURE 5-6***. These events must reflect the simulation conditions, since that is the simulator purpose.

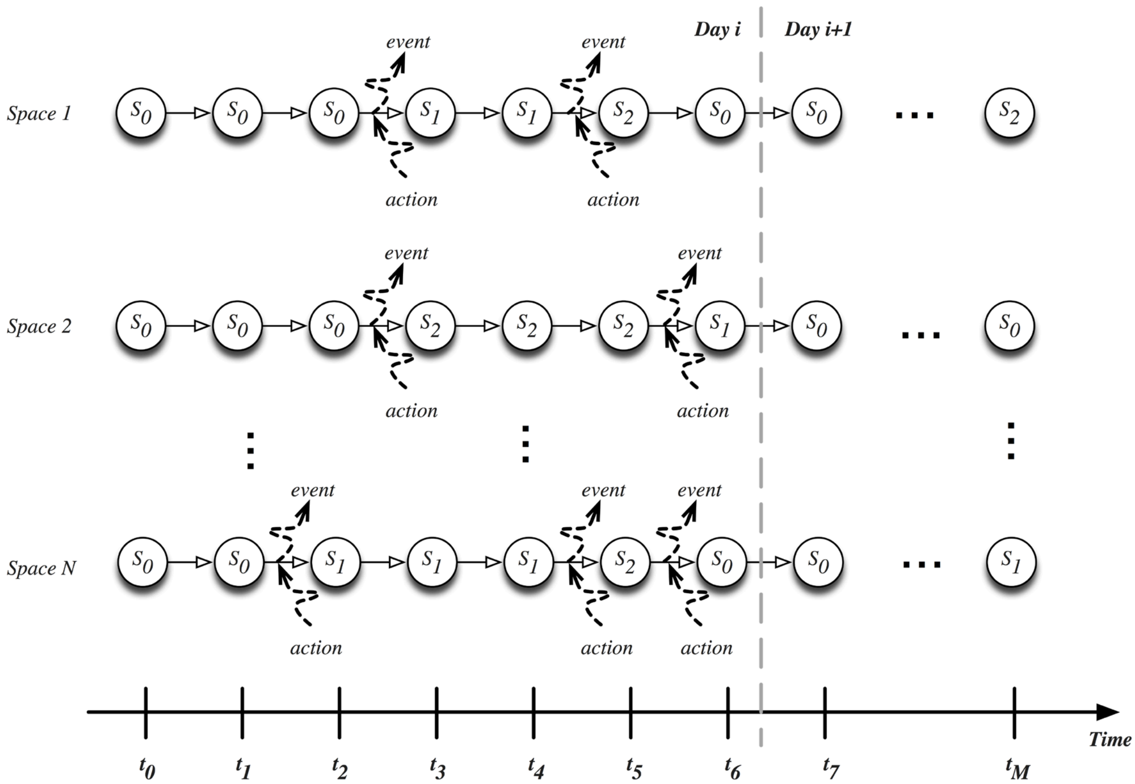

FIGURE 5-6: Representation of the relation between actions and events

As depicted in ***FIGURE 5-6***, when an action occurs, the space's state change and an event is emitted. This emission simulates the presence of a sensor in the space that detects the occupant's action and records the event. *How is the action produced? Or the event? And what* *are the space's states?* The answer to these questions will be addressed below. Given this, the simulation process is divided in three steps: (1) Building model selection; (2) Occupants specification and (3) Simulation parameters selection.

1. **Building model selection**

This is the first step of the simulation process and it consists of selecting the building model that will be used in the simulation.

2. **Occupants specification**

After selecting the building model, the next step is specifying the occupants. In order to achieve a more flexible and reliable simulation, one could select the desired number of the occupants for each simulation. Moreover, it is possible to modify the dynamics of each user separately. Finally, the behavioral model is chosen. This behavioral model could be loaded for each one of the occupants or for the building population.

3. **Simulation parameters selection**

The last step of the simulation process consists on modifying the simulation parameters. In order to control the simulation, it is possible to specify the simulation period, that is, choose how many days will be simulated. Other import parameter is the number of *time slots*. With the goal of separating the computational time from the simulation period and to provide a methodology for verify the energy consumption, the day was divided into time slots. Consequently, the occupant actions will be generated those slots. For example, 24 time slots correspond to time steps of 1 hour. Finally, it is possible to specify the day schedule. For example, for an office building simulation, this schedule consists in the starting working hour, lunch period and end of the working day. For a commercial building simulation, just the opening and closing hours could be specified. *What about the simulation, how will it work?*

After starting the simulation, there are two major phases, which are consistent until the simulation ending. The first phase consists of allowing one agent to run, to perform a determined action that is, synchronizing the agents. Secondly, according to the outcome of the user's action, the new state of the user and the building must be updated, that is, infer the new world's state. These two phases can be referred as *selection phase* and *inference phase*.

Although the system allows multiple agents running, to guarantee coherency in the system facts, just one agent can perform an action at a time. The simulation process is illustrated in ***FIGURE 5-7***. As depicted in this figure, the simulation controller is responsible for controlling the evolution of the simulation. For each simulation iteration, the controller checks if there is more days for simulating, and if there are it gives order to start another simulation iteration by launching the agents through the agent's controller. This agent controller starts all the agents for further interaction with the building and prevents the same agent to be launched twice. If that would be case, the results could be compromised.

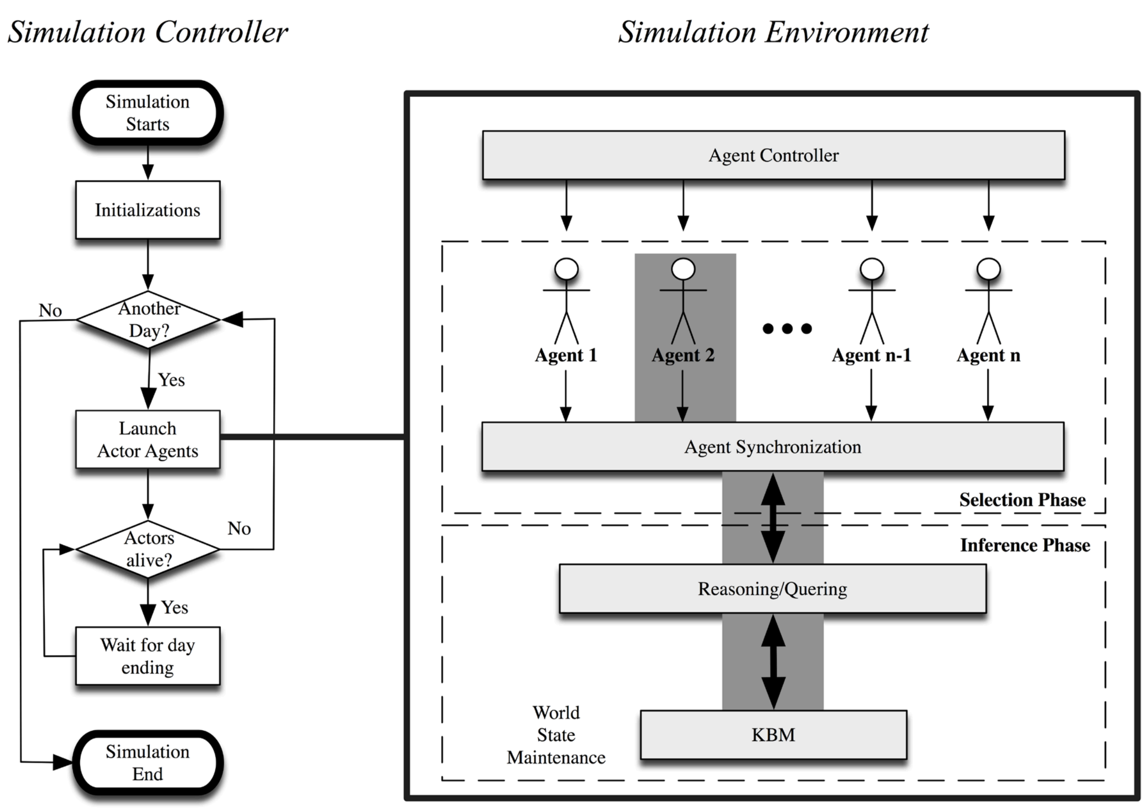

FIGURE 5-7: Simulation process diagram

- **Selection phase**

As stated before, this phase is crucial, since it is responsible for allowing an agent to execute its life cycle. If all agents just stopped then no action would be produced and the simulation would never end, a scenario defined as *deadlock*. The agent is selected according to a methodology similar to the *token ring*. All the agents are concurring for one token, when some gets it the others stay blocked until a new token is available, as illustrated in a sequence diagram in ***FIGURE 5-8***.

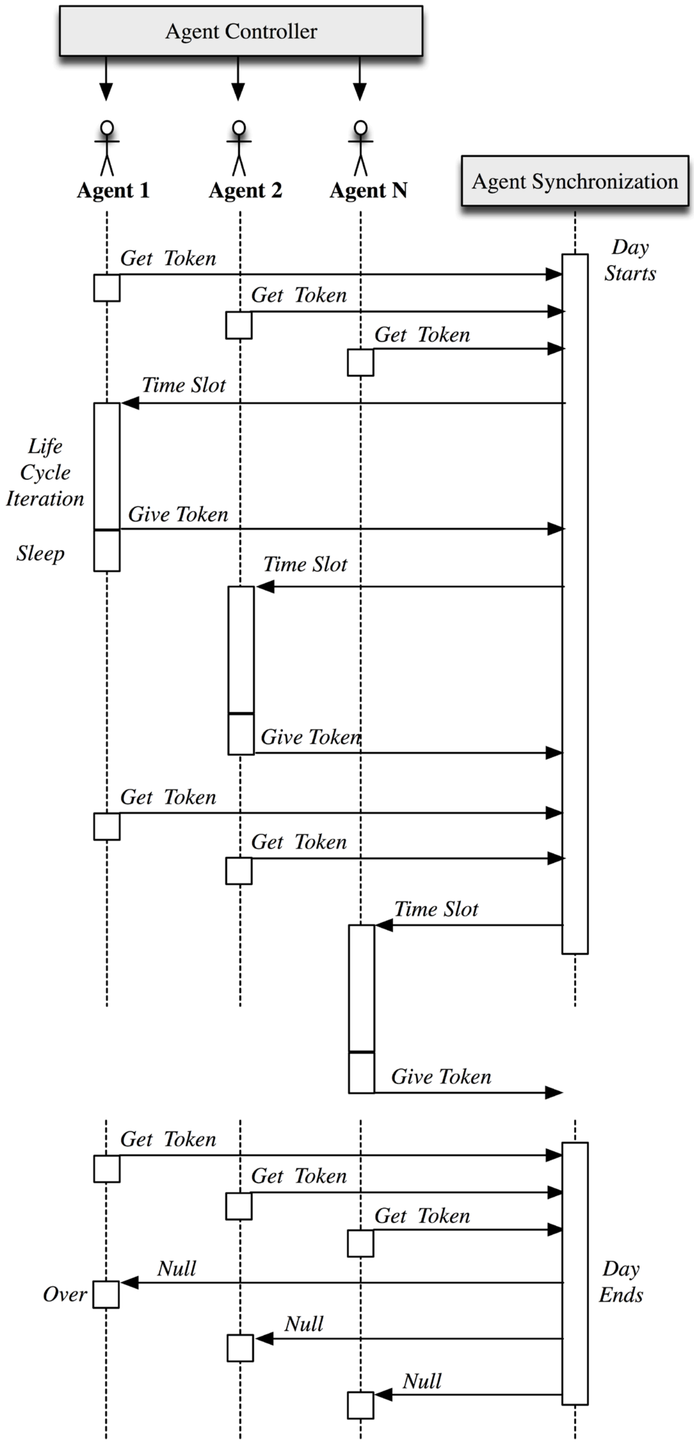

FIGURE 5-8: Actors synchronization sequence diagram

- **Inference phase**

After the agent performing an action, an event is produced and the space state is updated. That is, the facts that were valid when this agent consults the world state are no longer valid. For example, when someone switches on the lights, there is a cause and a consequence. The cause is that someone performed an action on the light's switch. The consequence is that the lights changed from off to on state. *What if a user leaves a room?* These actions could be translated into rules such as:

Rule 1	***IF*** user turns on the lights on space S_i ***THEN*** create an event ***AND*** update world's state
Rule 2	***IF*** user exits a space S_J ***THEN*** create an event ***AND*** update world's state

The update of world's state consists in updating all facts in the knowledge based that were affected by the action. In the first example, after the action, there is a new state of the lighting system. In the second example, after the action, there is a new state for the space and the user is no more on that space, that is, the state space has changed. *How is the occupant represented? And how are the building's spaces represented?* The following section will answer these questions while describing its principal characteristics.

5.3.2 Building's Occupants Representation: Actor Agent

The ***FIGURE 5-9*** depicts the implemented agent structure, which is composed of the behavioral model, its dynamics and the life cycle.

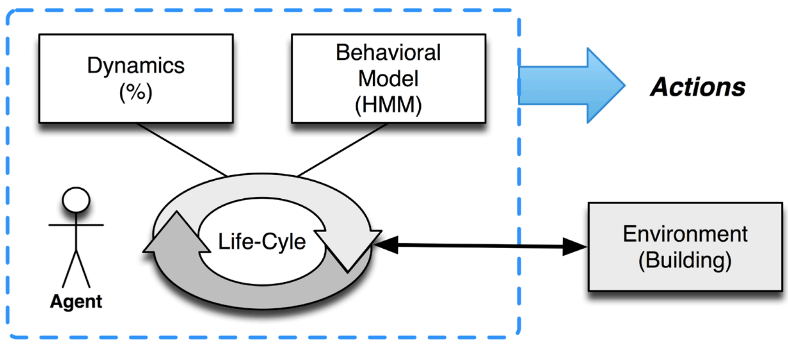

FIGURE 5-9: Actor agent structure

The behavioral model is addressed in the following section. The dynamics represent a measure of the agent movements and actions, that is, if the occupant is lazy or active. The life cycle is responsible for the agent's life. Accordingly to the current environment state, the agent will decide to do something. If this is the case than it will produce one action.

Although the behavioral model is an important aspect of the agent, the life cycle is responsible for the interaction between the agent and its environment. In this way, the implemented algorithm is illustrated in ***FIGURE 5-10***.

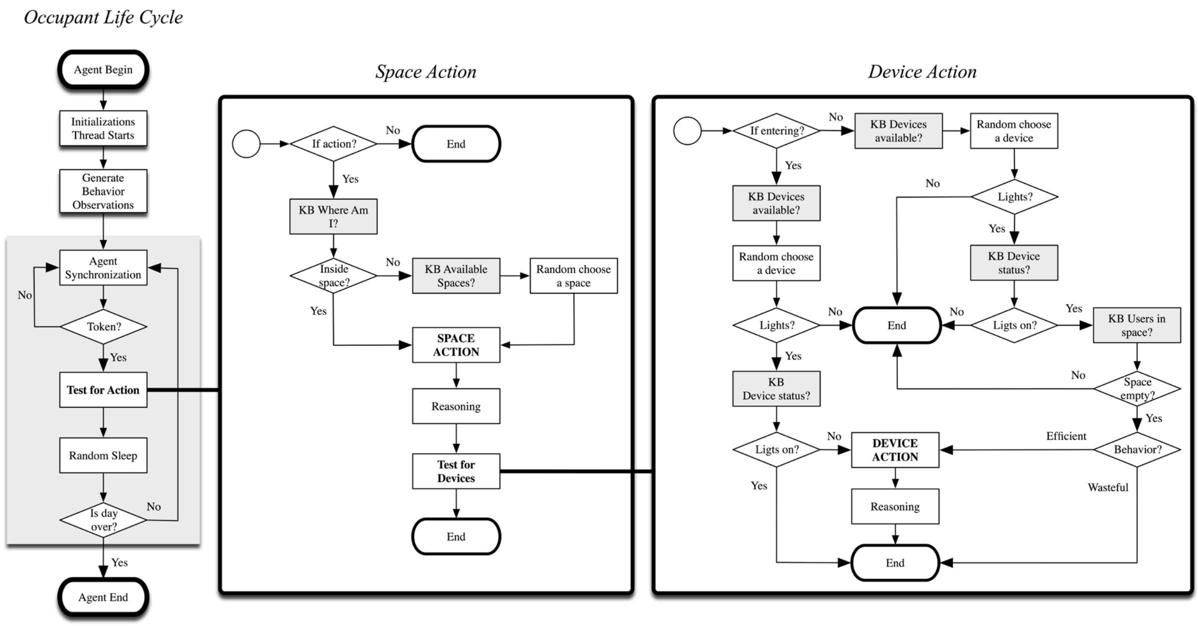

FIGURE 5-10: Actor agent life cycle flow chart

5.3.3 Occupant Behavior Modelation

As described in previous chapters, the objective is not to understand the human behavior. The objective is to reproduce how the occupant may behave. That is, when an occupant enters in a space, will he switch on the lights? Will he use some device once in the space? Will he switch off the lights when exiting a space? From this perspective, the occupant behavior is defined through the observations of his actions within the spaces and is expressed as the probability of doing something. From this perspective, the behavior modelation becomes almost natural. The hidden Markov models are a probabilistic model consisting of observable and hidden states, as described in chapter 6. The observable states represent the symbols that the model can emit and represents the actions that the occupants perform, such as: turning off the air-conditioning; modifying the thermostat level or switching on the lighting system. However, the motivations for these actions are often difficult to access or see. For example, someone's personal values, economics or even emotional states. So when building the behavioral model the non-observable states models these factors. A generic behavioral model and a concretization model are depicted in ***FIGURE 5-11***.

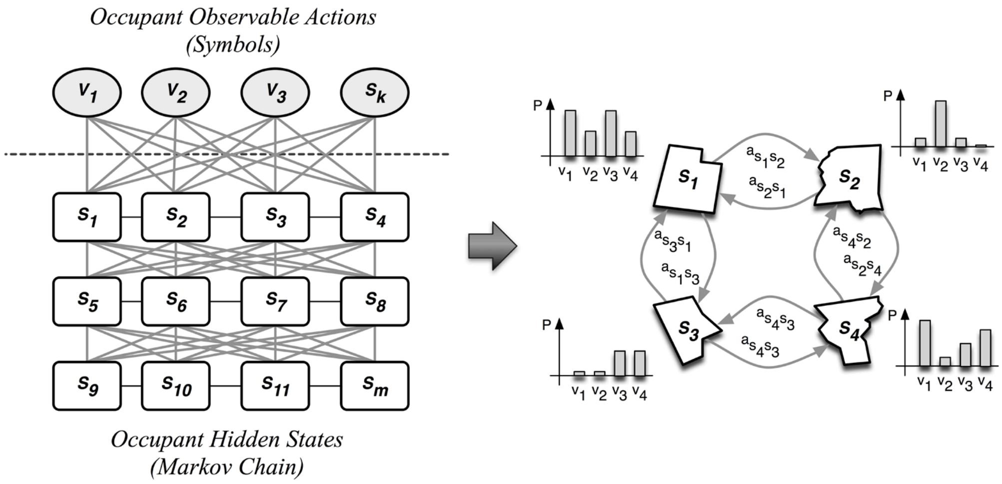

FIGURE 5-11: Example of a behavioral model described by a HMM.

However, these actions are a result of a complex behavior and are strongly depended of each occupant's education, responsibility and other factors. Because of these constrains, the occupant actions are also influenced by its current state, that is, if he is tired, sad or stressed, for example. Consequently, it is possible to characterize the occupant's behavior as a composition of observable states that represents his actions, and hidden states, which represents the complex behavior that has influenced the observed action. From this point of view, the application of a HMM to model the occupant behavior becomes intuitive. As described in chapter 4, HMM are composed of hidden and observable states. In the current modelation approach, the hidden states should be interpreted as the inaccessible human psychological states and the observable states should be interpreted as the observable behavior when performing an action.

5.3.4 Space Modelation: Space States

Uncertainty is always present when modeling, predicting and simulating systems and buildings are no exception. It arises due to many factors that affect the building's performance, which cannot be known with certainty when the building is planned, designed, built, managed and operated. Uncertainty also arrives due to the complex and unpredictable nature of human behavior.

The building is a set of spaces. In this way, ***FIGURE 5-12*** depicts a building with nine spaces and illustrates possible space's configurations as a result of the occupant's interaction with the lighting system over different time instants.

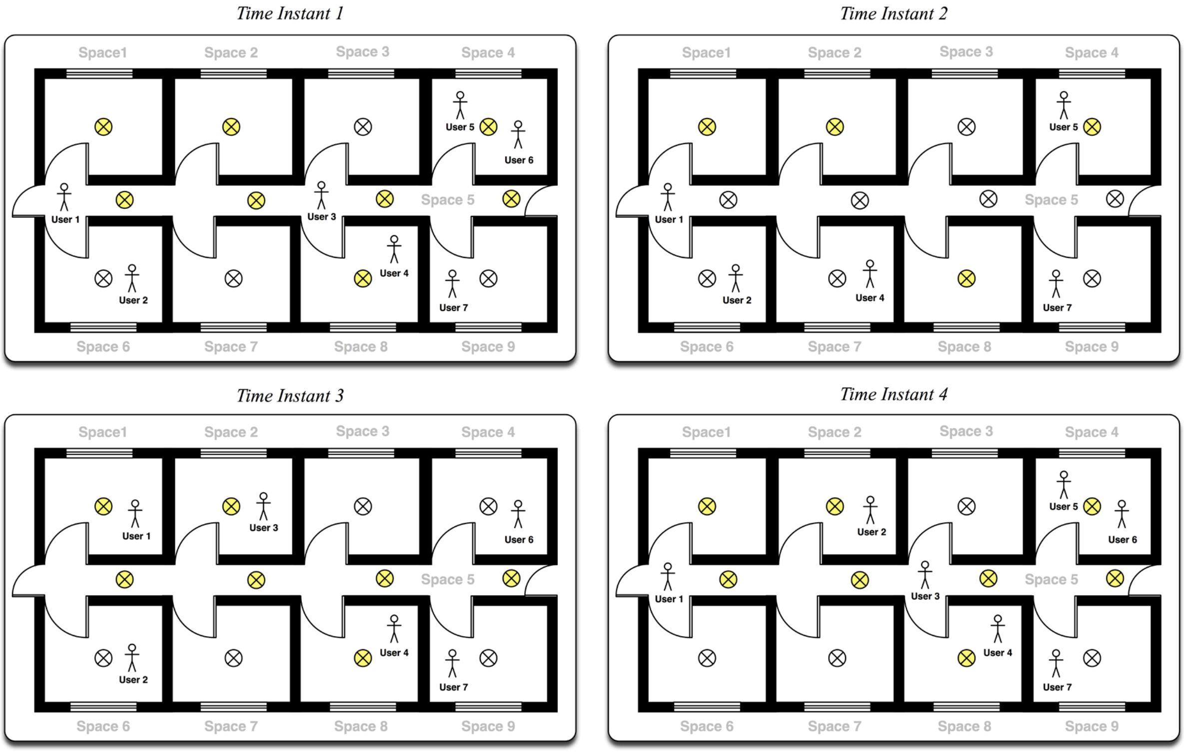

FIGURE 5-12: Possible building spaces configurations over different time instants

Given this description the spaces can be modeled using the space states approach. These states are categorized in ***FIGURE 5-13***.

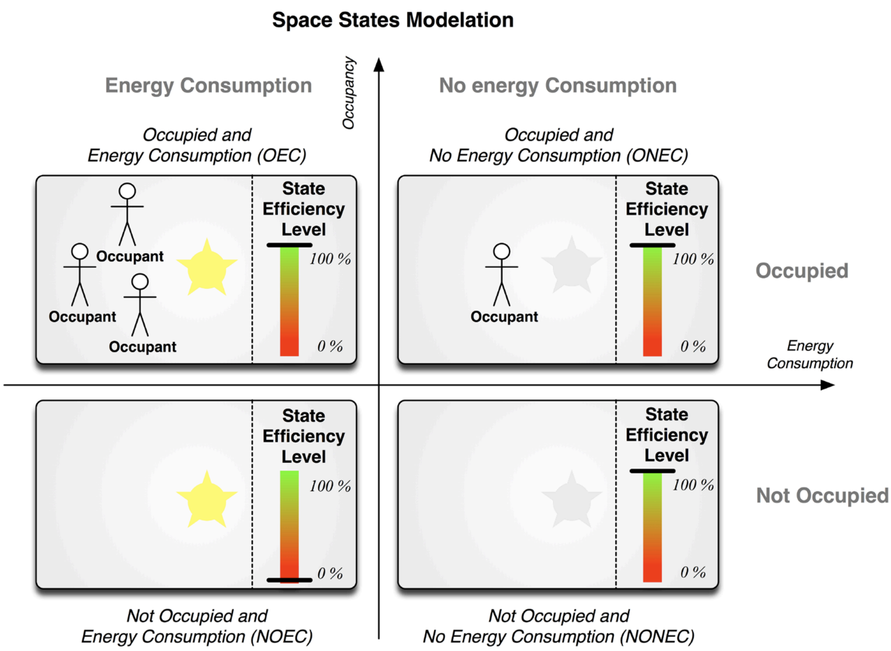

FIGURE 5-13: Interpretation of the possible space's states

These states are strongly influenced by the stochastic nature of the occupant's behavior. From this perspective, they also have a stochastic nature. *In what state is the space at a specific* *time?* To answer this question, the modeling of these spaces is made through a Markov chain, which is supported in chapter 4. A generic space model is depicted in ***FIGURE 5-14***.

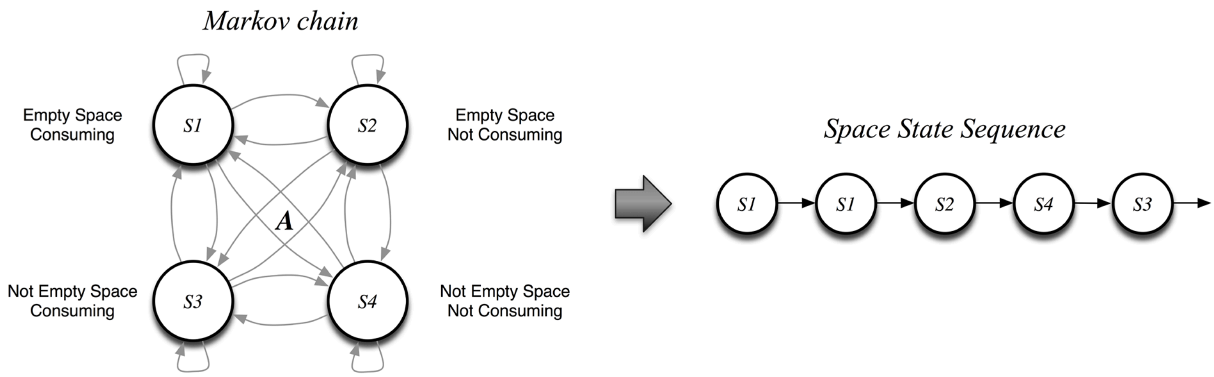

FIGURE 5-14: Generic space state model and an example of a space state sequence

For the lighting system the space model is composed of four states. The final energy consumption model (ECM), for predicting the building consumption and analyzing potential opportunities of energy savings, is a cluster of models like this one for all building spaces. *How to create this models based on the events?* This aspect will be addressed in the next section. Finally, the applicability and validation of these models is performed in chapter 6.

5.3.5 Event Processing Methodology

So far, the spaces have been described as a sequence of states. Moreover, a Markov chain as the one illustrated in ***FIGURE 5-14*** generates this sequence. In order to build the model it is crucial to have access to the space's states to be able to apply the equations **(4.5)**, **(4.6)** and **(4.7)**. That is, it is necessary to analyze the frequency of each state and the corresponding probabilities. Furthermore, it is also necessary to calculate the probabilities of the state transitions. When comparing these steps with ***FIGURE 5-14***, the process is the calculation of the stochastic matrix $\boldsymbol{A}$, as introduced in ***FIGURE 4-4***. The space model can be described as:

$$\begin{cases} x(k+1) = \boldsymbol{A}x(K) \\ \quad y(k) = \boldsymbol{C}x(k) \end{cases} \tag{5.1}$$

In equation **(5.1)**, the matrix $\boldsymbol{A}$, is the *space transition matrix*, where the spaces belongs to space set $\boldsymbol{S} = \{s_1 = OEC, s_2 = ONEC, s_3 = NOEC, s_4 = NONEC\}$. The matrix $\boldsymbol{C}$, is the *output matrix*, and it represents the state $x(k)$ contribution for to the space energy consumption y. In this way, the problem is that the available information about the building is a collection of events and not information about the building spaces states. In order to solve this problem, an algorithm has been developed and it is referred to as *frame-scene decomposition algorithm*. This algorithm is implemented in the pattern extractor block of the MAPEM. The ***FIGURE 5-15***, depicts the inputs and outputs of this module while introducing some concepts adopted.

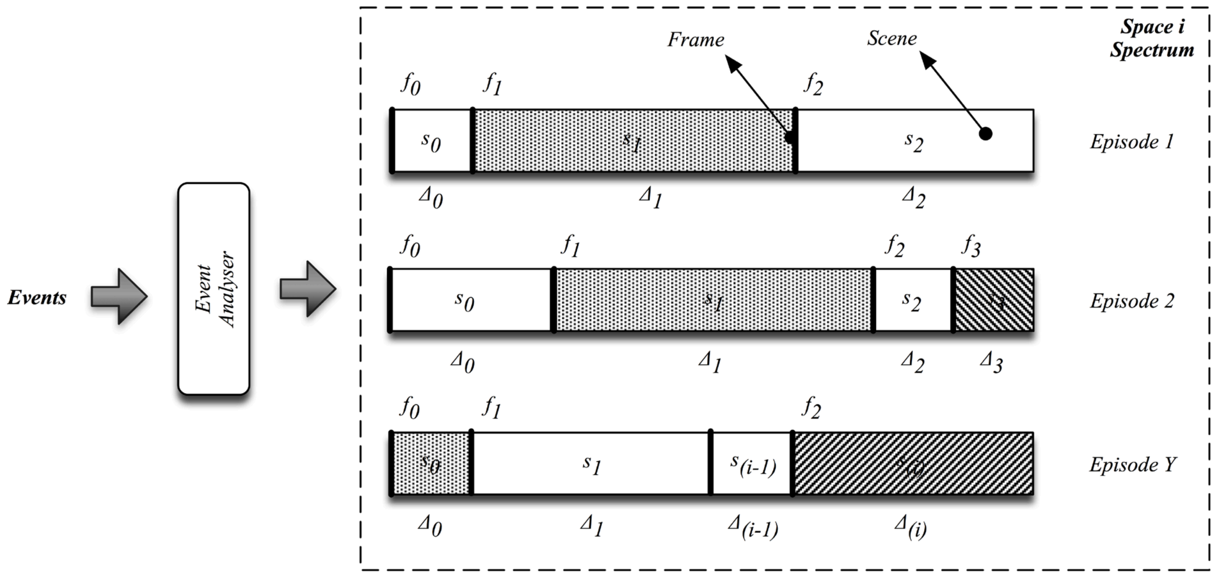

FIGURE 5-15: Block diagram of the frame-scene decomposition algorithm

This algorithm was inspired by the work in (Wada & Matsuyama, 2000) that regards to behavior recognition in a video sequence. The ***FIGURE 5-15*** introduces a few new concepts such as: *frame*; *scene*; *episode* and *spectrum*. *What are these and what does it have to do with video analysis?* As mentioned above, the concept of event is a modification of the knowledge base facts, which is translated as a modification in the state of the world. More specifically, it represents a modification of the space configuration. Given this, a *frame* is interpreted as a snapshot of a space at one instant. In this way, a frame corresponds to a space configuration at one instant. Moreover, it is important to consider that physical systems and humans have a latency period. This implies, that most probably a frame will be valid for a few number of instants. This leads to the concept of *scene*. A *scene* is an extension of a frame over a time period. In this way of thinking, a sequence of actions will originate a sequence of scenes. *What if two actions occur in the same time instant?* That would raise the creation of two different frames for the same time instant, which leads to a conflict. To avoid this from happening, the token ring system was implemented that only allows one occupant at a time as described in the simulation methodology section. Finally, one *episode* is a sequence of scenes during one day and the *spectrum* is the sequence of episodes during the simulation period as depicted in ***FIGURE 5-16***.

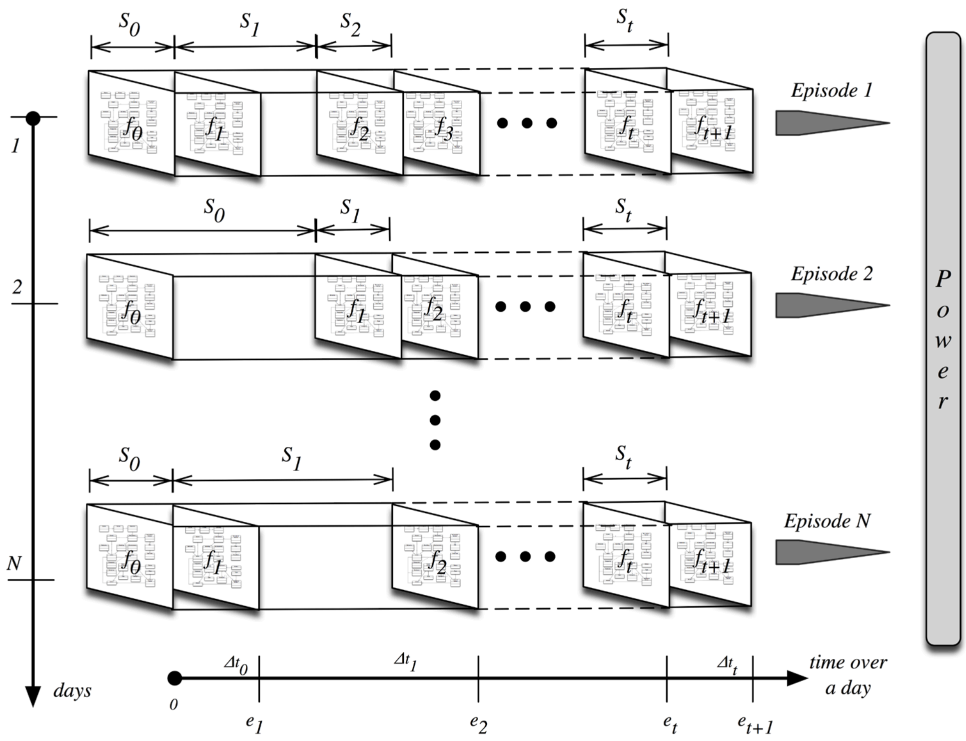

FIGURE 5-16: Spectrum illustration in the frame/Scene decomposition algorithm

After running this algorithm for all spaces, it is almost possible to construct the Markov model for each one of them. But, *what is the relation between the states and scenes?* As stated above, the day is divided into time slots, and in each time slot a space state is observed. However, a scene is the time in which a frame is valid, and this occurs between two events. So, in this line of thought, a scene is a range of states. With this method, a sequence of states is now available for each space. After constructing the spectrum for the spaces, *what is next?*

In this models it is assumed of existing stationarity, that is, the system may evolve in time, but its parameters are static, such as state transitions distribution. Because the objective is not to learn a specific signal, but to learn its parameters, the obtained data was divided into two clusters. One cluster is for model estimation and the other one is for model validation, as illustrated in ***FIGURE 5-17***. After the process of creating the space's spectrum, the episodes are divided in half for creating the estimation and validation clusters. The estimation cluster is for train the ECM and the validation cluster is to verify the adaptability of the model by comparing the models predictions with the measures.

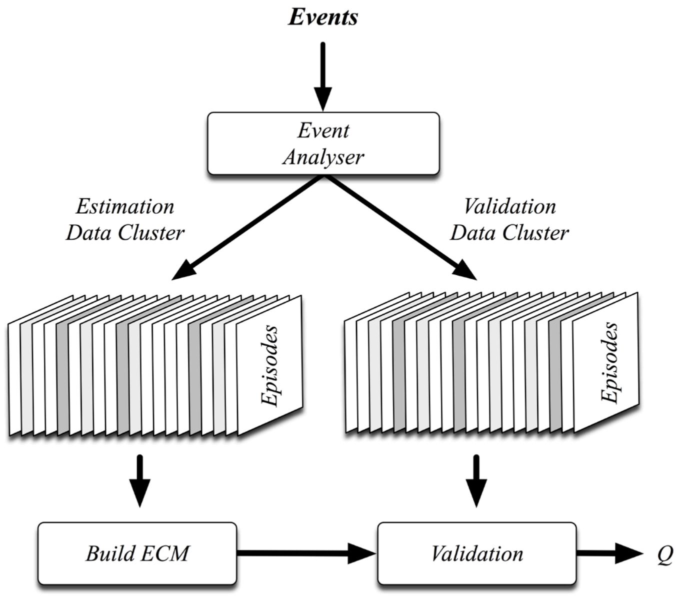

FIGURE 5-17: Estimation and validation data clustering process

5.3.6 Energy Consumption Model

The building is composed by spaces and each space is modeled with a Markov chain. Therefore, the energy consumption model is a combination of the Markov chains for all spaces, that is:

$$ECM = \bigcup_{i=1}^{Spaces} MC_{s_i} \tag{5.2}$$

This research focuses a special case for illustrating the methodology applicability, in which just the lighting system is considered. *What if the space has more devices, such as, computers or HVAC systems? What if the building has elevators and escalators?* This ECM can be extended to account for these devices. This leads to a transformation of the presented concept of the ECM into a multi-stochastic model, that is, a combination of multiple ECM. Instead having one ECM associated with the space, the ECM can be associated with each device, and the space model would be a multi-ECM **(5.3)**. For each instant, the current state would be a combination of all ECM states. To accomplish this goal, two fundamental transformations are needed. Firstly, for simulation proposes, the domain of the behavioral model must be augmented. That is, for each new device more emitted symbol must be defined. Secondly, for each new device, a space state model is required.

$$multiECM = \bigcup_{i=1}^{Spaces} ECM_i = \bigcup_{i=1}^{Spaces} \bigcup_{j=1}^{Devices} MC_{s_{ij}} \tag{5.3}$$

Finally, in order to account for energy efficient technologies adoption, the model could be described as:

$$\begin{cases} x(k+1) = \boldsymbol{A}x(K) + \boldsymbol{B}u(k) \\ y(k) = \boldsymbol{C}x(k) + \boldsymbol{D}u(k) \end{cases} \tag{5.4}$$

That is, the new technology would have an impact in the space state and a direct impact in the overall energy consumption. One interesting approach is the utilization of the rule expert system to model these direct and indirect effects.

5.3.7 Building's Energy Prediction

The building's energy consumption prediction is based on the analysis of the ECM. It must be remembered that the ECM is the cluster of all MC models of the building spaces, as specified in equation **(5.2)**. In order to predict the energy consumption, first is necessary to predict the space's states for all spaces. Since the ECM is a non-deterministic model, that is, a stochastic model, in each space states sequence prediction, a new sequence will be produced, as illustrated in ***FIGURE 5-18***.

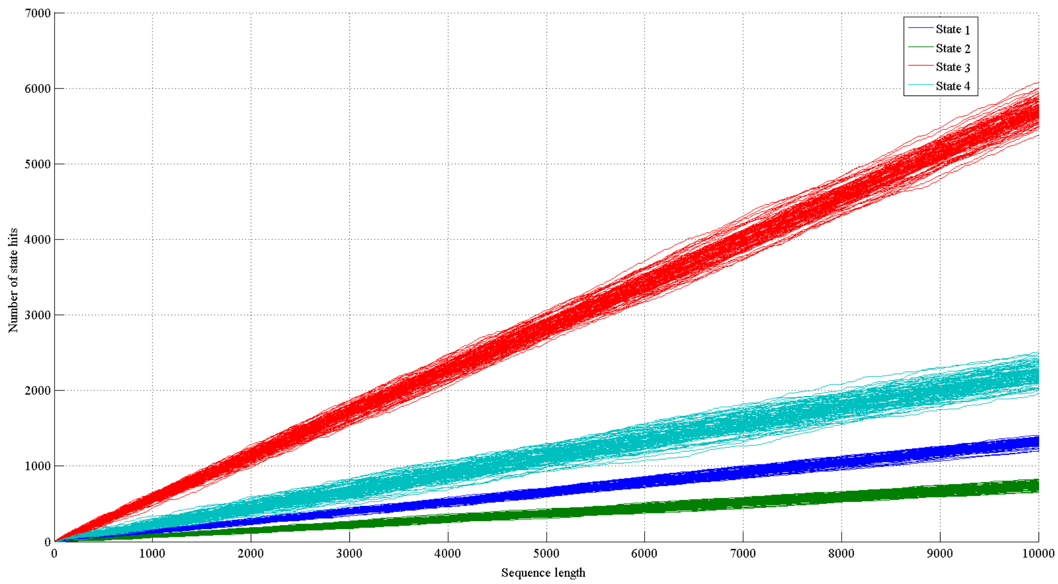

FIGURE 5-18: Simulation of a Markov chain with four states over 10000 steps for state analysis

In this figure, this characteristic is illustrated with a Markov chain simulation composed with four states (red, green, cyan and blue). This model was used for predicting 100 sequences of 10000 states each and represents the sum of each predicted state as a function of the state sequence length over various simulations. Applying the same methodology as before but at each instant diving by the corresponding sequence length, the results are illustrated in ***FIGURE 5-19***. In this case, the figure represents the cumulative state distribution, and the convergence to a certain distribution, that is, convergence to the stationary state distribution, as introduced in chapter 4 and illustrated in ***FIGURE 4-6*** and ***FIGURE 4-7***.

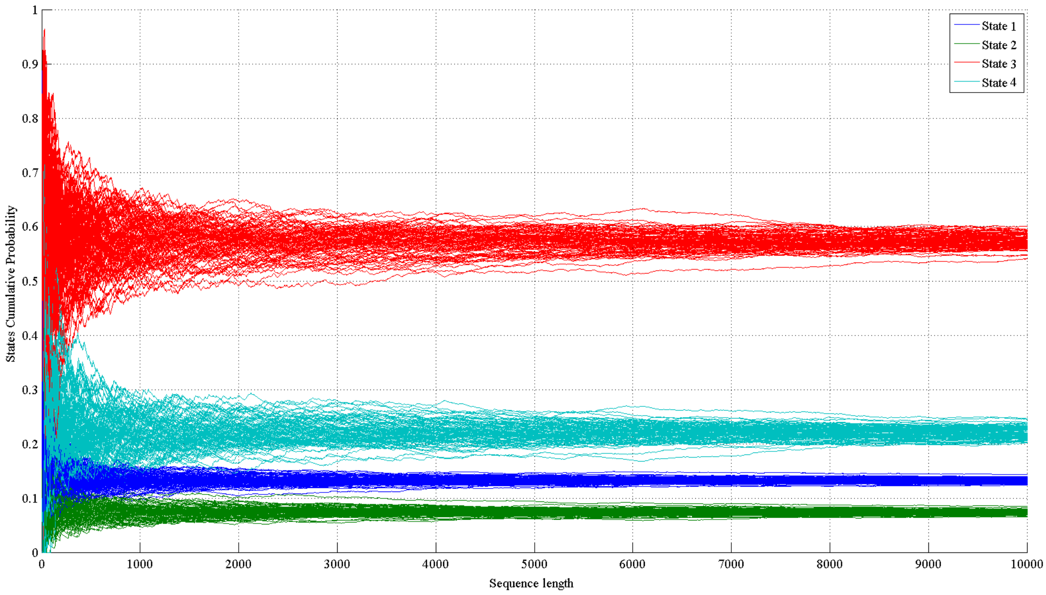

FIGURE 5-19: Simulation of a Markov chain with four states over 10000 steps for stationarity analysis

The important analysis of ***FIGURE 5-18*** and ***FIGURE 5-19*** is that different simulations result in different state sequences. This is a consequence of the randomness nature of these models. Since these models are used for prediction purposes, this is a problem. The outcome of the analysis cannot depend on the instant in which the analysis is performed, that is, the analysis made in one instant must be same in any instant. Moreover, since the same model produces different state sequences with the same parameters, a few questions arise: *How to repeat the same state sequence in different simulations?* And, *what is the best state sequence?*

One important aspect in computation is that, usually, for dealing with random numbers, a pseudo-random number generator (PRNG) is used. This applies an algorithm for generating a sequence of numbers that approximates the properties of random number. One fundamental condition of this algorithm is that a PRNG can be started from an arbitrary starting number, called the *seed*, and it will always produced the same sequence as long as initialized with the same seed. So, to achieve a random number generator, the key is to use different seeds. In the ***FIGURE 5-18***, although were used the same model over the simulations, each simulation applied different seeds. So, in order to solve the previously sated problems, the solution is to discover the best seed for each model and associate that seed with the respective model. That is, under the same initial conditions, a non-deterministic process becomes a deterministic one, where each model simulation results in the same output. Given this, *how to discover the best seed?* And, *how to measure the accuracy of an ECM state sequence prediction?* In (Yalcintas, 2008) the following error measurement parameters were used in evaluating the performance of the their model. Since they provide useful information for the developed ECM model validation, they also will be applied in the ECM model. The error measures are:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{5.5}$$

$$RMSPE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}}{\bar{y}} \tag{5.6}$$

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5.7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{x_i}\right| \tag{5.8}$$

In the above equations, RMSE is the root mean square error, RMSPE is the root mean square percentage error, R is the correlation coefficient, and MAPE is the mean absolute percentage error. The parameters x_i are measured data, y_i are the ECM model predictions, n is the number of data points, $\bar{x}$ is the mean value of the measured data and $\bar{y}$ is the mean value of the ECM model predictions.

To deal with this problem two algorithms have been developed. The first one is static (1), and calculates a seed using the model parameters (*open-loop*). The second one is dynamic (2), and searches the best seed accordingly to a metric (*closed-loop*). To resume, the first algorithm solves the non-determinism issue by transforming the model in a deterministic model. The second algorithm, not only do the same as the previous algorithm but also addresses the problem of discovering the best state sequence in a specific context.

1. *Static algorithm for seed discover*

The objective of this algorithm is to associate a seed with a model in a direct way, illustrated in ***FIGURE 5-20***.

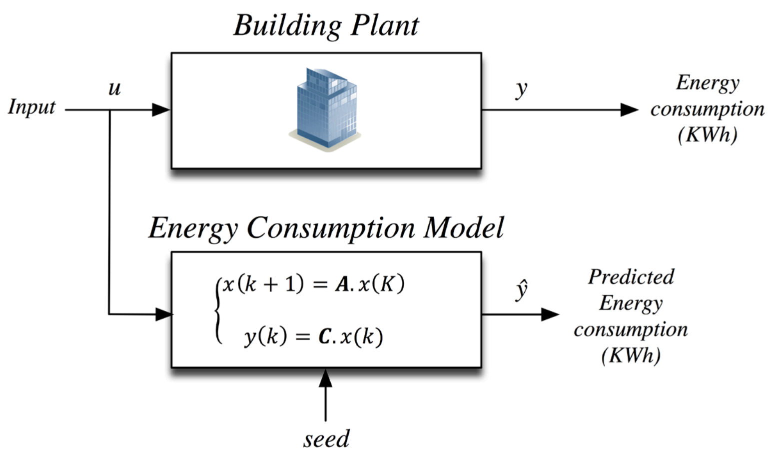

FIGURE 5-20: Functional block diagram illustrating the seed discover static algorithm

This algorithm calculates the seed as follows: Consider the state transition matrix $\boldsymbol{A}$.

$$\boldsymbol{A} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mn} \end{bmatrix} \tag{5.9}$$

The seed is calculated as,

$$\text{seed} = 1000 \times \sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij} \tag{5.10}$$

The advantage of this algorithm is that it can be directly executed just by looking at the model parameters, and in this way, the seed can be considered as a property of the model. However, the drawback is that this algorithm does not consider any output feedback and thus the obtained sequence could be the worst-case prediction.

2. *Dynamic algorithm for seed discover*

The objective of this algorithm is to account with the model output feedback, illustrated in ***FIGURE 5-21***.

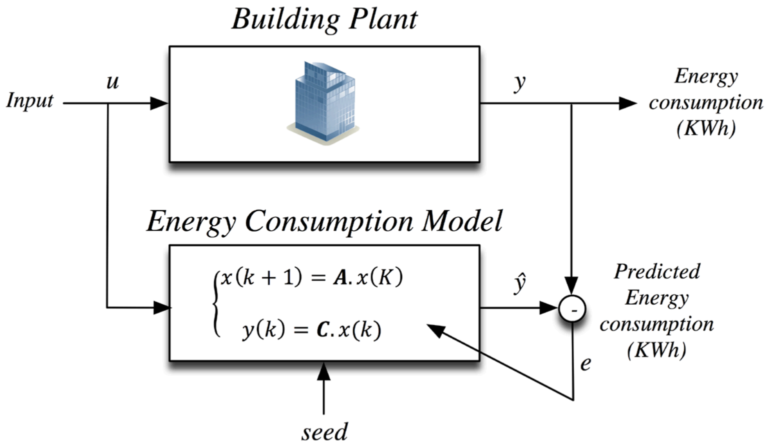

FIGURE 5-21: Functional block diagram illustrating the seed discover dynamic algorithm

The goal is to select the best seed within an interval that minimizes some metric in order to achieve the optimal state sequence. One important question when considering the optimal state sequence is, *what is the optimal state sequence?* In this research, the optimal state sequence is the one that minimizes the RMSE (root mean square error) or, in percentage, RMSPE (root mean square percentage error). Additionally, it also has to minimize the quadratic error between the validation data and predictions. In this way, the optimal state sequence can be described as follows:

a) Root mean square percentage error,

$$RMSPE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}}{\bar{y}} \tag{5.11}$$

b) Validation data and predicted state distribution parameters quadratic error,

$$QE = \sum_{k=1}^{States} \left(P(\overline{s_k}) - P(\widehat{vs_k})\right)^2 \tag{5.12}$$

Finally, these metrics in **(5.11)** and **(5.12)** can be combined as.

$$seed^{*} = \underset{seed_k}{\operatorname{argmin}} \left\{ \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}}{\bar{y}} \right\} \cap \underset{seed_k}{\operatorname{argmin}} \left\{ \sum_{k=1}^{States} \left(P(\bar{s_k}) - P(\widehat{vs_k})\right)^2 \right\} \quad (5.13)$$

After specifying the dynamic algorithm, the building energy consumption can be calculated as,

$$\mathrm{P_{BEC}} = \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{EC_{Space_i}} \quad (5.14)$$

Where the variables in **(5.14)** have the following meaning:

$\mathrm{P_{BEC}}$ = Predicted building energy consumption

$\mathrm{EC_{Space_i}}$ = Energy consumption of space i

N = Number of spaces in the building

Additionally, the energy consumption of space i ($\mathrm{EC_{Space_i}}$) is calculated as,

$$EC_{Space_i} = \sum_{i=1}^{N} \sum_{k=1}^{S} \left(\frac{P_{\mathrm{ik}}}{1000} \frac{\Delta_{ik}}{1000 \times 60 \times 60} \right) (KWh) \quad (5.15)$$

Where the variables in **(5.15)** have the following meaning:

P_{ik} = Power of the state k of the space i

Δ_{ik} = Number of predicted states

N = Number of spaces in the building

S = Number of states for space i

After describing the implemented methodologies and specifying the algorithms, the next chapter presents some simulations results based on the developed prototype that supports all the methodologies and algorithm models described in this chapter.

6

Simulation Results

In this chapter, some simulations results are presented. These results are performed in the developed prototype.

6.1 Introduction

The simulations are performed in the developed framework prototype and are executed in different buildings under different initial conditions. In the implementation chapter the methodology, algorithms and models were discussed. This chapter will be concerned with the model's applicability, interpretation and validation. The simulation's features consist of the building, occupants, occupant's behavioral model and simulation time analysis. After the simulation, the produced data is modeled and the building's spaces occupancy is analyzed. The outcome is to predict the building energy consumption and analyze the spaces occupancy, which is directly reflected by the type of usage given by the building's occupants. Moreover, the opportunity of improving the energy consumption is discussed.

The ***FIGURE 6-1*** represents the analysis of the building's energy consumption and the simulations goals. By changing the type of behavior that the occupants have within the building, there will be more or less wasted energy. In this context, in one extreme there will be scenarios were the occupants have an efficient behavior, which correspond to an efficient scenario where the potential energy savings are expected to be low or even zero. In the other extreme, there will be scenarios were the occupants have wasteful behavior, that corresponds to an inefficient scenario where the potential energy savings are expected to be maximized. Moreover, other scenarios are between these two, in which the occupants have a mixture behavior and the potential energy savings are expected to be greater than zero.

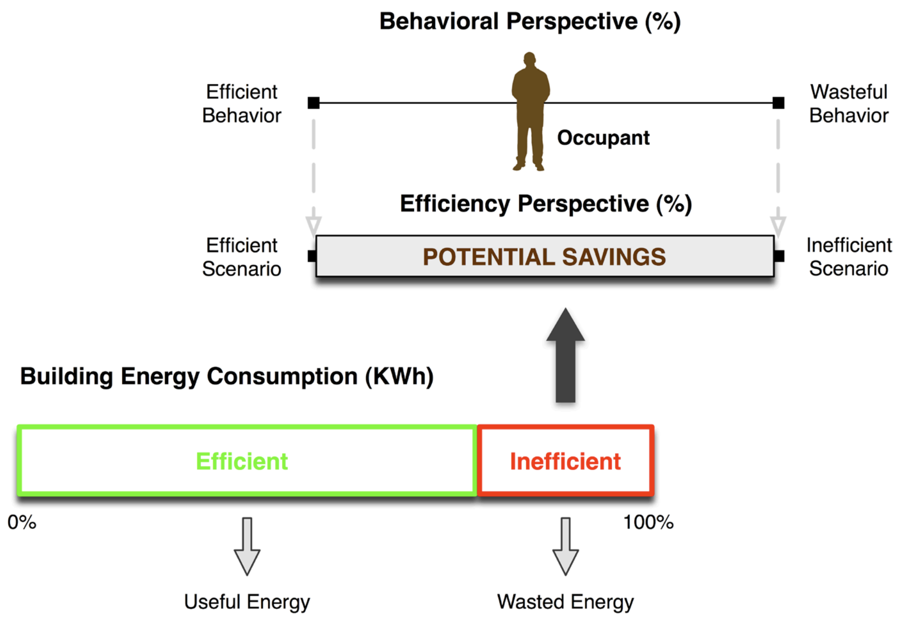

FIGURE 6-1: Analysis of the building energy consumption and expected simulation analysis

6.2 Simulations

The simulations are focused on state prediction and analysis. In order to simplify this process, the different possible states are numbered and shown in ***TABLE 6-1***.

TABLE 6-1: Description of the space's states

State	State Description
1	Non occupied space with energy consumption
2	Non occupied space with no energy consumption
3	Occupied space with energy consumption
4	Occupied space with no energy consumption

One important question is, *how is the building represented?* The ***FIGURE 6-2*** depicts the static domain in a class diagram used for representing the building model.

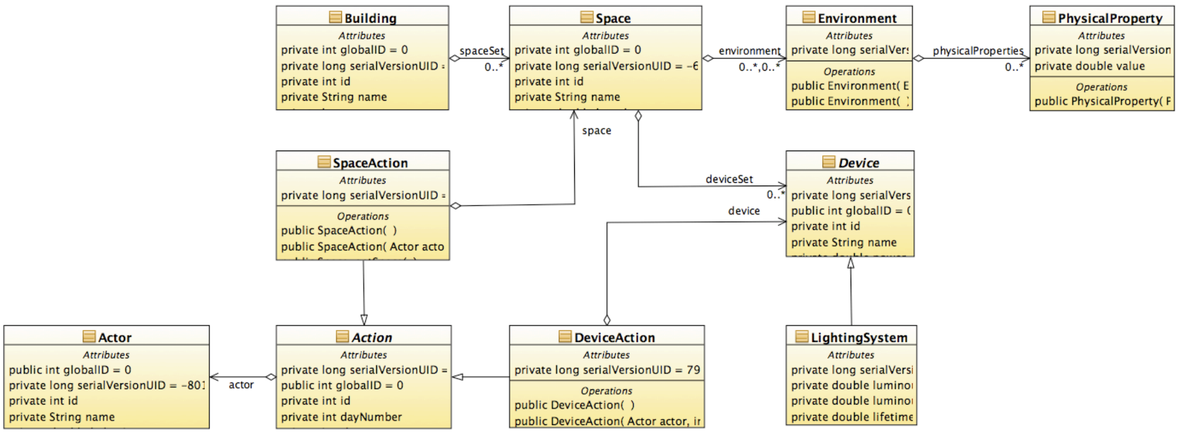

FIGURE 6-2: Static domain for the building

Here, the simulations are performed across three different buildings, which are described in ***TABLE 6-2***. As mentioned in previous chapters, the focus will be the interaction with the lighting system. Consequently, each building space is just equipped with the lighting system and is represented by LS.

TABLE 6-2: Simulated buildings compact description

Building	N. º Spaces	Device	Power W/space	Total Power (W)
A	1	LS	1000	1000
B	4	LS	$1000{*}2^{i-1}$	9000
C	50	LS	Variable	-

The reasons for chosen these buildings are: Building A has one space for testing the model predictions in the simplest case where the ECM has just one Markov chain; Building B has four spaces to allow a detailed analysis of each one of the four Markov chains: Finally, building C has 50 spaces to verify the performance and scalability of the ECM. In this case, the ECM is composed of 50 Markov chains.

The next sections will focus on different occupancy scenarios using the same building for each cluster of simulations.

6.2.1 Simulations on Building A

This section is divided into multiple simulations with the objective of representing different occupancy patterns of the building A, in order to validate the energy consumption model predictions. The simulations conditions are specified in ***TABLE 6-3***.

TABLE 6-3: Simulation conditions specification for building A

Simulation	Analysis Period (Days)	Number of Occupants	Occupant Behavior	Number Time Slots	Time Slot Size (Min)	Number of events
A.1	360	2	Pure efficient	48	30	2722
A.2	360	2	Pure wasteful	48	30	1863
A.3	360	2	Mixture Behavior	48	30	3194
A.4	360	2	Pure efficient + Pure wasteful	48	30	5558

The next se will present the results for each simulation. Furthermore, these results will be compared in the last point.

- ***Simulation A.1 conditions:***

The purpose of this simulation is to represent a purely efficient behavioral scenario. In this scenario is expected no energy waste, which results in no opportunity for energy savings measures. This must be reflected in the energy consumption through the elimination of the wasted energy portion, as illustrated in ***FIGURE 6-1***. Given these simulation conditions, the ***FIGURE 6-3*** illustrates the simulator output representing the building's energy consumption measurements.

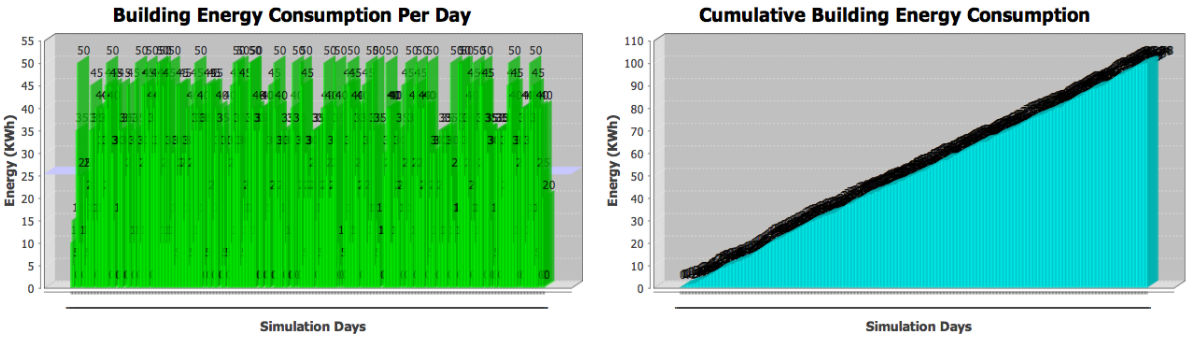

FIGURE 6-3: Prototype output for the building energy consumption over a period of 360 days

In the ***FIGURE 6-3***, on the right is depicted the building's energy consumption per day and on the left is depicted the cumulative energy consumption over the 360 days. This means that the value set at day 360 is the total building's energy consumption. After the simulation, the first step is to build the model as described in the previous chapter. For this simulation, the resulting ECM is depicted in ***FIGURE 6-4***.

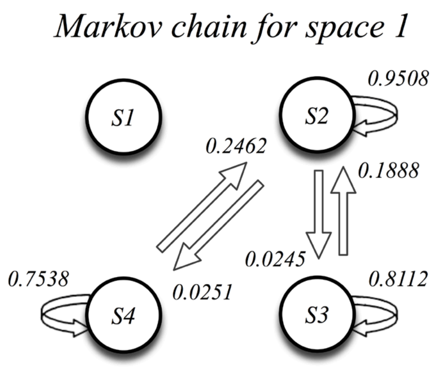

FIGURE 6-4: Building A ECM for simulation A.1

As described in the previous chapter, due to the nature of these models, each time they are simulated they produce a different state sequence. This characteristic for the obtained ECM is depicted in ***FIGURE 6-5***. The *red line* represents the building's cumulative energy consumption. All the others represent predictions with the ECM. Even though the presented predictions were produced with the same model they differ between them, which results in poor and unreliable energy predictions. The *blue lines* represent predictions when applying a random seed for the model. The *black line* represents the prediction when applying the static algorithm for seed calculation. Finally, the *green lines* represent the predictions when applying the dynamic algorithm for seed discover.

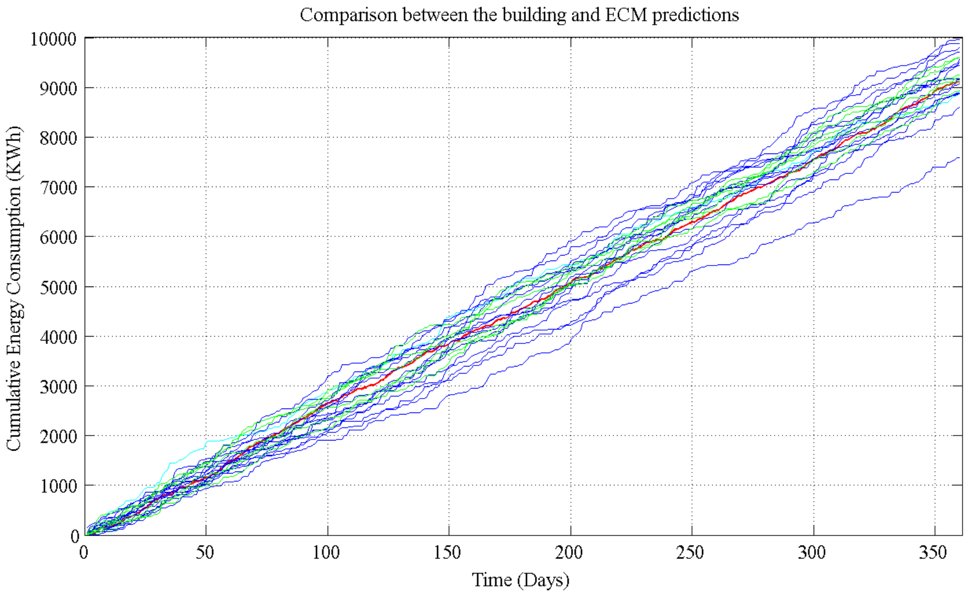

FIGURE 6-5: Comparison between the building measures and ECM predictions

As illustrated in ***FIGURE 6-5*** the seed is an important factor to have in consideration when using these models. To help make the decision, an analysis based on the RMSPE (root mean square percentage error) is performed. This metric was calculated for all the simulations and is illustrated in ***FIGURE 6-6***. The bar's color is mapped with the previous description.

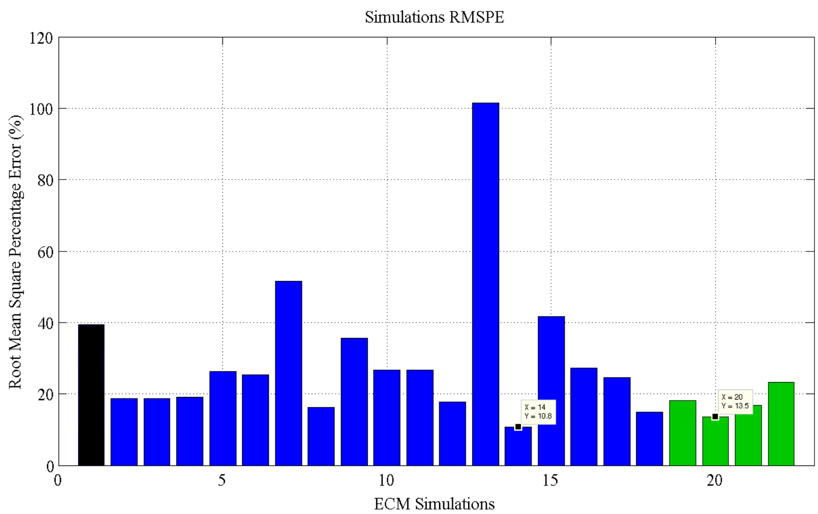

FIGURE 6-6: Calculation of the RMSPE metric for the simulations in A.1

As shown in ***FIGURE 6-6***, the static algorithm seed provided a state sequence with a RMSPE of almost 40%. When considering the dynamic algorithm the RMSPE is below 20%. This value is not the minimum value because with a random seed smaller values can be achieved. However, since a random seed is not the solution because it does not provide a way of replicate the prediction, the dynamic algorithm provides a solution between the two alternatives. Given the seed provided by the dynamic algorithm and resultant state sequence, ***FIGURE 6-7*** illustrates the energy consumption model output representing the building's energy consumption prediction. When comparing this prediction with the building measures in ***FIGURE 6-3***, the daily predictions differ, although the energy patterns are similar. In spite of this first result being slightly disappointing, one interesting characteristic is that both the building measurements and predictions have an equal average energy consumption of approximately 25 KWh.

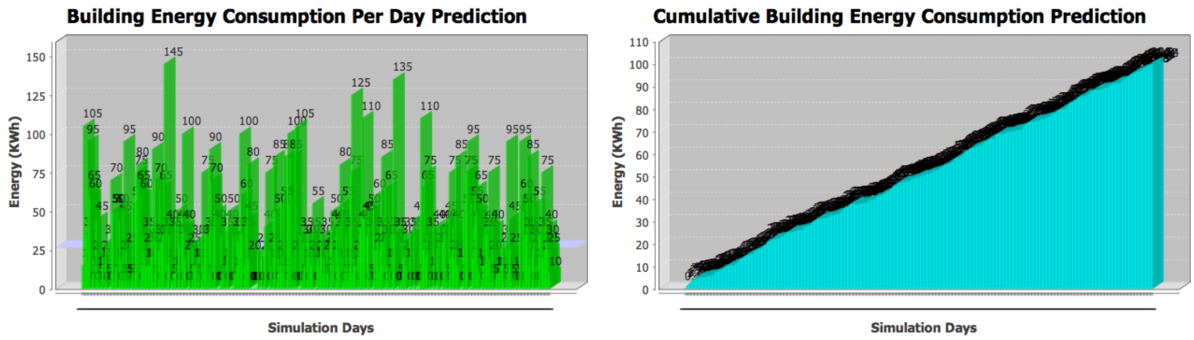

FIGURE 6-7: Prototype output for the building energy consumption prediction with ECM over a period of 360 days

The ***FIGURE 6-8*** illustrates the building energy measures and the ECM predictions. The result shows that the ECM prediction follows the building consumption. This indicates that although the predictions are locally different, when analyzing globally they provide a reliable energy prediction.

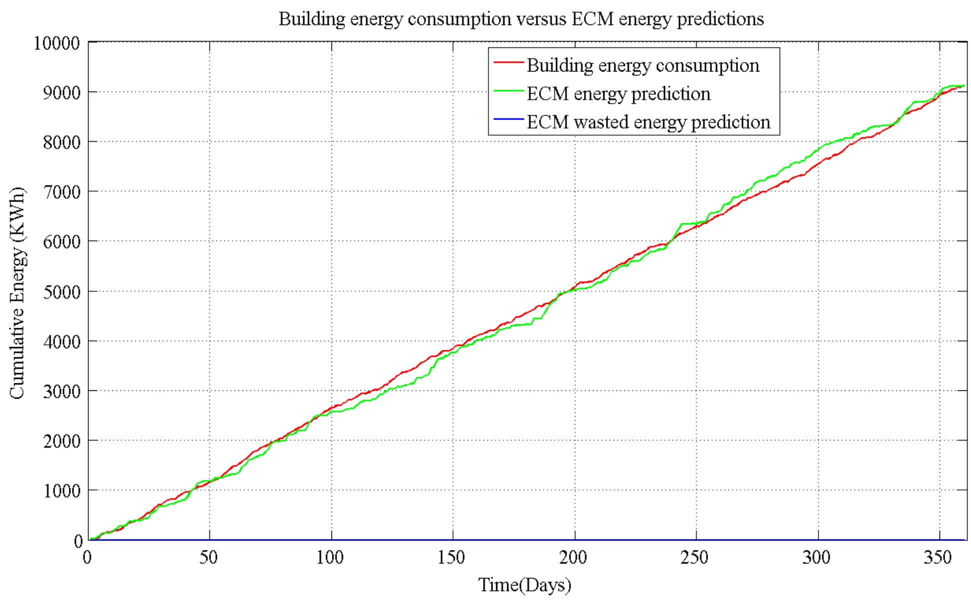

FIGURE 6-8: Comparison between building energy consumption and ECM predictions and potential energy savings

Moreover, since the simulation is based on a pure efficient behavior, this means that no energy waste was expected. This characteristic is predicted by the model and is represented in ***FIGURE 6-8*** through the continuous blue line at zero.

- ***Simulation A.2 conditions:***

The purpose of this simulation is to represent a purely wasteful behavioral scenario. This scenario represents the opposite of the previous scenario in the sense that the wasted energy is maximized.

The ECM predictions are depicted in ***FIGURE 6-9***. These predictions are similar in the way that they do not differ and follow the building's energy consumption. This is justified due to the nature of the occupant behavior. In this behavioral scenario, once the lighting system is switched on it will permanently remain turned on. As a result, the space will stay in an energy consuming state and the model just transits between two states, both consuming energy.

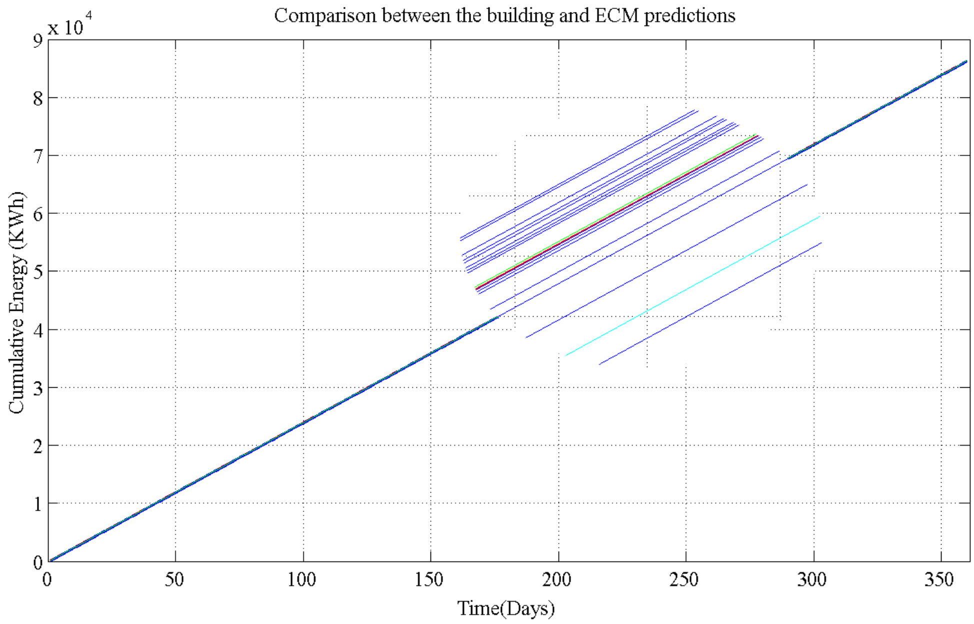

FIGURE 6-9: Comparison between the building measures and ECM predictions

Additionally, ***FIGURE 6-10*** illustrates the building energy measured and the ECM prediction along with the predicted wasted energy. As expected, the wasted energy represents a large percentage of the energy consumption when comparing to the total predicted. Consequently, other behavioral scenarios should waste less energy than this one.

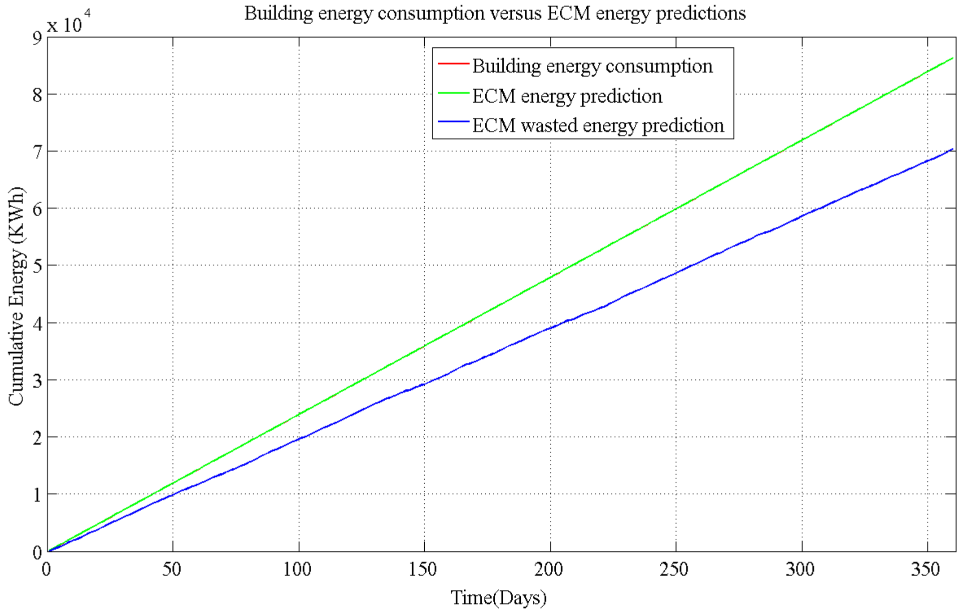

FIGURE 6-10: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulation A.3 conditions:***

The purpose of this simulation is to represent a mixed behavioral scenario (a combination of efficient and wasteful behaviors). The predicted wasted energy is expected to be between the wasted energy in previous scenarios. The ECM predictions are depicted in ***FIGURE 6-11***.

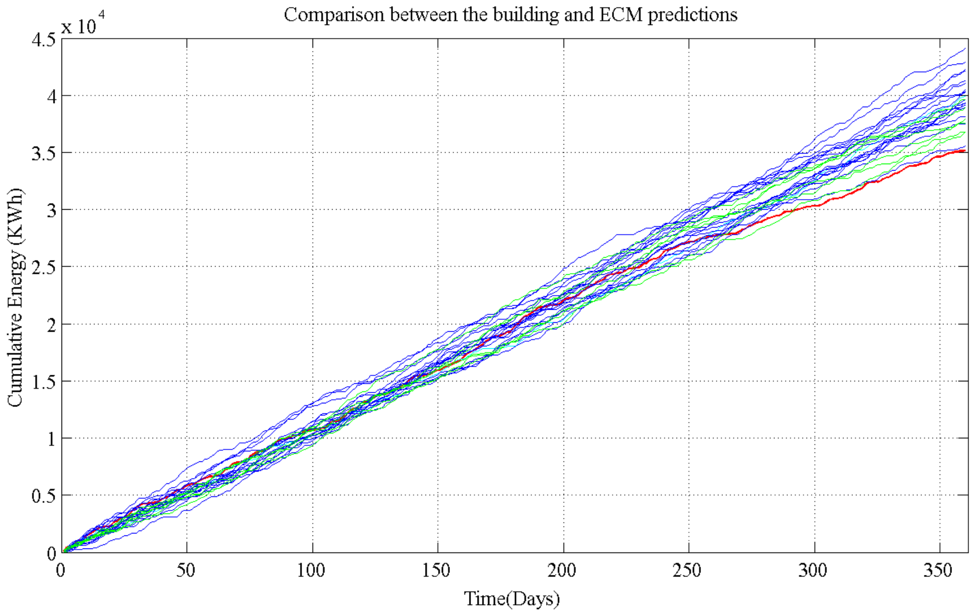

FIGURE 6-11: Comparison of Building and ECM energy consumption measures

Moreover, ***FIGURE 6-12*** illustrates the building energy measures and the ECM prediction along with the predicted wasted energy.

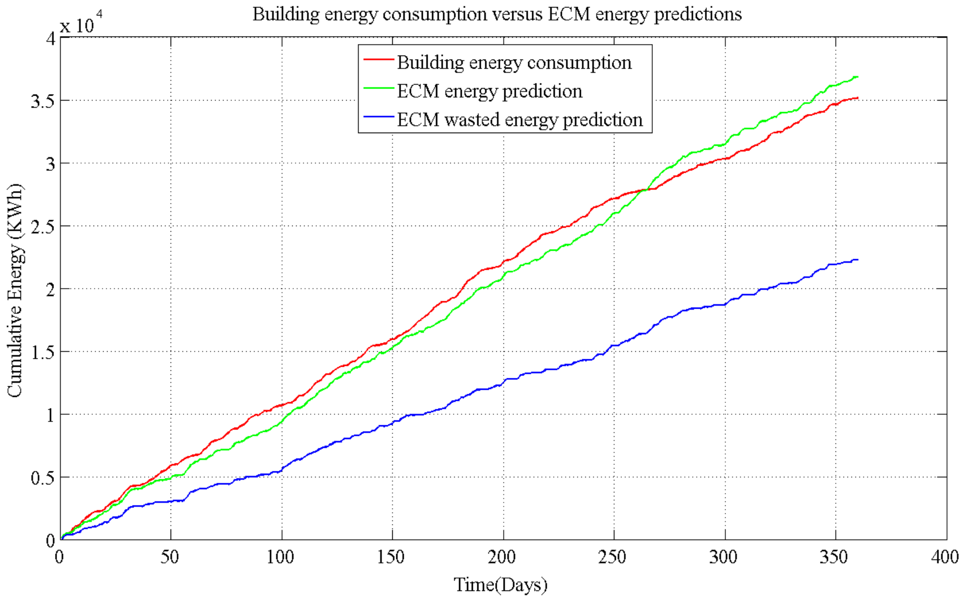

FIGURE 6-12: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulation A.4 conditions:***

The purpose of this simulation is to represent a hybrid behavioral scenario (pure efficient and pure wasteful behaviors). The predicted wasted energy is also expected to be between the wasted energy in previous scenarios. The ECM predictions are depicted in ***FIGURE 6-13***.

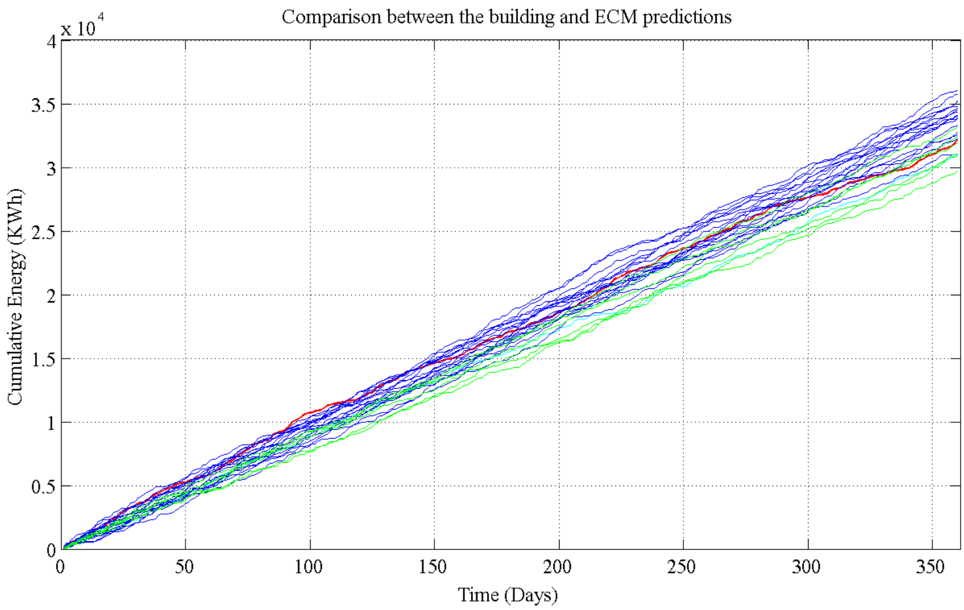

FIGURE 6-13: Comparison of Building and ECM energy consumption measures

The ***FIGURE 6-14*** illustrates the building energy measure and the ECM prediction along with the predicted wasted energy.

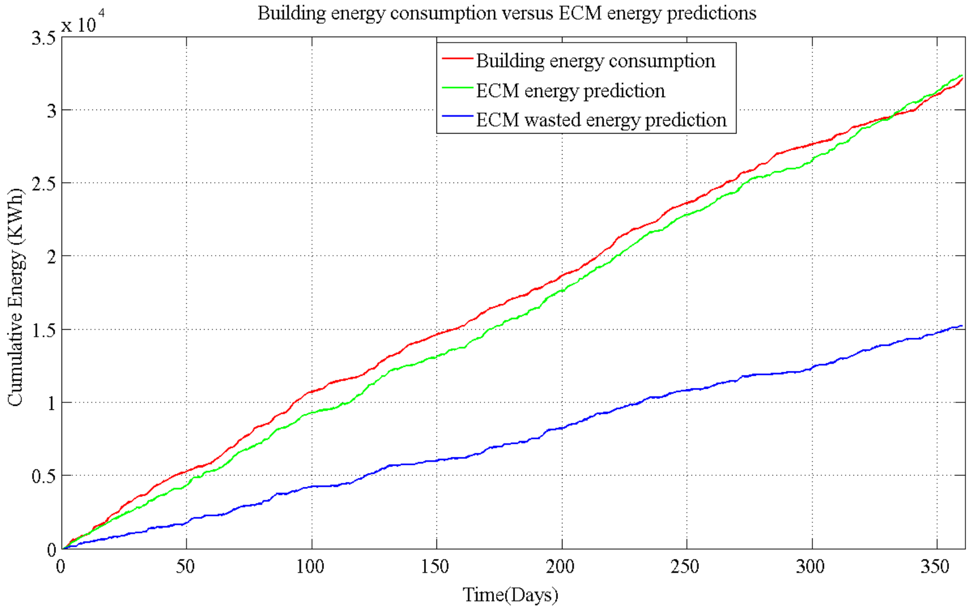

FIGURE 6-14: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulations Analysis:***

According to the presented results, each simulation results in different models for the building. When calculating the steady state for each model, it is possible to determine the space's states probability distribution. These values are presented in

TABLE 6-4: ECM steady-state distributions for the building A

Simulation Spaces	$A.1$	$A.2$	$A.3$	$A.4$
Space 1				
$P(S_1)$	0.0	0.8167	0.2884	0.1921
$P(S_2)$	0.8118	0.0	0.4949	0.5434
$P(S_3)$	0.1055	0.1833	0.1677	0.2028
$P(S_4)$	0.0828	0.0	0.0491	0.0613

The values in ***TABLE 6-4*** directly indicate an estimation of the total energy consumed in each space just by multiplying with the time interval of relevance. Moreover, they can be interpreted as the probability of finding a specific space in a specific state. For example, in simulation $A.1$ the building's space has a zero probability of being in state S_1, that is, this space is never empty with the lighting system turned on. In the simulation $A.3$ the building's space has a 0.49 probability of being in state S_2, that is, the space is half of the time empty with the lighting system turned off. Moreover, this space has a 0.54 probability of being in a state with energy consumption, and a 0.46 probability of being in a state with no energy consumption. One important analysis is that the model parameters are different for each simulation. This means that the model is capable of learning different occupancy patterns and predicting different energy consumption scenarios for the same building. As a result, the predictions tend to reliably represent the building consumption as illustrated in ***FIGURE 6-8***, ***FIGURE 6-10***, ***FIGURE 6-12*** and ***FIGURE 6-14***. To validate these predictions, the absolute error between the model prediction and the building measurements for each simulation is presented in the ***FIGURE 6-15***.

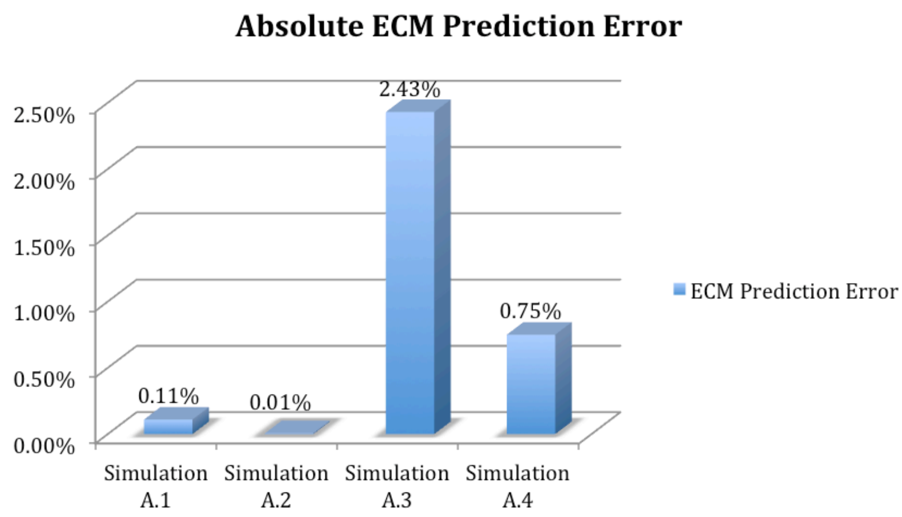

FIGURE 6-15: ECM prediction error for the building A

The prediction errors are less than 2.5%, which indicates that these models can be applied with accuracy for prediction purposes. In this way, according to each simulation, the predicted wasted and used energy is depicted in ***FIGURE 6-16***. The wasted energy is mapped with the potential energy savings. That is, in simulation $A.1$, 100% of the energy consumption is not wasted. This indicates that energy savings in this building are potentially zero. Moreover, in simulation $A.4$, 46.98% of the energy consumption is wasted, which results in potential energy savings in retrofitting projects.

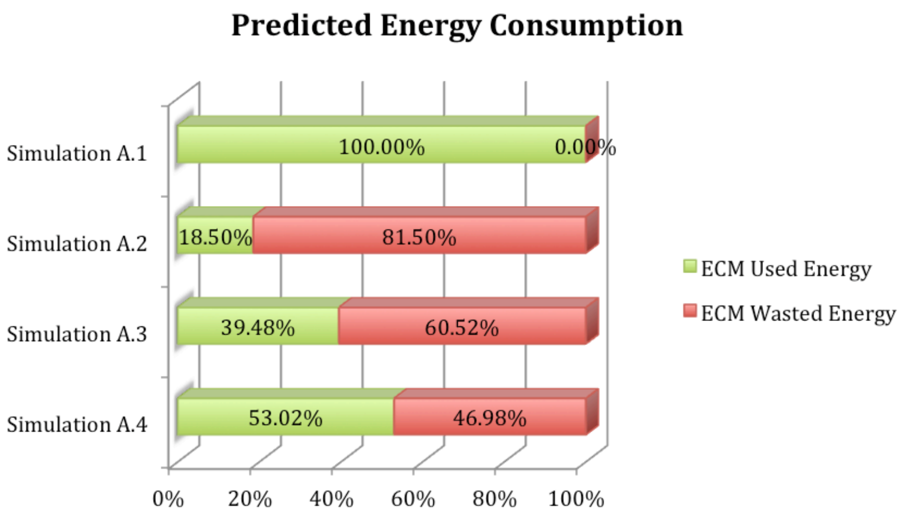

FIGURE 6-16: ECM energy consumption prediction decomposition for the building A

6.2.2 Simulations on Building B

This section is divided into multiple simulations with the objective of demonstrating different occupancy patterns of building B, in order to validate the ECM predictions. The simulation conditions are specified in ***TABLE 6-5***. These simulations will follow the same sequence as the previous simulations. Although this is a different building, the same behavioral models will be applied, which leads to similar occupancy patterns.

TABLE 6-5: Simulation conditions specification for building B

Simulation	Analysis Period (Days)	Number of Occupants	Occupant Behavior	Number Time Slots	Time Slot Size (Min)	Number of events
1	360	4	Pure efficient	48	30	5450
2	360	4	Pure wasteful	48	30	3714
3	360	4	Mixture Behavior	48	30	4914
4	360	4	Pure efficient + Pure wasteful	48	30	4941

- ***Simulation B.1 conditions:***

The purpose of this simulation is to represent a purely efficient behavioral scenario. In this scenario no energy waste is expected, which results in no opportunity for energy savings measures. This must be reflected in energy consumption through the elimination of the wasted energy portion, as illustrated in ***FIGURE 6-1***. Given these simulation conditions, the ***FIGURE***

6-17 illustrates the simulator output representing the building's energy consumption measures. In ***FIGURE 6-17***, on the right the building's energy consumption per day is depicted and on the left the cumulative energy consumption over the 360 days is depicted.

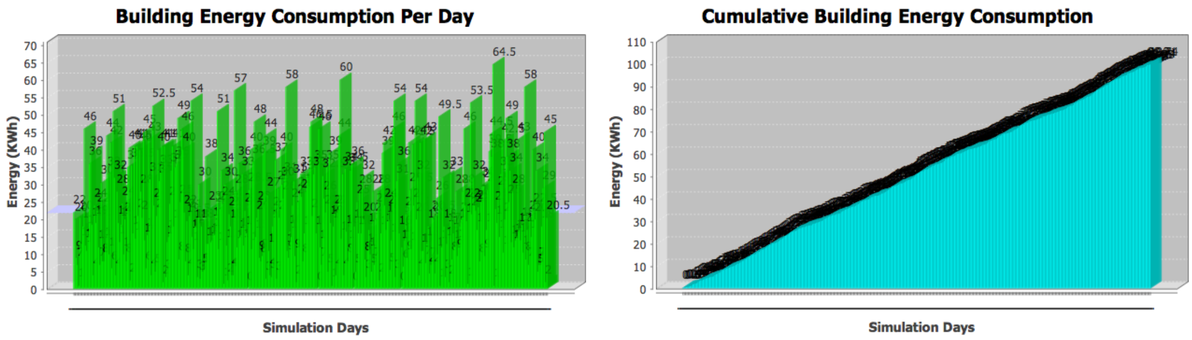

FIGURE 6-17: Prototype output for the building energy consumption over a period of 360 days

For this simulation, the resulting ECM is depicted in ***FIGURE 6-18***. Since this building has four spaces, the ECM is constituted with four Markov chains. Each one represents the occupancy patterns in a specific space. In this example, all the Markov chains have the same transitions, however each space could have completely different structure and parameters.

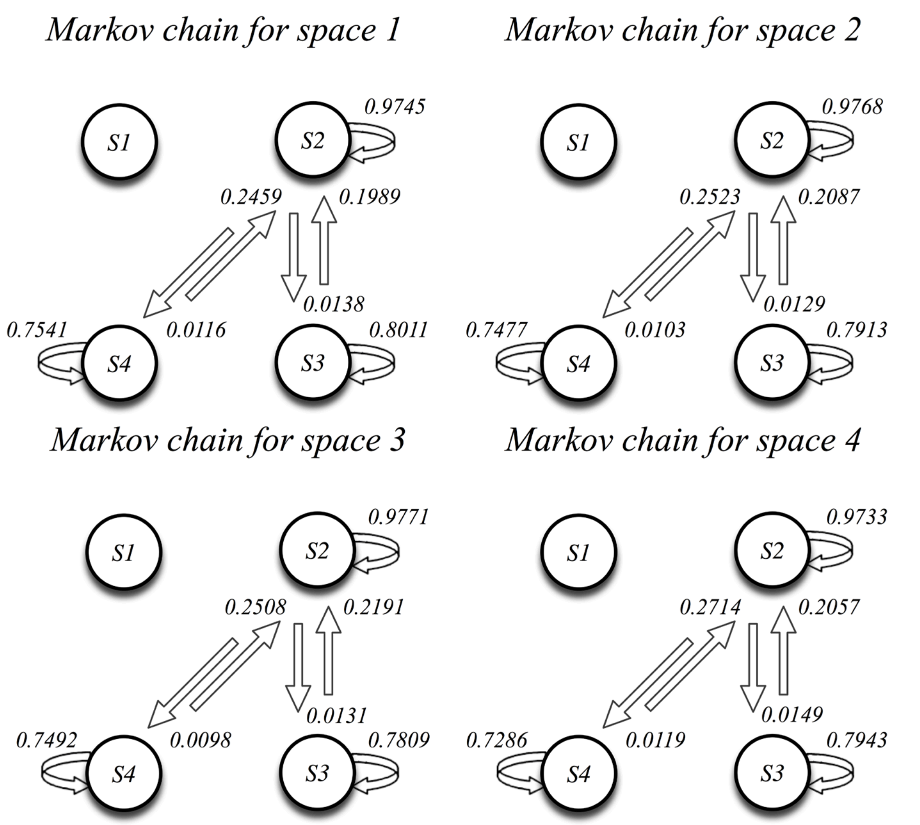

FIGURE 6-18: Building B ECM for simulation B.1

The ECM predictions for this building are depicted in ***FIGURE 6-19***. The RMSPE calculation for each simulation is represented in ***FIGURE 6-20***.

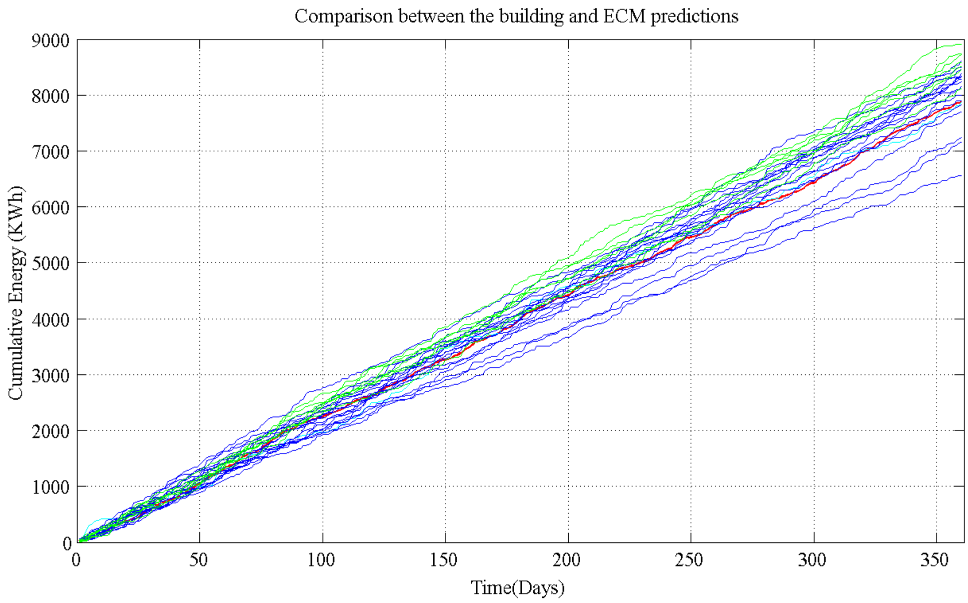

FIGURE 6-19: Comparison of Building and ECM energy consumption measures

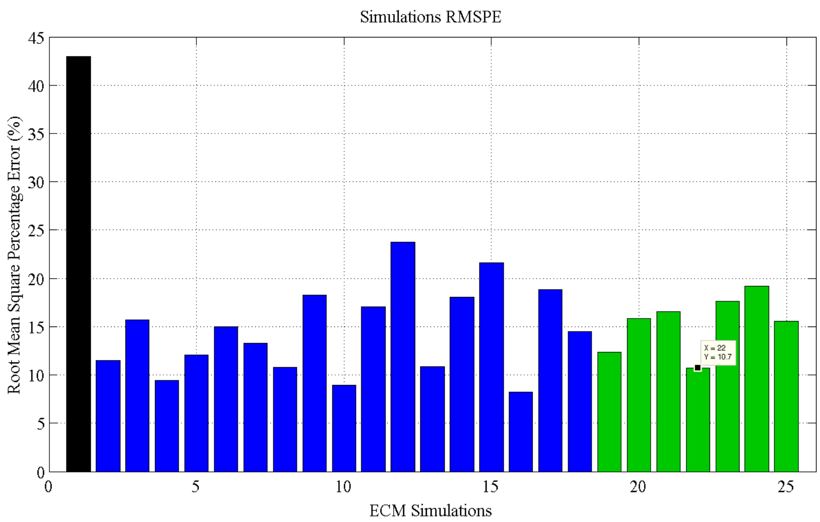

FIGURE 6-20: Calculation of the RMSPE metric for the simulations in A.1

As expected, the dynamic algorithm does not minimize the RMSPE error, however it provides an acceptable compromise between the static and the random methods. When using this seed for prediction, the energy consumption model output prediction provided by the prototype is illustrated in ***FIGURE 6-21***. In this simulation the daily predictions differ from the building measurements, however, when considering the average energy consumption, both have the same value of, approximately 22 KWh. This could be a problem if it was important to predict the exact consumption in a specific day.

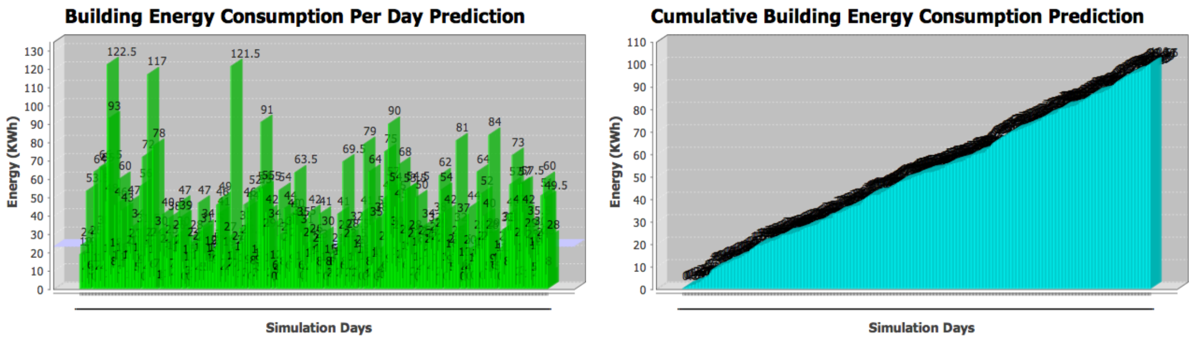

FIGURE 6-21: Prototype output for the building energy consumption prediction with ECM over a period of 360 days

The objective is the overall energy consumption and the total energy consumption. In this analysis is more important a reliable average consumption prediction is more important than an unreliable one. The ***FIGURE 6-22*** illustrates the building energy measures and the ECM prediction. As before, the ECM prediction follows the building energy consumption and the model predicts no wasted energy.

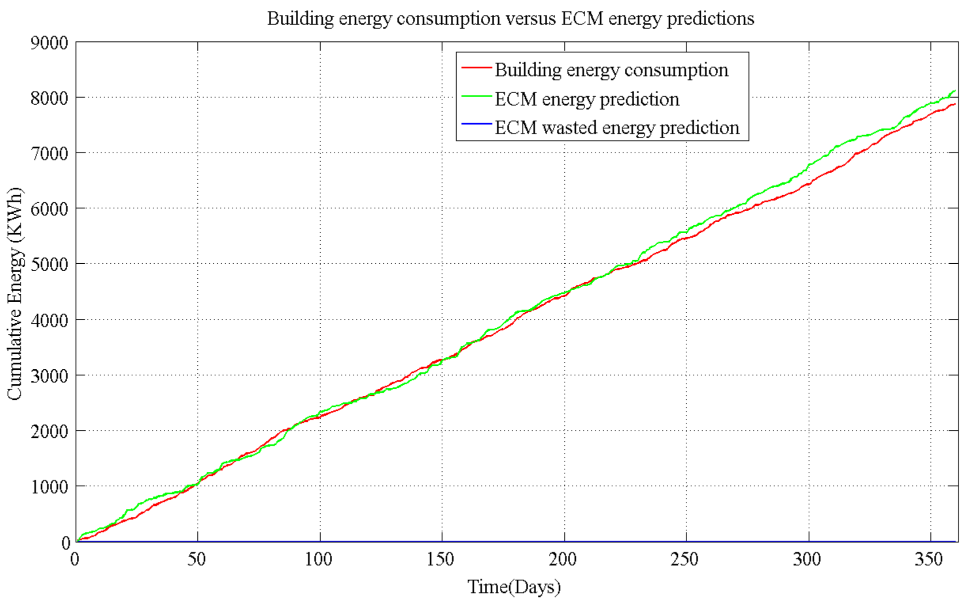

FIGURE 6-22: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulation B.2 conditions:***

The purpose of this simulation is to represent a purely wasteful behavioral scenario. This scenario represents the opposite of the previous scenario in the sense that the wasted energy is maximized. The energy consumption model predictions are illustrated in ***FIGURE 6-23*** and the ***FIGURE 6-24*** illustrates the building energy measure and the ECM prediction along with the predicted wasted energy.

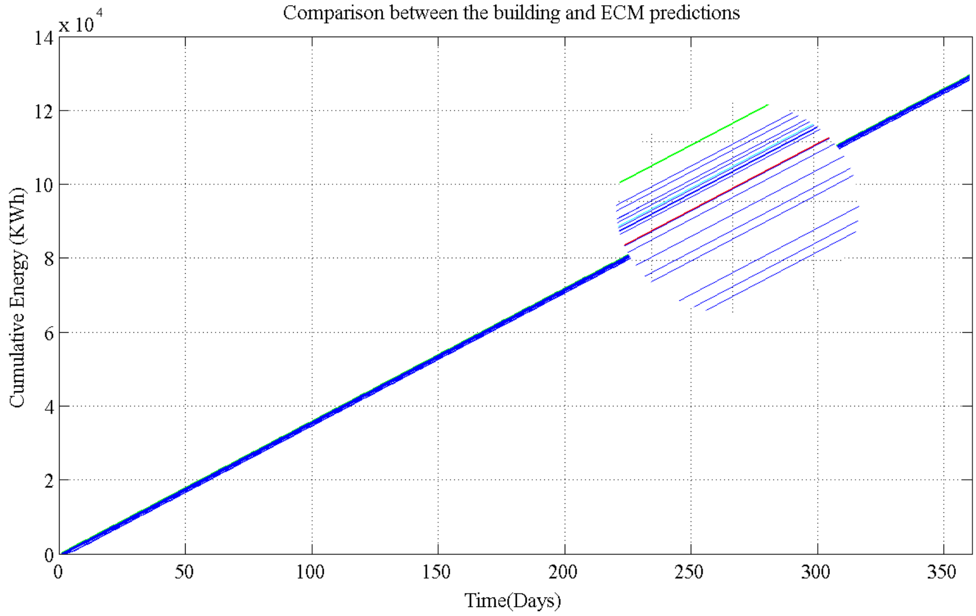

FIGURE 6-23: Comparison of Building and ECM energy consumption measures

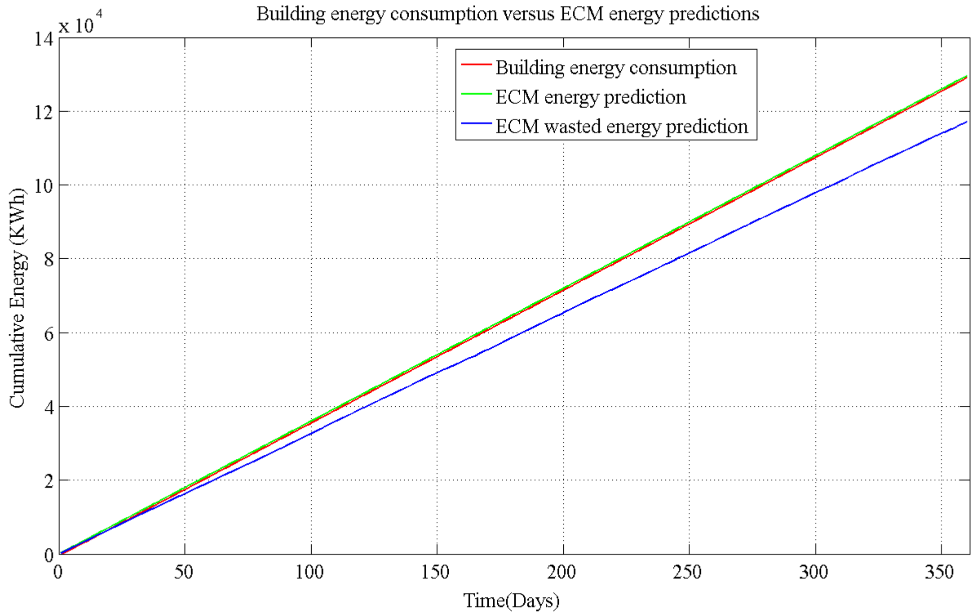

FIGURE 6-24: Comparison between building energy consumption and ECM predictions and potential energy savings

This occupancy scenario is similar to the simulation A.2 the patterns are also analogous. As expected, the wasted energy represents a large percentage of the energy consumption when compared to the total predicted. Furthermore, other behavioral scenarios should waste less energy than this.

- ***Simulation B.3 conditions:***

The purpose of this simulation is to represent a mixed behavioral scenario (a combination of efficient and wasteful behaviors). The predicted wasted energy is expected to be between the previous scenarios. As mentioned before, each space could have different model structure. For this simulation, the resulting ECM is depicted in ***FIGURE 6-25***. In this example, the Markov chains have the different state transitions, which is a consequence of the usage patterns.

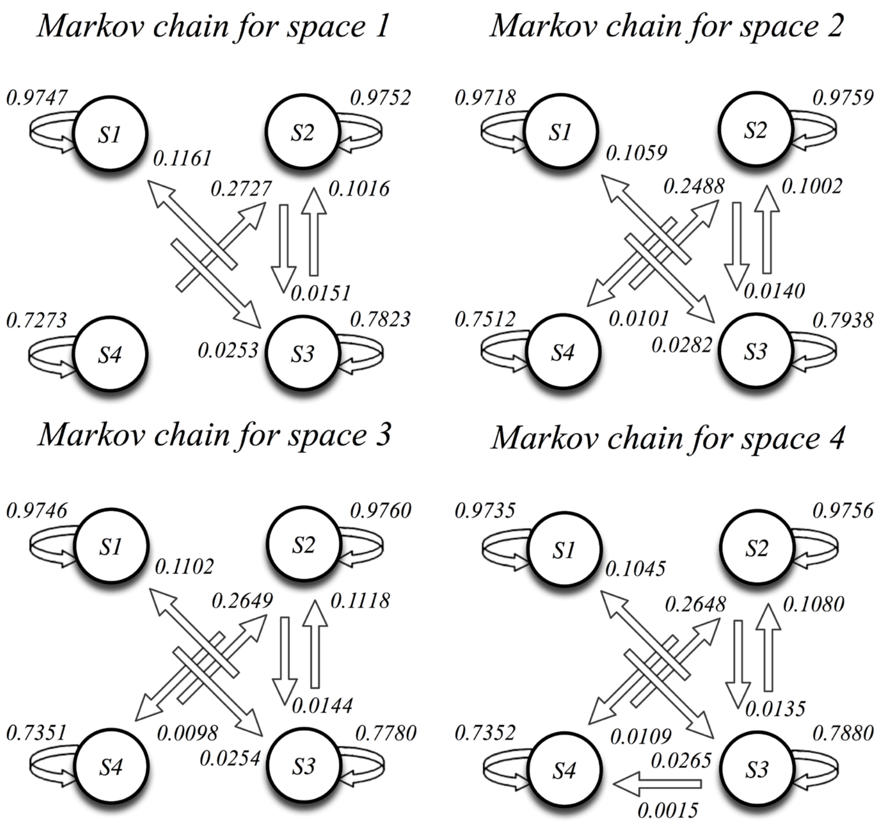

FIGURE 6-25: Building B ECM for simulation B.3

The ECM predictions are depicted in ***FIGURE 6-26*** and the comparison between the building energy measures and the ECM prediction are illustrated in ***FIGURE 6-27*** along with the predicted wasted energy.

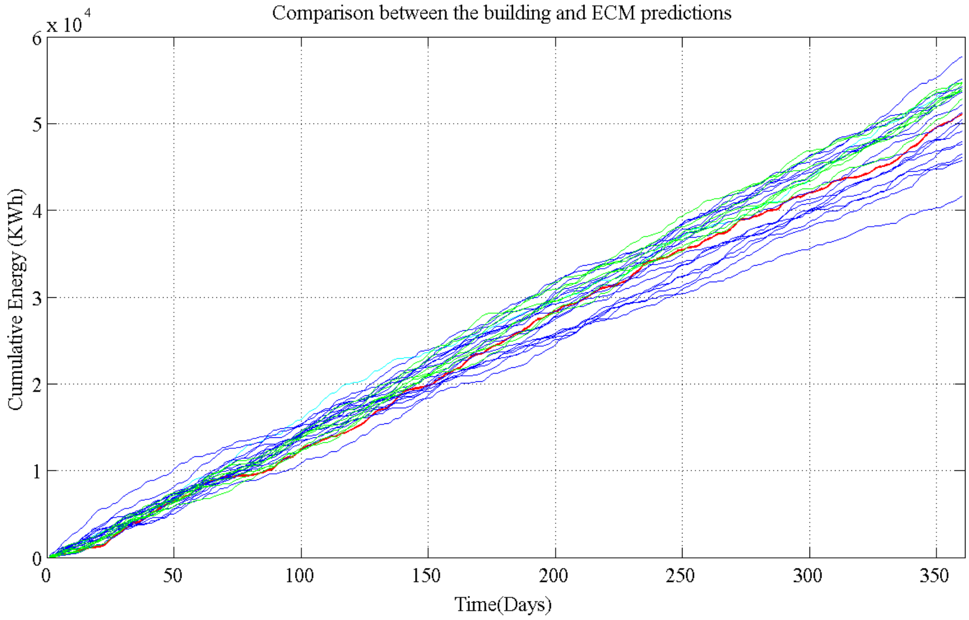

FIGURE 6-26: Comparison of Building and ECM energy consumption measures

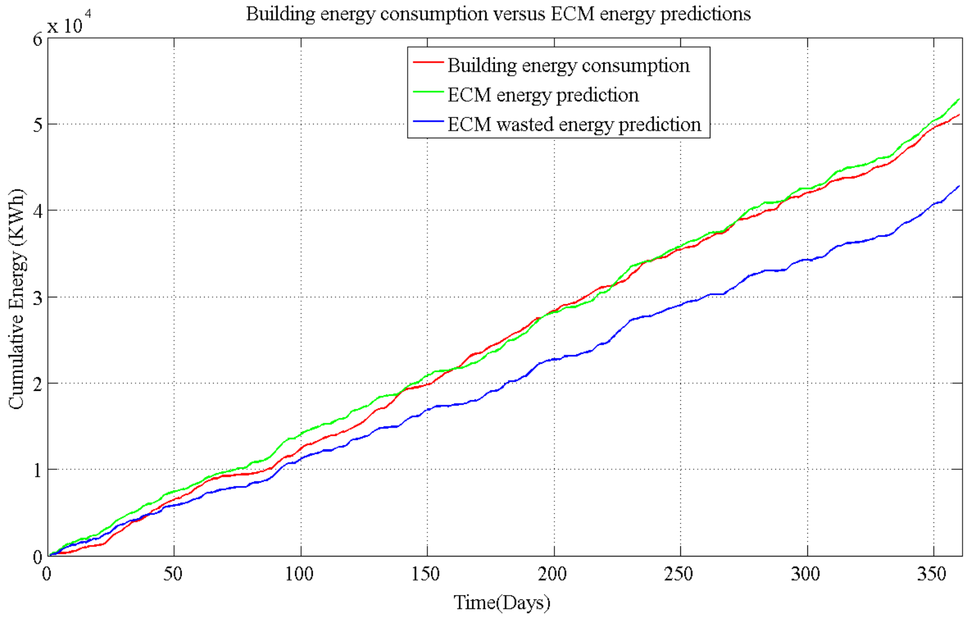

FIGURE 6-27: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulation B.4 conditions:***

The purpose of this simulation is to represent a hybrid behavioral scenario (pure efficient and pure wasteful behaviors). The predicted wasted energy is expected to be between the previous scenarios. The ECM predictions are depicted in ***FIGURE 6-28***.

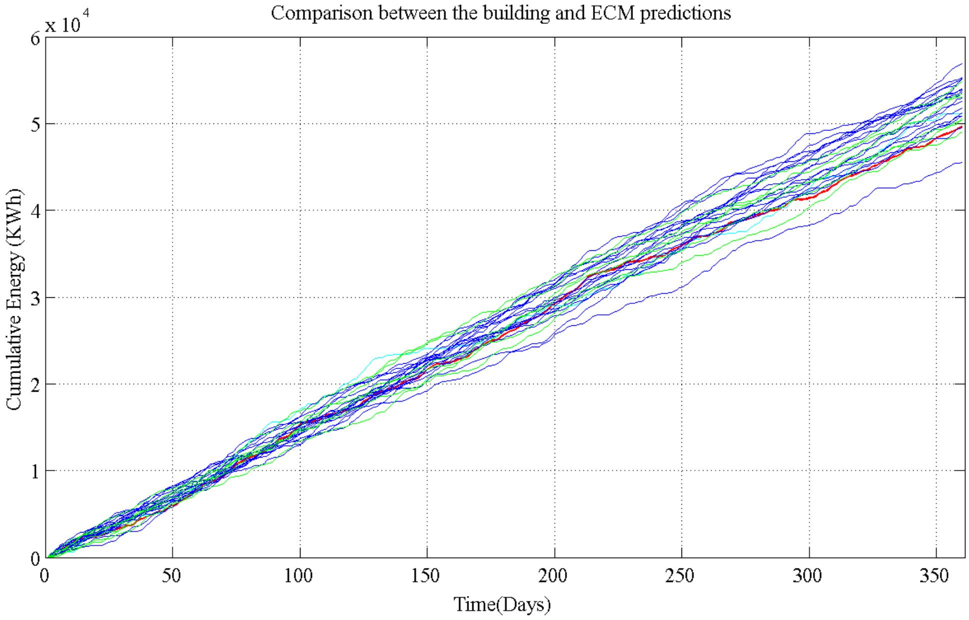

FIGURE 6-28: Comparison of Building and ECM energy consumption measures

The ***FIGURE 6-29*** illustrates the building energy measure and the ECM prediction along with the predicted wasted energy.

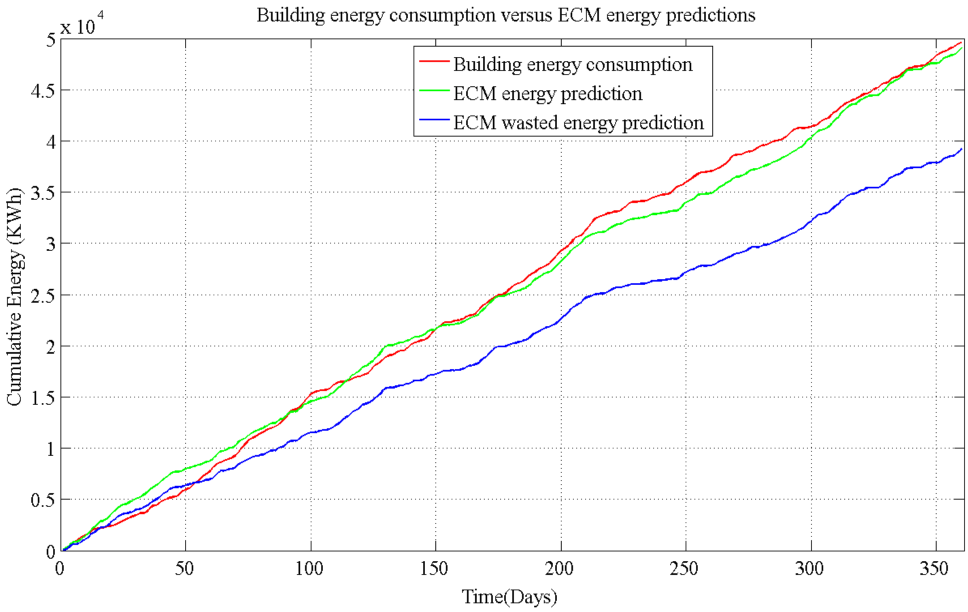

FIGURE 6-29: Comparison between building energy consumption and ECM predictions and potential energy savings

- ***Simulations Analysis:***

According to the presented results, each simulation results in different models for the building. When calculating the steady state for each model, it is possible to determine the space's states probability distribution. These values are presented in ***TABLE 6-6***.

TABLE 6-6: ECM steady-state distributions for the simulation B

Simulation	***B*.1**	***B*.2**	***B*.3**	***B*.4**	**Simulation**	***B*.1**	***B*.2**	***B*.3**	***B*.4**
Probability		*Space 1*			*Probability*		*Space 2*		
$\boldsymbol{P(S_1)}$	0.0	0.9038	0.3653	0.2374	$P(S_1)$	0.0	0.9015	0.3073	0.3465
$\boldsymbol{P(S_2)}$	0.8954	0.0	0.5358	0.6637	$P(S_2)$	0.9068	0.0	0.5870	0.5451
$\boldsymbol{P(S_3)}$	0.0623	0.0962	0.0798	0.0730	$P(S_3)$	0.0560	0.0985	0.0820	0.0906
$\boldsymbol{P(S_4)}$	0.0424	0.0	0.0191	0.0258	$P(S_4)$	0.0372	0.0	0.0237	0.0178
Probability		*Space 3*			*Probability*		*Space 4*		
$\boldsymbol{P(S_1)}$	0.0	0.8979	0.3239	0.2742	$P(S_1)$	0.0	0.8983	0.2979	0.3316
$\boldsymbol{P(S_2)}$	0.9101	0.0	0.5803	0.6278	$P(S_2)$	0.8961	0.0	0.6013	0.5699
$\boldsymbol{P(S_3)}$	0.0544	0.1021	0.0746	0.0772	$P(S_3)$	0.0647	0.1017	0.0757	0.0759
$\boldsymbol{P(S_4)}$	0.0355	0.0	0.0211	0.0209	$P(S_4)$	0.0392	0.0	0.0251	0.0227

Accordingly to the previous simulations, the model parameters are different between each space and for each simulation. This means that each model is capable of learning different space occupancy patterns for the same building. To validate these predictions, the absolute error between the model prediction and the building's measurements for each simulation is presented in the ***FIGURE 6-30***.

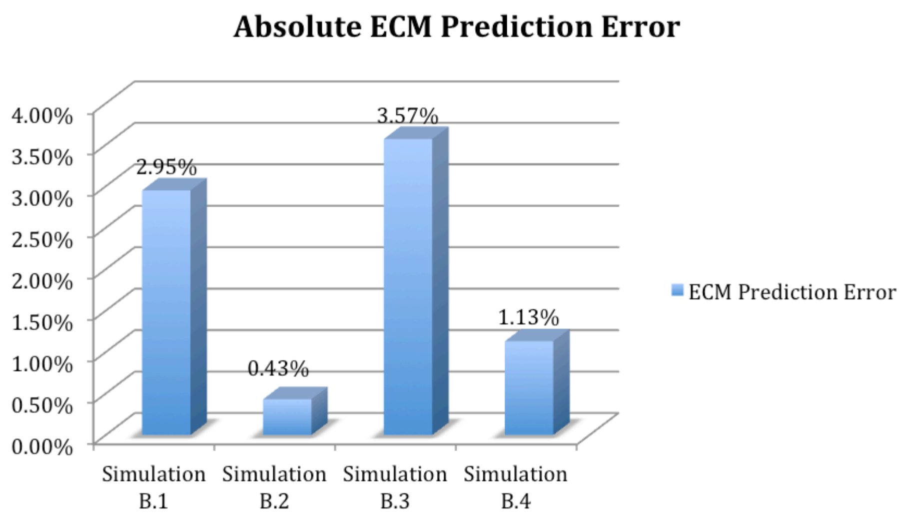

FIGURE 6-30: ECM prediction error for the building B

For these simulations the prediction error are less than 3.75%, which indicates that these models could be applied with accuracy for prediction purposes, as previously stated. For each simulation, the predicted wasted and used energy is depicted in ***FIGURE 6-31***. Although considering a different building in these simulations, the energy consumption is also accurately predicted through the applicability of the proposed models. Moreover, the occupant behavioral model produce similar occupancy patterns regardless the building they are applied, which validates the modeling approach.

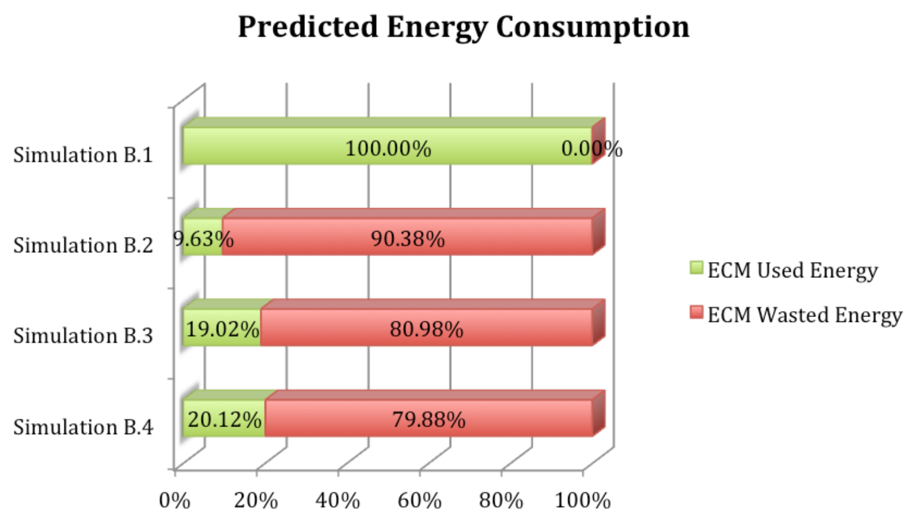

FIGURE 6-31: ECM energy consumption prediction decomposition for the building B

In these simulations the number of building spaces increased and so the prediction error. *Does an increase in ECM dimension results in increased energy prediction error?* The next simulation section presents the results when consider a building twelve times bigger in the number of spaces and with seven times more occupants.

6.2.3 Simulations on Building C

This section has just one simulation with the objective of analyze the performance and scalability of the ECM composed by with 50 Markov chains. The simulation condition is specified in ***TABLE 6-7***.

TABLE 6-7: Simulation conditions specification for building C

Analysis Period (Days)	Number of Occupants	Occupant Behavior	Number Time Slots	Time Slot Size (Min)	Number of events
360	30	Random per occupant	120	6	29934

The previous simulations demonstrated that the occupant behavioral model represents a valid methodology as the results represent the expected occupancy patterns. Given this, in this simulation, the occupant behavioral model was chosen randomly, that is, each occupant has a unique and unknown model a priori. The expected results are, therefore, unpredictable. The objective is to approximate the simulation to reality, since each occupant is different. The ECM prediction and building consumption are illustrated in ***FIGURE 6-32***.

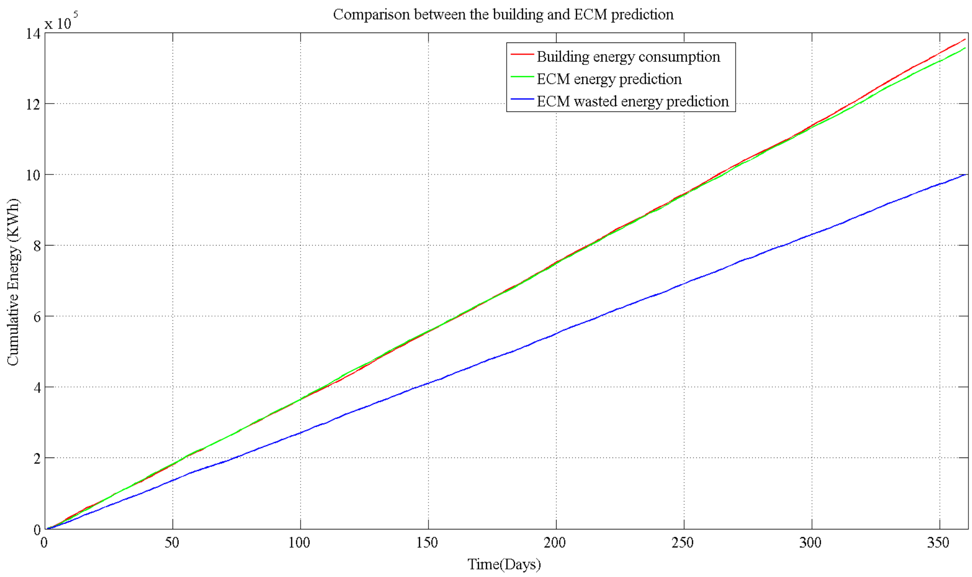

FIGURE 6-32: Comparison between building energy consumption and ECM predictions and potential energy savings

FIGURE 6-32 illustrates that even with the dimension of this simulation data and variables, the ECM can accurately predict the building energy consumption with a prediction error of 1.83% as depicted in ***FIGURE 6-33***.

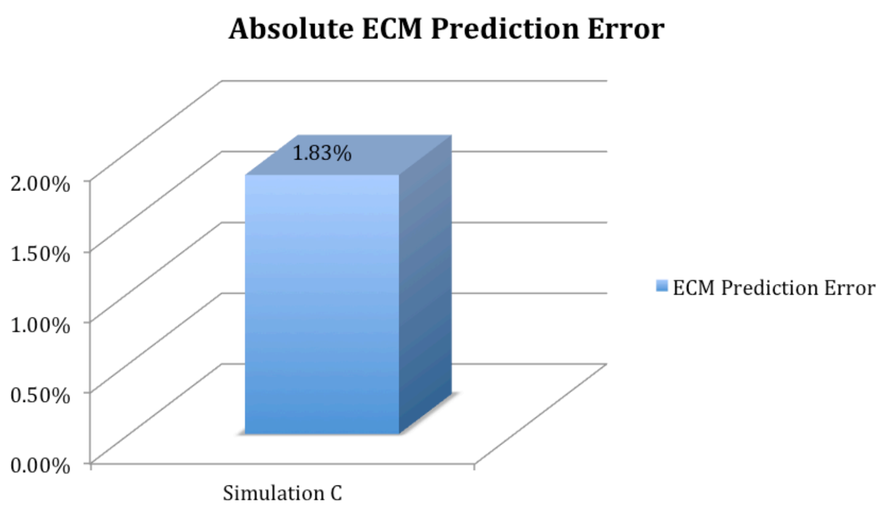

FIGURE 6-33: ECM prediction error for the building C

This answers the previous question and demonstrates that the ECM is scalable and its performance is not affected. The ***FIGURE 6-34*** depicts how the predicted energy consumption is distributed. In this case, there is opportunity to reduce the building consumption by an amount of 73.68% as a result of an inefficient utilization of the lighting system.

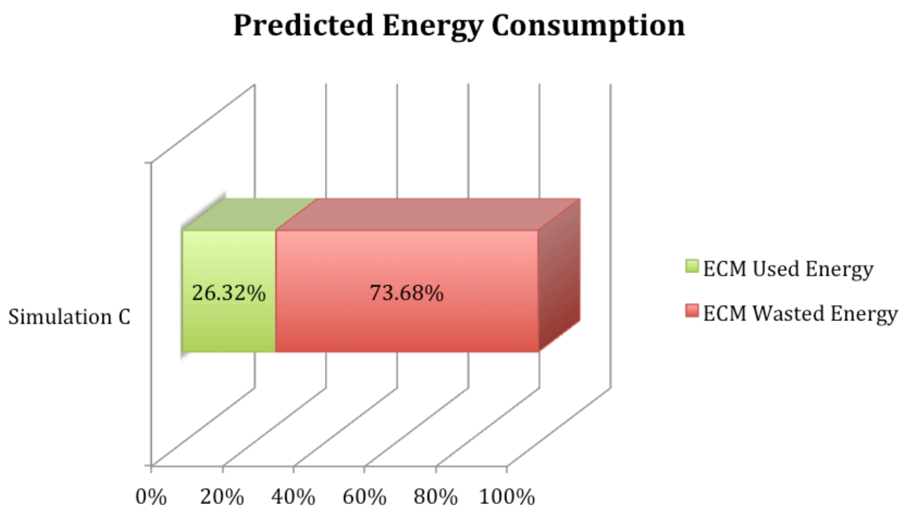

FIGURE 6-34: ECM energy consumption prediction decomposition for the building C

7

Conclusions and Future Work

This chapter presents the research conclusions while addressing future work

7.1 Conclusions

Buildings have been identified as the biggest culprit for world energy consumption and climate change. As a result it is crucial to improve the way energy is used to manage its increasing demand.

As buildings standards improve, so will increase the relative impact of occupants on resource use. It thus seems inevitable that better models of their presence and interaction will be necessary. The set of models discussed in this research are an attempt to simulate the influences that occupants may have on a building in terms of resource consumption, utilization and waste. Their output provides valuable information for the simulation of a single building. Central to this set is the stochastic model of occupant presence. It can also produce added value to tools already using simulations of occupant behavior such as Lightswich or EnergyPlus, by providing them with more reliable inputs. The stochastic models of occupant behavior (regarding the use of the lighting system) represent the variety of occupant behaviors and their randomness over time.

The reliability of results obtained from building performance simulation applications depends not only on the validity of computational algorithms, but also on the input assumptions. While there has been significant progress concerning methods and practices for specification of building geometry, material properties, and external conditions, the resolution of input information regarding occupancy, occupant presence and behavior in buildings still needs to be improved.

The obtained results from this research demonstrate that it is important to consider the behavior analysis of occupants within the building as different occupancy patterns results in different patterns of energy consumption. Moreover, the simulations results demonstrate that it is possible to use stochastic models to accomplish the proposed research goals. The models proposed for predicting the building's energy consumption and to model the occupant behavior produce reliable predictions. Additionally, they can accurately capture space utilization and predict different scenarios and supporting a reliable decision making for investing in potential areas for energy savings.

The developed prototype provides a basis for supporting the applicability and validation of the stochastic models and proposed methodologies. The proposed knowledge framework appears as an interesting platform for simulation purposes and especially for systems that embraces decision support. Finally, its modular structure allows an extension of the developed models.

7.2 Future Work

Throughout the previous chapters, some suggestions of how to extended the applicability of these models have been addressed. In this research, the lighting system supported the study of the proposed models. One interesting extension of these models would be to consider a complete set of devices within the building. Moreover, the model seed selection has been pointed out a fundamental piece for a reliable energy consumption prediction. As a result it is necessary to discover the best seed for each model that minimizes the prediction error. These models are based in numerous stochastic processes that influence the outcome of a simulation. A future study of how to calculate boundaries for the predictions is required. The door is left open to extend this research from a larger perspective. Future developments in this area are expected to facilitate a detailed and dynamic simulation of environmental processes in buildings via comprehensive multiple-coupled representations that dynamically capture the states of occupancy, building, and context.

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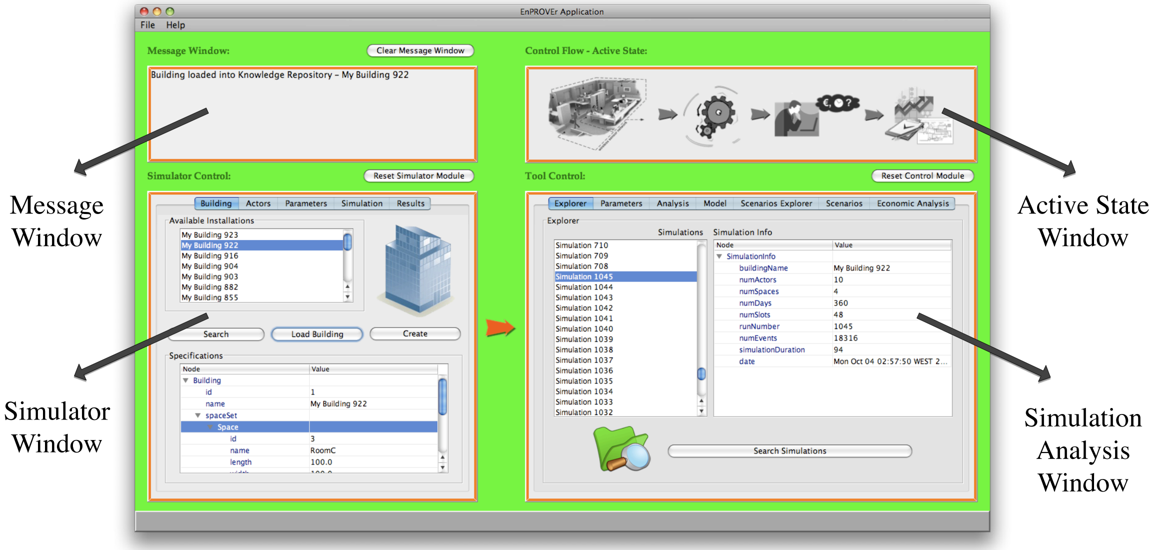
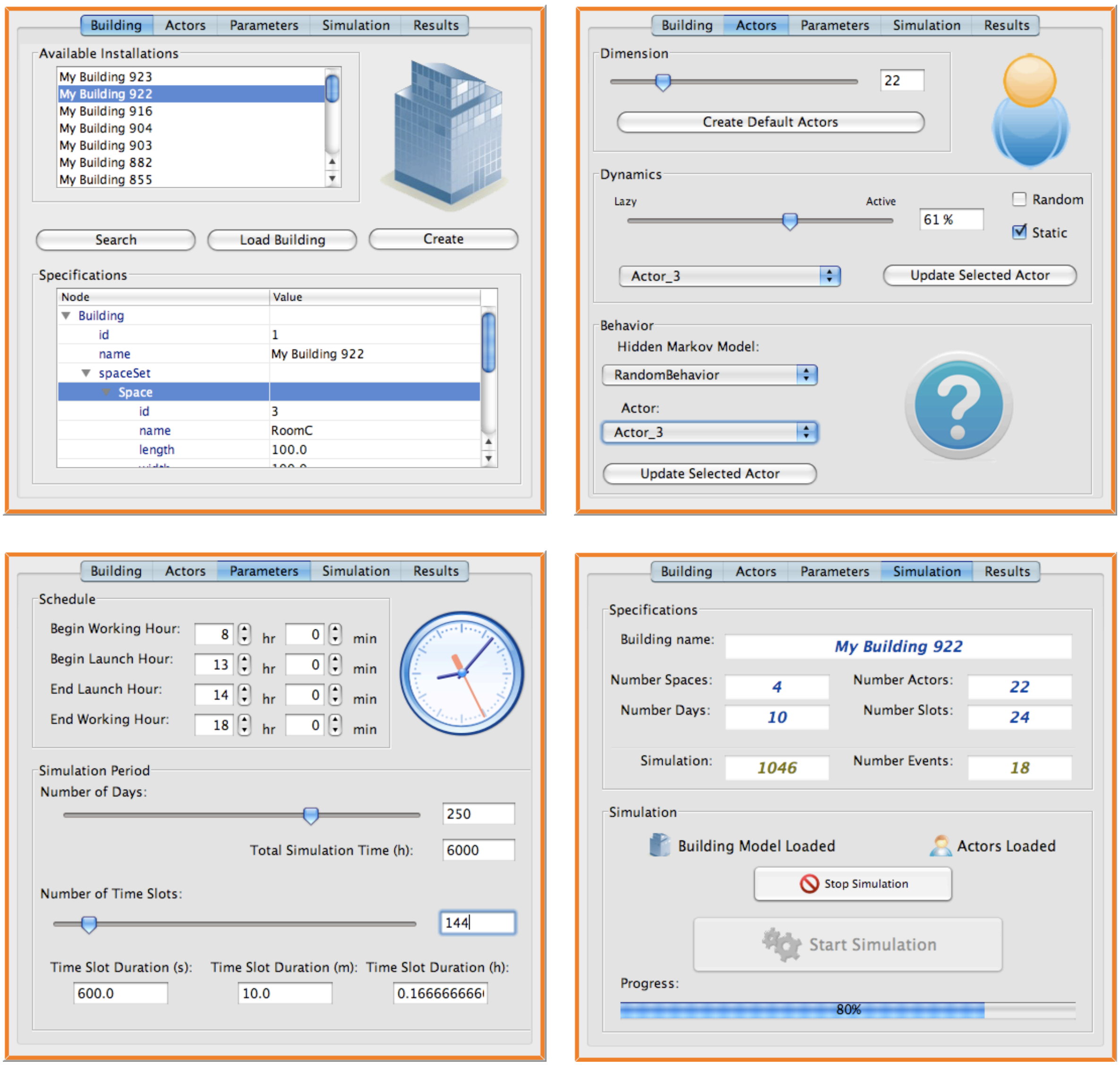
Appendix I

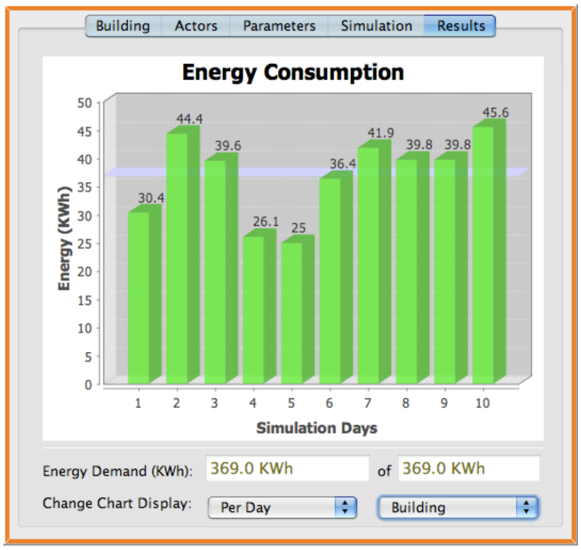
Developed framework prototype snapshots

- ***Prototype framework graphical user interface***



- ***Simulator module window***





- ***Modelation and prediction module window***