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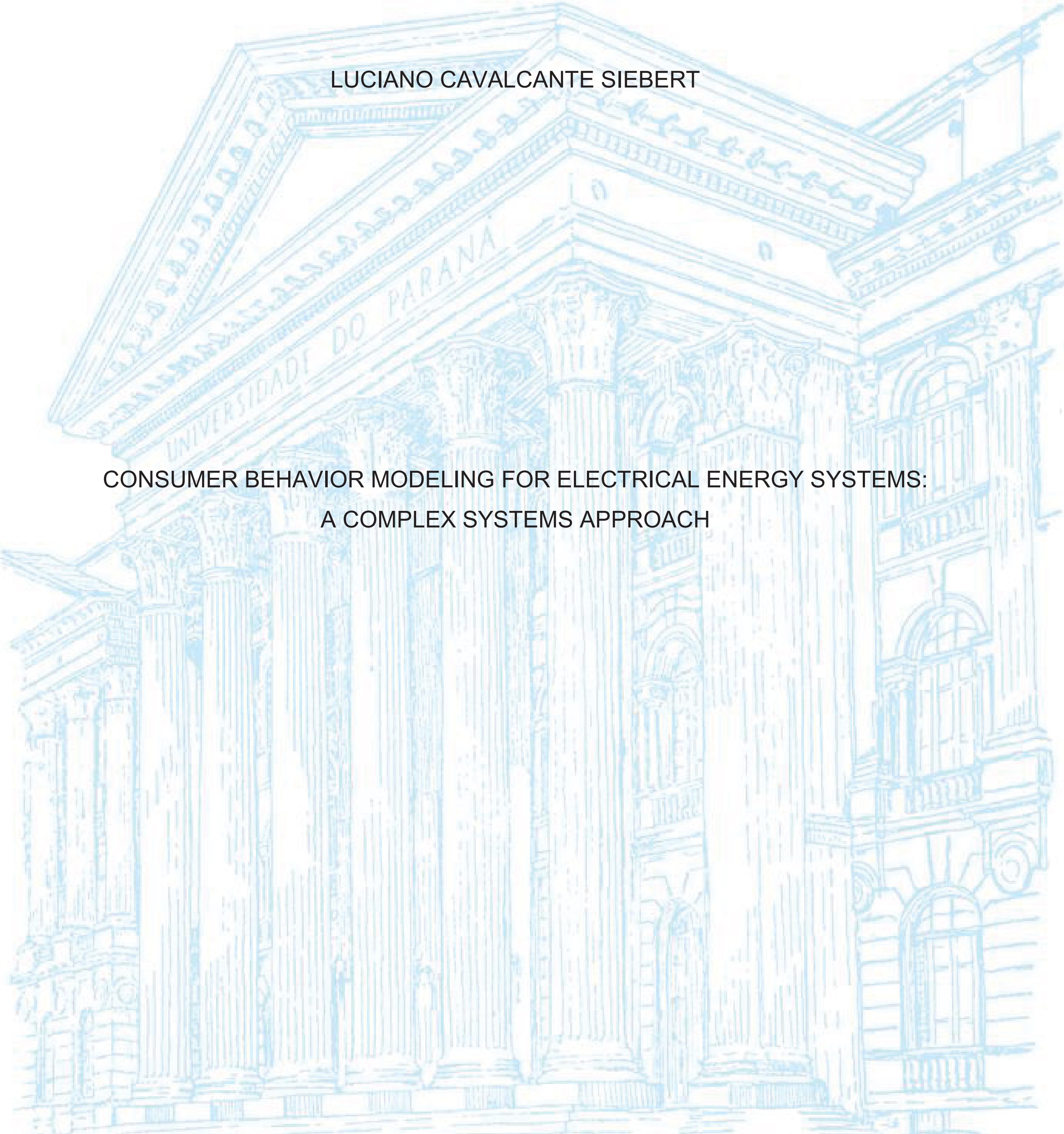


LUCIANO CAVALCANTE SIEBERT

# CONSUMER BEHAVIOR MODELING FOR ELECTRICAL ENERGY SYSTEMS: A COMPLEX SYSTEMS APPROACH

CURITIBA

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# CONSUMER BEHAVIOR MODELING FOR ELECTRICAL ENERGY SYSTEMS: A COMPLEX SYSTEMS APPROACH

Tese apresentada ao curso de Pós-Graduação em Engenharia Elétrica, Setor de Tecnologia, Universidade Federal do Paraná, como requisite parcial à obtenção do título de Doutor em Engenharia Elétrica.

Orientador: Alexandre Rasi Aoki

Coorientador: Germano Lambert-Torres

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## TERMO DE APROVAÇÃO

Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em ENGENHARIA ELÉTRICA da Universidade Federal do Paraná foram convocados para realizar a arguição da tese de Doutorado de **LUCIANO CAVALCANTE SIEBERT** intitulada: **CONSUMER BEHAVIOR MODELING FOR ELECTRICAL ENERGY SYSTEMS: A COMPLEX SYSTEMS APPROACH**, após terem inquirido o aluno e realizado a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.

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Curitiba, 27 de Fevereiro de 2019.

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To my parents Luiz Carlos Siebert (*in memoriam*) and Maria das Graças Cavalcante Siebert.

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Everything is simple and neat—except, of course, the world.

(GOLDENFELD; KADANOFF, 1999).

# RESUMO

Um sistema complexo é um sistema composto de muitas partes que interagem entre si, de modo que o comportamento coletivo emergente dessas partes é mais do que a soma de seus comportamentos individuais. O sistema elétrico de potência pode ser considerado um sistema complexo devido à sua diversidade de agentes heterogêneos inter-relacionados e a emergência de comportamento complexo. Sistemas de potência estão aumentando em complexidade com novos avanços relacionados à redes elétricas inteligentes tais como tecnologia de informação e comunicação, geração distribuída, veículos elétricos, armazenamento de energia e, especialmente, uma crescente interação e participação de um grande número de consumidores heterogêneos dispersos geograficamente. O sistema elétrico de potência pode ser estudado como um sistema técnico-socioeconômico complexo com múltiplas facetas, e a teoria de sistemas complexos pode fornecer uma base teórica sólida para seus desafios de modelagem e análise. O presente trabalho trata da aplicação da teoria de sistemas complexos em sistemas de potência, focando a análise no consumidor e no seu comportamento relacionado ao consumo de eletricidade, utilizando técnicas do campo da economia comportamental. Comportamentos complexos e emergentes sobre o consumo de eletricidade, bem como seu impacto nas redes elétricas, são analisados através da modelagem do comportamento dos cliente em uma simulação baseada em agentes, considerando quatro categorias de consumidores. A análise da simulação, aplicada a um estudo de caso em uma rede de distribuição de média tensão radial com dados reais, mostrou que premissas ligeiramente diferentes sobre o comportamento do consumidor no nível micro levam a resultados macro muito distintos e com comportamento não linear. Entender e modelar adequadamente o comportamento dos consumidores é de grande importância para o planejamento e operação de redes de energia, e a economia comportamental serve como uma base teórica promissora para modelar o comportamento no consumo de eletricidade. Os resultados deste trabalho mostraram que a teorias de sistemas complexos fornece ferramentas adequadas para lidar com sistemas de potência cada vez mais complexos, considerando-os não mais como um sistema independente agregado, mas como um sistema complexo integrado.



Palavras-chave: distribuição de energia; consumo de eletricidade; teoria de sistemas complexos; simulação baseada em agentes; economia comportamental.

## ABSTRACT

A complex system is a system composed of many interacting parts, such that the collective emergent behavior of those parts is more than the sum of their individual behaviors. Electrical energy systems may be considered a complex system due to its diversity of interrelated heterogeneous agents and emergent complex behavior. Energy systems are increasing in complexity with new advances related to the smart grid such as information and communication technology, distributed generation, electric vehicles, energy storage, and, especially, increasing interaction and participation of a large number of geographically distributed heterogeneous consumers. Power systems can be studied as a complex techno-socio-economical system with multiple facets, and Complex System Theory (CST) may provide a solid theoretical background for these modeling and analysis challenges. The present work deals with the application of CST into electrical energy systems, focusing the analysis on the consumer and their behavior on electricity consumption, using insights from the field of behavioral economics. Emergent complex behaviors on electricity consumption as well as its impact on power grids are analyzed by modeling customer behavior on an agent-based simulation, considering four different consumer categories. The analysis of the simulation, applied on a case study on a radial medium voltage distribution grid with real-world data, showed that slightly different assumptions on consumer behavior at the micro-level lead to very different and non-linear macro outcomes. To properly understand and model consumer behavior is of great importance to the planning and operation of electrical grids, and behavioral economics serves as a promising theoretical background to model behavior on electricity consumption. The results of this work showed that CST provides suitable tools to tackle electrical energy systems' increasing complexity, by considering the electrical power systems not as an aggregated independent system anymore, but as an integrated complex system.

Keywords: power distribution; electricity consumption; complex systems theory; agent-based simulation; behavioral economics.

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## LIST OF ACRONYMS

| | |
|---|---|
| ADP | Adaptive Dynamic Programming |
| BFS | Backward / Forward Sweep |
| CLD | Causal Loop Diagram |
| CSP | Consumption Satisfaction Parameter |
| CST | Complex Systems Theory |
| DER | Distributed Energy Resources |
| DG | Distributed Generation |
| DSM | Demand-Side Management |
| IEEE | Institute of Electrical and Electronics Engineers |
| ICT | Information and Communications Technologies |
| ODD | Overview, Design concepts, and Details |
| P2P | Peer-To-Peer |
| SOC | Self-Organized Criticality |
| SoS | System of Systems |
| T&D | Transmission and Distribution |
| TOU | Time-Of-Use |
| VPP | Virtual Power Plant |

## LIST OF SYMBOLS

| | |
|---|---|
| $s_k$ | Satisfaction level at iteration $k$ |
| $SP$ | Satisfaction Parameter |
| $q_k$ | Monthly electricity consumption at iteration $k$ |
| $p_k$ | Electricity price at iteration $k$ |
| $\varepsilon$ | Electricity price elasticity |
| $CP$ | Consumption Parameter |
| $R_{inv}$ | Random value to assess if an investment is made |
| $inv_k$ | Investment level at iteration $k$ |
| $DRAI$ | Decrease Rate After an Investment |

**SUMMARY**

# 1 INTRODUCTION

Since the first electric power system was built in 1882, it developed into one of the largest industries in the world with networks covering practically the whole globe, becoming an essential resource for industries and people (ASTROM, 2011, p.2). This growth came with an exponential increase in system complexity, through the inclusion of several interacting subsystems with different focuses such as increased grid stability, protection coordination, distribution automation, grid observability, facilitate the integration of distributed renewable energy sources, and decrease operational costs. These focuses are many times not only independent but also conflicting. Still, several societal, environmental, economic, operational, geographical, and reliability-related challenges must be tackled while developing these solutions.

And this is only the beginning. As more and more distributed energy resources (DERs), virtual power plants (VPPs), storage systems and micro-grids integrate distribution systems, while interacting in real-time with many market players including a massive volume of prosumers and active interacting consumers supported by increasing smart metering infrastructure (EPE, 2018), complexity tends to exponentially increase.

The smart grid concept came to support the overcoming of these challenges. Smart grids include a modern electricity management system that uses widespread sensors networks, information and communications technologies (ICT), automation, and integrated systems for electrical systems improvements in both efficiency and system security level. Momoh (2012) advocates that the smart grid, when fully developed, will allow the engagement of customers as well as improvements in the generation, transmission, and distribution, by using tools that allow the minimization of system vulnerability as well as an increase in security, reliability and power quality.

Many times, the planning, design, and operation of power system are based on deterministic techniques. These have been used by utilities for decades, but Billinton (1996) argues that probabilistic techniques are more suitable for understanding and modeling stochastic system behavior. Bompard et al. (2012) extends this suggestion arguing that smart grids must be studied and understood as a non-deterministic complex techno-socio-economical system with multiple facets such as physical, cyber, social, policy, and decision-making layers, which also interact with unstable external conditions (economic cycles, technological innovation, and prevailing and changing weather and climatic conditions).

Special attention should be given to customer behavior and their social and cultural backgrounds, putting people, for whom the energy will finally bring all the benefits, on the center of the analysis. Such analysis should go beyond financial aspects since although monetary incentives can lead to changes in the load profile of given customers, it is indeed a much more complex topic. In some specific cases, financial incentives may even increase the behavior that was intended to be minimized, since people think they ‘bought’ the right to not be efficient (PARAG; SOVACOOL, 2016).

Using a proper framework analysis and modeling, the present growth in technologies to consumers, combined with changes in the electricity market and policies, offers a unique opportunity for positive, synergistic interactions of prosumers with the smart grid (PARAG; SOVACOOL, 2016).

## 1.1 MOTIVATION

Power systems are increasing in complexity and should be studied as a complex techno-socio-economical system with multiple facets. It may be considered a complex system due to its mutual dependency among agents, emergent complex behavior, increasingly decentralized control actions, among other properties.

Since the second half of the 20$^{th}$-century complex systems theory (CST) has been developed and successfully used to analyze and model several complex phenomena on a wide range of applications such as ecosystems, economics, societies, and immune systems. CST, by analyzing how simple rules and interactions can emerge complex behavior, may lead to a better understanding of the dynamics and evolution of power systems.

Moreover, the main agent of the power grid, the consumer (or even better, the customer), for whom all infrastructure is built, and for whom energy is delivered, is many times not properly analyzed. People’s behavior on energy consumption is complex and deficiency on properly considering cognition process and decision-making processes can lead to overly simplified behavioral assumptions, that may jeopardize or even make unfeasible modeling of consumer energy behavior. Behavioral economics, an important and current field of economics research that considers human computational capacity and information processing as limited. Such an approach may help in this modeling process.

This work will consider solid and relevant contributions from other scientific fields to understand its relation and applicability to the development of power systems. This may lead to the application and development of new innovative approaches for modeling and analyses for consumer behavior on electricity consumption, that may allow a better understanding in our age of increasing volume of data, interaction, and artificial intelligence.

## 1.2 OBJECTIVES

The main aim of this thesis is to study the application of CST to electrical energy systems, centering the analysis of customer behavior on electricity consumption, using insights from the field of behavioral economics. Emergent complex behaviors on electricity consumption as well as its impact on power grids will be analyzed by modeling customer behavior and their interactions on residential electricity consumption. In order to reach such a general aim, specific aims were designed as follow:

- To study the CST and understand its possible contribution to smart grid modeling and analysis;
- To analyze customer behavioral modeling and analysis, especially using concepts from the behavioral economics field, and understand how it can be applied in a complex systems environment for power systems;
- To build an agent-based simulation on the application of CST and behavioral economics concepts to the power systems;
- To apply the simulation model to a case study on a distribution grid;
- To analyze the emerging patterns of the simulation scenario and its implication to modeling, analysis, operation, and planning of power systems.

## 1.3 ORIGINAL CONTRIBUTIONS

The present thesis contributes to the study and application of CST to electrical energy systems, considering consumer behavior under the framework of behavioral economics. Expected original contributions are:

- Development of an agent-based simulation model that uses behavioral economic insights to understand residential electricity consumption, and allows to examine how the interaction of heterogeneous agents at the micro-level produces relevant macro outcomes to power systems;
- Analysis of emergent properties and grid impacts of the simulation, considering a complexity science framework of analysis.

## 1.4 OUTLINE

The following chapter of this document focuses on the CST, discussing the main concepts involved and presenting a structured search and review of the state of the art of its applications to power systems.

In the third chapter, consumer behavior and modeling of power systems are discussed. Special attention is given to the area of behavioral economics, including its origins, main concepts, and applications. Tools that will be applied to the methodology such as agent-based simulation and power flow techniques are also briefly presented.

The fourth chapter describes the methodology and specifications of the agent-based model developed, while chapter five presents and discussed the main results of this thesis. Finally, chapter six presents the conclusions of the work, guidelines for future research and a list of the publications undertaken on the period.

## 2 COMPLEX SYSTEMS THEORY

Weaver (1948) divided the problems of science into three main categories:

- Problems of simplicity;
- Problems of disorganized complexity;
- Problems of organized complexity.

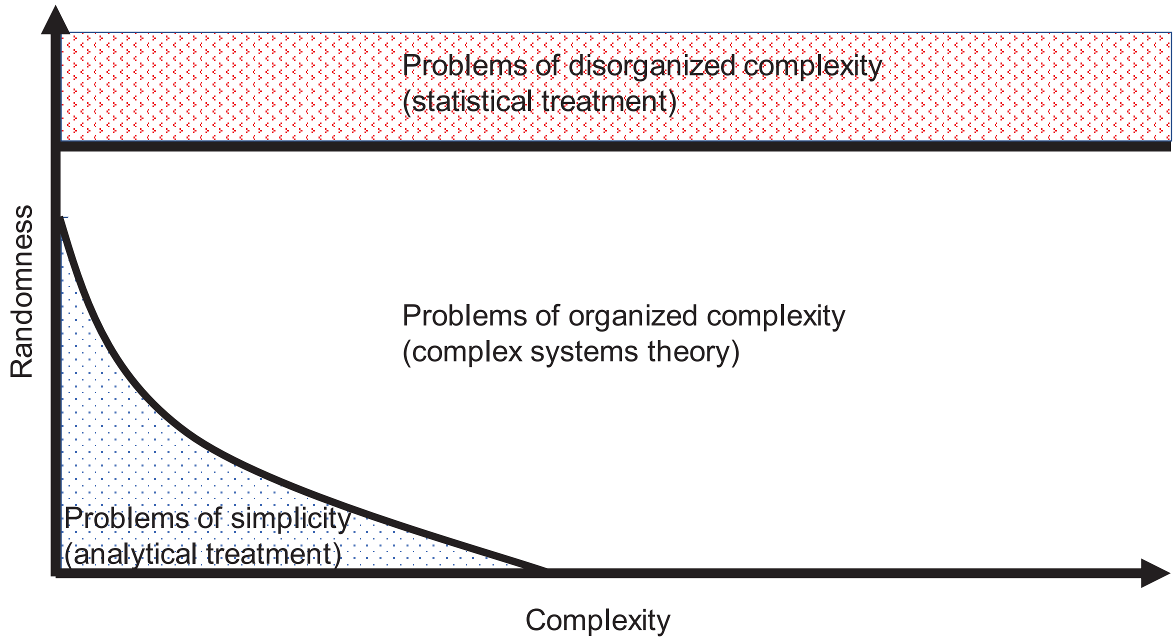
The first category depicts the science developed in the $17^{th}$, $18^{th}$ and $19^{th}$ century, which brought many of the inventions we use on a daily basis such as telephones, radios, cars, airplanes, and power generators. The term 'problems of simplicity' refers to the fact that in these kinds of problems usually few variables are considered.

In the $19^{th}$ century, some scientists started to explore problems with a wider range of variables, through the development of probability theory and statistical techniques. Weaver (1948) described this category as problems of disorganized complexity, i.e. a problem in which the number of variables is very large, and one where each of the many variables has a behavior that is individually erratic or perhaps totally unknown, while the system as a whole possesses certain orderly and analyzable average properties. Examples of disorganized complexity problems include the calculation of the temperature in a room filled with trillions of air molecules, pricing method for an insurance company, and the behavior of several billiard balls moving simultaneously in a very large billiard table.

Spite of the great efforts of the aforementioned methods when dealing with problems of disorganized complexity, a great field was left untouched between these and the problems of simplicity. This middle region deals with problems with a sizable number of variables that are interrelated into an organic whole, where conventional statistics may not cope with. These are the problems of organized complexity and can be dealt with CST.

FIGURE 1 summarizes these three main categories. In short, problems of simplicity consider a smaller amount of variables that behave in a way that can be analytically predicted, problems of disorganized complexity consider a large number of variables that are individually erratic but present orderly behavior as a whole, and problems of organized complexity present emergent behavior that cannot be directly assessed from the individual behavior of the parts.

FIGURE 1 – PROBLEMS OF SCIENCE AS CLASSIFIED BY WEAVER (1948)



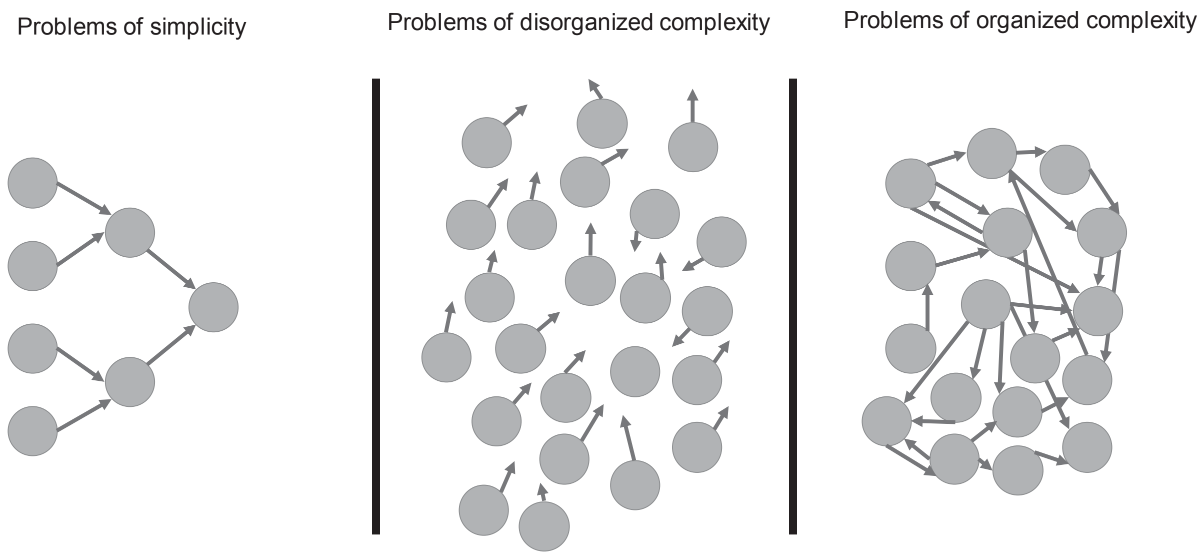

SOURCE: Adapted from Weinberg (2001).

These three categories differ not only on the number of variables, randomness, and complexity. The dynamics involved are very different. In problems of simplicity, dynamics can be inferred from the behavior of individual parts, while in problems of disorganized complexity it can be usually assumed that agents are independent, and emergent behavior can be assessed by statistical treatment. Problems of organized complexity present an emergent complex behavior on which agents are mutually dependent. FIGURE 2 illustrates expected patterns of dynamics on these different kinds of problems.

A growing interest on the study of CST took place on the 19$^{th}$ century, starting with an early eruption in the 1920s and 1930s, which gave birth to term holism, the idea that systems and their properties should be viewed as a whole, not just a collection of parts, summarized by the famous expression that "the whole is greater than the sum of its parts" (SIMON, 1996).

Following the 1940s and 1950s, initial approaches were made towards system theory, artificial intelligence, and the concept of cybernetics, coined by Norbert Wiener. During the 1960s and 1970s, formulations on what is known as complexity science were made for market systems phenomena. Later on, other fields such as network theory, game theory, agent-based modeling, fractals, and chaos theory were found

FIGURE 2 – DYNAMICS OF PROBLEMS OF SCIENCE




SOURCE: The author (2019).

to be closely related to complexity science. Since then, this interdisciplinary field has been a focus of research into different domains such as statistical physics, social, biological and computer sciences, sometimes with quite diverse scopes (KREMERS, 2012a).

CST comes as opposition to reductionism since the later was not able to explain situations such as the unpredictability of weather and climate, the adaptive nature of living organisms, and the behavior of societies (MITCHELL, 2009). As Goldenfeld and Kadanoff (1999) reasons: “Everything is simple and neat, except, of course, the world”.

Spite of the significance and applicability of CST to understand the world that surrounds us, there is no generally accepted formal definition of a complex system. Follows some definitions of a complex system:

- A complex system may be described as a large network of simple components with no central control that exhibits emergent complex behavior (MITCHELL, 2006)
- A system that can be analyzed into many components having relatively many relations among them, so that the behavior of each component depends on the behavior of others (SIMON, 1996);
- A system in which a large network of components with no central control and simple rules of operation give rise to complex collective behavior,

sophisticated information processing, and adaptation via learning or evolution. In short, a system that exhibits nontrivial emergent and self-organizing behaviors (MITCHELL, 2009);

- A system composed of many interacting parts, such that the collective behavior of those parts together is more than the sum of their individual behaviors (NEWMAN et al, 2011);

As a matter of fact, the aforementioned definitions have the same main notion: emergence refers to the fact that the system's global behavior is not only itself complex but arises from the collective actions of its simple components. Thus, the mapping of individual actions towards collective behavior is non-trivial, i.e. the conjecture of nonlinearity is brought as the whole is more than the sum of the parts (MITCHELL, 2006).

Complex systems are systems characterized not only by a large number of components but also by the diversity of these components, their relationships, and interactions. Still, they should be classified neither as a simple nor as a complete mess. Complexity is different from both, as although it often is a result of rather simple dynamics, it includes iteration and most often also the adding of some randomness to the process (KREMERS, 2012a). Complex systems are located somewhere between order and chaos and are usually made up of a large number of components (as previously illustrated in FIGURE 1).

Illustrating the concept, Simon (1996) discusses the behavior of ants, both as individuals and as a collective group, which underlines important insights to point out the difference between simplicity, which is attached to the idea of reductionism, and complexity, strongly linked with holism. An ant, viewed as a behaving system, is quite simple. The apparent complexity of its behavior over time is largely a reflection of the complexity of the environment in which it finds itself.

Goldenfeld and Kadanoff (1999) points out that complexity means that structures have variations, thus, a living organism is complex because it has many different working parts, each one formed by variations of the same genetic code.

It is important to distinguish the difference between a complicated and a complex system. In a complicated system, the various elements that make up the system maintain a degree of independence from one another. Thus, removing one element does not fundamentally alter the system’s behavior, although it may be compromised. Complexity arises when the dependencies among the elements become important and, therefore, the removal of one element may destroy system behavior to an extent that goes beyond the significance of the particular element removed (MILLER; PAGE, 2007).

Some factors usually associated with the degree of complexity on engineered systems are (EISNER, 2011, p. 18):

- Size: system complexity tends to increase with size;
- Functionality: the complexity of systems tends to increase as they carry out new functions;
- Operation mode: system complexity tends to increase as more parallel operations rather than serial are demanded;
- Real-Time Operation: systems with real-time operation are usually more complex;
- Number of interfaces: the greater the number of interfaces with different systems and other elements, the larger is the complexity of the system. It also applies to the number of different types of interfaces and the degree of interaction.

A particular type of complex system is one that results from integrating a set of complex systems, thereby constructing a SoS (EISNER, 2011, p. 21). Jamshidi (2009) defines SoS as large-scale integrated systems that are heterogeneous and independently operable on their own but are networked together for a common goal. The five main criteria commonly recognized in a SoS, as originally architected by Maier (1996), are:

- Operational independence of the individual systems;
- Managerial independence of the systems;
- Geographic distribution is often large;
- Emergent behavior, i.e. a SoS performs functions and carries out purposes that do not reside in any component system;
- Evolutionary development, as a SoS is never fully formed or complete.

Classic examples of complex systems include ecosystems (LEVIN, 1998), economy and financial markets (FARMER; GENAKOPLOS, 2009), cities (BETTENCOURT; WEST, 2010), the brain and the immune system, the internet (MITCHELL, 2006), collective motion (HELBING, 1997), the aviation system, telecommunication, stock markets, and the power transmission and distribution (T&D)

system (EISNER, 2011). In Gorod et al. (2015) several case studies on SoS are presented in areas such as banking, logistics, supply chain risk management, education, wind energy systems, hospital and health-care systems, disaster response, air traffic system, large-scale construction sites, and military applications.

## 2.1 MAIN CONCEPTS ON COMPLEXITY SCIENCE

To understand, model, and eventually control complex systems, a multi-disciplinary perspective is needed, linking elements and concepts derived from different areas such as economics, social sciences, mathematics, biology, information theory, computer science, artificial intelligence, and statistics. To allow a better discussion on the main concepts related to complexity science, some of the core concepts will be briefly presented in the following sections.

### 2.1.1 Emergence

Aristotle's famous quote "The whole is more than the sum of the parts" (around 350 BC) outlines the main idea of emergence. The notion of emergence refers to the fact that the system's global behavior is not only complex but arises from the collective actions of simple components, and that the mapping from individual actions to collective behavior is non-trivial (MITCHELL, 2006).

It happens because the individual components usually have mutual collective behaviors that are not readily understood from the behavior of the parts in isolation. It is necessary to study the parts in the context in which they are found to be able to tackle such properties. In CST focus is usually given to global emergent properties, which depend on the entire system, therefore requiring many times extensive and elaborate mathematical treating (BAR-YAM, 1998, p. 11).

On problems of disorganized complexity collective behavior can be analyzed using theorems such as the central limit theorem and the law of large numbers. On complex system (problems of organized complexity) unanticipated statistical regularities often emerge, moving beyond the usual bounds covered by such tools. In problems of disorganized complexity, interactions may cancel one another out and result in a smooth bell curve. In complex systems, interactions are not independent, they reinforce one another (through negative and positive feedbacks that alter system dynamics), and result in behavior that is very different from the norm (MILER; PAGE, 2007).

### 2.1.2 Power Law

A power law is a functional relationship between two variables, where a relative change in one results in a proportional change in the other quantity, in other words, one variable varies as a power of another. A power law may be described as follows:

$$p(k) \approx k^{-y} \qquad (1)$$

where $p(k)$ is the probability of an event $k$. If $y = 1$, therefore the likelihood of events or conditions for $k = 100$ are one-hundredth as likely of events of $k = 1$.

Power-law-like behavior has been found in a variety of systems, including the use of words in texts, the distribution of income in a society, the size of cities, the magnitude of earthquakes and forest fires (MILLER; PAGE, 2007), and the probability of a given outage in a power system (BAKKE et al., 2006).

A common way to test if a given distribution follows a power-law behavior is to construct a histogram representing its frequency distribution, and plot that histogram on doubly logarithmic (log-log) axes. If it is approximately a straight line it is expected to follow a power law, with a scaling parameter given by the absolute slope of the straight line (CLAUSET et al., 2007). Nevertheless, on specific conditions, this method can lead to some mistakes. Refer to Clauset et al. (2007) for a more robust method for analyzing power law data that combines maximum-likelihood fitting methods with goodness-of-fit tests based on the Kolmogorov–Smirnov statistic.

### 2.1.3 Complex Networks

Complex networks are usually non-homogeneous structures that exhibit a power law form in their distribution degree (number of links per node). They deal with the non-trivial topological features of simple networks which can be observed in reality, including patterns which are neither completely regular nor completely random (KREMERS, 2012a, p. 14).

To study and understand complex networks is very important because structure always affects function. For instance, the topology of social networks affects the spread of information and disease, and the topology of the power grid affects the robustness and stability of power transmission (STROGATZ, 2001). Other examples of complex networks include the internet, airline networks, particular networks of protein-protein interactions, biochemical pathways, and polymer networks (GALE; KARIV, 2014). Graph theory provides a standardized language with which to discuss and quantify its structure and properties of complex networks.

### 2.1.4 System Dynamics

Dynamical systems theory concerns the description and prediction of systems that exhibit complex changing behavior at the macroscopic level, emerging from the collective actions of many interacting components. In general terms, it describes the ways in which systems change, what types of macroscopic behavior are possible, and what kinds of predictions can be made about that behavior (MITCHELL, 2009). A dynamical system consists of a set of possible states, together with a rule that determines the present state in terms of past states.

System dynamics has been applied to issues ranging from corporate strategy, through the dynamics of diabetes, the cold war, and the human immune system (STERMAN, 2000). System dynamics has also been applied to power systems, as presented in the review paper Ahmad et al. (2016). Specifically in Brazil, the works of Alves (1997), Silva (2009), Souza (2012), and Ebert (2015), among others, also presented relevant contributions to the topic.

To capture or represent causes of dynamics, Causal Loop Diagrams (CLD) is a useful tool, since it represents the feedback structure of systems. CLD consists of variable connected by arrows denoting the causal influence among the variables. Variables are related by causal links, shown by arrows, campaigned by positive (+) or negative (-) signs to indicate how the affected variables change when the source variable changes positively. The closed loops are also indicated either by a letter R, indicating that it is a reinforcing positive loop, or by the letter B, indicating that it is a negative balancing feedback loop (STERMAN, 2000, p. 137).

### 2.1.5 Chaos

The defining idea of chaos is that there are some systems, in which even minuscule uncertainties in measurements of initial position and momentum can result in huge errors in long-term predictions of these quantities. Chaotic behavior can be observed in experiments and in computer models of behavior from all fields of science.

Historically it was regarded as an inconvenience that should be designed out if possible. But, since the initial studies by Henry Poincaré in the 1880s, it has been understood that many chaotic behaviors could provide potential usefulness when treated accordingly (KAPITANIAK, 1996). Nevertheless, the understanding of chaos theory eventually laid to rest the hope of perfect prediction for all complex systems, quantum or otherwise (MITCHELL, 2009).

### 2.1.6 Self-Organization

ftabKeating et al. (2003, p. 45) describes self-organization as a process by which the inherent order of a system increases and its internal organization becomes more complex without intervention by an outside source. Examples of self-organized systems are present in many natural phenomena such as galaxies, tornados, canyons, and ecosystems.

Braha, Bar-Yam, and Minai (2006, p. 13) suggests that self-organization is present in human processes associated with engineered systems, as economic actors, teamwork, the improvements in a system, among others; hence characterizing real-world structure and dynamics may lead to the development of guidelines for coping with self-organized complex behavior.

## 2.2 THE ELECTRICAL POWER SYSTEM AS A COMPLEX SYSTEM

Since the deregulation of the power and energy sector and the increasing use of automation and distributed control, the electrical power system has increased not only in size and on the number of participant agents, but also on complexity (LUO, 2014). This tendency is emphasized with the increasing participation of consumers on both generation (prosumers) and flexibility actions (such as demand response) for the power system. New business models and technologies such as automated demand response and Peer-To-Peer (P2P) Electricity markets and the increasing participation of electric vehicles and distributed energy storages are also accounted to change the landscape of power systems (ZIO, 2016). Also, as batteries and heating networks' participation on the grid increase, it will be increasingly complex to balance the local goal of maximizing asset lifespan alongside the global goals of efficiency, reliability, and profitability (HOWELL et al., 2017).

Regarding such energy transitions, Sovacool (2016) argues that given these attributes of complexity, most transitions have been and will continue to be path dependent rather than revolutionary, i.e. cumulative rather than fully substitutive. This fact only increases complexity levels and the number of interrelated agents.

Although power systems may present continental scales, it is not this feature that gives them the characteristic of being a complex system, since size itself does not infer complexity. Considering strictly a physical point of view on dynamic systems theory, a power system can (and has been) modeled by a (huge) set of differential and algebraic equations, even if sometimes with several simplifying assumptions (LUO, 2014).

Electrical power system complexity comes from the interactions of the physical layer with the rest of hierarchical levels governing and using the infrastructure (LUO, 2014). Many heterogeneous agents acting on different layers such as physical-layer (generators, transformers, substations), cyber-layer (communication units, data management), and human decision layer, leading to some emergent phenomena that cannot be studied with a set of equations in any form. Its complexity, therefore, lays on the multiplicity of interacting players that operate with, and within, a defined environment as independent decision-makers, with autonomous behaviors, goals, and attitudes. These broader socio-technical networks form a community with high levels of interaction and integration among its actors (BOMPARD et al., 2012). Yu and Xue (2016) argues that smart grid developments cannot be done in isolation with environmental, social, and economic environments.

This increasing complexity may limit the applicability of traditional modeling techniques since agents are heterogeneous and exhibit nonlinear feedbacks (RYLATT et al., 2015). Besides that, new market mechanisms and control techniques provide real-time feedback information into the system, making prediction and modeling of power system even more difficult (BAKKE et al., 2006).

Research in smart grid has focused on the development of each smart grid functionality in an object-oriented manner, while the interface variables among these functionalities, that could assess the complexity of the smart grid, are many times not taken into account. To understand what these interface variables are and how they relate to the global efficiency of the smart grid is very challenging. CST may provide a theoretical framework to effectively access large volumes of raw data from several sources and transform them into useful decision-aid models for the smart grid.

Thus, the smart grid should not be treated as an aggregated independent system anymore, but as an integrated complex system. CST has a big potential in coordinating such interdisciplinary modeling in which different functionalities and knowledge areas must work together to model the smart grid. All of them are unified by the same "complex view", which allows a decision aid model where all the stakeholders involved may benefit from.

As discussed so far, by analyzing the main characteristics of the smart grid, one may consider it a complex system for several reasons. Some of the most relevant features that allow a smart grid to be considered a complex system are discussed in TABLE 1.

Power grids have also been widely acknowledged as a typical complex network because of their size, structure, and complex interactions. Section 2.2.1.3 will further demonstrate the similarities and the applicability of complex network theory to the smart grid. In addition, the smart grid may as well be considered a SoS, since they cover extensive geographical regions and are composed of many diverse components with operational and managerial independence (JAMSHIDI, 2009, p. 12).

TABLE 1 – COMPLEX SYSTEM VERSUS SMART GRID FEATURES

| Complex system feature | Smart grid feature |
|---|---|
| Diversity of interrelated heterogeneous agents | The smart grid comprises diverse interacting heterogeneous agents, e.g. households, businesses (from different sizes), industries, prosumers, generators, investors, regulators, grid operators, flexibility operators, and telecommunication companies, which interact and are influenced by each other (GUÉRARD et al., 2012; BALE et al., 2015). These agents are multi-state, multi-scale on the time domain, and are connected to multi-level hierarchies (ZIO; AVEN, 2011; ZIO, 2016). |
| The behavior of each component depends on the behavior of others, and agents have the capacity to learn and adapt | There is a strong nonlinear interaction among agents in both physical but also the social aspect. Smart grids can change structurally over time with changing populations, lifestyles, technology, environmental concerns, among others. (BALE et al., 2015). For example, consumers can learn the effects of unconstrained demand for example through direct feedback from smart meters or smart plugs. |
| Exhibits emergent complex behavior and the mapping of individual actions towards collective behavior is non-trivial | The smart grid presents several emergent properties, both intended (e.g. system stability) and unintended (e.g. large-scale blackouts). Self-organizing emergent behavior on energy system arises that cannot be predicted by understanding each of the component elements separately (BALE et al., 2015). It is not possible to accurately predict future energy demand based on historical information and knowledge of individual users because of the impossibility of previously knowing the effect of multiple non-linear feedbacks due to new interactions or changes behaviors (BALE et al., 2015). The extent of interconnectedness, the number, and variety of power sources and generators, of controls and loads, make electric power grids among the most complex engineered systems (ZIO, 2016). |
| No central control | In a broader sense, decisions are taken at multiple levels (households, communities, governmental, internationally) which influence decision making (BALE et al., 2015). It presents relevant local decisions such as protection systems, distributed generation, self-healing systems, among others.) (GUÉRARD et al., 2012). Since data needed for decision making in the smart grid is growing exponentially in the last few years, there is a move for decentralization and hierarchical control strategies. A complex character is indeed ultimately conferred on these energy networks by the establishment of additional (hierarchical) control levels (LABANCA, p. 42, 2017). |
| Simple rules of operation | The smart grid has several elements that usually ‘play’ by known physical rules or policies. Although those may not always be simple (counterpointing the complicated) they are usually possible to be modeled by an equation set (for physical layers) or simple rules of each agent can be estimated. The complexity arises not from the rules of operation of each agent, but through their interaction and emergent patterns. |

SOURCE: The author (2019).

### 2.2.1 State of the Art

A structured process of forming a bibliographic portfolio[1] was used on the theory and application of the electrical power system as a complex systems, using the guidelines described in Ensslin et al. (2010). This process as a whole lead to a better comprehension of the state of the art of the research on the electrical power system as a complex system, where it was explicit the relevance of the consumer on such analysis. Therefore, special focus on this thesis is then given to how to present a better model of consumer behavior, considering aspects from the behavioral economics within a framework compatible with the CST. Unfortunately, due to time limitations, it was not possible to apply the same structure process also for consumer behavior and modeling on power systems.

The first step to create the bibliographic portfolio was to define the research axis and associated keywords for the gross database, which were chosen aiming to surround most relevant publications on CST applications to power systems. Axis 1 relates to CST and Axis 2 to power systems. The search was performed by combining each keyword of one axis with the other axis, using the software “Publish or Perish[2]”, that obtains the raw citations metadata through the Google Scholar database. A limitation of the software “Publish or Perish” is that it considers not all references in a given keyword search, but the 1,000 most relevant works. Still, it was considered enough for the aim of this study. TABLE 2 shows the axis used in phase 1.

In total, the first gross database was composed by 7,831 documents. This large number of documents was found since the keywords “complex systems” and “power systems” are used in several different contexts, from law studies, politics, international relations, automotive control systems to psychology and ergonomics.

The initial filtering step was the analysis of the documents’ title. After this analysis, 556 documents remained in the database. The next step was to remove all non-relevant conference papers, non-relevant books, leaving in the database only journal papers, technical reports of renowned institutions, academic thesis and book

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[1] The reference date of this process was July/2016. After that additional papers were added manually reflecting the most relevant publications of the authors and journals mapped.
[2] https://harzing.com/resources/publish-or-perish

TABLE 2 – KEYWORDS AND NUMBER OF PAPERS FOUND

| # Search | Keyword Axis 1 | Keyword Axis 2 |
|---|---|---|
| **Search 1** | System of Systems | Power systems |
| **Search 2** | System of Systems | Smart grid |
| **Search 3** | System of Systems | Demand response |
| **Search 4** | Systems theory | Power systems |
| **Search 5** | Systems theory | Smart grid |
| **Search 6** | Systems theory | Demand response |
| **Search 7** | Complex systems | Power systems |
| **Search 8** | Complex systems | Smart grid |
| **Search 9** | Complex systems | Demand response |

SOURCE: The author (2019).

chapters on case studies. Furthermore, we removed all duplicated papers, remaining 262 documents on the database.

The last step was the analysis of the abstract and main contributions of the remaining documents to have a glimpse of its importance and application to the field. Some remaining conference papers were removed, as well as publications that were not accessible. The final database is composed of 81 documents. This final database will be briefly discussed in the following subsections.

TABLE 3 presents the distribution of the papers according to the defined areas, considering that a few papers may be classified simultaneously in more than one area. The more cited journals are presented in TABLE 4..

TABLE 3 – DISTRIBUTION OF THE PAPERS IN AREAS AND YEAR OF PUBLICATION

| Areas / Year | Theoretical considerations, frameworks, and architectures | Modeling and simulation using CST | Power grids as complex networks | Analysis of events on power grids | Control applications | TOTAL BY YEAR |
|---|---|---|---|---|---|---|
| **2006** | - | - | - | 2 | - | **2** |
| **2007** | 1 | 1 | - | 1 | - | **3** |
| **2008** | - | - | - | 2 | - | **2** |
| **2009** | - | - | 1 | 4 | - | **5** |
| **2010** | - | - | 1 | 1 | - | **2** |
| **2011** | 2 | - | 1 | 2 | - | **5** |
| **2012** | 5 | 1 | 1 | - | 1 | **8** |
| **2013** | 3 | 3 | 2 | 1 | - | **9** |
| **2014** | 6 | 2 | 5 | 1 | 1 | **15** |
| **2015** | 6 | 4 | 3 | 1 | 1 | **15** |
| **2016** | 6 | 5 | 1 | 1 | - | **13** |
| **2017** | 1 | - | 2 | - | - | **3** |
| **2018** | - | 1 | - | - | - | **1** |
| **TOTAL BY AREA** | **30** | **17** | **17** | **16** | **3** | |

SOURCE: The author (2019).

TABLE 4 – MOST CITED JOURNALS

| Journal | Publisher | Citations | Impact-Factor (as of January 2019) | Qualis “Engenharias IV” (Quadriênio 2013-2016) |
|---|---|---|---|---|
| **Physica A: Statistical Mechanics and its Applications** | Elsevier | 5 | 2.132 | B1 |
| **IEEE Systems Journal** | IEEE | 4 | 4.337 | A1 |
| **Applied Energy** | Elsevier | 4 | 7.900 | A2 |
| **IEEE Transactions on Smart Grid** | IEEE | 4 | 7.364 | A1 |
| **IEEE Transactions on Power Systems** | IEEE | 3 | 5.255 | A1 |
| **Energy** | Elsevier | 2 | 4.968 | A2 |

SOURCE: The author (2018).

#### 2.2.1.1 Theoretical considerations, frameworks, and architectures

The concept of the smart grid concept is still fuzzy, and no unifying definition exists. Several frameworks have been proposed to address the main concepts of the smart grid and to provide the main guidelines for modeling and analysis, as well as implementation (GUÉRARD; BEN AMOR; BUI, 2012). Since the smart grid may be considered a complex system, CST is, therefore, suitable to provide a unifying approach to develop frameworks and architectures for the smart grid that allows the integration of multiple agents. These CST-based frameworks can enable the identification of emerging problems and provide new solutions and approaches (BOMPARD et al., 2012) (BALE; VARGA; FOXON, 2015).

Büscher and Sumpf (2015) analyzes trust and confidence as socio-technical characteristics in the transformation of energy systems since the public’s role is expected to change from passive service abiders to active service providers, as anticipated by the visions of prosumers. A qualitative functionalist method is used to analyze the prerequisites of the public’s participation, concluding that the social mechanisms of trust and confidence are more vital for consumers, investors, and others affected than previous researches have noticed.

Suleiman et al. (2012) concerns with the lack of understanding of various inter-domain relationships and dependencies among technical and business domains within the smart grid and proposes an inter-domain analysis of the complex technical and business domains within the smart grid using Domain-Link Matrices.

Arnautovic and Svetinovic (2012) proposed to integrate value network models into analysis and design of complex sustainable systems, i.e. SoS spanning across several technical domains and organizations such as energy systems, information technology systems, transportation systems, and buildings. It is argued that besides actors, value objects, activities that generate values, and their dependencies, value network models for power systems should also include information about environmental impact.

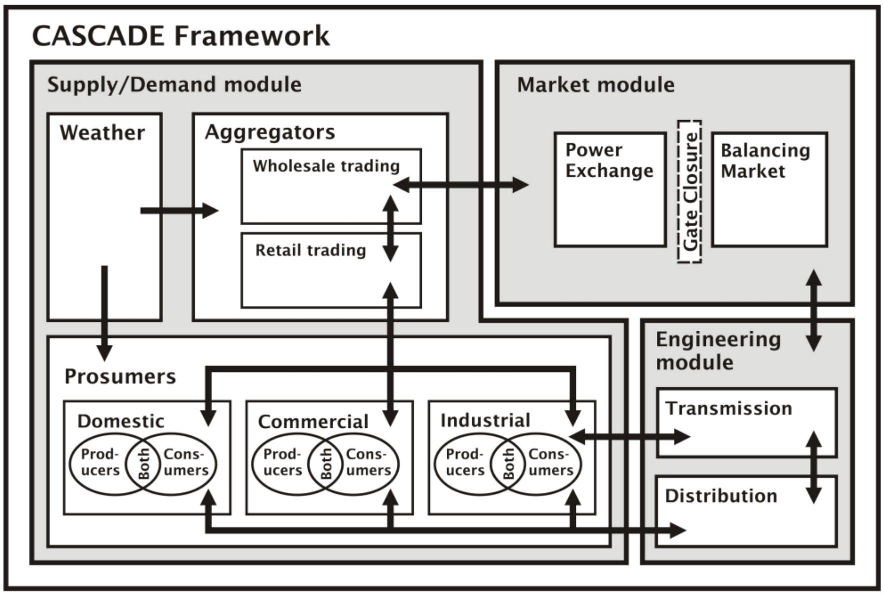
Dall’Anese et al. (2017) argues that electricity, natural gas, water, and district heating/cooling systems should be jointly planned and operated as a complex SoS at multiple spatiotemporal scales since it can bring significant benefits from socioeconomic, operational efficiency, and environmental standpoints

Guérard, Ben Amor and Bui (2012) analyzes the similarities between smart grids and complex systems discussing the concepts involved in the planning of the smart grid consists of multiple microgrids with a local behavior in interactions with each other, focusing their analysis on its emergent properties and system dynamics. Also on system dynamics, Marija D. Ili´C (2007) discusses the modeling, monitoring, and control of electric power systems from the point of view of large-scale dynamic systems, focusing on the shift from hierarchical to multilayered open access paradigms.

Taking into account this increasing complexity and system dynamics, the importance and contributions of the computational intelligence field for developing the dynamics, stochastic, computational, and scalable technologies needed for sense-making, situational awareness, control and optimization in smart grids are presented in Venayagamoorthy (2011). Its relevance lies in the need for innovative technologies to hand the growing complexity of the smart grid.

A relevant example of a framework for complexity using CST is the CASCADE framework (RYLATT et al, 2015), which describes the smart grid with three linked modules: a Supply/Demand module; an Engineering module (representation of the physical network); and a Market module. These modules interact with each other, trough physical, economic and social rules, in feedback loops to determine overall system behavior (FIGURE 3). Although this framework considers several interacting agents, many other areas such as regulation, environmental issues, and other energy carriers are not taken into account.

FIGURE 3 – CASCADE FRAMEWORK AND ITS INTERACTIONS




SOURCE: Rylatt et al (2015)

In a different perspective, Zio and Aven (2011) proposes a general framework of analysis on the challenges posed to the representation and treatment of uncertainties in the performance assessment of smart grids, given their complexity and high-level of integration of novel technologies. Focusing on the companies point of view, Farid et al. (2016) presents a holistic framework for “enterprise control” assessment of the future power grid.

Wang (2015) addresses the vulnerability analysis of safety-critical systems (illustrated on the paper by nuclear power plants) within a framework that combines the disciplines of risk analysis and multi-criteria decision-making. A quantitative hierarchical model to characterize the susceptibility of safety-critical systems to multiple types of hazard is developed and a set of protective actions, which effectively reduces the level of vulnerability of the critical system, are identified.

Focusing on policies, Powell (2014) describes a modeling framework that focuses on finding the best policy from a set of four fundamental classes of policies consisting of policy function approximations, cost function approximations, policies based on value function approximations, and look-ahead policies.

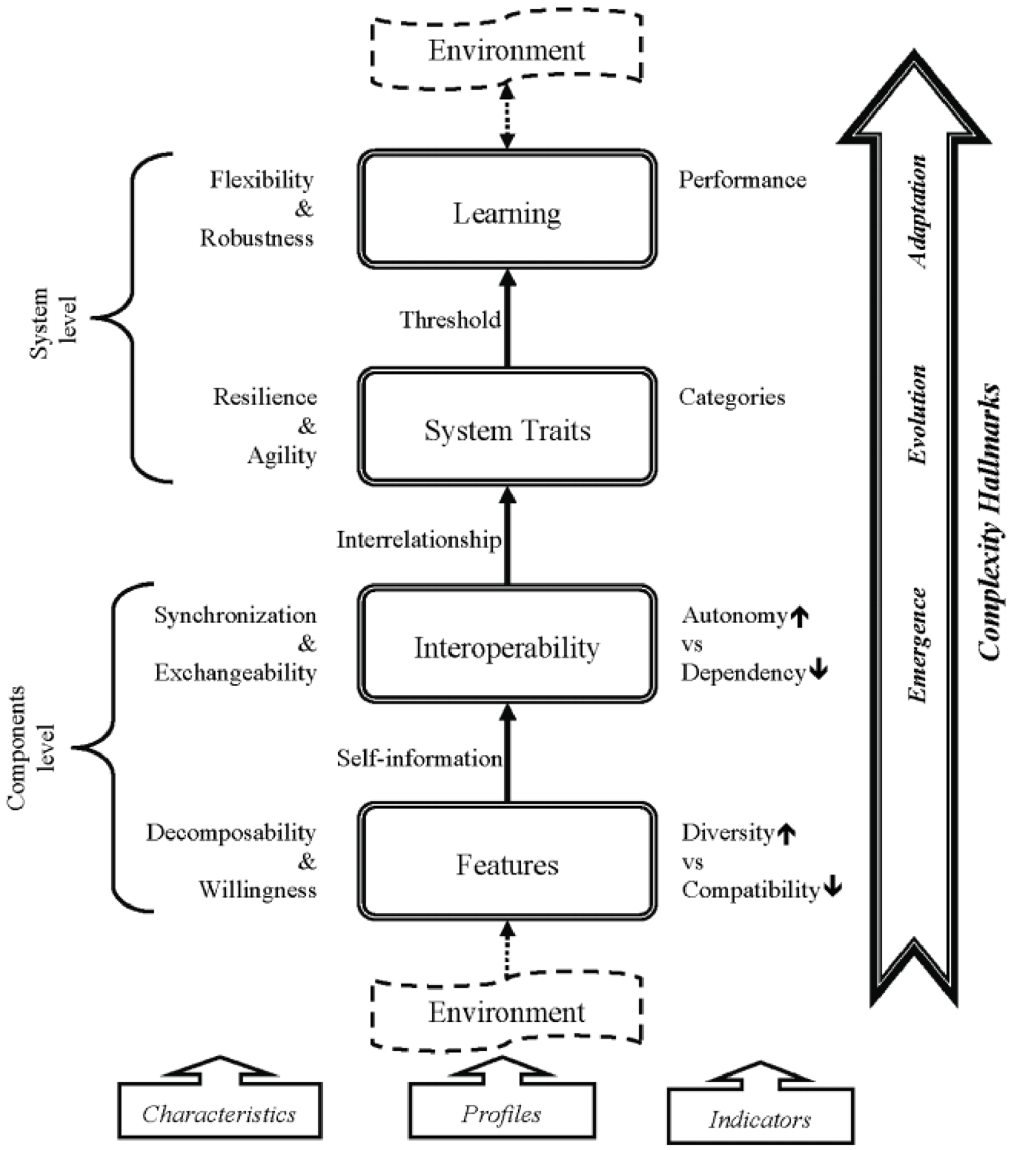
Frameworks are also found in the literature focusing on the analysis of the electrical power system (or specific parts of the power system) as a SoS:

- Johnson and Gheorghe (2013) proposes a framework for analyzing and measuring antifragility based on SoS concepts;
- Kargarian Marvasti et al. (2014) presents a SoS framework for optimally operating active distribution grids, defining both distribution company and microgrids as independent systems, and identifies the process of information exchange among them;
- In the transmission level Kargarian and Fu (2014) presents a decentralized decision-making framework to determine a secure and economical hourly generation schedule for a transmission system encompassing several active distribution grids;
- In Mahmoud and Al-Sunni (2015) the microgrid is devised in a SoS framework consisting of three distributed generation units as three subsystems supplying a load and is modeled as a network control SoS which is subjected to random packet losses. Further, the controller design which stabilizes the system in the presence of packet losses is presented and elucidated by simulation results;
- Mo et al. (2016) develops a SoS Monte Carlo simulation-optimal power flow computational framework that is capable of generating consecutive time-dependent operating scenarios, accounting for the impact of degraded communication networks on DG systems performance.

Haghnevis and Askin (2012) proposes an integrated framework to study emergent behavior and consequences of evolution and adaptation in engineered complex adaptive systems, as illustrated in FIGURE 4. It is developed for any domain, but the paper illustrates its applicability on a case study on electrical power demand.
Andrén, Stifter, and Strasser (2013) proposes an integrating semantic-driven design method for the smart grid, which could act as a common framework for different domain models, namely: application, communication, physical, and control. On this framework, the authors argue that model-driven engineering should then be used to develop new smart grid applications. Other researchers also support the use of model- driven

engineering on smart grid frameworks such as Evora, Hernandez and Hernandez (2015), focusing on a method to deal with the evaluation of the emergent behavior in complex systems, and Evora (2014), which uses such techniques, combined with business intelligence and swarm intelligence, to deal with the complexity of demand-side management.

FIGURE 4 – FRAMEWORK FOR ENGINEERED COMPLEX ADAPTIVE SYSTEMS




SOURCE: Haghnevis and Askin (2012)

Some approaches consider the application of systems theory to the development of analytical frameworks. Systems theory is a well-established in engineering and in biological and physical sciences because it is a convenient and useful way to see a whole as a collection of its interacting parts, and its general principles allow consideration of any phenomena at any nested level as an open system (BALE et al., 2015).

Polese and Carrubbo (2012) suggest that the Viable Systems Approach, a methodological key based on systems theory and relationships, useful for the interpretation of complex phenomena, might be promising to support world community discussions upon energy.

The principle of model archaeology as a formal method to quantitatively examine the balance and evolution of energy system models, through the ex-post analysis of both model inputs and outputs using a series of metrics was developed in Dodds, Keppo, and Strachan (2014) and applied to energy systems.

Piriou, Faure, and Deleuze (2016) proposes a meta-model developed for a power plant. Its contribution to support the integration of dependability concerns is demonstrated by the proposal of a method to build systematically, from the instance diagrams derived from the proposed meta-model.

According to Andrén et al. (2013), for the application domain of smart grids to be developed based on frameworks, there are no standards or other existing models which can be directly applied to represent a Smart Grid application model, and they suggest the development of a Smart Grid Application Description Language for this purpose. Nevertheless, applications have been developed using commonly used description and modeling languages such as Modelica, Systems Modelling Language (SysML) (LUBEGA; FARID, 2016; LOPES; LEZAMA; PINEDA, 2011), Unified Modelling Language (UML), and Business Process Modelling Language (BPML).

Different architectures are also proposed to address the complexity of the smart grid. In Danekas (2014) the Smart Grid Architecture Model, proposed in the context of the European standardization mandate M/490 is presented. Its aim is to provide a common understanding of architectural elements and means of classification to the smart grid, to cope with its continuously increasing complexity.

Using the concept of holons (a logical entity that is both a whole and a part), in Frey et al. (2015) a generic holonic control architecture is proposed to help the development and integration of ICT control systems on multiobjective and multiscale smart microgrids.

In Lopes, Lezama, and Pineda (2011) a SoS approach to analyzed and design smart grids using model-based systems engineering is presented. Detailed architectural artifacts of a smart grid as a SoS are analyzed, considering a logical, behavioral, physical and techno-economical perspective for the optimal integration of various systems. Finally, Lubega; Farid (2016) proposes a reference system architecture for the water-energy nexus.

#### 2.2.1.2 Modeling and simulation using CST

Models for energy systems usually are either equation-based, also known as ‘top-down’ models, or agent-based models, also know as ‘bottom-up’ models (BALE et al., 2015).

Equation-based models include systems dynamics. For instance, Qudrat-Ullah (2013) presents a dynamic simulation model for Canada’s electricity system using a system dynamics approach. The model results indicate that substantial new investments in generation and efficiency areas are needed to achieve a sustainable electricity supply and demand system.

In Kargarian, Fu, and Wu (2015), a chance-constrained SoS based decision-making approach is presented for stochastic scheduling of power systems encompassing active distribution grids. Based on the concept of SoS, the independent system operator and distribution companies are modeled as self-governing systems, collaborating with each other to run the entire power system in a secure and economical manner. The effectiveness of the proposed simulation model is evaluated on a 6-bus and a modified IEEE 118-bus power systems.

Tannahill and Jamshidi (2014) presents a proposal on how to construct a bridge between SoS and Data Analytics to develop reliable models for such systems. The subject material for this demonstration is using data analytics to generate a model to forecast produced photovoltaic energy to assist in the optimization of a microgrid SoS, using tools like fuzzy interference, neural networks, principal component analysis (PCA), and genetic algorithms. While focusing on the active distribution expansion planning considering demand response and DG, Arasteh et al. (2016) uses the concept of SoS to model the expansion of DGs that are owned by private investors.

Jonkeren et al. (2015) presents a tool, which is a combined systems engineering and dynamic inoperability input-output model, to estimate the economic impact of critical infrastructure network failure, resulting from a hazard, on the regional or national level. The case study presented the Italian power blackout that took place on September 28th, 2003. Also discussing critical infrastructures, Zio (2016) analyzes vulnerability and risk for the protection and resilience of these infrastructures.

Marija D. (2016) suggest that composite control-based hierarchical control is a good approach to supporting large-scale regulated monopolies under a complex perspective which includes social and ecological perspectives.

Using the methodology of dynamical complex networks (a tool for analyzing the dynamics of complex systems characterized by interactive nodes), Zhong et al. (2018) presents a DR model of vehicle-to-grid mobile energy network in which the electric vehicle moves across different districts represented as network nodes, trough the implementation of a differential equation system.

On agent-based models several different studies are found on the literature, such as applications on demand response (MILLER; GRIENDLING; MAVRIS, 2012; HAGHNEVIS, 2013; KREMERS; GONZÁLEZ DE DURANA; BARAMBONES, 2013; KREMERS, 2012b), renewable power generation (KREMERS, 2012b), multi-carrier energy networks (DE DURANA et al., 2014), and global warming (KHANSARI et al., 2015). Agent-based models offer a flexible architecture that allows for a detailed representation of complex agent systems, including the behavior of agents, their social interactions and the physical and economic environments surrounding them (RAI; HENRY, 2016). Follows additional information on the cited works:

- Miller, Griendling, and Mavris (2012) presents an approach that uses an agent-based model combined with probabilistic analysis to show the sensitivity of the performance of demand response in a collaborative SoS smart grid scenario, to understand the uncertainty in human's decision to participate in a direct load control program[3];
- Haghnevis (2013) proposes an agent-based modeling platform with application to demand response in electricity markets. The approach integrates social networks, social science, complexity theory, and diffusion theory;
- Kremers, González De Durana and Barambones (2013) presents a multi-agent simulation model to analyze the possibilities of improving grid stability on islanded systems by local demand response

[3] In direct load control programs, the power utility has the permission to control remotely customer's equipment.

mechanism. Using a simple under-frequency load shedding strategy, emergent phenomena such as synchronization effects appeared in the simulation, which can have undesirable impacts on the system;

- Kremers (2012b) presents the modeling and simulation of electrical energy systems through a complex system approach using agent-based models. Two case studies were presented. The first is of a wind farm to address the production side, that allows visualizing the behavior of the wind farm at different time scales and the relation of individual wind turbines and the aggregated wind farm. The second case study addresses the demand side through a multi-level model that couples the simulation of individually modeled consumers representing frequency behavior, focusing on the consumption of refrigerators due to their availability and thermal storage abilities;
- De Durana et al. (2014) addresses the modeling of a local multi-carrier energy network. This problem was considered as an extension of modeling a low voltage distribution network. Instead of using an external power flow analysis package to do the power flow calculations, it integrated a multiagent algorithm to perform the task, in a concurrent way to the other simulation tasks, and not only for the electricity but also for a number of additional energy carriers;
- Khansari et al. (2015) provides a comprehensive system dynamics model, based on systems thinking approach, to address the issue of global warming, in terms of households' energy consumption behaviors;
- Even considering a much simpler physical layer of an electrical grid, a circuit composed by a power source and resistors in parallel, an agent-based simulation developed in Kühnlenz and Nardelli (2016) shows a significant complexity level on analyzing the effects of number of agents (system size), communication network topology, communication errors and the minimum power gain that triggers a behavioral change on the system dynamic.

#### 2.2.1.3 Power grids as complex networks

Modeling of systems using network theory is considered a thriving field of investigation. Based initially in graph theory, network theory considers a system as a network of nodes, some of which are connected to each other via edges (BALE et al., 2015).

Chu and Iu (2017) presents a survey on the application of complex network theory for modern smart grid applications. In Pagani and Aiello (2013) a survey of the most relevant scientific studies investigating the properties of power grids as a complex network analysis is presented. There is also studies on the modeling of power grids as a network of networks, for instance on Zendehdel and Yazdi (2015), where a six-layered hierarchical structure is used for its analysis, each layer considered as an automaton and its autonomous performance is described by a hybrid function, mathematically.

On a broader sense, Yu et al. (2014) discusses the theory of complex networks and its possible application to smart grids, mentioning guidelines for future studies on grid properties, distributed control, and optimization.

Comparisons on different network topologies for smart grids are also discussed. In Sánchez (2009) the topology, electrical structure, and attack/failures tolerance of power grids are compared with those of theoretical graph structures such as regular, random, small-world, and scale-free networks. Pagani and Aiello (2014) presents an investigation on how different network topologies and growth models facilitate a more efficient and reliable network, and whether they can facilitate the emergence of a decentralized electricity market. Cuffe and Keane (2015) proposes various complex network models in which electrical distance might be defined for power systems and records how well each candidate distance measure may be embedded in two dimensions.

Luo (2014) analyses the application and extension of complexity science and complex network theory in power system. The first study was on the use of topological methods to analyze the vulnerability and the correlation of topological analysis with real malfunction data for some major European power transmission grids. Secondly, hierarchy control levels were analyzed and, finally, the application of complex network theory to power distribution network analysis.

In Pagani and Aiello (2016) a methodology for evolving any existing physical power grid to a smart grid model, through topological changes, is presented. This foundation for a decision support system for utilities and governmental organizations shows how increasing connectivity may be beneficial in realizing more efficient and reliable networks.

Specifically analyzing transmission systems, Marvel and Agvaanluvsan (2010) studied its representation as complex networks, showing that most grids can be characterized by the Gaussian Orthogonal Ensemble, an indicator of chaos in many complex grids. However, it is also discussed that under certain circumstances, grids may be described by Poisson statistics and indicators of regularity.

As the smart grid is composed not only by its physical layer (wires), Hu et al. (2014) considers the interaction problem between the power system and its communication module from the perspective of the topological structure. The statistical properties and the interactive relationships of the main power system and its communication module (abstracted as two complex heterogeneous networks) of one province in China were described.

Analysis of the interaction of the smart grid as a complex network with other energy caries are analyzed in Lubega and Farid (2014) and Winkler and Dueñas-Osorio (2011). Thacker et al. (2017) performed a disruption analysis considering an integrated electricity domestic network and the flight network for England and Wales.

Bond graphs were used to develop models that characterize the salient transmissions of matter and energy in and between the electricity, water and wastewater systems in Lubega and Farid (2014). These models, when combined, make it possible to relate a region’s energy and municipal water consumption to the required water withdrawals in an input-output model.

Winkler and Dueñas-Osorio (2011) introduces a performance assessment methodology for the topological properties of interface networks connecting electrical substations to water pumping stations and natural gas compressors (coupled infrastructures).

Two final topics discussed were dynamics and vulnerability. Colbaugh and Glass (2012) presents an approach for analyzing the dynamics of complex networks in which the network of interest is first abstracted to a much simpler representation (the required analysis is performed on the abstraction) and analytical conclusions are then mapped back to the original network. The potential of the approach is illustrated in an electric power grid case study.

Zio and Sansavini (2013) analyzes the vulnerabilities of the electric power grid and associated communication network, assessing how the integration of both systems copes with a request to increase power generation. The probability that a reduction in the functionality of the communication system yields a faulty condition in the power grid is quantified.

#### 2.2.1.4 Analysis of events on power grids

Besides its topology, the analysis of events such as blackouts on power grids may also support the premise that they are complex systems and complex networks. This work can be undertaken by analyzing empirical data of blackout events or developing simulation models.

On empirical data analysis, Bakke, Hansen, and Kertész (2006) studied the size distribution of power blackouts for the Norwegian and North American power grids. Through the development of a model with global redistribution of the load when a link in the systems fails, the paper evidenced that the outage size distribution follows power laws, as expected in a complex system.

Xianzhong and Sheng (2010) analyzed time series of failures in four transmission and distribution systems, finding prominent long-time correlations and that the probability distribution of faults per day has a power law tail. Thus, the time series of power system fault shows consistency with SOC.

Newman et al. (2011) also analyzed blackout size distribution data and confirmed that they have a power law form over much of their range, indicating that blackouts behave as a complex dynamical system. A practical and very interesting implication presented in the paper is that mitigation efforts need to be approached with care since they can move the system to a new dynamic equilibrium. While reducing the absolute frequency of blackouts of all sizes, the underlying forces can still cause the relative frequency of large blackouts to small blackouts to remain the same or even increase. It may happen because large and small blackouts are found not be mutually independent, but strongly coupled with the complex dynamics.

Focusing on the comparative effects of conservative generation dispatch (performed in order to minimize stress on the system and therefore attempt to minimize possible outages and blackouts) versus nonconservative generation dispatch (attempting to maximize the stress), Fitzmaurice et al. (2011) analyzed time series of blackouts and its power law dependency of blackout size with respect to frequency. It was found that the nonconservative dispatch although attempting to maximize the immediate risk reduces the frequency of blackouts of all sizes over the conservative dispatch in the long term.

Dobson et al. (2007) focused on large blackouts of electric power transmission systems caused by cascading failure, studying the statistics and dynamics with approximate global models instead of assessing the details of particular blackouts. The responses to a particular blackout event (e.g. increasing capacity, making more frequent maintenance, adjusting or adding system alarms or control) are directed towards the components involved in causing it. The paper suggests that these opposing forces, together with the underlying growth in customer load and diversity, give rise to a dynamic complex system equilibrium, controlled by a power law equilibrium.

Also considering the concept of SOC, i.e. the property of dynamical systems that have a critical point as an attractor, Weng et al. (2006) analyzed the mechanism of blackouts in China's power system, showing that the function of blackout probability vs. blackout size also exhibits power law distribution. Zhao and Zhangh (2009) analyzed blackout data in the China power system from 1981 to 2002. The probability distribution functions of various measures of blackouts size presented a power law behavior in its tail, suggesting that SOC dynamics may play an important role in the dynamic of blackouts.

Also on the analysis of empirical data, but not focused on blackouts, Sornette, Maillart and Kroeger (2013) uses risks in a database of 99 events on nuclear power plants as an example and documented a robust power law distribution.

Kiesling and Chassin (2009) presented and analyzed, using complexity science, the result of a field experiment of real-time pricing for residential electricity customer in Washington State, USA, where customers saved money and their peak demand fell. This combination of technology and institutional design enabled decentralized coordination, showing the real-time market outcomes were those of a self-organizing and scalable complex adaptive system. Also analyzing field data from pilot projects, Morris, Vine and Buys (2015) applied field data discovered through qualitative in-depth interviews of residential households to a Bayesian Network complex system model to examine whether the system model could explain successful peak demand reduction in the case study of an electricity demand reduction project within an Australian community in 2008.

Moving on to the analysis of events using testbeds and simulation models, Dueñas-Osorio and Vemuru (2009) concludes that topological changes are needed to increase cascading robustness in transmission systems at realistic tolerance levels instead of improvements in network components, by analyzing IEEE 118-node and 300-node networks, used for reliability studies. Particularly it is observed that improvements in network component tolerance alone do not ensure system robustness or protection against disproportionate cascading failures.

In Arianos et al. (2009) a new parameter called net-ability is proposed to evaluate the performance of power grids, since power grids exhibit patterns of reaction to outages similar to a complex network, following power laws on a blackout. An approach to examining the vulnerability of a power system (considered a complex network) against cascading failure threats on an extended topological metric is proposed on Yan, He and Sun (2014). The proposed approach adopts a model called extended betweenness that combines network structure with electrical characteristics to define the load of power grid components, presenting simulation results from a standard IEEE 118-bus test system.

Also on cascading failure, Cai et al. (2016) models interdependencies between power systems and dispatching data networks, taking the IEEE 39-bus system and China's Guangdong 500-kV system as examples. Simulation results showed show that the dispatching data networks with double-star (scale-free networks, which presents few hub nodes with more neighbors) configuration has a lower probability of catastrophic failures than with a mesh structure (small-world networks, where distributions of degree and betweenness are more balanced).

The analysis found in this present study also considered relations with chaos theory, e.g. in Li and Chiang (2008) the presence of structure-induced bifurcation at both small and large-scale power systems and its consequence are discussed. It is concluded that the structure-induced bifurcation produces an immediate instability induced by generator reactive power limits and, therefore, not taking it into account may result in overly optimistic operating limits. Also, Shahverdiev, Hashimova, and Hashimova (2008) investigates chaos, trough synchronization analysis between two uni-directionally coupled simple chaotic power systems, specifically a single-machineinfinite-bus system. The paper presents the coupling strengths necessary for the synchronization between the systems to occur.

#### 2.2.1.5 Control applications

Control applications explicitly deriving from CST were scarce in the literature, nevertheless, interesting works on centralized control (OUAMMI; DAGDOUGUI; SACILE, 2015), decentralized control (JIANG; JIANG, 2012), and model-based control (AMGAI; SHI; ABDELWAHED, 2014) were found.

In Ouammi, Dagdougui, and Sacile (2015) a centralized control model for optimal management and operation of microgrids as a SoS is designed, incorporating storage devices, various distributed energy resources (DER), and loads. The proposed model is evaluated through a case study in the Savona district, Italy, consisting of four microgrids that cooperate together to the main grid.

Jiang and Jiang (2012) presents an approach to decentralized control design of complex systems with unknown parameters and dynamic uncertainties using the theory or Robust Adaptive Dynamic Programming (ADP). The effectiveness of the proposed algorithm was demonstrated in a case study on online learning control of multimachine power systems.

In Amgai, Shi and Abdelwahed (2014) the formulation of a generic, higher layer model-based limited lookahead control approach, based on the theory of autonomic computing, is presented and tested on a nine-bus multi-machine power system benchmark for voltage control applications. Autonomic computing was considered able to deal with the complexity of the smart grid due to its self-healing, self-configuration, self-optimization and self-protection schemes.

## 2.3 FINAL DISCUSSION

This chapter first presented a theoretical background related to CST, providing the necessary information to analyze and comprehend the remaining of the documents, including the proposed contributions. One of the most important messages is that real-world problems, engineered or not, usually involve in some degree of complexity and that disregarding this complexity on its analysis may jeopardize the comprehension, modeling, and design of solutions to several fields.

After setting the foundations of CST, the chapter discussed the electrical power system as a complex system, arguing the reasons why CST may be a suitable tool to analyze the smart grid. After that, an extensive literature survey was presented, trying to demonstrate the state of the art of the use of CST to power systems.

Several works discuss frameworks and models to better understand and model such complexity that emerges on modern power systems. A few works considered the modeling of human behaviors in such complex approaches, but most approaches considered the power systems as a complex cyber-physical system, not taking into account human decision making or cognition processes into account. Since the main goal of a power system is basically to provide, directly or indirectly, service and comfort to people, approaches that would provide a better in-depth analysis of the consumers are needed. The next chapter will outline and discuss some of these issues.

# 3 CONSUMER BEHAVIOR AND MODELING ON POWER SYSTEMS

## 3.1 CONSUMER'S BEHAVIOR ANALYSIS OF ELECTRICITY CONSUMPTION

Consumer[4]'s behavior analysis of electricity consumption may be very challenging since, in contrast to other consumer goods, the customer does not 'see' the energy bought, but only perceives the work it performs. However, it is an essential product to provide comfort, connectivity, information, and security of modern societies. In the transition to new energy systems through innovations, the roles of users in the different stages are considered to be crucial (SCHOT; KANGER; VERBONG, 2016).

Analysis of consumer behavior and modeling on power systems should go beyond financial aspects since although monetary incentives can lead to changes in the load profile of given customers, it is indeed a much more complex topic. To increase the likelihood of success of interventions with customers, the choice and design of interventions should be well understood and evidence-based (EPE, 2018).

Prices clearly affect energy behavior, but many times as not as influential as one may assume, since in many cases energy is rather cheap compared to other parts of a household budget, making behavioral change seem not to be 'worth the effort'. In some specific cases, financial incentives may even increase the behavior that was intended to be minimized, since people think they 'bought' the right to not be efficient (PARAG; SOVACOOL, 2016).

Van Der Werff et al. (2018) argues that monetary incentives (such as demand response) are associated with several downsides such as rebound effects[5]. When monetary savings are relatively small (or take a long time to happen), people that focus exclusively on the private cost versus benefits are not likely to change their consumption pattern, therefore highlighting monetary benefits may undermine people's intrinsic motivation to engage in energy-saving behaviors.

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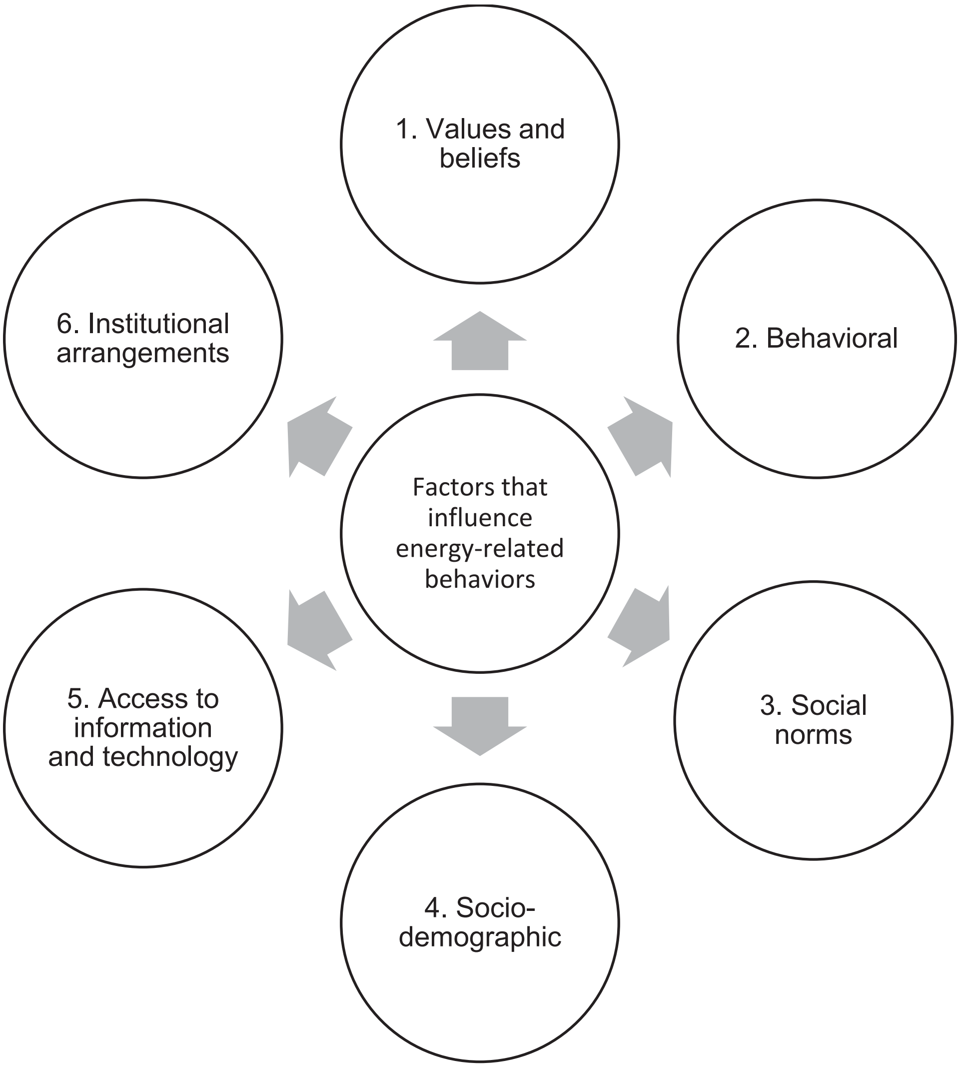
[4] The usually applied term consumer may reflect the fact that the 'human-side' inside the meter premises are not researches and engineer`s focal point. An alternative for this term is 'customer' (BILLINTON, 1996) 'client', since it reflects the idea of some engagement in a more qualitative relationship. Both terms are used interchangeably throughout this document.

[5] The purchase of new energy-efficient equipment leads to saving money and, possibly, the purchase of other services and products that may increase energy consumption.

According to Steg et al. (2018) choices, preferences, and behaviors of individuals are major direct influences on energy demand, and they also shape the acceptability and effectiveness of technologies, strategies, and policies to bring a sustainable energy transition. Many factors influence energy-related behaviors, both intrinsic as extrinsic, which can be divided into six main areas, as illustrated in FIGURE 5. The discussions in this section will focus only on residential electricity consumption.

FIGURE 5 – FACTORS THAT INFLUENCE ENERGY-RELATED BEHAVIORS




SOURCE: The author (2019).

### 3.1.1 Values and Beliefs

Values are defined as general goals that people strive for in their lives, which can be divided into hedonic values (what makes people feel good and reduce effort), egoistic values (how to increase their owns resources), altruistic (benefit other), and biospheric values (which focus on nature and the environment), endorsed by all people around the world but on different extensions. Energy-related actions related to values are of particular interest because they can affect a wide range of behaviors, making them an important target for promoting consistent sustainable energy behavior, nevertheless, they are usually very hard to change (STEG et al., 2018). For instance, a survey by the Brazilian regulatory agency showed that for 45% of the customers that installed micro DG were mainly motivated by the ‘sustainable development’ (ANEEL, 2015).

A person’s sense of identity and the way of perceiving themselves also represents a strong factor for developing certain behaviors. People are more likely to take up new information that is compatible with their existing beliefs. If a given action is consistent with one’s beliefs it may motivate them to act this way again to be consistent and act in line with how they see themselves, what is called the positive spillover effect. Negative spillover, also known as the ‘rebound effect’, may happen if people feel they already did their share (STEG et al., 2018).

Understanding the values and beliefs that lead the end-users to form certain preferences is especially relevant to the introduction of novel technological concepts for behavioral changes (LOBASENKO, 2017). However, to understand and direct actions toward specific values is very difficult since what people say and what they do are sometimes very different things. For example, people may know about, intrinsically value, hold positive attitudes towards, and genuinely intend to act in some socially desirable way, but not translate it into actual behavior (FREDERIKS et al, 2015a).

### 3.1.2 Behavioral

It is important to understand the paradigms that shape the behavior and decision-making process of people (LOBASENKO, 2017)(FREDERIKS; STENNER; HOBMAN, 2015). A growing body of scientific research demonstrates that people are rarely the rational decisionmakers envisaged by traditional economic models of human behavior (FREDERIKS et al., 2015a). Therefore section 3.2 will discuss behavioral economics and how this field of study has been applied to the energy field, specifically to residential electricity consumption.

### 3.1.3 Social norms

Social norms, i.e., guidelines and expectations regarding ones' behavior shape the decisions of people to conform to what is socially acceptable (FREDERIKS; STENNER; HOBMAN, 2015). People also tend to contribute to a given cause because it makes them feel good about themselves or how they are perceived by other people, the so-called warm glow effect (POLLITT; SHAORSHADZE, 2011)(YANG; SOLGAARD; REN; 2018).

As regards public goods, such as electricity, most individuals will collaborate or contribute to a given goal (such as energy efficiency) only if others do the same (POLLITT; SHAORSHADZE, 2011). Highly visible behavior like driving an electric vehicle or installing residential solar panels can be socially rewarding, while less visible behavior like installing an efficient air-conditioning system not.

As people tend to compare themselves to other people, peer-based comparative feedback can serve as a stimulating tool for changing the behavior of people regarding energy (AYRES; RASEMAN; SHIH, 2009), for example when people learn that others act more sustainable than they do and the comparison group is similar to the receiver (STEG et al., 2018). Nevertheless, it must be considered that different types of customers respond to different stimuli. This means that customized feedback is required in order to achieve the desired result (WANG et al., 2018).

### 3.1.4 Socio-demographic

Factors directly related to the user that form the context of their individual surroundings, such as various socio-demographic indicators (age, gender, education, employment status, household type, income) also play an important role on energy consumption (FREDERIKS; STENNER; HOBMAN, 2015B) (LAMPROPOULOS; VANALME; KLING, 2010). The living arrangements such as the type, size, geographical location, and ownership of the living dwelling determine to a certain extent the users' electricity patterns of consumption.

However, on profiling users, it was found that socio-demographic characteristics explain only a small part of variance regarding energy and pro-environmental behavior. Moreover, they were less suitable in predicting energy-saving behavior than attitudinal and behavioral variables (SÜTTERLIN; BRUNNER; SIEGRIST, 2011). This shows that socio-demographic characteristics come secondary and serve as an additional explanation on top of other internal factors.

### 3.1.5 Access to information and technology

Primarily technological advances such as DG, storage systems, smart meters, and home automation technologies enable users to be active participants in the electricity system (PARAG; SOVACOOL, 2016). The distribution system operators have better insight in the operation of their networks and are able to manage bi-directional power flows and resolve local problems in the networks also through using services offered by users, such as demand response (LAVRIJSSEN; PARRA, 2017).

Digitalization and the application of ICT in electricity networks have opened the possibilities for direct and more individualized communication with users. For instance, smart meter data can be visualized on in-home-displays, web portals, or smartphone apps, and therefore companies can provide household electricity consumption feedback, tailored energy conservation tips, and specific alerts to inhabitants when a given device is malfunctioning. This kind of information may help citizens to make better-informed decisions regarding their energy use (TIEFENBECK, 2017).

Even with abundant information human computational capability is limited, therefore rational optimal decisions are not commonplace. This will be discussed in-depth on section 3.2. Specifically, on the adoption of household PV systems, Parag and Sovacool (2016) states that such actions are many times imped by information asymmetries, false expectations about performance, and resistance among both home builder and owners.

### 3.1.6 Institutional arrangements

Policies should allow and facilitate customer behavior related to energy that is aligned with all agents aims. Even with enough information and technological access, regulations that are too restrictive can inhibit or even prevent desired energy-related behavior. For instance, on the Brazilian electricity retail sector large scale consumers can purchase electricity from an open market, while smaller consumers are bounded to their local retailer. According to Vizioli (2017), consumers on the open market are much more sensitive to tariff variations than the average consumer.

Policies and market-based instruments tend to have a relatively narrow view of the user as a consumer making conscious rational choices on the energy market from a set of pre-defined options. Although this approach enables the optimization of current user behavior it does little to stimulate large-scale transformations (SCHOT et al., 2016). Policies to encourage sustainable energy behaviors will be more effective when important drivers of the relevant behavior are targeted and significant barriers to change are removed. Policy can be aimed at rewarding or facilitating sustainable energy behavior (pull measures) or punishing and inhibiting undesired behavior (push measures). The related behavior change can be voluntary or imposed. Measures that punish or inhibit undesired behavior can be effective but generally meet more public resistance than reward or facilitating measures (STEG et al, 2018).

## 3.2 BEHAVIORAL ECONOMICS

Traditional economic theory is distinguished by the belief that human decision-making and behavior can be explained by assuming that agents have stable well-defined preferences and make rational choices consistent with those preferences (THALER, 1988). In other words, people want to maximize their utility, which represents the advantage, pleasure, or fulfillment a person gains from obtaining or consuming a good or service. The viewpoint that people maximize utility in a rational and selfish way was, and still is, in many contexts, a common sense on the field of economics. Empirical results for which implausible assumptions are necessary to align it with traditional economic theories were called anomalies.

These anomalies may be related to market, individual choices, intertemporal choices, among others. Richard Thaler (awarded with the 2017 Nobel Memorial Prize in Economic Sciences) published on The Journal of Economic Perspectives two series of papers, with collaborations from several leading authors on behavioral economics and related fields, describing and discussing several anomalies. The first series was published from 1987 until 1991, totaling 14 papers, and the second one from 1995 until 2006, totaling six additional papers. Selected relevant anomalies on these series are disused on TABLE 5.

Other important studies on market anomalies were analyzed more recently by Dan Ariely, professor of Psychology and Behavioral Economics at Duke University, USA, and colleagues. In Shampanier et al. (2007) the value of free products were analyzed by several experiments, leading to the conclusion that, as opposed to standard economic perspectives (where people will choose the option with the highest cost–benefit when selecting one of several available products), decisions about free (zero price) products differ, in that people do not simply subtract costs from benefits but instead, they perceive the benefits associated with free products as higher. Another study (NORTON et al., 2012) analyzed the so-called IKEA Effect, where people significantly increase the valuation of self-made products. Participants saw their amateurish creations as similar in value to experts' creations and expected others to share their opinions. Both studies are also discussed on the book entitled Predictably Irrational (ARIELY, 2010).

These anomalies made clear that traditional economic theories were not enough to explain human behavior and decision making. Critiques have been answered by a series of increasingly elaborate rational traditional economic models, but these models still could not answer many of the imposed questions. Thaler (p.9, 2015) argues that it was time to stop assuming that rational economic models are accurate descriptions of behavior and stop basing policy decision on such flawed analysis. Efforts on trying to better explain such anomalies led to the development of behavioral economics, a field which studies the effects of psychological, social, cognitive and emotional factors on the decisions of individuals and institutions. Such anomalies may consider also contextual factors. For a broad discussion on some anomalies for the Brazilian sector one can refer to Fonseca and Muramatsu (2008) and Ávila; Bianchi (2015).

Some key elements that have been introduced by behavioral economics originate from concepts sustained by Herbert Simon (SIMON, 1955) who stated that, due to the psychological limitations of the organism (particularly with respect to computational and predictive ability[6]), actual human rationality-striving can at best be an extremely crude and simplified approximation to the global rationality that is implied. In the context of firms Simon (1959) has listed several arguments that support this hypothesis, e.g. the ambiguity whether short-run or long-run profit (benefits) is to be maximized, the presence of other ‘psychic incomes’ that should be considered in

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[6] For example, the maximum speed at which an organism can move establishes a boundary on the set of its available behavior alternatives. Similarly, limits on computational capacity may be important constraints entering into the definition of rational choice under particular circumstances (SIMON, 1955).

TABLE 5 – SELECT PUBLICATIONS ON THALER'S ANOMALIES SERIES

| Reference | Topic | Main discussion |
|---|---|---|
| **Thaler; Kuhn (1987)** | The January effect | People have a natural tendency to search for confirming rather than disconfirming evidence (confirmation bias), and this bias can be accentuated when unwarranted assumptions make some kinds of disconfirming evidence seem unlikely. The authors discuss seasonal patterns on the stock exchange, looking for an anomaly on the hypothesis that efficient markets follow a random walk (therefore not predictable). In fact, the average monthly return in January exceeds the average return for the whole year, arguing that taxes do not explain the whole subject. |
| **Thaler; Dawes (1988)** | Cooperation | The role of selfish rationality in economic models needs careful scrutiny since much cooperation can be observed in laboratory experiments and in real-world situations. One popular explanation is the reciprocal altruism, where people tend to reciprocate actions (kindness with kindness, hostility with hostility). Another explanation is the pure altruism, where people 'take pleasure in other's pleasure'. |
| **Thaler (1988)** | The winner's curse | On the hypothetical case of oil companies interested in purchasing drilling right on a common value auction, Thaler argues that given the difficulty of estimating the amount of oil on a given location, estimation by experts will vary substantially. Firms whose experts provided high estimates will tend to bid more than the firms whose experts guessed lower, leading that the firm that wins the auction will be the one whose experts provided the highest estimates and the winner of the auction is likely to be a loser (by either the winning bid exceeding the value of the deal, or the value of the deal being less than the expert estimate, leading to disappointment). |
| **Loewenstein; Thaler (1989)** | Intertemporal choice | Intertemporal choices are decisions in which the timing of costs and benefits are spread out over time. Anomalies on school teachers that choose 12 monthly installments instead of nine in a year (being the total amount the same), people that buy appliances that are not energy efficient (even though they could get the price difference back in less than a year), among other situations which people do not appear to discount money flows at the market rate of interest or any other discount rate are discussed. |
| **Kahneman et al. (1991)** | The endowment effect, loss aversion, and status quo bias | Endowment effect, loss aversion, and status quo bias are terms proposed by, respectively, Thaler, Samuelson and Zeckhauser, and Kahneman and Tversky, that describes an asymmetry of value related to the evidence that the disutility of giving up an object is greater than the utility associated with acquiring it. For example, a person that buys a bottle of wine for $10 a long time ago, and could sell it now for $200, but do not agree to sell it (decides to drink it) and neither to buy an additional bottle for $200. A similar effect can be observed on tickets purchase for entertainment events. |
| **Rabin; Thaler (2001)** | Risk aversion | Although risk aversion is also considered in many traditional economic models, this paper discusses how the explanation provided by expected utility theory does not cover many real-world cases. The authors argue that risk aversion can be explained by loss aversion (tendency to feel the pain of a loss more acutely than the pleasure of an equal-sized gain) and mental accounting (related to the tendency to assess risks in isolation rather than in broader perspective). |

Source: The author (2019).

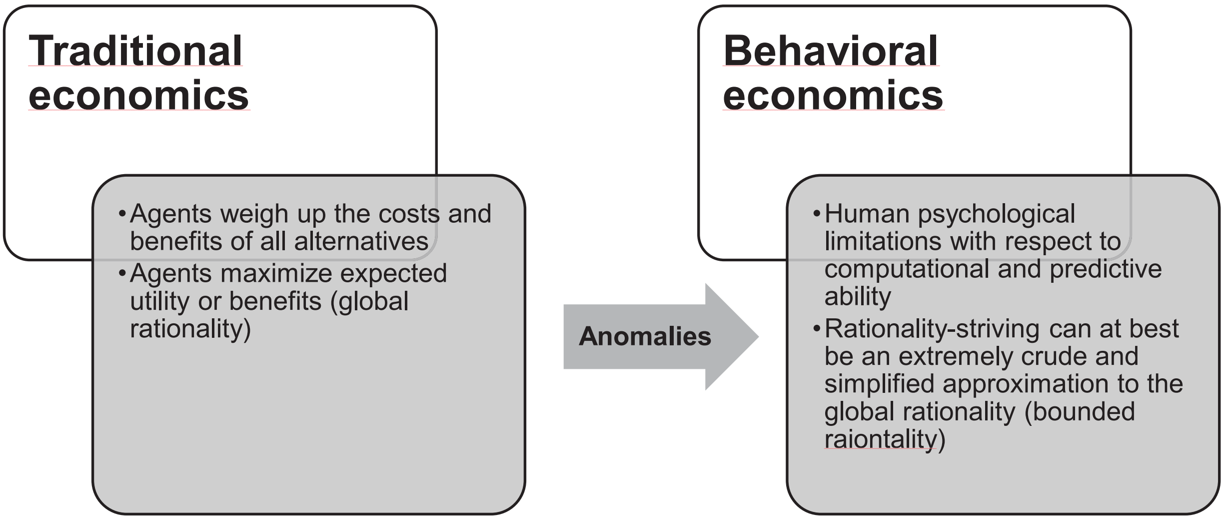
addition to the monetary reward, and the fact that the entrepreneur may not care to maximize. If decision-making is somehow related to rationality, then it should involve something simpler than the maximization of consumer utility and company profits (KATONA, 1953).

There are three basic hypotheses, interrelated but distinct, to understand the boundaries of rationality by Simon (especially applied for consumer's behavior analysis) (SBICCA, 2010):

- The computational capacity of human beings is restricted;
- The information in which people rely on to make decisions is typically incomplete;
- The decision-making on how to adapt to perceived situations can be conscious or unconscious, as people use simple procedures, called rules of thumb or heuristics, to guide their actions.

FIGURE 6 illustrates the main differences that originated the field of behavioral economics.

FIGURE 6 – FROM TRADITIONAL TO BEHAVIORAL ECONOMICS




Source: The author (2019).

Contributions from the field of psychology have brought important insights for the establishment of behavioral economics (KATONA, 1953; SIMON, 1979), e.g. the notion of satiation that usually plays no role in classical economic theory but has prominent importance into the treatment of motivation in psychology (SIMON, 1959). This notion led to the 'satisficing' term, a mix between satisfaction and sufficiency that explain business behavior in terms of the firm's goals to be not maximizing profit but attaining a certain level or rate of profit, holding a certain share of the market or a certain level of sales. This is linked to limited computational capability and information asymmetry, and its effects can be perceived not only on individuals but also on the analysis of companies' performance and macro level analysis.

Indeed, the relationship between economics and psychological studies isn't new. For example, in 1738 Bernoulli studied the need to measure the utilities that individuals obtain from a given good, since it is dependent on the particular circumstances of the person, and realized that the more we have the less we are willing to pay to get more (BERNOULLI, 1954)[7]. In other words, people's happiness (or utility) increase as they get wealthier, but at a decreasing rate.

In the 1940s, nevertheless, von Neumann and Morgenstern redefine utility back to monetary terms for the economic studies. Friedman and Savage attempted to continue Bernoulli's research using von Neumann and Morgenstern axiomatic constraints of the individual's preferences but failed. After this economics and psychology go separate ways, economics employing Friedman's positive-normative distinction; psychology uses Savage's normative descriptive distinction usually through experiments (HEUKELOM, 2007).

Other leading exponents in human decision-making are Kahneman (Nobel Prize in Economic Sciences, 2002) and Tversky, whose works have analyzed anomalous behaviors using heuristics (TVERSKY; KAHNEMAN, 1974). Such an approach, called heuristics and biases, has been used in the analysis of many empirical events in business, law, economics, and medicine. Its assumption relies on people's limited number of heuristic principles that reduce the complex task of assessing probabilities and predict values to simpler judgmental operations.

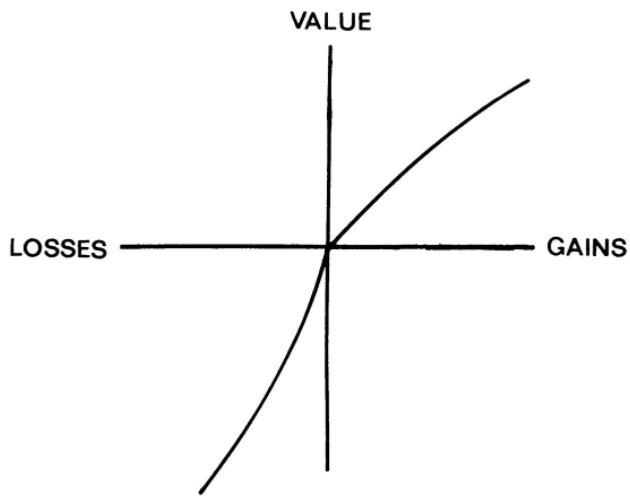
Another very important theory by Kahneman and Tversky is the prospect theory of decision under risk (KAHNEMAN; TVERSKY, 1979). Different from traditional economic theories, the prospect theory is descriptive instead of normative. In other words, instead of trying to be a guide to rational choice, it tries to predict the actual choices real people make (THALER, 2015). One of the most relevant features of the prospect theory is that monetary changes are a concave function of the magnitude of the change. For example, the difference in value between a gain of 100 and a gain of

[7] Translation from Latin to English of the original paper published in 1738.

200 appears to be greater than the difference between a gain of 1,100 and a gain of 1,200. Another important characteristic is that the value associated with losing a sum of money is greater than the value associated with gaining the same amount. This hypothesis is illustrated in FIGURE 7.

On policymaking, behavioral economics is applied under the concept of nudge (SUNSTEIN; THALER, p.6, 2009), a term referring to aspects of the choice architecture that alter people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. This concept is used for policymaking in many countries around the world.

FIGURE 7 – HYPOTHETICAL VALUE FUNCTION




SOURCE: Kahneman and Tversky (1979)

With the 'reunion' of psychology and economics, economists have increasingly turned their attention to experimental models of the physical sciences as a method to understand human behavior. Laboratory experiments allow the investigator to influence the set of prices, budget sets, information sets, and actions available to actors, enabling a measurement of the impact of such factors on behavior within the context of the laboratory (LEVITT; LIST, 2007). Several economists discourage and criticize the use of laboratory experiments that use hypothetical questions (even with financial compensations), arguing that focus should be given to what people do, not to what people say they do. Nevertheless, it is very hard to run experiments where people actually lose large amounts of money. Opposing to this line of thought, Kahneman and

Tversky argue that the use of hypothetical questions relies on the assumption that people often know how they would behave in actual situations of choice, leading to the fact that it should at least create a presumption of doubt on normative traditional theories (THALER, p. 38, 2015).

The behavioral economics approach to economic agents emphasizes its complex feature and allows the use of CST tools and methodologies to model, simulate and analyze consumer behavior. Although laboratory experiments may significantly help to understand human behavior, it is usually not advisable to analyze the emergence of behaviors in complex systems. Agent-based simulation techniques, that will be described in section 3.3, may assess this gap (TESFATSION, 2005).

The development of behavioral economics instigated applications in several other different fields e.g. conflict resolution EUKELOM, 2007), regulations (LODGE; WEGRICH, 2016), the transport sector (MARKOVITS-SOMOGYI; ACZÉL, 2013), health (HANSEN ET AL., 2013), and even applications for the energy sector

### 3.2.1 The Energy Sector and Behavioral Economics

When performing studies and analysis on the energy sector that involve people's behavior and decision-making processes, it is of great importance to understand the paradigms and variables involved (LOBASENKO, 2017)(FREDERIKS; STENNER; HOBMAN, 2015). Behavioral economics comes as a suitable approach to understand, model, and evaluate behavior, programs, and policies related to energy consumption.

Household energy consumption is neither driven only by financial incentives nor by the rational pursuit of material interests. Indeed, monetary rewards may even impair intrinsic motivations for sustainable energy behaviors. People sometimes respond in unexpected and undesirable ways to rewards and sanctions to support sustainable behaviors (FREDERIKS et al., 2015a), leading to the development of simple heuristics to energy consumption that derive from traditional rational economic models (FREDERIKS; STENNER; HOBMAN, 2015; POLLITT; SHAORSHADZE, 2011), and such heuristics are not always accurate. This derivation comes from different sources, e.g. the restricted or limited information, cognition biases, risk or loss aversions, or short-sight on nearby or immediate cost/benefits.

While knowledge is important, it is seldom sufficient (STEG et al., 2018). People minimize their effort on information processing when making a decision by using easily accessible information from their past experience and surroundings, and that they aim for simplicity and tend to choose satisfactory options rather than the one which grants them the largest benefit if the choice appears complicated (POLLITT; SHAORSHADZE, 2011). The existence of habits also leads to difficulty in expecting consumers to be capable of exercising control over their consumption of energy in reaction to given incentives (MARÉCHAL, 2009).

The question of how behavioral economics may be applied to energy and climate policy, investment in energy efficiency, and provision of public goods was as well assessed in a few works. This is very important since, as pointed out on Gillingham and Palmery (2014), individuals make decisions about energy efficiency that leads to a slower diffusion of energy-efficient products than it would be in comparison with the rational assumption of consumers' decision making. This gap may be reduced by better understanding aspects such as hidden costs, consumer heterogeneity, uncertainty, overestimated savings, and the rebound effect.

In Sullivan et al. (2012), an augmented model with approaches derived from behavioral science is used to better encourage individuals to purchase, install, and properly use energy-efficient technologies, aiming at complying with legal mandates and least-cost service obligations, in which utilities must help their customers save energy. Particular attention was devoted to exploring techniques that incorporate psychology, design, and behavioral economics insights into the utility of energy-efficient programs. Santarius and Soland (2018) studies 'rebound effects', focusing on how energy efficiency improvements may increase energy service demand not considering a static rational choice model, but incorporating psychological theories to understand how such improvements affect processes of decision-making and customers preferences.

Tsvetanov and Segerson (2011) presents a welfare analysis of taxes and energy efficiency standards based on an alternative time-consistent behavioral model. The authors concluded that temptation or self-control might be a contributing factor in explaining the energy efficiency gap and that standards might be used as a commitment device to address inefficiencies in consumer choice that stem from temptation.

On another mindset, Pollitt et al. (2013) argues that behavioral economics seems unlikely to provide the “magic bullet” to reduce energy consumption; however, it offers new suggestions as to where to start looking for potentially sustainable changes in energy consumption. The study suggested that the most useful role within climate policy is addressing issues of public perception of the affordability of climate policy and to facilitate the creation of more responsive energy demand, better capable of responding to weather-induced changes in renewable electricity supply.

The efficacy of using nudge concepts to energy efficiency audits was assessed by Gillingham and Tsvetanov (2018). Basically, they developed a personalized notecard and sent to participants 14 days prior to the scheduled audit. This simple message, that considered basic social norms, increased the probability of a household to follow through with an already scheduled audit by 1.1 percentage points.

For both energy efficiency and demand response programs, which essentially involve customer direct action or decision making, utilities focus their attention on technical and legal aspects, which are essential for secure and reliable operation, leaving aside important aspects that lead to consumer engagement. The majority of programs are designed on a purely rational mindset, considering only financial incentives and hoping that people will follow expected rational behavior (TIEFENBECK, 2017). Follows the discussion on some guidelines to design and implementation of programs that could be applied to energy efficiency, demand response, renewable energy, among others, using concepts from the behavioral economics fields:

- *Status quo* bias: Providing a default option might be viewed as the best possibility for many people, leading to ‘go with the flow’ behaviors that, if correctly designed, may lead to the achievement of the objectives of the program (FREDERIKS et al., 2015a; CAMARA et al., 2017). Dramatic differences were reported in green energy use in German cities where consumers must opt-in as a ‘default’ (*status quo*) instead of opt-out when purchasing energy (SUNSTEIN, 2013);
- ‘Satisficing’: Simplification strategies may help reduce cognitive overload and facilitate more effective decision-making in regard to energy consumption, e.g. using automation or minimizing uncertainty (FREDERIKS et al., 2015a; CAMARA et al., 2017);

- Endowment effect: Frame messages to reduce the perception of past investment in energy-inefficient items (sunk costs), and focusing on ongoing costs due to these investments (or even facilitating the disposal and trade of such items) (FREDERIKS et al., 2015a);
- Social influence: Frame energy savings or participation as socially desirable, and appropriate feedback regarding their peer (FREDERIK et al., 2015a). A survey with 1022 respondents from Denmark showed that a positive framing regarding signing up to a renewable energy contract (most Danish signed it) has a significant impact when compared no negative framing (YANG et al., 2018);
- Risk aversion: Focus on low-risk investments, leaving new technologies for early adopters only (FREDERIKS et al., 2015a; CAMARA et al., 2017).

To simulate consumer behavior under a behavioral economics framework may be challenging. Several models have been proposed in the literature to explain the human behavior aspect of the customers, but mostly still considering classical utility function on equation-based models. For instance, in Mohajeryami et al. (2015) the impact of two time-based rates demand-response programs have been investigated on the peak reduction considering loss-aversion and its impact on the perception of the customers. This study was expanded on Mohajeryami et al. (2016).

Classical analytical models on power systems usually show difficulty to represent complex emergent phenomena. Agent-based simulation enables the simulation of these behaviors on the micro level and aggregating their behavior to a macro level, avoiding unrealistic assumption from the ‘optimization agent’ by using a realistic description of agent behaviors, interaction, and heuristics (GALLO, 2015). A brief introduction to agent-based simulation will be presented in the following section (3.3).

An agent-based social simulation model was developed in Kangur et al. (2017) to explore how policies may interact with consumer behavior on the diffusion of electric vehicles over a long time. The model was based on four types of needs: financial, functional, social and environmental, differently from our proposed model that focused on simple heuristics under a bounded rationality scenario.

Also on the field of electric vehicles, Poghosyan et al. (2015) presented an agent-based simulation focused on their influence on the low voltage network over 10 years. Social influences, i.e. a neighbor of an electric vehicle owner is more likely to also purchase an electric vehicle, were considered and results indicated that it can increase the peak demand on a local level, creating higher demand than current British governmental studies suggest.

The use of agent-based modeling to model consumer behavior on energy consumption incorporating the actions of individual homeowners in a long-term domestic stock model was demonstrated by Lee et al. (2014). The results showed that current subsidy in the British energy market seems to offer too much support to some technologies for energy efficiency, which in turn leads to the suppression of other technologies that have a greater energy saving potential. The model was aimed at addressing the technology purchase decision-making process of individual householders considering a highly-disaggregated stock model.

## 3.3 AGENT-BASED SIMULATION

Agent-based simulation allows the building of systems composed of autonomous agents that, with limited information and computational abilities, can solve or mimic complex emergent behaviors. This approach of simulation can also be used at reverse-engineering emergent phenomena as typified by ant colonies, the economy, and the immune system (VIDAL, 2010).

To better understand the concept of agent-based simulation, it is also important to define what an agent is. Russell and Norvig (2016) defines an agent as anything that can be viewed as perceiving its environment through a sensor and acting upon that environment through actuators. An agent sensor may give access to the complete state of the environment at each point in time, being considered fully observable, or, because of lack of communication, noise or sensor failure, be considered partially observable. If the next state of the environment is completely determined by the current state the environment is deterministic, otherwise, it is stochastic.

Other important characteristics of an agent-based simulation involve if it is episodic or sequential. The first means that the following iteration does not depend on previous actions taken, while the latter relates to the property that current decision affects all future decisions. If an environment can change while an agent is deliberating, then the environment is dynamic, otherwise static. Finally, regarding the number of agents involved, a simulation can either be single or multiagent (RUSSEL; NORVIG, 2016).

Complex systems are usually partially observable, stochastic, sequential, dynamic, and multiagent. Therefore agent-based simulation is usually advisable as a tool to help understand the emergence of patterns and behaviors of complex systems (TESFATSION, 2005). Still, models with agent-based objects are easily scaled. Once the behavior of a single agent is described, it is usually easy to explore the behavior of systems of essentially arbitrary size by simply adding more agents to the system (MILLER; PAGE, 2007).

Agent-Based simulation is, therefore, a powerful tool for representing the complexities of energy demand, such as social interactions and spatial constraints. Unlike other approaches for modeling energy demand, agent-based simulation is not limited to studying perfectly rational agents or to abstracting micro details into system-level equations (RAI; HENRY, 2016).

## 3.4 POWER FLOW

The calculation of power flow in an electrical network consists of determining the state (complex bus voltages), flows (active and reactive powers flowing through lines and transformers) and some other variables of interest and is used both in the planning and operation (STOTT; ALSAC, 1974).

The Newton-Rhapson method and its variants have been developed for transmission (meshed) networks. It has a high computational burden for large-scale networks, but for transmission networks approximations can be made by decoupling the active and reactive power of the magnitude and voltage angle, respectively, and by approximating the Jacobian can by a constant matrix, resulting in the rapid decoupling method (TINNEY; HART, 1967; STOTT; ALSAC, 1974).

These approximations cannot be performed for distribution networks due to its high resistance/reactance ratio (R/X). Several algorithms were proposed to effectively solve power flow in radial distribution networks. One of the most commonly used is the Backward / Forward Sweep (BFS), particularly suitable for purely radial systems, but adaptable to meshed systems. It presents different formulations, e.g. current summation method, the power sum method, and impedance sum method, all established according to Kirchoff's laws and Ohm's law (BARAN; WU, 1989). These approaches have in common the fact that the solution algorithm follows two directions of calculation along the feeder bars, hence being called a direct reverse sweep.

The approach used in this thesis, as also used and described in Siebert (2013) and Siebert et al. (2018), is as presented in Zimmerman (1995), which consists of two basic steps, the reverse and direct sweep, which are repeated until convergence. The reverse sweep is a sum of the current flows, while the direct sweep is the calculation of the voltage drop considering current flow updates.

## 3.5 FINAL DISCUSSION

This chapter discussed consumer behavior and modeling on power systems. First, a brief overview of the factors that influence energy-related behaviors was presented. As in many aspects of human decision making and reasoning, it was possible to demonstrate that it is a complex phenomenon, related to several interrelated factors. Behavioral economics was then presented as an approach, opposing to traditional economic perspective of fully rational agents, that could lead to relevant insights on better understanding consumer behavior. The applications of behavioral economics to the energy sector so far were also discussed.

After that, a brief theory on agent-based simulation was presented as a possible approach to model such consumer energy behavior, which could incorporate insights from behavioral economics into the agent’s heuristics, and also allowing emergent properties to arise, not limiting the model complexity. Finally, some concise and brief comment on power flow analysis were presented. Power flow will be used on this thesis to evaluate the impact of different consumer energy behaviors into a power grid.

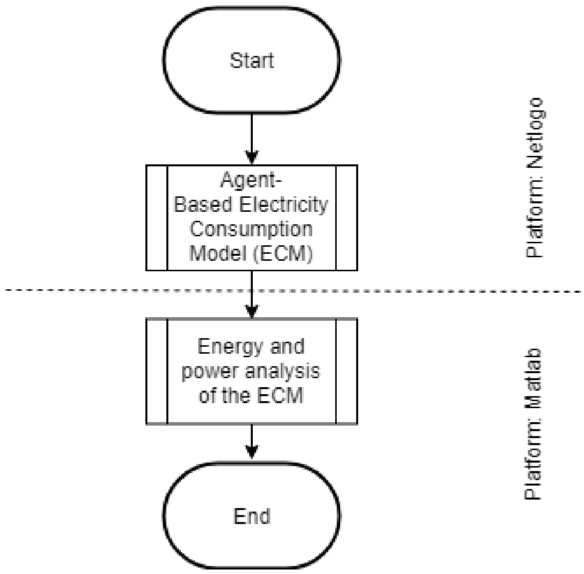
# 4 METHODOLOGY AND MODEL SPECIFICATIONS

This section will present the developed methodology to analyze emerging patterns on the energy consumption of residential customers considering concepts from CST and insights from the field of behavioral economics, and its impacts on the power grid. The main objective of the methodology is to support analysis that leads to a better a comprehension on how different customer heuristics on electricity consumption affect overall electricity consumption for different scenarios, and therefore also how it affects planning and operational aspects related to power systems. It focuses on how different parameters e.g. social interactions, investment on energy efficiency, price elasticity, and DSM programs affect residential electricity consumption, given the premise that energy consumption is complex and can be modeled by agent-based simulation.

The impact of such emergent complex behaviors on power systems is analyzed by considering how different consumers decision-making process may affect the grid, in terms of both energy (for planning studies, for instance) and power (considering both planning and operational aspects).

FIGURE 8 presents the two main parts of the proposed methodology. The first part is related to the Electricity Consumption Model (ECM), that will be described in detail in section 0.

FIGURE 8 – MAIN PARTS OF THE PROPOSED METHODOLOGY




SOURCE: The Author (2019)

This EMC is the core and main contribution of the proposed methodology. By using as input variables such as the number of consumers in different categories, energy price, and expected social interactions, as well as specific parameters, it enables the analysis of emerging patterns on electricity consumption and related variables. In short, specific heuristics for electricity consumption on the micro-level (consumer) on the ECM result in emerging electricity consumption patterns over the iterations. These iterations represent the dimension of time, nevertheless it was decided to use throughout the document the term iteration, since it was chosen not to make a strong correlation on how much time a given iteration relates, therefore allowing the model to remain more generical to several uses. The EMC must be executed multiple times to prevent random values to bias the results.

The ECM uses the Netlogo platform, a programmable modeling environment for simulating natural and social phenomena. NetLogo is well suited for modeling complex systems developing over time, where modelers give instructions to agents all operating independently, allowing the comprehension of patterns that emerge from their interaction (WILENSKY, 2018). NetLogo was first created in 1999 by Uri Wilensky at the Center for Connected Learning and Computer-Based Modeling, Tufts University, originally designed in particular for teaching children in the education community, and for researchers in different fields (such as economics, biology, chemistry, and psychology) without a programming background. NetLogo is free and open source, and since its release, it was used in hundreds of scientifical articles[8], was the subject of several books, and used in teaching in many universities.

Using the output from the ECM, the second part of the methodology is concerned with performing power and energy analysis, using the Matlab platform. In short, how electricity consumption and power flow evolve over time are analyzed, relating it to several aspects of the ECM. These energy and power analyses are crucial for a more meaningful comprehension of possible impacts of such modeling to planning and operation of power systems.

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[8] See https://ccl.northwestern.edu/netlogo/references.shtml for an update references list.

## 4.1 ELECTRICITY CONSUMPTION MODEL (ECM)

To analyze consumer behavior in energy consumption, this thesis uses agent-based computer simulation. As consumer behavior is complex, this technique shows itself as a suitable instrument because, given initial parameters set, different situations can be modeled, allowing for the analysis of a particular behavior and the emergence of a global behavior (YIN et al., 2016; LEE; YAO, 2013; DA SILVA FILHO et al., 2010).

To incorporate the insights of behavioral economics into the model, several assumptions were necessary, significantly simplifying the overall environment. One may disagree with these assumptions and simplifications made; nevertheless, it is important to point out that the main objective of this thesis is not to precisely model consumer behavior in energy consumption but to understand how the use of simple heuristics may help in the analysis of systems with complex behavior such as the power system. Still, all the equations and relations proposed in this section are to be considered as a first step of the model based on the author’s best understanding and the mentioned theoretical backgrounds. Future contributions can significantly incorporate new relevant factors, modify assumptions, and its dynamics, in other words, improve the model.

To develop the model first the main variables associated with electricity consumption were listed and their mutual relations analyzed, aiming to assess how changes in these variables could impact energy consumption. After that, the main characteristics of different consumers categories were outlined, considering mostly aspects related to the specific case of Brazilian electricity residential consumers.

Finally, the outline characteristics were then further detailed into heuristics. The developed heuristics consider the varying electricity price, willingness to invest in new technologies, social interactions, marketing strategies by the power utility, and consumer’s satisfaction level (or satisficing, in Simon’s sense). Regarding the last factor mentioned, it is important to elucidate that here we consider customer satisfaction only as crude estimation of customer’s response to the perceived discrepancy between prior expectations and the actual costs or interactions with the power utility, although it is indeed a much more complex subject related to several exogenic and endogenic components such. A more in-depth study of customer satisfaction to the power and electricity can be found in Catapan et al. (2017).

The key factor in this model is the analysis of the social interactions between the consumers and their relationship with the power utility, as well as its implications on the overall electricity consumption. Electricity consumption is hard to be predicted from the individual behaviors modeled for each consumer category and can only be assessed by the analysis of the global patterns that emerge from the simulation scenarios.

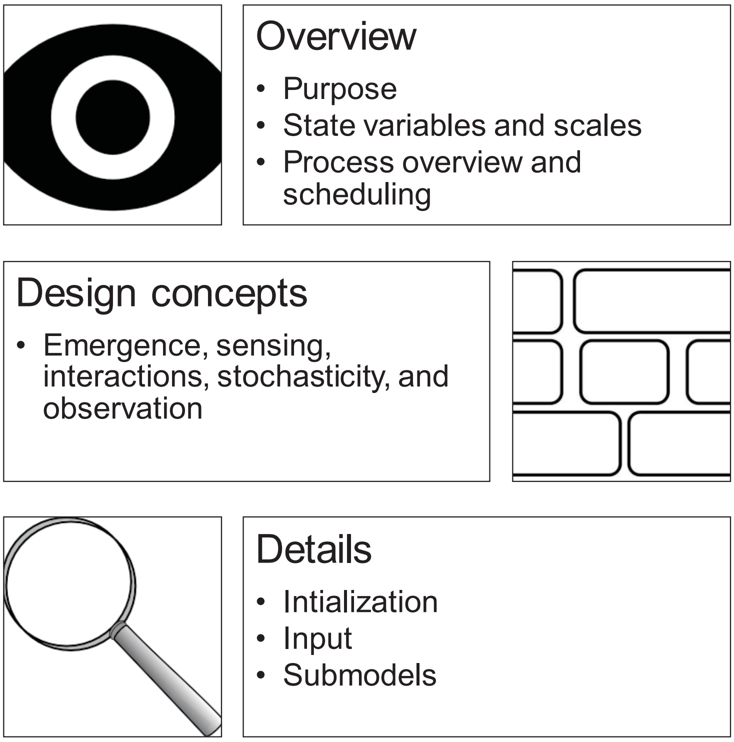
Electricity consumption changes, given the developed heuristics of all agents involved in each simulation, for each iteration of the agent-based model. Nevertheless, it is important to clarify that the focus of this work is not to directly relate iterations to specific durations of time. Therefore, throughout the discussions on the case study, no direct relations with absolute durations of time will be undertaken. For this to be possible, future works on the sensibility of the model and its relation to real-world scenarios should be undertaken. The model's focus is to understand how the different heuristics modeled lead to emergent properties on the simulations.

The ODD (Overview, Design Concepts, and Details) protocol (GRIMM et al., 2006) will be considered to present the model specification. It is a standard protocol for describing simulation models that describe autonomous individual organism or agents, aiming to make it more comprehensible and replicable. The basic idea of the protocol is always to structure the information in the same sequence (FIGURE 9).

The logic behind the ODD sequence is:

1. Context and general information are provided first (overview, section 4.1.1), allowing readers to quickly get an idea of the model's focus, resolution, and complexity;
2. More strategic considerations (design concepts, section 4.1.2) are then presented, describing not the model itself, but the general concepts underlying the design of the model, linking it to general concepts on the field of CST;
3. Finally, more technical details (Details, section 4.1.3) are provided, including information required to re-implement the model.

FIGURE 9 – ELEMENTS OF THE ODD PROTOCOL




SOURCE: Adapted from Grimm et al. (2006).

In addition to the ODD protocol, the system dynamics of the model will be presented in section 4.1.4, and a step-by-step procedural description of the ECM is provided on the Appendix 1. Description of the developed model and preliminary results of this thesis were published on Siebert et al. (2017).

### 4.1.1 OVERVIEW

The model's purpose is to study residential electricity consumption as a complex system, using a behavioral economics framework under the influence of four different interacting categories of agents (representing energy consumers). Specifically, it aims to observe the emergent properties of the consumer's heuristic in different simulation scenarios. The central idea of the model is that electrical loads should not be modeled only due to its electrical characteristics, but as well take into account that they provide comfort and services to people.

The model includes two basic entities: consumers and the power utility. The consumers are characterized by their category, monthly consumption, satisfaction level, willingness to invest in energy efficient technologies, and their elasticity to electricity prices. The power utility is characterized by its electricity price (which varies according to random[9] price flags), and their DSM program.

Agents are divided according to their consumption class, but all have an initial randomly assigned position in the simulation world, except for the power utility that is fixed. The simulation world is basically a spatial 2-dimensional board where agents can move. According to their absolute and relative position on the grid different functions and heuristics can be triggered.

In other words, for each time step, agents move randomly to one portion of the simulation world, where they may interact with another consumer at the same place or with the power utility, which, as previously mentioned, is fixed in a given portion of the grid. Based on these interactions, the other mentioned variables, and their previous state, the model updates the consumption level of all consumers.

FIGURE 10 provides a basic framework of the model's operation. The central component of the model is the consumer's heuristics, i.e. the decision-making process, which happens at the level of the individual agent. Four categories of consumer agents were modeled, each one with individual heuristics. The factors related to the inputs are related to (they will be discussed in detail in section 4.1.3.):

- Factor 1: Economic growth and price;
- Factor 2: Social interactions;
- Factor 3: Energy efficiency and investments.

The developed heuristics take action for every iteration of the simulation and vary according to given inputs, which are related to factors that will be detailed in section 4.1.3. These inputs may be set by the utility (e.g. energy prices), by the agent's intrinsic behavior, social interaction between agents and interaction with the power utility, for example in a marketing/DSM program. Notice that for every iteration of the simulation, the inputs for an agent will depend on its previous iterations.

The most relevant output analysis data are the number of interactions with the utility, number of interactions among agents, investment made by customers on energy efficiency, the utility income, total consumption, and the overall satisfaction level.

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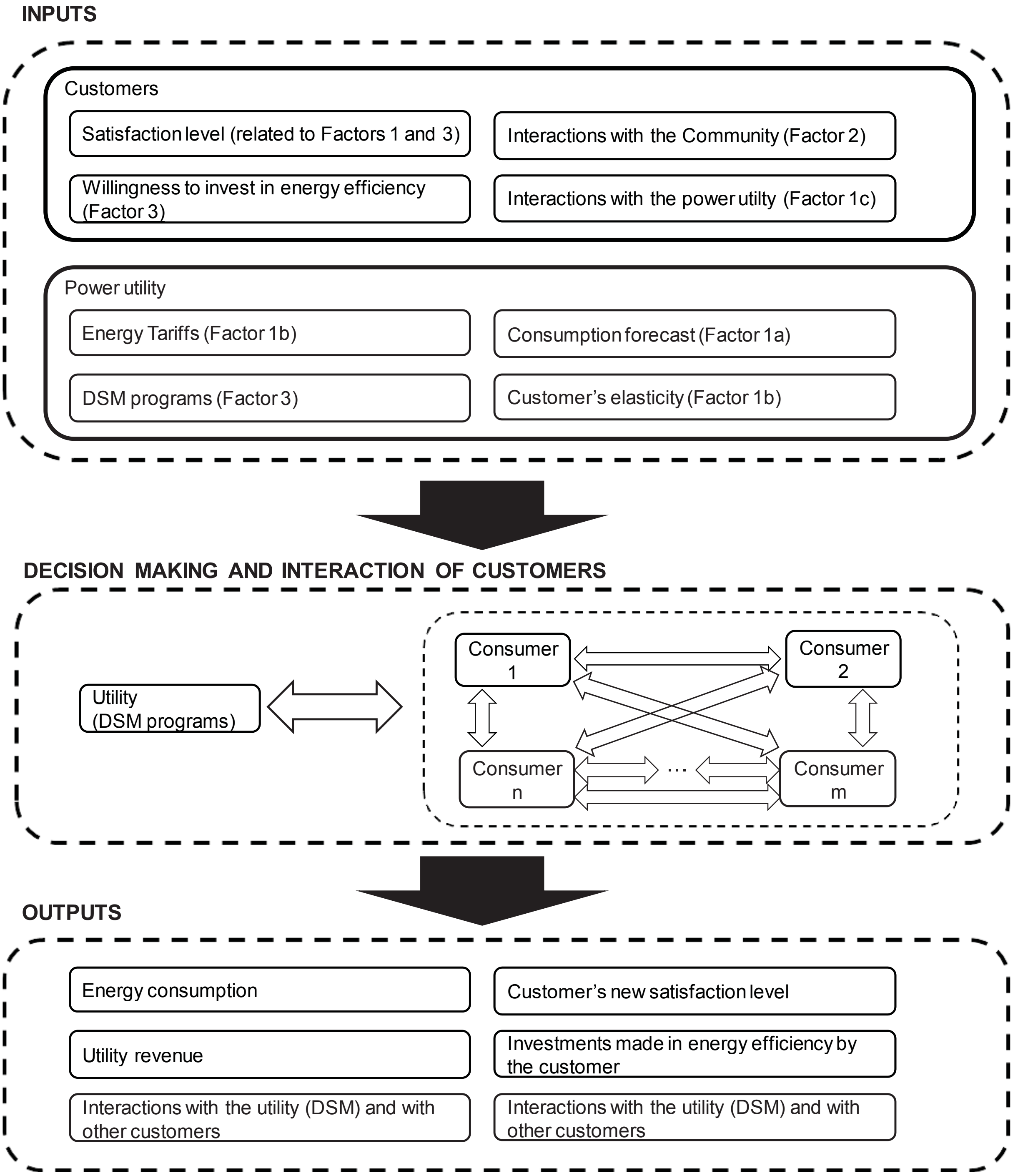
[9] Random in the context of this methodology and case study refers to numbers in a given range generated by an uniform distribution.

FIGURE 10 – BASIC FRAMEWORK OF THE MODEL




SOURCE: The Author (2019)

### 4.1.2 DESIGN CONCEPTS

The main design concepts are:

- Emergence: The most important emergent effect, focused on using behavioral economics concepts to model and simulate electricity consumption, is the total consumption level after several interactions between the agents. The individual customer satisfaction levels and the number of investments made in energy efficiency technologies also emerge from the interactions;

- Sensing: Consumers have access to the electricity price, how many times they invested in energy efficient technologies, and may have access to other customers' consumption level while interacting with them;
- Interactions: Consumers interact with other consumers and with the power utility;
- Stochasticity: Stochasticity is used to simulate spatial variability, initial consumption level and satisfaction level of the consumers, initial investment level and which investment the customers choose to do, and the electricity price flag;
- Observation: For model testing, the spatial distribution and consumption level of the consumers were observed.

### 4.1.3 DETAILS

Basically, the electricity consumption that a given customer increases or decreases in a given iteration may be influenced by five factors, divided into three groups (as presented in FIGURE 10), computed sequentially:

- Factor 1a: A fixed increase rate on electricity consumption, considered to mimic changes in consumer behavior due to economic growth and the more frequent use of technologies;
- Factor 1b: Their elasticity to electricity price variations;
- Factor 1c: The interactions with the power utility through DSM programs;
- Factor 2: Their interactions due to social interactions;
- Factor 3: The investments made in energy-efficient technologies.

How these factors vary is closely related to which category a given consumer belongs and may also relate to their satisfaction level.

#### 4.1.3.1 Initialization

On the initialization process a random assignment of the consumption, satisfaction, and investment level for each individual agent is performed (this assignment has upper and lower boundaries, which will be presented on section 4.1.3.3).

#### 4.1.3.2 Inputs

The number of agents representing consumers in each category can be manually set by the user, as well the space on the simulation world designed for the power utility (related to DSM programs), the initial electricity price, consumers' price elasticity, and the base consumption level growth.

#### 4.1.3.3 Submodels

- **Categories of Consumers**

Four categories of consumers were modeled, aiming at addressing different human behaviors in electricity consumption. TABLE 6 summarizes the main characteristics of the modeled categories and its overall electricity consumption, which were inspired by some of the main characteristics and social/financial division of the Brazilian scenario (PAIVA et al., 2013).

Consumers in category one represent consumption classes A and B, which compose ca. 15.89% of the Brazilian population and have a higher income. Because electricity price does not compromise a significant part of their income, it was assumed that they are inelastic to tariff changes. At the other end, consumers in category two have a low income (i.e. classes D and E, representing 41.38% of the Brazilian population) and, because of this, when properly encouraged, may significantly change their energy use pattern. Consumers in category two usually make changes due to social interaction, to reduce electricity expenses.

TABLE 6 – CATEGORIES OF CONSUMERS

| Category | Main Characteristics | Initial Consumption |
|---|---|---|
| 1 | Not sensible to tariff changes<br>Invests in energy efficiency when possible<br>Occasionally change habits due to social interaction | High (500–1000 kWh/month) |
| 2 | Strongly sensible to tariff changes<br>Does not invest in energy efficiency<br>Change habits due to social interaction | Low (10–100 kWh/month) |
| 3 | Sensible to tariff changes<br>May invest in energy efficiency<br>Sometimes change habits due to social interaction | Average (100–500 kWh/month) |
| 4 | Sensible to tariff changes<br>Invests often in energy efficiency<br>Sometimes change habits due to social interaction | Average–High (100–1000 kWh/month) |

SOURCE: The Author (2019)

Category three represents the consumption class C, a category of consumers that have a higher income than category two but lower than category one and represent 42.73% of the Brazilian population. It is assumed that this category behaves with a more ‘satisficing’ than optimizing approach for all criteria. Additionally, to the income criteria, we considered another division, category four, which comprises the ‘early adopters’, i.e. consumers that may or not have a high income, but their most distinguishing feature is the urge to invest in new technologies, being represented on this model by the investment in energy-efficient technologies such as retrofitting of air-conditioning systems and rooftop solar panels.

- **Customer Satisfaction**

On the model, customer satisfaction varies due to changes in electricity expenses. For consumers in category 4, satisfaction also depends on the amount invested in energy efficiency, as presented in TABLE 7.

TABLE 7 – CAUSES FOR CHANGES IN THE SATISFACTION LEVEL

| Category | Satisfaction Increase | Satisfaction Decrease |
|---|---|---|
| 1 | Little or no changes | Little or no changes |
| 2 | Consumer reduced energy expenditure | Consumer increased energy expenditure |
| 3 | Consumer reduced energy expenditure | Consumer increased energy expenditure |
| 4 | Consumer reduced energy expenditure<br>Consumer invested in energy efficiency | Consumer increased energy expenditure<br>Consumer didn't invest in energy efficiency |

SOURCE: The Author (2019)

Basically, customer satisfaction goes up when their expenditure goes down and vice versa, except for customers in a category that may be insensitive to expenditure variations (category one). Additionally, customers in category four can also increase their satisfaction via investing in energy efficiency. The satisfaction level outset is randomly between 50 and 100 for all consumer categories. Satisfaction level varies according to:

$$s_k = s_{k-1} - SP \cdot \left(\frac{q_k \cdot p_k - q_{k-1} \cdot p_{k-1}}{q_{k-1} \cdot p_{k-1}}\right) \tag{2}$$

where $s_k$ is the satisfaction level at the current iteration, $s_{k-1}$ is the satisfaction level at the previous iteration, SP is the Satisfaction Parameter, a numerical value based on the verbal description of TABLE 8, $q_k$ is the customer's monthly consumption at the current iteration, $q_{k-1}$ is the customer's monthly consumption at the previous iteration, $p_k$ the electricity price at the current iteration, and, finally, $p_{k-1}$ the electricity price at the previous iteration.

Besides, whenever consumers in category four do not invest in a given iteration, their satisfaction with the power utility decreases by 0.1%. On the contrary, when they invest, their satisfaction is increased by 0.1%.

- **Consumption Variations and Price Changes (Factor 1)**

The fixed increase rate, factor 1a, is considered the same for all categories of consumers. For factor 1b, it is important to point out that different energy pricing schemes, e.g. the use of time-of-use (TOU) tariff, are not considered in this model, although it may bring several benefits to the utility. Customer's elasticity to price changes is considered only on standard one-rate energy prices.

TABLE 8 shows customer's actions that are dependent on price changes according to their category. It is considered that customers in category one are not very sensitive to price changes since their expenses related to electricity consumption do not compromise a significant part of their monthly budget. Customers in category two, on the other hand, have a higher elasticity level aiming to reduce expenses. Finally, customers in category three and four vary their consumption not only aiming at financial aspects but also according to their satisfaction level.

TABLE 8 – PRICE CHANGES

| Category | Tariff Increase | Tariff Decrease |
|---|---|---|
| 1 | Not or very little sensitive to price changes | Not or very little sensitive to price changes |
| 2 | Decreases consumption significantly | Increases consumption significantly |
| 3; 4 | Decreases consumption depending on own satisfaction level | Increases consumption depending on own satisfaction level |

SOURCE: The Author (2019)

This factor considers the concept of price elasticity, related to the intuitive idea of a sensitivity level and indicates how much the demand of a product varies when its price increase or decrease 1% from a baseline. It enables the establishment of demand curves, which represent how the consumption of a given good varies according to its market price (SIEBERT, 2013). A demand curve generally has two assumptions (KIRSCHEN et al., 2000; HAGE et al., 2011):

- It should be understood as *ceteris paribus*, i.e. everything else constant (customer income, prices of other energy inputs, among others);
- It is linearized around a given point, due to the unfeasibility of obtaining a real demand curve for all demand levels.

Electricity price elasticity can then be defined by (HAGE et al, 2011):

$$\varepsilon = \frac{\Delta q / q_0}{\Delta p / p_0} \tag{3}$$

where $\Delta q / q_0$ is the percentage change in the amount of energy from the point $q_0$ and $\Delta p / p_0$ the percentage change in the price of energy from the price $p_0$.

The variation of electricity consumption for customers in category one and two due to price changes can then be defined as:

$$q_k = q_{k-1} \cdot \left(1 + CP \cdot \varepsilon \cdot (p_k - p_{k-1})\right) \tag{4}$$

where *CP* is the consumption parameters that is valued according to customer's category 1 or 2 characteristics presented on TABLE 8, and $\varepsilon$ is the elasticity basis level.

Customers of types three and four vary their consumption affected also by their own satisfaction level, according to:

$$q_k = q_{k-1} \cdot \left(1 + f_q(s) \cdot \varepsilon \cdot (p_k - p_{k-1})\right) \tag{5}$$

where $f_q(s)$ is a function that influences the consumption value according to the satisfaction level of customer's category three or four.

On the model, the power utility sets the energy price monthly, taking into account the current energy flag. The energy flag is a concept present in Brazil since 2015, where there may be a price increase on the energy price due to the current generator's dispatch and its dependencies on natural resources. The green flag means low cost to generate energy (in Brazil, meaning more hydrogeneration) and therefore no price increase. The yellow flag indicates attention (an increase of R$ 0.015 for every kilowatt-hour; R$ meaning Brazilian currency). Lastly, the red flag indicates that the former situation is getting worse and the supply of energy to meet consumer demand occurs with higher generation costs, (an increase of R$ 0.03 for every kilowatt hour). In the proposed model, the energy flags varied randomly for each iteration, however, as a matter of fact, they vary monthly according to Brazil's electricity generation costs.

Finally, factor 1c is related to the DSM actions taken by the utility. On the developed agent-based model, DSM actions are considered as an area of the 'simulation world'. All consumers move at random for each iteration, and when they 'stop' by the utility marked area, they are influenced as follows:

- Consumption decreases by 1% and;
- Satisfaction level increases by 1%.

These DSM programs may be considered as customer-focused marketing actions.

- **Social Interactions (Factor 2)**

In the developed model, each agent moves along the ‘simulation world’ randomly at every iteration, allowing each agent to eventually meet each other. Whenever they are at the same place, it is considered that a social interaction took place. Social norms regarding class mixing are not considered in the model, therefore every customer has the same likelihood to meet another customer in the simulation (but not necessarily make a social interaction, as indicated by the gaps in TABLE 9), regardless of their category.

TABLE 9 – SOCIAL INTERACTION SCHEME

| **Category Affected** | **Category That Affects (Consumer Met)** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| **1** | — | — | — | Increases investment level |
| **2** | Increases consumption | — | — | — |
| **3** | — | Decreases consumption | Decreases consumption (if the consumer met consumes less) | Increases investment level |
| **4** | Increases consumption | — | Decreases consumption (if the consumer met consumes less) | Increases significantly investment level |

SOURCE: The Author (2019)

The behavior between each consumer’s category is described in TABLE 9, where the rows describe the consumer affected. These social interactions happen for both customers but not necessarily in the same way, e.g. if a consumer in category 2 meets a consumer of category 1, the former increases their consumption, although the latter does not. In short:

- Category four affects categories one, three, and four to increase investment level, leading to a possible increase in electricity consumption on future iterations;
- Category three affects categories three and four to decrease consumption, given that the consumer met consumers let;
- Category two affects category three to decrease consumption;
- Category one affects categories two and four to increase consumptions.

- **Customer Investments in Energy Efficiency (Factor 3)**

Factor 3 influences customer behavior on investments in energy efficiency. For every iteration, each agent evaluates if a given random number ($R_{inv}$) on the range of 0 to 1 is minor than the squared value of the investment level on the previous iteration ($inv_{k-1}^2$), i.e. if it meets the following statement:

$$R_{inv} < inv_{k-1}^2 \tag{6}$$

It this statement is true, then one of the options of energy efficiency investment is randomly chosen:

- Retrofit of energy-efficient equipment such as a refrigerator (decreases consumption in 8.4 kWh/month);
- Installation of a solar system 2 kW grid-tie (decreases consumption in 200 kWh/month);
- Retrofit of electric showers, which are commonly used in Brazil, to natural gas (decreases consumption in 110 kWh/month);
- Retrofit of an air-conditioning system (decreases consumption in 7.4 kWh/month).

Still, if an investment in energy efficiency happens at a given iteration, the customer involved is expected no to invest again in the short future, due to budget or other reasons. TABLE 10 presents the customers' initial investment level range and their behavior after an investment.

TABLE 10 – INVESTMENT

| Category | Initial Investment | Behavior after an Investment |
|---|---|---|
| 1 | 40–60% | Will wait a reasonable time to invest again |
| 2 | 0% | Don't want to invest again in a long time |
| 3 | 15–35% | Will wait a reasonable time to invest again |
| 4 | 65–85% | Will invest again soon |

SOURCE: The Author (2019)

The decrease in the investment level is implemented by the following equation:

$$inv_k = inv_{k-1} \cdot DRAI \quad (7)$$

where $inv_k$ is the investment level at the current iteration, $inv_{k-1}$ is the investment level at the previous iteration, and DRAI is the decrease level after an investment, which varies according to TABLE 10..

Finally, regardless if a consumer invested or not in energy efficiency in a given iteration, their willingness to invest in energy efficiency varies as follows:

$$inv_k = inv_{k-1} + f_{inv}(s) \quad (8)$$

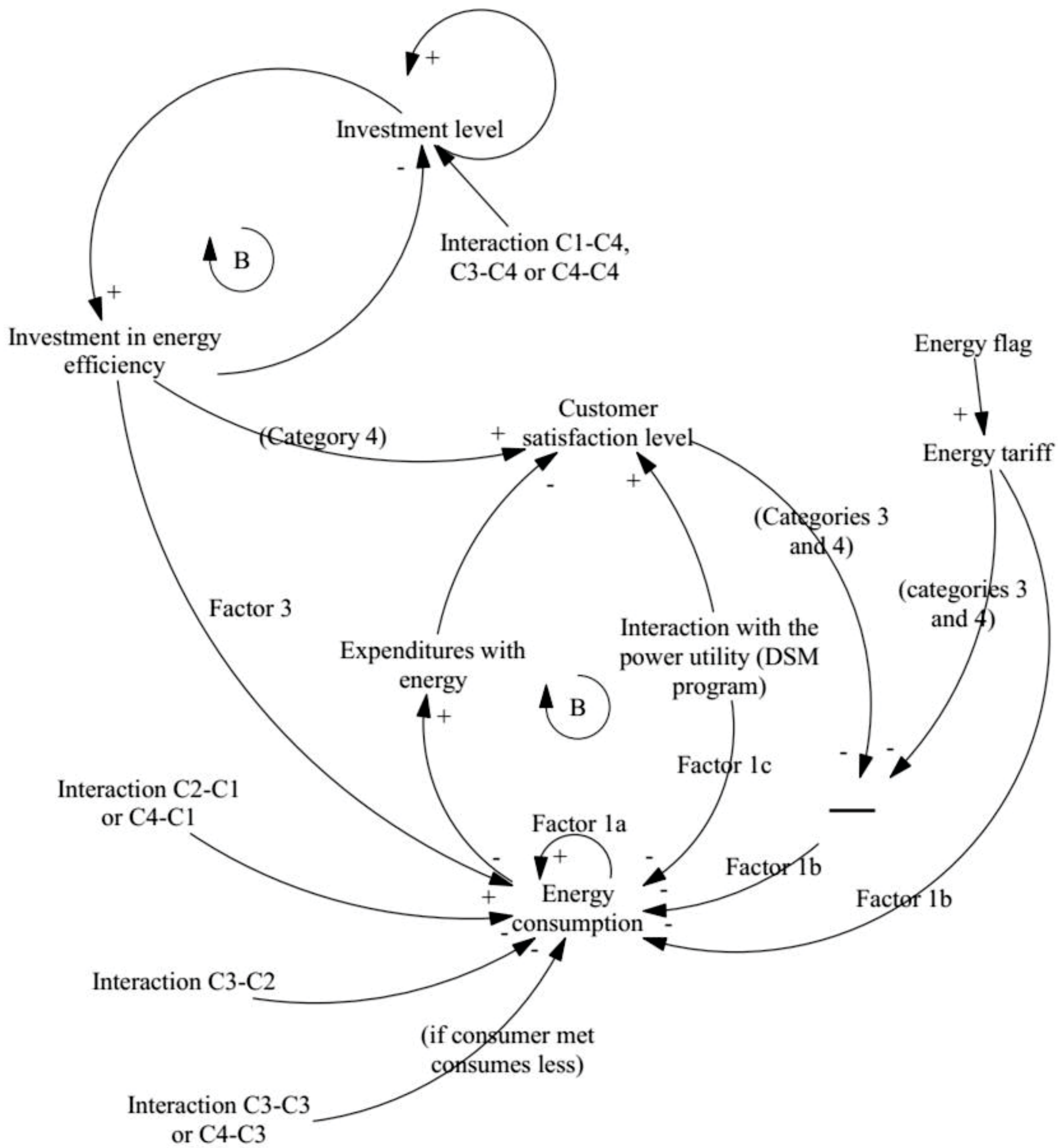
where $f_{inv}(s)$ a function that alters a given consumer's willingness to invest in energy according to their satisfaction level.

### 4.1.4 SYSTEM DYNAMICS

In addition to the ODD protocol (GRIMM et al., 2006), this section presents the causal loop diagram (CLD) of the model in FIGURE 11. The main aspects of the CLD can be found on section 2.1.4.

As can be perceived in FIGURE 11, the main variable and focus of the analysis of the model is the energy consumption. Every variable on the causal loop diagram that is not somehow connected to a precedent variable is a variable randomly generated by the simulation for every time step, as detailed on section 4.1.3.

FIGURE 11 – CAUSAL LOOP DIAGRAM OF THE MODEL




SOURCE: The Author (2019)

Starting from the upper left corner, a balancing loop on the investment in energy efficiency is presented. The variable "Interaction C1-C4" represents, as mentioned on TABLE 9, that consumer category one is affected by category of consumer four, the same logic being applied to C3-C4 and C4-C4, and all other variables related to customer interaction on the diagram. Basically, when these interactions take place they increase investment level of the affected agents. A higher investment level increases the probability of investments in energy efficiency taking place, and the event of investments in energy efficiency in its turn decrease investment level, decreasing the likelihood that such event happens again in the near future. Investment level can also change for every iteration, according to the customer satisfaction level. Finally, investment in energy efficiency directly decreases energy consumption but also increases customer satisfaction levels for consumers on category four.

Still, on interactions, when they happen on C2-C1 and C4-C1, there is a direct relationship with energy consumption, and when it happens related to C3-C2 there is an inverse relation. An inverse relation also happens on interaction C3-C3 and C4-C3, but only if the consumer met consumer less then the consumer affected. With a direct relation to energy consumption, there is also the fixed energy consumption self-loop (Factor 1a).

Since electricity is considered purchased in term of its relative price ($/kWh), an increase of ‘Energy consumption’ leads to an increase with on ‘Expenditure with energy’. It is also assumed that if a larger part of a family’s house is dedicated to electricity expenditure their perceived satisfaction with the power utility (‘customer satisfaction level’) decreases.

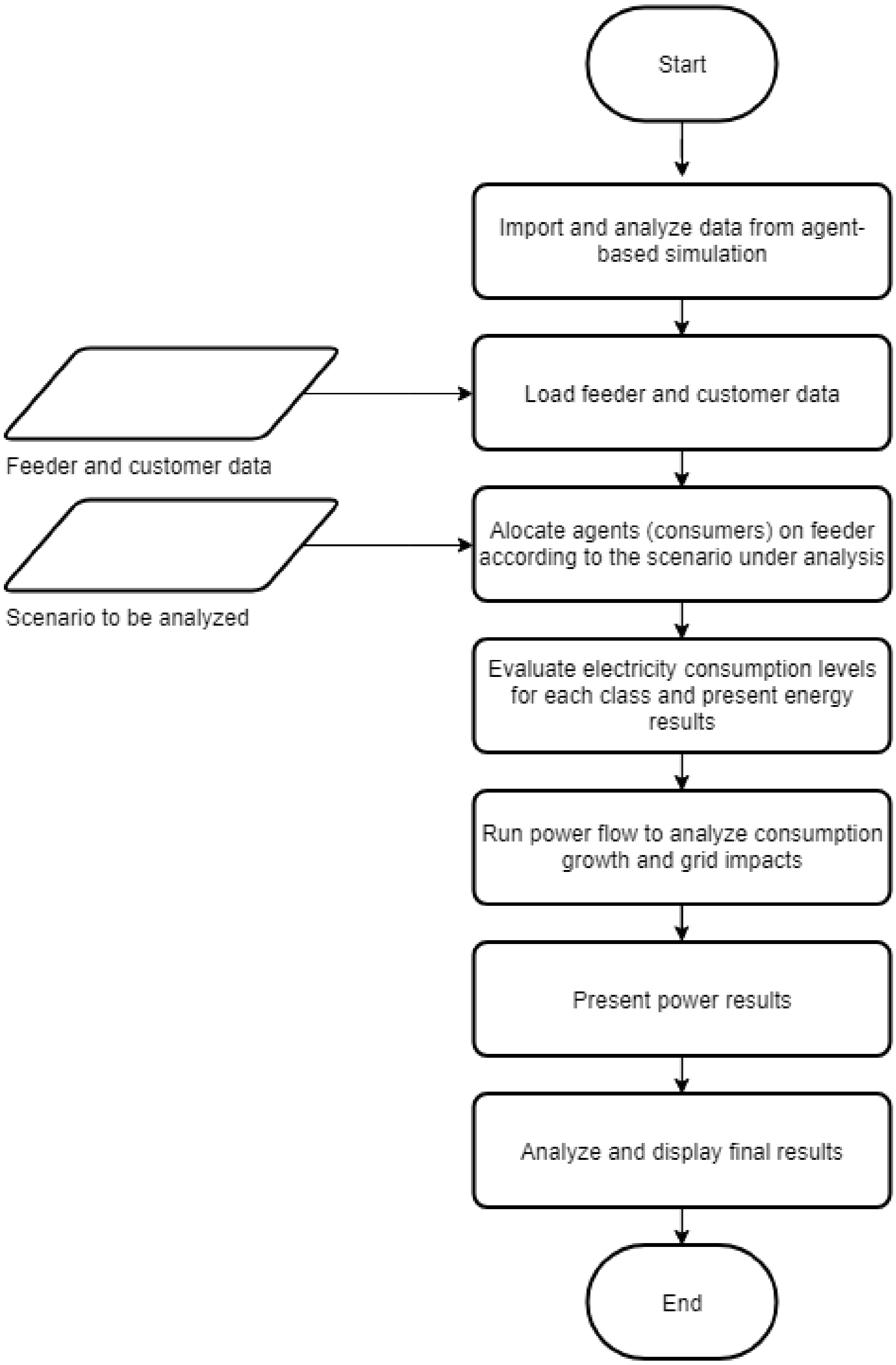
Another relevant fact is related to DSM programs. Interactions with the power utility lead to both decrease in energy consumption and increase on the customer satisfaction level.

Last but not least, energy tariffs also play an important role in the model. It is influenced (an increase in its base value) by the energy flags. An energy tariff increases cause a decrease in energy consumption, being directly related to consumers on categories one and two and related to the satisfaction level for consumers on category three and four.

## 4.2 ENERGY AND POWER ANALYSIS

As previously mentioned, the second part of the methodology is concerned with performing power and energy analysis, using the Matlab platform. FIGURE 12 presents a flowchart with the main steps of the energy and power analysis.

FIGURE 12 – ENERGY AND POWER ANALYSIS OF THE METHODOLOGY




SOURCE: The Author (2019).

The first step is to load all grid data (e.g. cables, lines, limits, transformers) and additional customer information (e.g. active and reactive load shape, allocation of customers on the feeder). Following, given the scenario to be analyzed in terms of agent distribution among the consumption classes modeled, consumers are randomly allocated to the distribution grid.

Then, it is possible to evaluate electricity consumption levels for the scenario. Results related to monthly energy consumption, as simulated on the ECM, are presented, along with the other outputs of the model.

After that, power flow analysis is undertaken considering the consumer's distribution and their load curve, not only for the original scenario but also for the forecasted energy levels. Results can then be displayed in terms of power flow, voltage levels, losses, among others.

Finally, the last step is to analyze and display the final results, including network analysis on the interactions among the agents.

## 4.3 FINAL DISCUSSION

This chapter presented the proposed methodology to analyze emerging patterns on the energy consumption of residential customers considering concepts from CST and insights from the field of behavioral economics. The focus was given to the ECM, which was described using the ODD protocol.

This methodology, added to the discussion and results of the case study to be presented in the next chapter, is the most relevant contribution of this thesis.

# 5 CASE STUDY

To demonstrate the application of the methodology a case study is proposed in the present section. Its main focus is on analyzing how emergent complex behaviors originate from different sets of consumers considering the four categories previously discussed. It also illustrates the unfeasibility of directly mapping emergent behavior from heuristics, and that complexity should be dealt with proper methods and tools.

Also, the impact of such different emergent patterns on a real-world power grid will be evaluated, aiming to understand the impacts of how consumers behavers to the planning and operation of power systems.

Specifically, this thesis proposes to analyze the emergent behavior on electricity consumption using a base scenario and four analysis scenarios, as described in TABLE 11.

TABLE 11 – SIMULATION SCENARIOS

| Scenario | Division of consumers |
|---|---|
| **Base** | All categories: 25% (equally divided) |
| **1** | Category 1: 62.50 %<br>Categories 2, 3, and 4: 12.50 % (each) |
| **2** | Categories 1, 3, and 4: 12.50 % (each)<br>Category 2: 62.50 % |
| **3** | Categories 1, 2, and 4: 12.50 % (each)<br>Category 3: 62.50 % |
| **4** | Categories 1, 2, and 3: 12.50 % (each)<br>Category 4: 62.50 % |

SOURCE: The Author (2019)

All the discussion will be made on how power, energy, and the remaining variables of the model evolve during the iterations. Although these iterations indeed represent the dimension of time, it was not to possible to make a strong correlation of those with specific periods of time, therefore. As it was not the goal of this thesis to make such direct correlation, it was chosen to use the term iteration throughout this case study. The EMC was executed 300 times to prevent random values to bias the results.

On the ECM model, a total of 16 agents representing consumers for each simulation is considered, divided as mentioned in TABLE 11. The base scenario is composed of 25% consumers of each category, i.e. four agents. Scenarios one to four considered, while maintaining the total number of consumers fixed, a significant increase of agents in categories one to four, respectively.

As previously mentioned in the flowchart describing the methodology (FIGURE 8), these proportions are then mapped into a case study on an urban distribution grid. The following subsections will describe the distribution feeder data and customer load curves used.

## 5.1 MATERIALS

### 5.1.1 Distribution feeder and customer load curve data

The case study presented on this thesis uses feeder data adapted from a real feeder of a Brazilian distribution company, as previously presented in Siebert (2013) and Siebert et al. (2018). This feeder was chosen due to its main characteristics be considered representative for several large Brazilian cities:

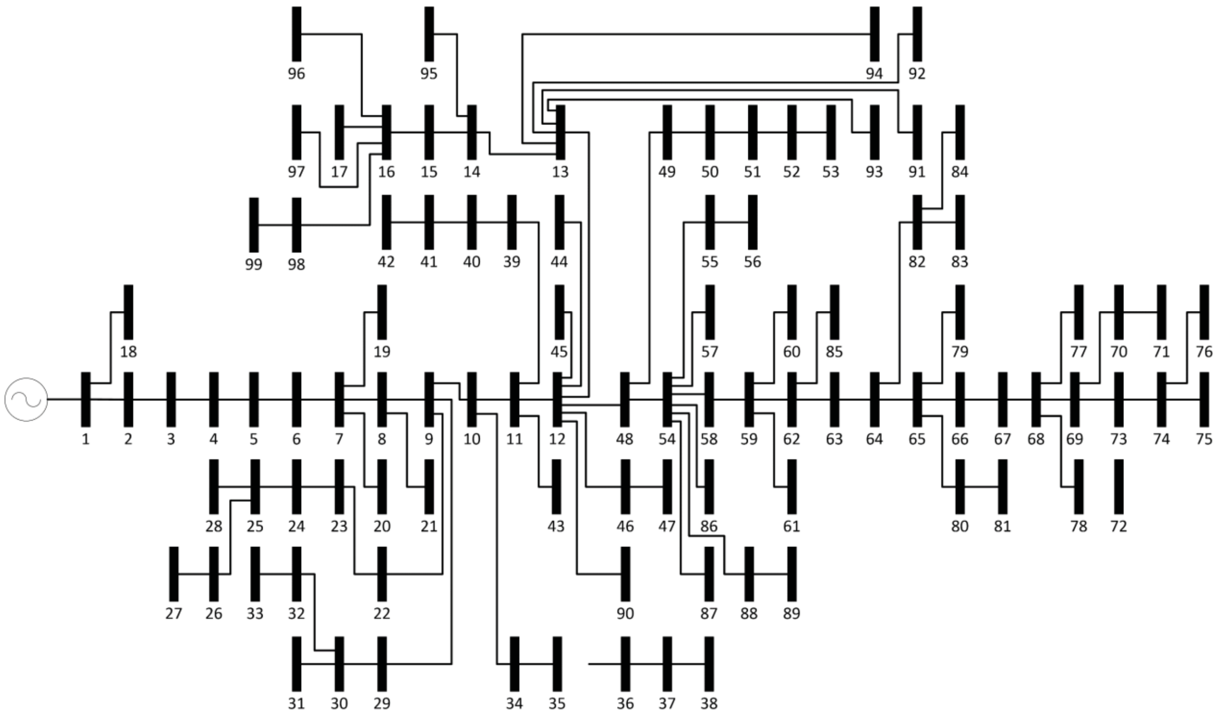
- Medium-voltage;
- Urban;
- Aerial;
- High consumer density.

Although feeder data were manipulated to obtain a suitable scenario for the system tests, they represent conditions consistent with the Brazilian scenario, with several customers connected to the same transformer and with a large length. The feeder is purely radial, aerial, urban and uses a medium voltage level of 13 kV. It has no distributed generation sources, voltage regulators or capacitor banks. The values of resistance and reactance of each section of the feeder are presented in Appendix C of Siebert (2013). The feeder has 99 buses, one of generation (substation) and the others load buses (distribution transformers), but on this thesis, only the 78 transformers, where 7299 customers are connected (low voltage), were considered.

The remaining buses were either assigned to street lighting or medium voltage commercial customers and were not considered to avoid distortions and allow focus only on the emergent properties of the energy consumption on residential feeders according to the ECM.

FIGURE 13 presents the single line diagram of the distribution feeder. Its current limit is 325.3 A at the head of the feeder.

FIGURE 13 – SINGLE LINE DIAGRAM OF THE FEEDER



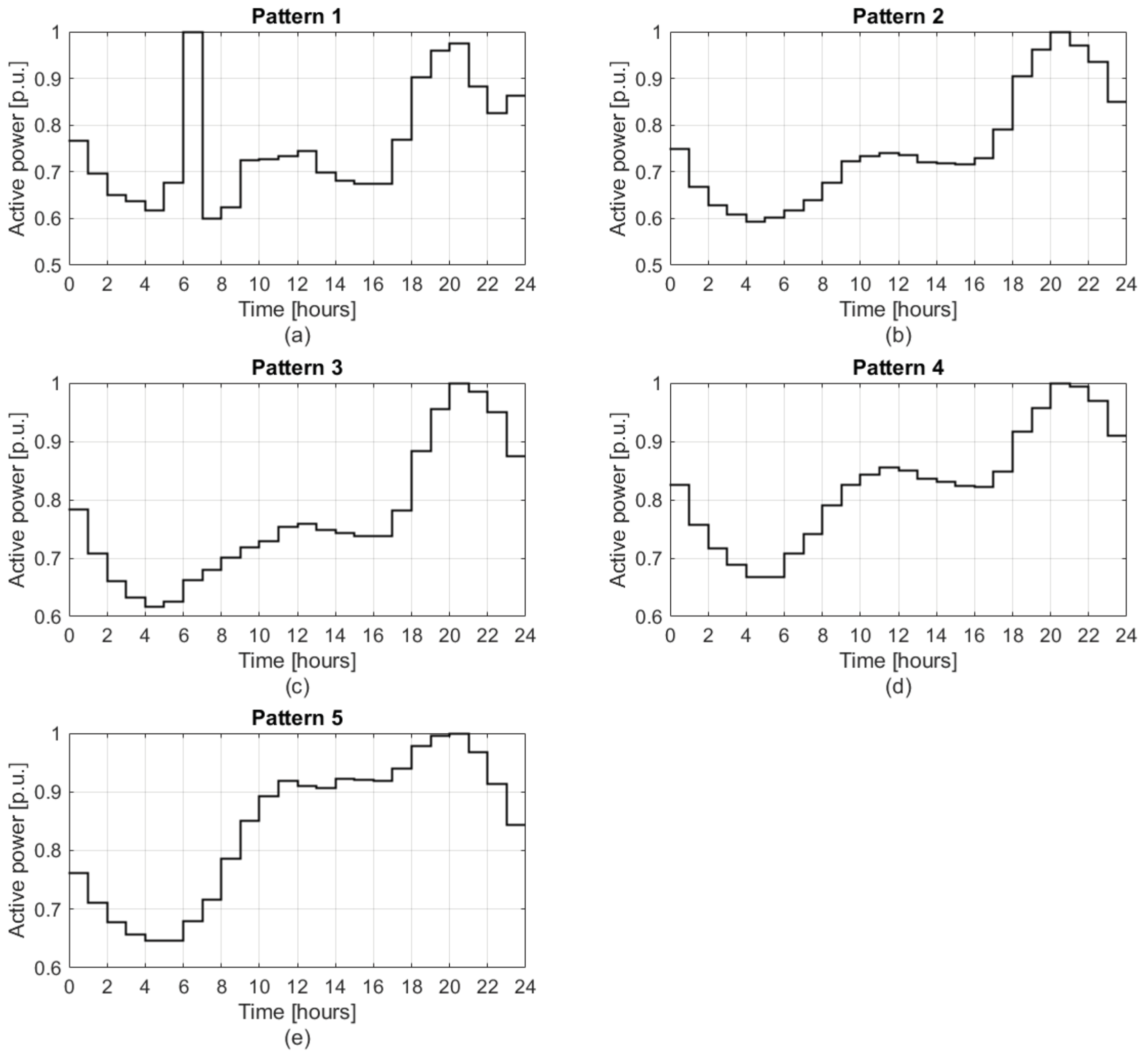

SOURCE: Siebert (2013).

As for the feeder data, customer load curves were also previously used and presented in Siebert (2013) and Siebert et al. (2018). The daily load and elasticity of 7044-residential low-voltage consumers, obtained from a smart metering pilot project on the city of Rio de Janeiro, Brazil, were stratified into five patterns according to their monthly energy consumption. These load curves, therefore, come from real data from a Brazilian distribution company, through the treatment of an extensive database. Due to the unavailability of reactive curve data from this same database, the reactive load curve was estimated from the power factors presented in Yamakawa (2007), as in Siebert (2013). FIGURE 14 and FIGURE 15 present, respectively, the normalized active and reactive load curve of the five patterns, divided as:

- Pattern 1: Below 80 kWh/month;

- Pattern 2: Between 80 and 220 kWh/month;
- Pattern 3: Between 220 and 500 kWh/month;
- Pattern 4: Between 500 and 1,000 kWh/month;
- Pattern 5: Above 1000 kWh/month.

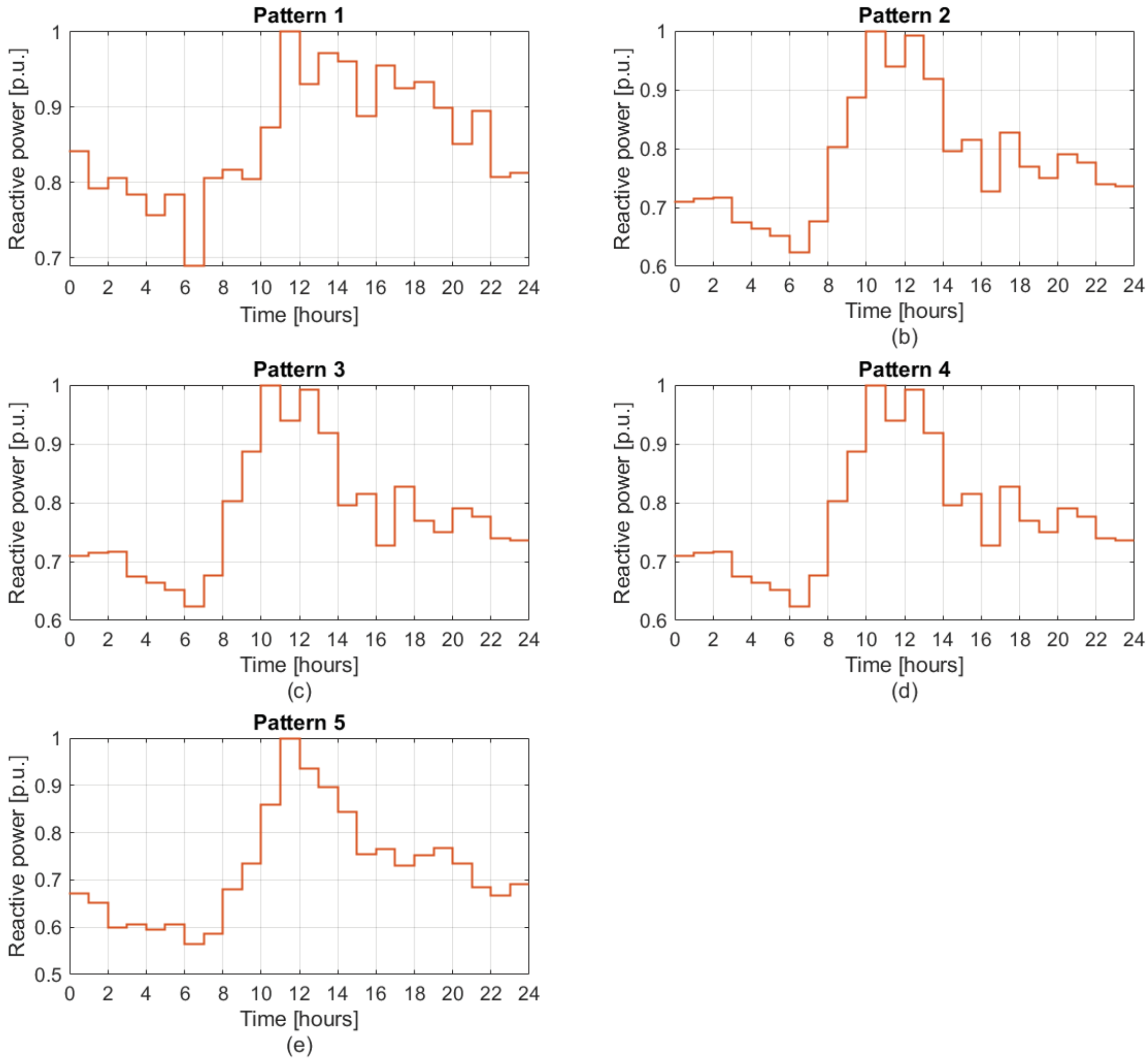
FIGURE 14 – NORMALIZED ACTIVE POWER LOAD CURVE FOR BUSINESS DAYS: (A) PATTERN 1; (B) PATTERN 2; (C) PATTERN 3; (D) PATTERN 4; (E) PATTERN 5




SOURCE: The author (2019).

Only the load curve for business days are presented here since the analysis will be focused on such days. Nevertheless, figures for the patterns on Saturdays and Sundays/Holidays can be found on Siebert (2013). Still, tabulated data of all load curves can be found in Appendix D of Siebert (2013), where the load value at a given time represents the average power demand for the last 60 minutes.

FIGURE 15 – NORMALIZED REACTIVE POWER LOAD CURVE FOR BUSINESS DAYS: (A) PATTERN 1; (B) PATTERN 2; (C) PATTERN 3; (D) PATTERN 4; (E) PATTERN 5




SOURCE: The author (2019).

TABLE 12 shows the association between the consumption categories of the ECM, as defined in TABLE 6, and the load curve patterns presented in FIGURE 14 and FIGURE 15. When more than one pattern is associated with a specific category it is randomly selected for each consumer when it is associated with the feeder.

TABLE 12 – ASSOCIATION BETWEEN LOAD CURVE PATTERNS AND CONSUMER CATEGORY

| Consumer category | Load curve pattern |
|---|---|
| 1 | 4; 5 |
| 2 | 1 |
| 3 | 2; 3 |
| 4 | 2; 4 |

SOURCE: The author (2019).

All the load curves were normalized according to their maximum power on a p.u. scale, to ease visualization. Therefore, after considering a given pattern, individual values of monthly energy consumption per agent are considered (an output of the ECM model) and the curves are then adjusted to represent such consumption, using an adjustment factor obtained for each customer, using the equation below:

$$af = \frac{E_{month}}{E_{BD} \cdot A_{BD} + E_{SA} \cdot A_{SA} + E_{SU} \cdot A_{SU}} \tag{9}$$

where $af$ is the calculated adjustment factor, $E_{month}$ is the monthly consumption of a given agent, $E_{BD}$ is the energy consumed by a given agent on a standard business day, $E_{SA}$ is the energy consumed on a Saturday and $E_{SU}$ is the energy consumed on a Sunday. $A_{BD}$, $A_{SA}$ and $A_{SU}$ represent, respectively, the amount of working days, Saturdays and Sundays or holidays in a month.

This adjustment is important to provide more real features to the analysis allowing it to be integrated with the results from the ECM.

## 5.2 PARAMETERS AND SUBFUNCTIONS CONSIDERED ON THE ECM

This section discusses the main parameters and sub-functions considered on the ECM. Firstly, TABLE 13 presents the subfunctions used in (5) and (8) to represent more complex interaction of a given phenomena:

TABLE 13 – SUBFUNCTIONS

| Equation | Subfunction | Comments |
|---|---|---|
| (5) | $f_q(s) = \cdot \left(\frac{1}{s_k^{CSP}}\right)$ | $CSP$ is a consumption parameter valued according to specific characteristics of customer on category three or four. Basically, $f_q(s)$ will lead to larger variations in electricity consumption as the values of CSP increases, given that $s$ varies in the range of 0 to 1. |
| (8) | $IF\ s_k \neq 0.8$ $THEN\ \ f_{inv}(s) = \frac{1}{(s_k - 0.8)\cdot 100}$ $OTHERWISE\ \ f_{inv}(s) = 0$ | If a customer has the satisfaction level is 0.8, $f_{inv}(s)$ will not impact their investment level. If it is greater than 0.8, their investment level will decrease; otherwise, it will increase. |

SOURCE: The Author (2019)

TABLE 14 presents the parameters used in (2-4) and (6), by defining fixed values to the verbal descriptions in TABLE 7, TABLE 8, and TABLE 10.

TABLE 14 – PARAMETERS

| Parameter | Consumption category | Value |
|---|---|---|
| CP | 1 | 0 |
| CP | 2 | 2 |
| CSP | 3 | 1 |
| CSP | 4 | 1 |
| SP | 1 | 0 |
| SP | 2 | 10 |
| SP | 3 | 5 |
| SP | 4 | 10 |
| DRAI | 1 | 0.4 |
| DRAI | 2 | 0.2 |
| DRAI | 3 | 0.4 |
| DRAI | 4 | 0.8 |

SOURCE: The Author (2019).

Several values were tested and subfunctions were tested for the case study, and the most suitable, i.e. the ones that lead to reasonable scenarios related to real-world systems, where the emergent properties of the model could be analyzed, were assumed.

Specifically, regarding the parameters CP and SP it is assumed that customers in category one are totally insensitive to how much they spend on electricity, therefore CP=SP=0 (zero). Several different sets of values were tested for all parameters and we concluded that the model is not very sensitive to the price elasticity level of consumers. For example, the biggest consumption difference due to variations of the parameters CP and CSP was when customers in category four have a CSP of 0.5 instead of 1, using scenario four as a reference. The difference in the final consumption for this alternate test set was only ca. 4.56 % lower.

Another important parametrization performed was regarding social interactions. The specific values used in TABLE 9 are:

- Increases investment level: 2.5%;
- Increases significantly investment level: 5%;
- Increases / decreases consumption: 5%;
- Decreases consumption (if the consumer met consumes less): average between both consumers.

The other initial values considered are as follows:

- Energy price at the first iteration: 0.5 R$/kWh;
- Fixed rate consumption increase: 0.1%/iteration;
- Base elasticity level: -0.146;
- Interaction with the utility / DSM action level: 36 (i.e. ~3.306% of the 33 x 33 simulation world – 1089 positions).

A fixed consumption (Factor 1a) is the percental rate that the electricity consumption would increase if a more traditional economic model that does not consider social interactions and the other aforementioned factors, was considered. All simulations are run for 1,000 iterations. Because of the randomness in the simulation, all scenarios were run 300 times each, and the results presented in the following are the average of all simulations.

## 5.3 COMPUTATIONAL PLATFORM

All simulations were performed in on a notebook equipped with an Intel i7-7500U @ 2.70 GHz processor, 16 GB of RAM, Windows 10 Pro 64-bit operating system. The ECM was developed using the software NetLogo version 6.0.4. The electrical analysis was performed on Matlab R2018a.

## 5.4 RESULTS AND ANALYSIS

To evaluate the emerging patterns of the agent-based simulation of the ECM and its implication on the modeling of consumer behavior and its impact on electrical distribution grids this section will describe the main results of the methodology. The analysis will be divided into power and energy.

The energy analysis will focus on the electricity consumption that emerged from the agent-based simulation performed with the ECM, considering the consumers are randomly allocated to the case study distribution feeder as described in section 5.1.1. The energy consumption will not be analyzed purely in terms of energy but also considerations will be made into how it relates to specific parameters of the model. This randomized process of allocating customer to the grid does not affect significantly the results, as presented and discussed in the Appendix 2 of this document.

The power analysis is responsible for assessing the impacts on the grid, in terms of current, power, and voltage levels. Other indicators such as technical losses will also be evaluated whenever necessary. This analysis considers the load curve patterns assigned to the agents as described in section 5.1.1. For the energy and power analysis will be performed for the base case and for the four scenarios, and also a comparative analysis will also be presented.

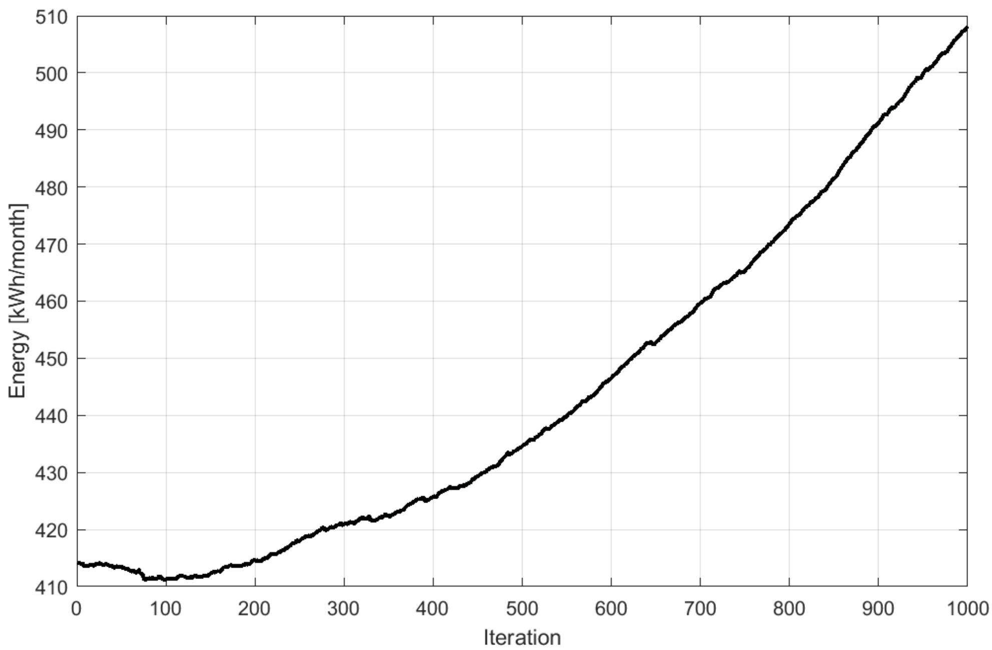
### 5.4.1 Base case

The base case considers all four categories of consumers equally divided (25% each), i.e. 1,825 consumers of each category.

#### 5.4.1.1 Energy analysis

In the base scenario, the average total consumption among all consumers started at 414.3 kWh/month, reaching its minimum level of 411.1 on iteration 99, and a maximum level of 508.1 on the last iteration. It results in an increase of ~22.64% from the beginning until the end of the simulation, as represented in FIGURE 16.

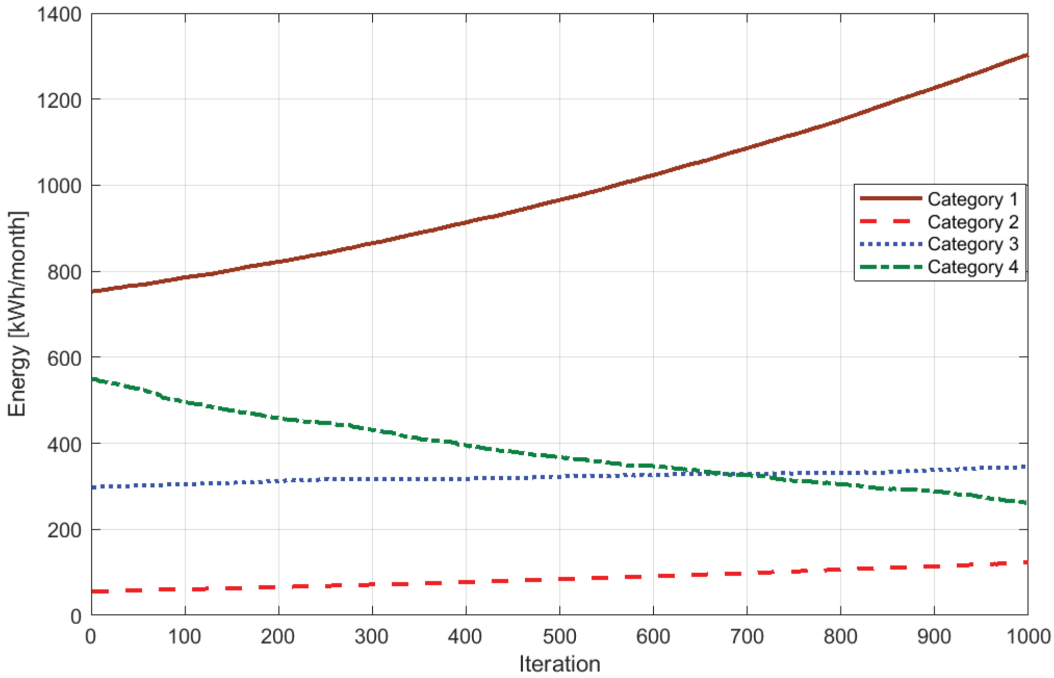
FIGURE 16 – AVERAGE MONTHLY ENERGY CONSUMPTION (BASE CASE)




SOURCE: The author (2019)

The evolution of the monthly energy consumption presented on FIGURE 16 is not linear: it presented smaller variations (both positive as negative) on the first 300 iterations, a slighter positive increase until iteration 500, followed by an increased slope after that in an average rate of ~3.17% per 100 iterations until the end of the simulation. This behavior is driven by the behavior of the all four different consumer categories, which are very different among themselves, as can be perceived in FIGURE 17.

FIGURE 17 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR EACH CONSUMER CATEGORY (BASE CASE)



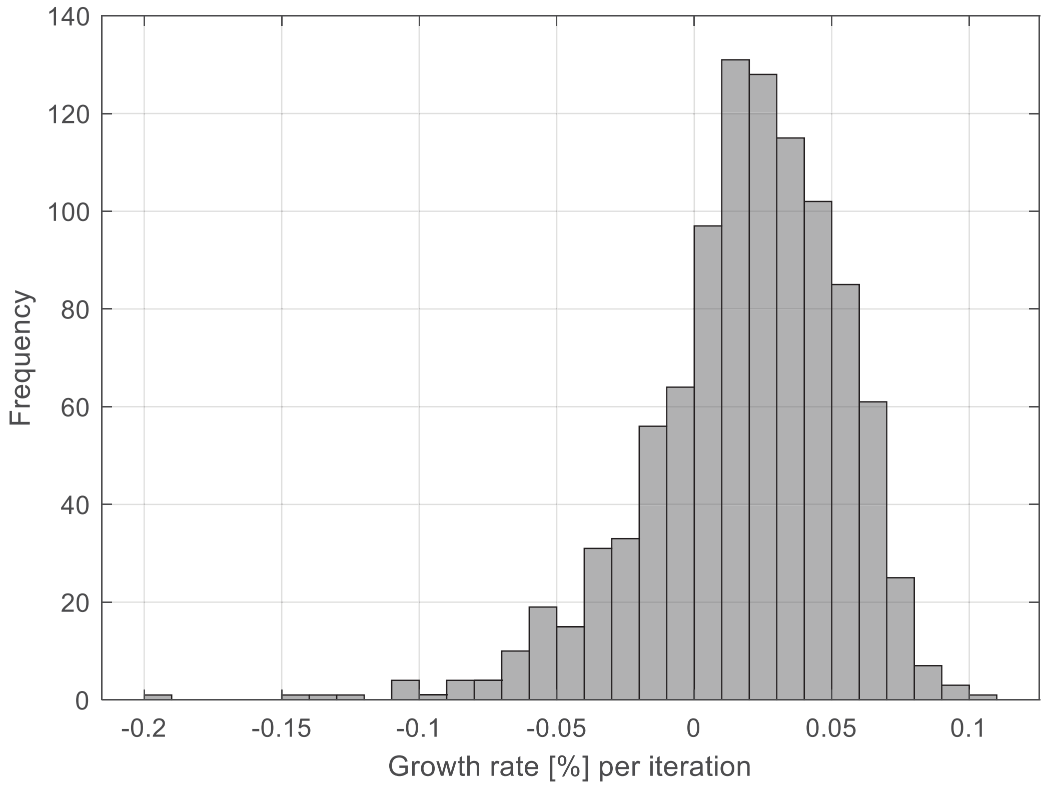

SOURCE: The author (2019).

Category four presents a significant decrease in consumption throughout the simulation, while categories one to three presented growth trends. The highest absolute difference comparing the first and last step of the simulation was on category one (551 kWh/month, an increase of 73.17%), nevertheless in proportional values it was category two that most evolved, from an average of 56.01 kWh/month to 122.8 kWh/month (increase of 119.25%).

Since the absolute values of the consumers on category one is higher, by its definition and initial consumption values presented on TABLE 6 and considering that the base case represents an equal proportion among all category of consumers, it is possible to have a glimpse on how the final average consumption presented in FIGURE 16 was formed. On the first iteration agents on category one represented 45.42% of the total of the consumption, while for the last iteration this share increased to 64.12%.

The histograms on FIGURE 18 and FIGURE 19 present the frequency distribution of the growth rate per iteration throughout the simulation, while TABLE 15 presents the main statistics of the distributions. The histograms were used firstly and

FIGURE 18 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION (BASE CASE)

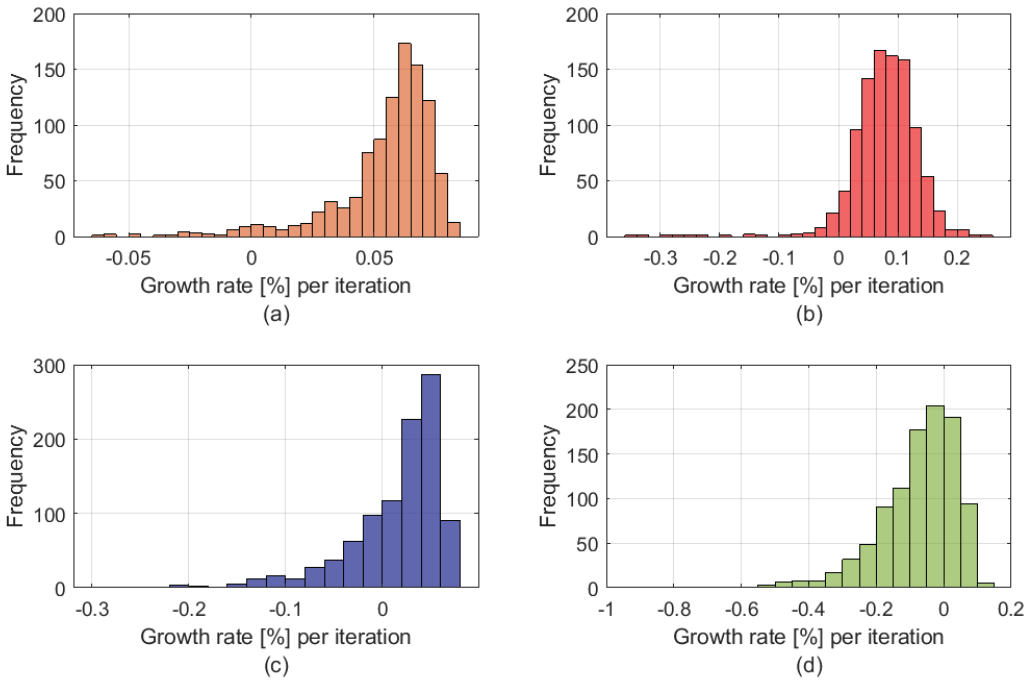



SOURCE: The author (2019).

mainly for internal validation of the model. Considering that the natural consumption growth, disregarding all other factors, was 0.1% per iteration, FIGURE 18 shows that the largest majority of the iterations for the base case were smaller than that.

In FIGURE 19 it can be perceived that each category has a considerably different distribution on the growth rate. While categories one, two, and three present predominantly positive values (96.8%, 95.5%, and 72.1% respectively), category four has 70.9% of consumption growth rate negative values. This larger frequency (and the absolute values of the growth rate) of negative values leads to a decrease in consumption resulted due to several reasons, being their interactions with other agents and investments in energy efficiency important points to be highlighted.

FIGURE 19 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION (BASE CASE): (A) CATEGORY 1; (B) CATEGORY 2; (C) CATEGORY 3; (D) CATEGORY 4




SOURCE: The author (2019).

Still, it is important to mention that all distribution presented asymmetric distributions with a long tail towards the negative values (as showed by the negative skewness values on TABLE 15). It happened since there are nonlinear (and even random) assignments of interactions among consumers, as well as due to interactions with the utility (DSM), and investments since these actions tend to decrease the electricity consumption when they take place. All distributions also presented high kurtosis values (given that kurtosis equals zero for a normal distribution). The highest kurtosis value is for category two.

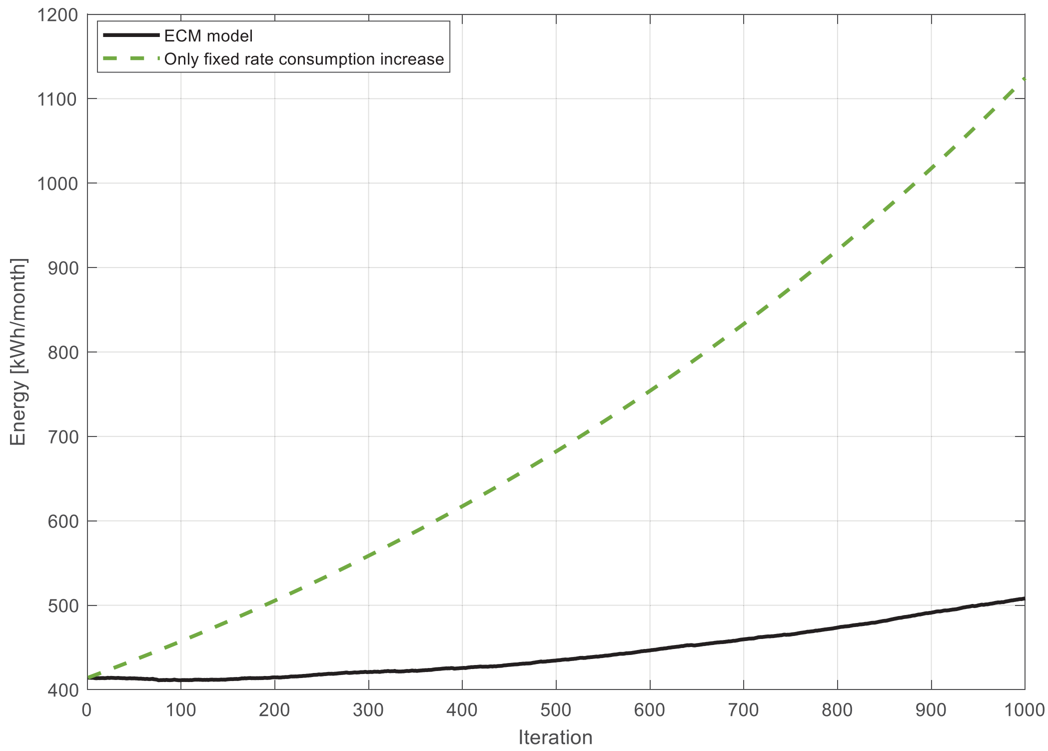
If the ECM only considered a fixed rate increase in energy consumption was to be considered of 0.1% iteration, as mentioned on section 5.2, the final average monthly consumption for all categories would be 1,125.6 kWh/month (FIGURE 20). It represents an increase that would be 2.22 times higher than the final value of the ECM, which considers social interactions, price elasticity, investment on energy efficiency, and DSM programs. Therefore, it can be perceived the relevant influence of these simple heuristics on the emergent properties of the model. Simulations of an increased fixed rate is presented on the Appendix 3 of this document.

TABLE 15 – STATISTICS OF THE ELECTRICITY CONSUMPTION GROWTH RATE (BASE CASE)

| | All categories | Category 1 | Category 2 | Category 3 | Category 4 |
|---|---|---|---|---|---|
| **Skewness** | -2.227 | -2.087 | -2.014 | -1.911 | -1.442 |
| **Kurtosis** | 11.144 | 8.748 | 15.278 | 7.842 | 6.415 |
| **Mean (μ)** | 0.018 | 0.055 | 0.079 | 0.015 | -0.074 |
| **Standard deviation (σ)** | 0.092 | 0.021 | 0.055 | 0.050 | 0.118 |
| **Maximum value** | 0.246 | 0.084 | 0.246 | 0.080 | 0.180 |
| **Minimum value** | -0.767 | -0.062 | -0.344 | -0.280 | -0.767 |

SOURCE: The author (2019).

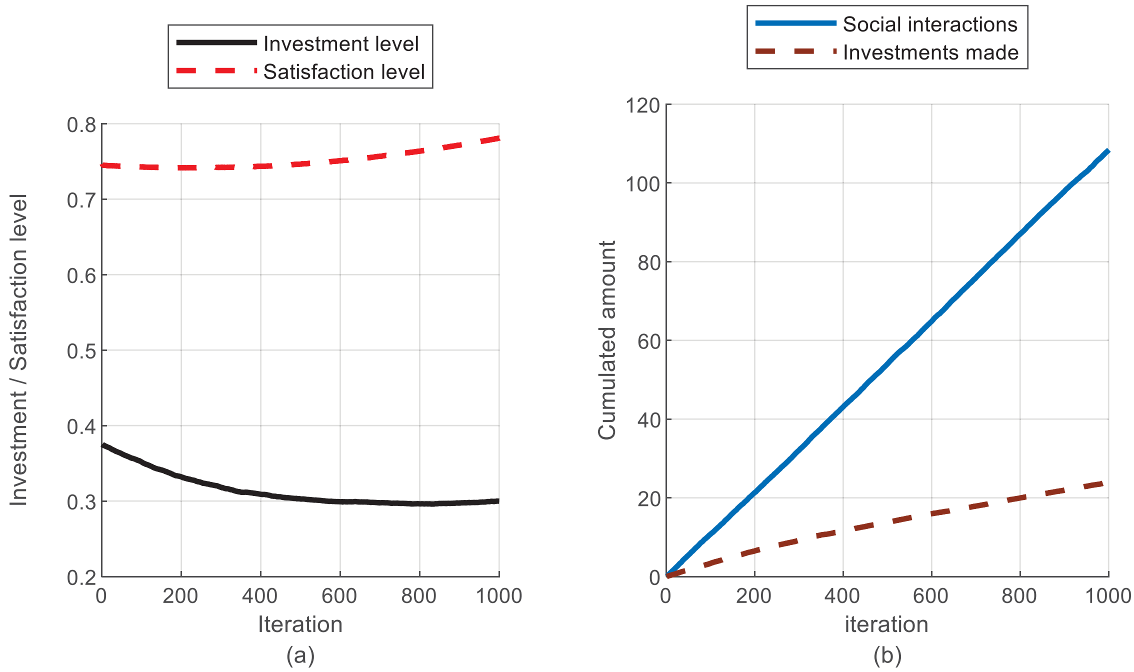
FIGURE 20 – COMPARISONS OF AVERAGE MONTHLY ENERGY CONSUMPTION OF THE ECM AND CONSIDERING ONLY FIXED RATE INCREASE (BASE CASE)




SOURCE: The author (2019).

FIGURE 21 (A) shows how the investment and satisfaction level evolved over time, while FIGURE 21 (B) presents the number of interactions among consumers, and investments made.

FIGURE 21 – EVOLUTION OF DIFFERENT VARIABLES (BASE CASE)



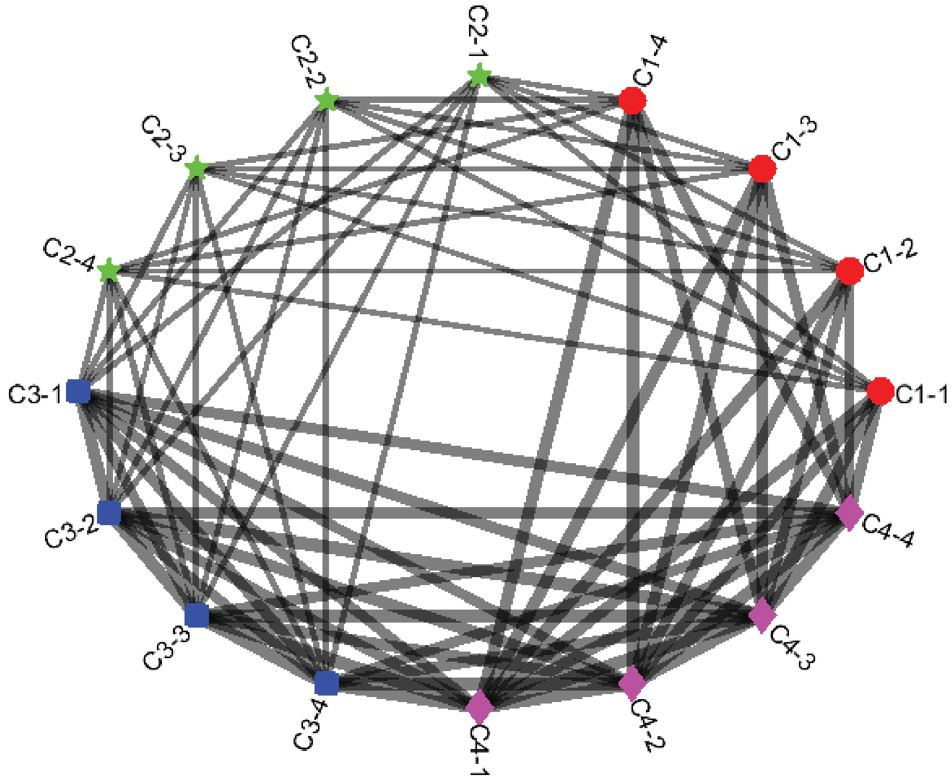

SOURCE: The author (2019).

The investment level in energy efficiency initially decreased but stabilized at around iteration number 600. The total of interactions with utility totaled 529,69. This value is very similar for all scenarios, including the base case, since the heuristics that determine whether a given agent makes interaction with the utility are the same for all consumer categories. Therefore, this variable will only be presented and discussed the comparative analysis.

The satisfaction level was initially relatively stable for the first 400 iterations and then started to slowly increase, reaching a final value of 0.78.

Social interactions varied in a quasi-linear way along the simulation, reaching an average total of 109.15. Given that the ECM considers 16 electricity consumption agents, and they are divided equally among all categories for the base case, FIGURE 22 presents the connected graph of the total amount of interactions among consumers, where the line thickness is an indicator of the total amount of interactions.

FIGURE 22 – NETWORK OF SOCIAL INTERACTIONS (BASE CASE)




SOURCE: The author (2019).

Categories one and two present a degree of eight (i.e. eight paths from each node), while categories three and four present 11 nodes each. As previously mentioned, the total of interactions on average (for the 300 runs) is 109.15, composed by ca. 42.78 for category one, 15.22 for category two, 39.86 for category three, and 11.3 for category four. Categories one and three, therefore, were the ones that influenced the most on the total of interactions.

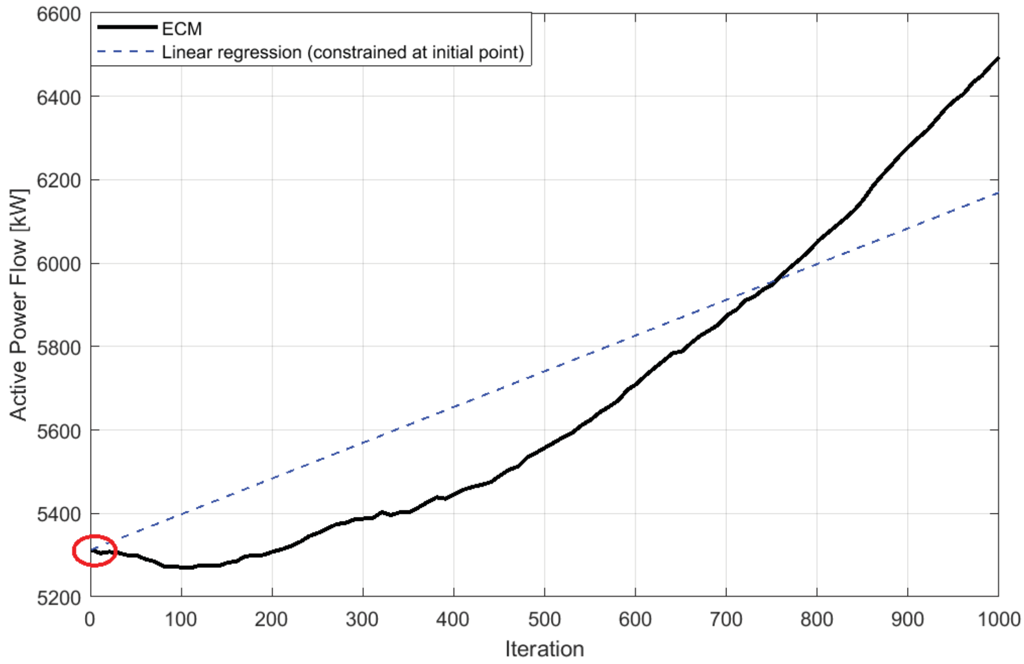
It is noteworthy to highlight that, for the base case as for all the other scenarios, the network of social interactions to be presented is composed of the average between all 300 simulations runs. If only the first iteration was to be considered for the base case, the total of interactions would be 90, the degree would vary between three and five for category one, between three and five for category two, between three and seven for category three, and between five and eight for category four. In a real-world complex system, therefore, one of the specific runs is to be expected, nevertheless, due to its high variability, analysis for this case study is more comprehensible and meaningful using the average values.

Additional simulations considering changes related to the time a consumer takes to make investments, and also disregarding all social interactions are presented in the Appendix 3 of this document.

### 5.4.1.2 Power analysis

FIGURE 23 presents the evolution of the load flowing from the substation to the grid on the hour of maximum loading. For this first load flow were simulated for the 24 hours of the day for 1 in every 10 iterations of the ECM. Following the tendencies of the electricity consumption previously presented of FIGURE 16, the load flow curve initially decreased from 5,313 kW until the minimum point of 5,269.7 kW and, after that, increase until reaching a value of 6,474 kW on the 1,000$^{th}$ iteration, i.e. an increase of 21.85% from the initial value. FIGURE 23 also shows that until around iteration 760, if a linear regression was to be considered it would overestimate the active power flow levels, when compared to the ECM, and underestimate after this iteration. The maximum overestimation of the linear regression occurs showed a difference of 214.88 kW, while the maximum underestimation is at the last iteration with a value of 325.14 kWh.

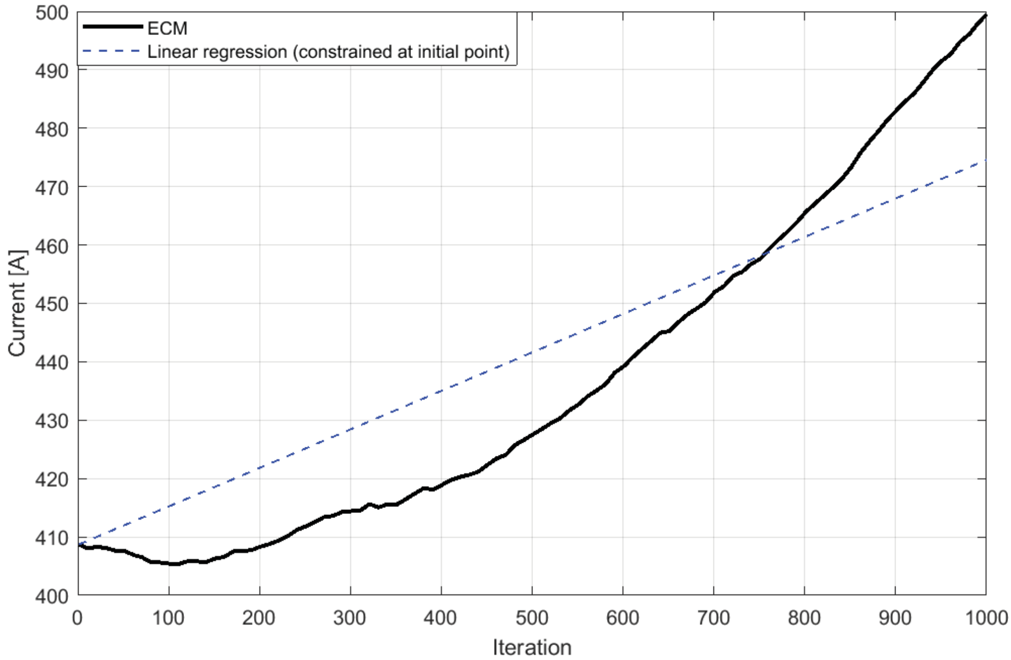
FIGURE 23 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (BASE CASE)




SOURCE: The author (2019).

FIGURE 24 24 presents the maximum current flowing from the substation at the time of maximal loading, while FIGURE 25 presents the minimum voltage value throughout the feeder for each evaluated iteration in a per unit scale (the nominal base voltage of the feeder is 13,000 V, as mentioned on section 5.1.1).

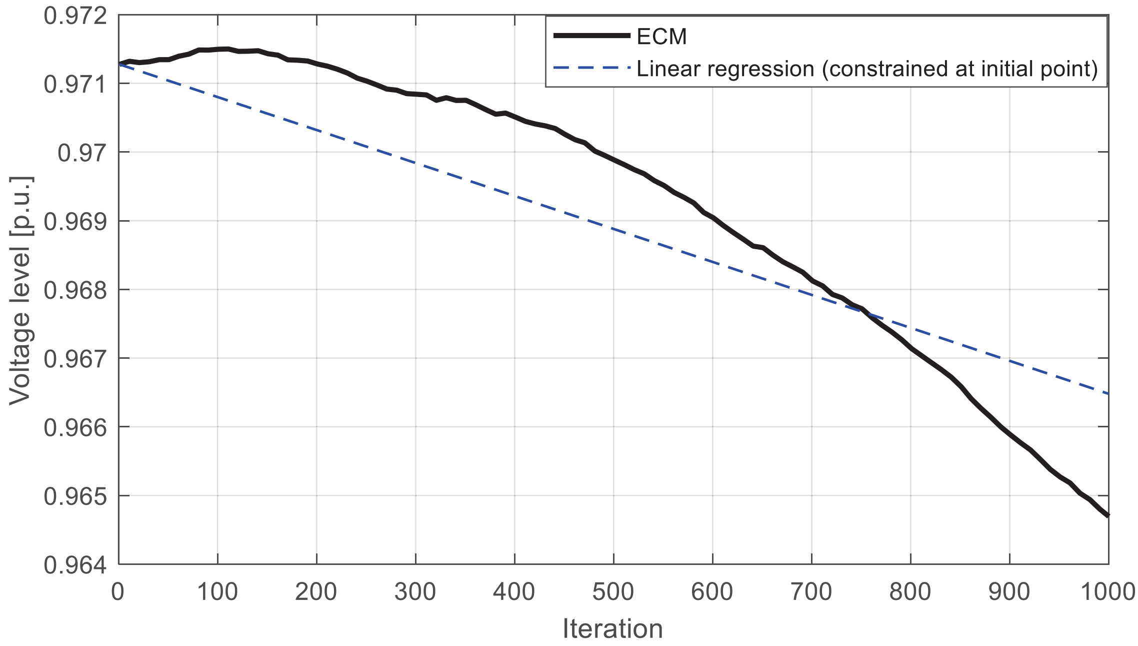
FIGURE 24 – CURRENT FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (BASE CASE)




SOURCE: The author (2019).

The dashed blue line on FIGURE 23, FIGURE 24 and FIGURE 25 represent a linear regression estimated via the least square method, considering a constraint on the initial point of analysis (circled in red on FIGURE 23). It is intended to demonstrate the difference of the proposed ECM with a linear homogeneous growth that, given an initial point (the present) could be considered to forecast future power scenarios.

FIGURE 25 – MINIMUM VOLTAGE LEVEL ON THE FEEDER (BASE CASE)

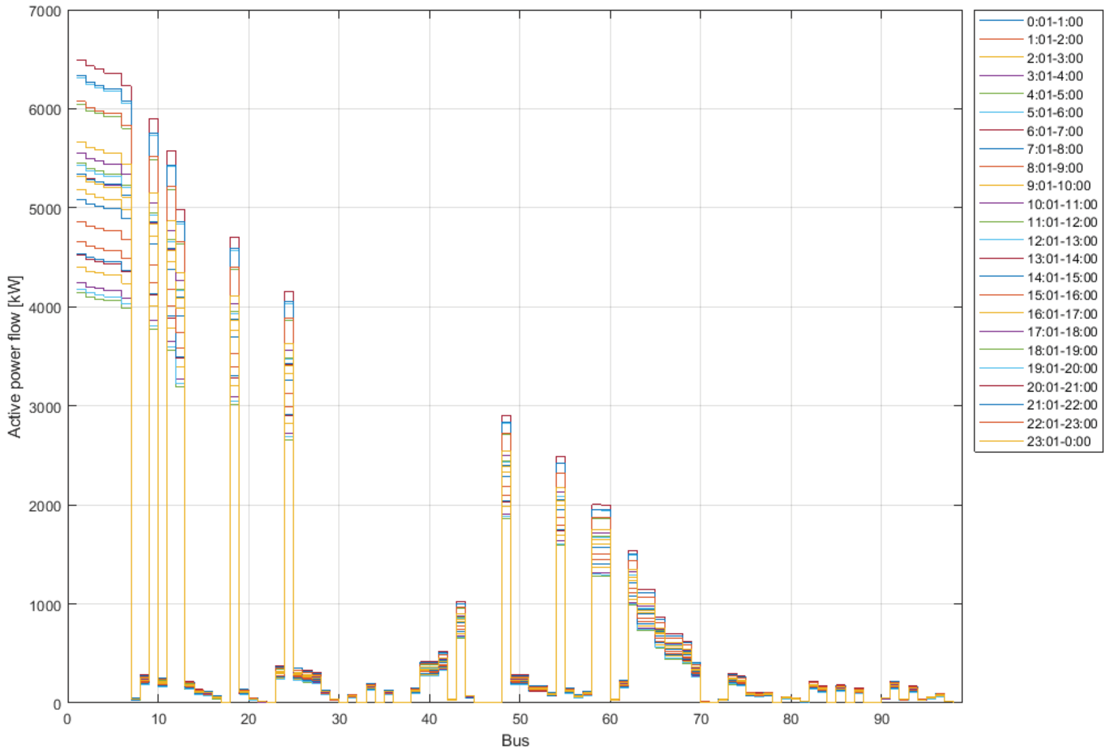



SOURCE: The author (2019).

The discussions for the analysis scenarios will be related comparing this base case with them since different compositions of the agent significant alter system dynamics and therefore their emergent behavior on power and energy.

Finally, FIGURE 26 presents the active power flowing from the substation at the iteration of maximum loading (1000$^{th}$ iteration) for all periods of the day.

FIGURE 26 – POWER FLOWING FROM THE SUBSTATION AT THE 1000TH ITERATION (BASE CASE)




SOURCE: The author (2019).

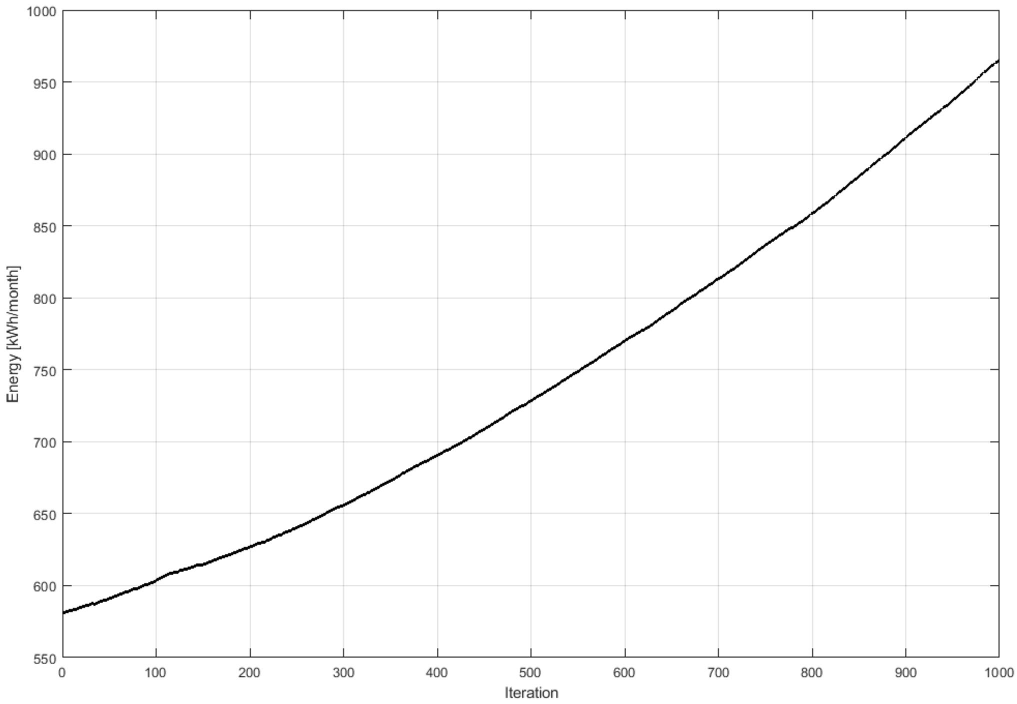
### 5.4.2 Scenario 1 (Focus on consumer category 1)

Scenario one considers category one with 4562 consumers (62.5) and the remaining categories with 912 consumers each (12.5% each).

#### 5.4.2.1 Energy analysis

The consumption level started at 581.3 kWh/month, a higher level than the base scenario due to the presence of more consumers in category one, which have a higher initial consumption. The average monthly consumption reached an end level of 965.6 kWh/month, as presented in FIGURE 27. A traditional economic model considering only the fixed rate consumption of 0.1%/iteration increase would reach a level of 1,579.3 kWh/month, a large difference, but not as large as in the base scenario, due to the huge presence of consumers from category one, whose modeled heuristics did not take into consideration investments and social interactions as much as other categories

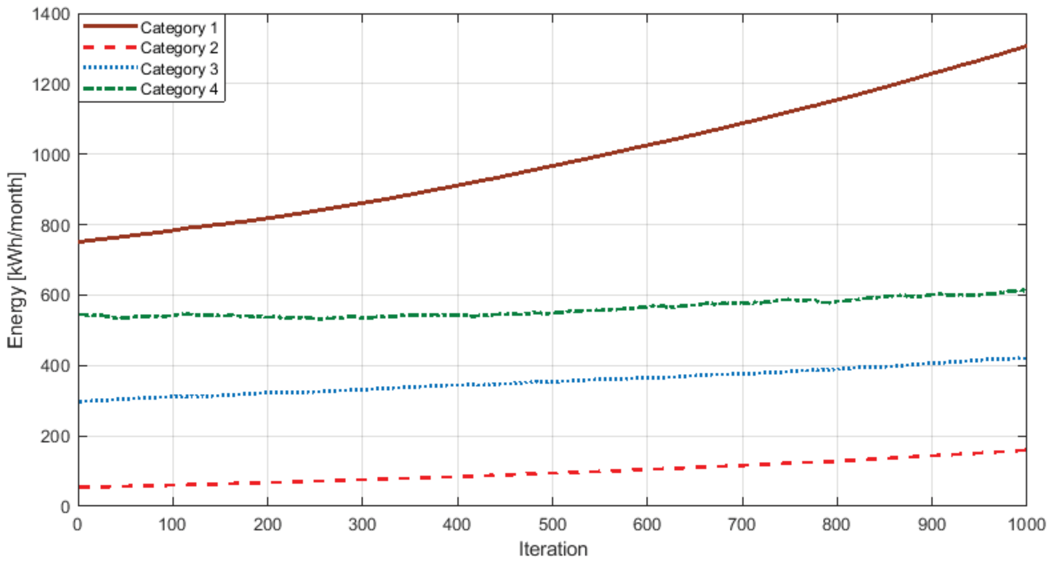
FIGURE 27 – AVERAGE MONTHLY ENERGY CONSUMPTION (SCENARIO 1)




SOURCE: The author (2019).

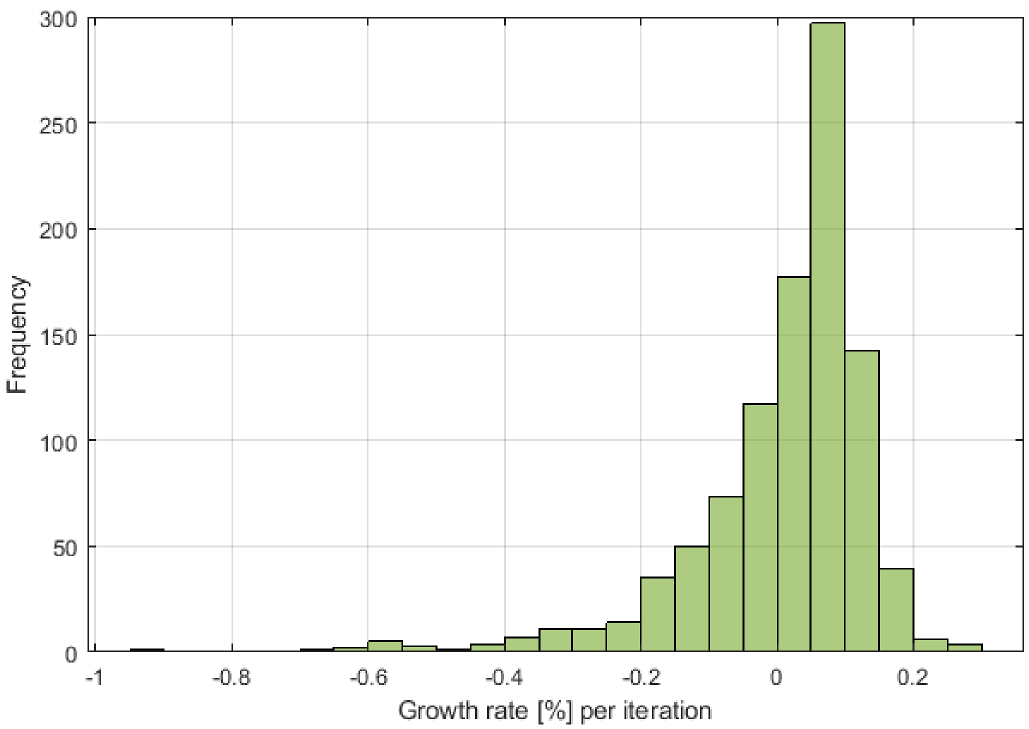
FIGURE 28 presents the average monthly consumption for each consumption category. Categories one, two, and three did not show relevant changes compared to the base case, which was not the case of category four. This category instead of presenting a significant drop on their average energy consumption (from 550.6 to 261.7 kWh/month, as on the base case), it, in fact, increased the consumption level in 12.29% (from 544.4 to 611.3 kWh/month). It is important to note that although category one was the one that increased in proportion on scenario one (from 25% to 62.5), while all other categories decreased their participation (from 25% to 12.5%), the emergent behavior only presented significant variation on their tendency on category four, showing that the overall emergent behavior of all consumers is not a simple average of the dominant category, and there is significant nonlinearity in the model. FIGURE 29 presents the histogram of the growth rate this positive tendency for category four.

FIGURE 28 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR EACH CONSUMER CATEGORY (SCENARIO 1)




SOURCE: The author (2019).

FIGURE 29 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION FOR CATEGORY 4 (SCENARIO 1)

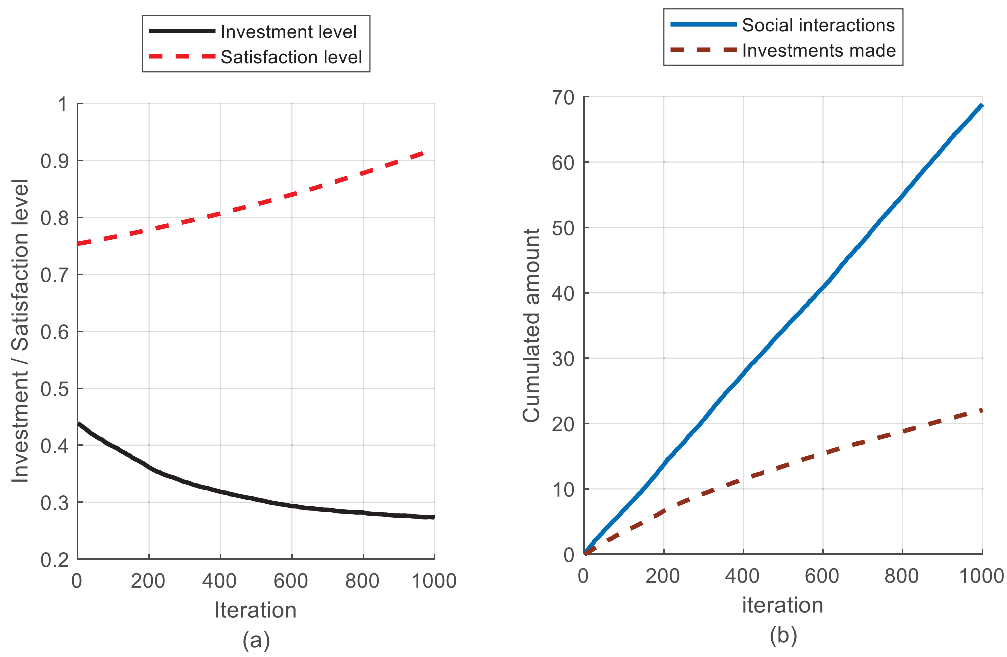



SOURCE: The author (2019).

Looking into the variables of the model (FIGURE 30):

- Investment level presented an initial level of 0.432 (0.06 higher than the base case) but a slightly steeper decay, reaching a final level of 0.273 (0.03 lower than the base case). This change did not impact significantly on the number of investments made;
- Satisfaction level increased significantly, reaching a value of 0.920 at the last iteration;
- The number of social interactions decreased from 109.15 on the base case to 69.12. It happened due to the lower amount of interactions done by category one, as previously presented in TABLE 9.

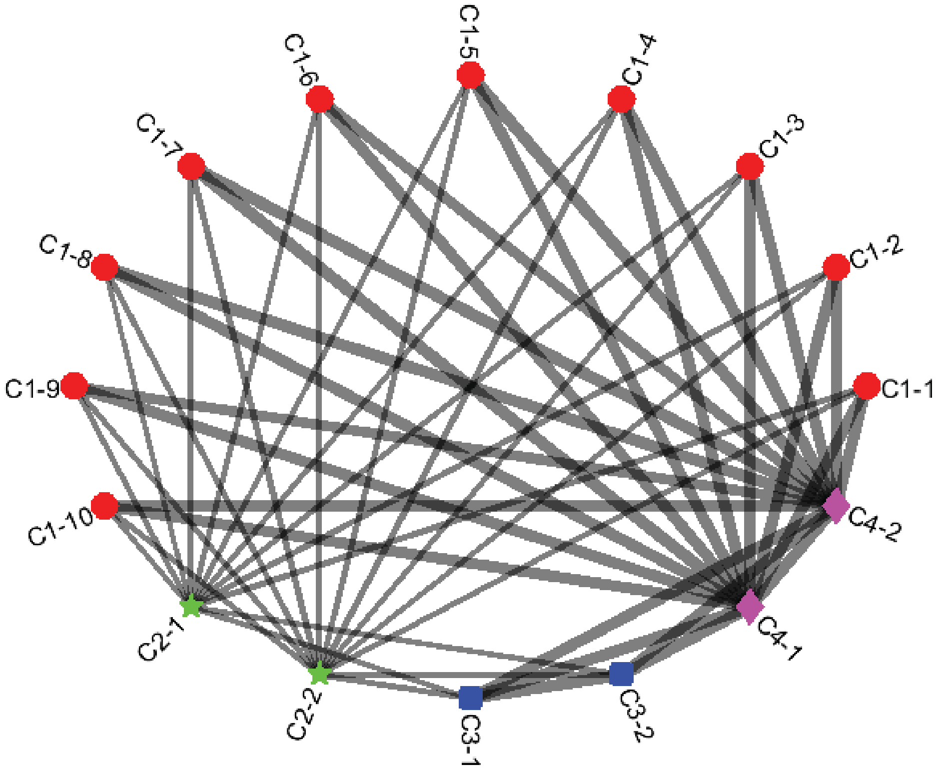
FIGURE 30 – EVOLUTION OF DIFFERENT VARIABLES (SCENARIO 1)




SOURCE: The author (2019).

FIGURE 31 presents the connected graph of the total amount of interactions among consumers. The graph although being fully connected, it is important to note the lack of interactions among customers of category one, for example, as defined by the social interaction scheme presented in TABLE 9.

FIGURE 31 – NETWORK OF SOCIAL INTERACTIONS (SCENARIO 1)




SOURCE: The author (2019).

Category one presents a degree value of four, followed by category three with five, category two with 12, and category four with 13. It happened due to the fact that customer on category one (highest share for scenario one), interacts most with category two and four.

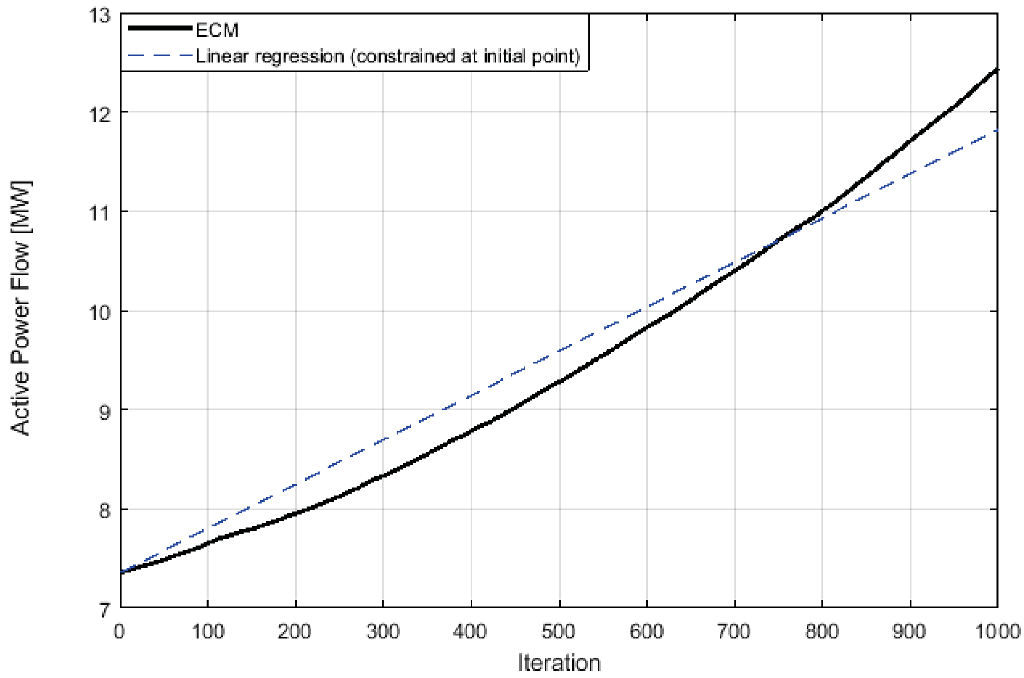
The total of interactions averaged 69.12, mostly composed by interactions of customers on category one (54.42).

#### 5.4.2.2 Power analysis

The load flowing from the substation to the grid on the hour of maximum loading for scenario 1 is presented in FIGURE 32 (with the y-axis scale in MW). As for the base case, initially, the slope of the curve increases over the iterations.

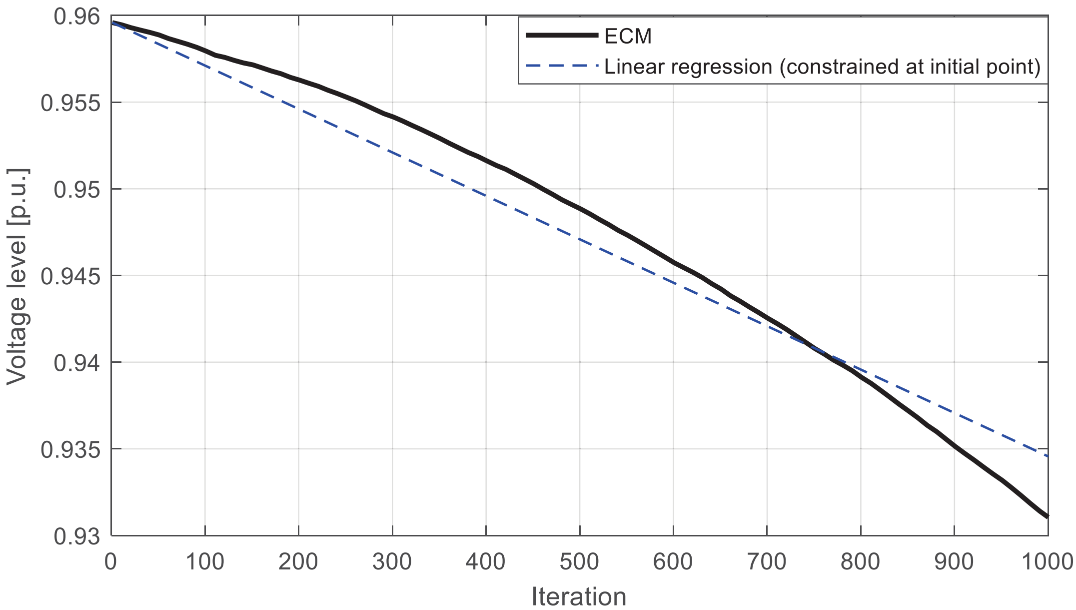
FIGURE 33 presents the minimum voltage level. If a linear rate was to be considered (blue dashed line), the voltage limit of 0.95 would be reached around iteration 390, while the ECM only trespassed this limit after iteration 461 (at bus 76, 20:01 – 21:00). On the last iteration, the time slot of 20:01 – 21:00 (maximal loading) 68.7% of the buses trespassed the voltage limit of 0.95 p.u.

FIGURE 32 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (SCENARIO 1)




SOURCE: The author (2019).

FIGURE 33 – MINIMUM VOLTAGE LEVEL ON THE FEEDER (SCENARIO 1)




SOURCE: The author (2019).

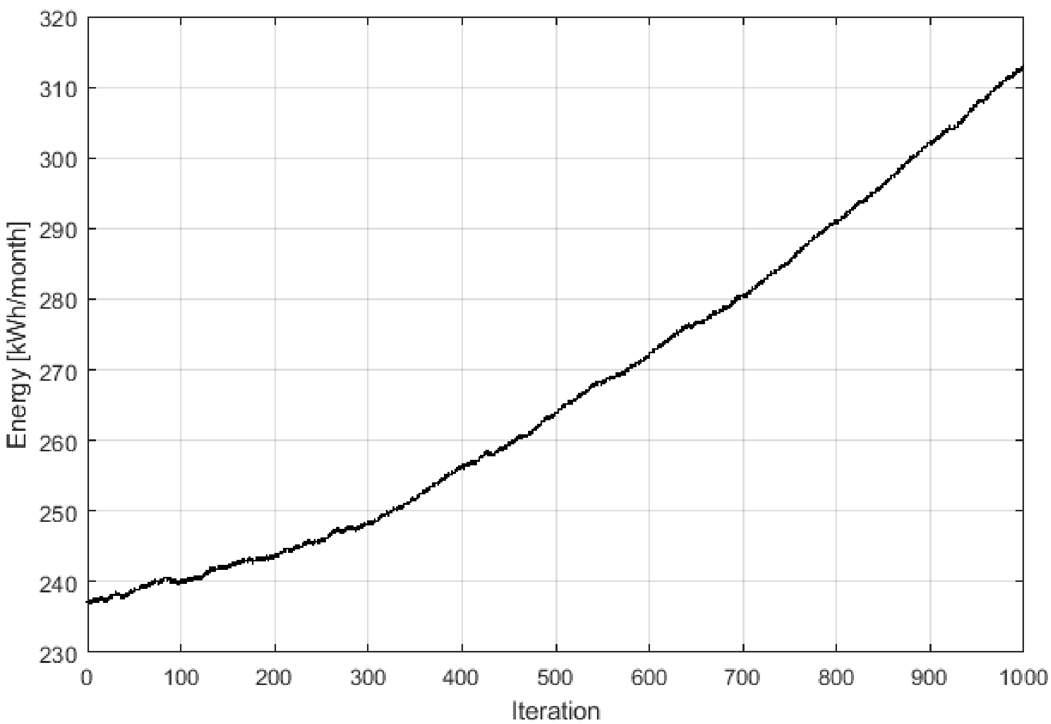
### 5.4.3 Scenario 2 (Focus on consumer category 2)

Scenario two considers category two with 4562 consumers (62.5 %) and the remaining categories with 912 consumers each (12.5% each).

#### 5.4.3.1 Energy analysis

As consumers in category 2 have a significantly lower initial consumption, the initial monthly consumption was 237.2 kWh, steadily increasing to reach a value of 313 kWh/month, as illustrated in FIGURE 34. Due to the social interaction scheme, their bigger price elasticity (CP = 2, as presented TABLE 14), and the few investments made, it is possible to verify that consumers in category two present a lower initial consumption level with a higher percental increase in electricity consumption than the base case.

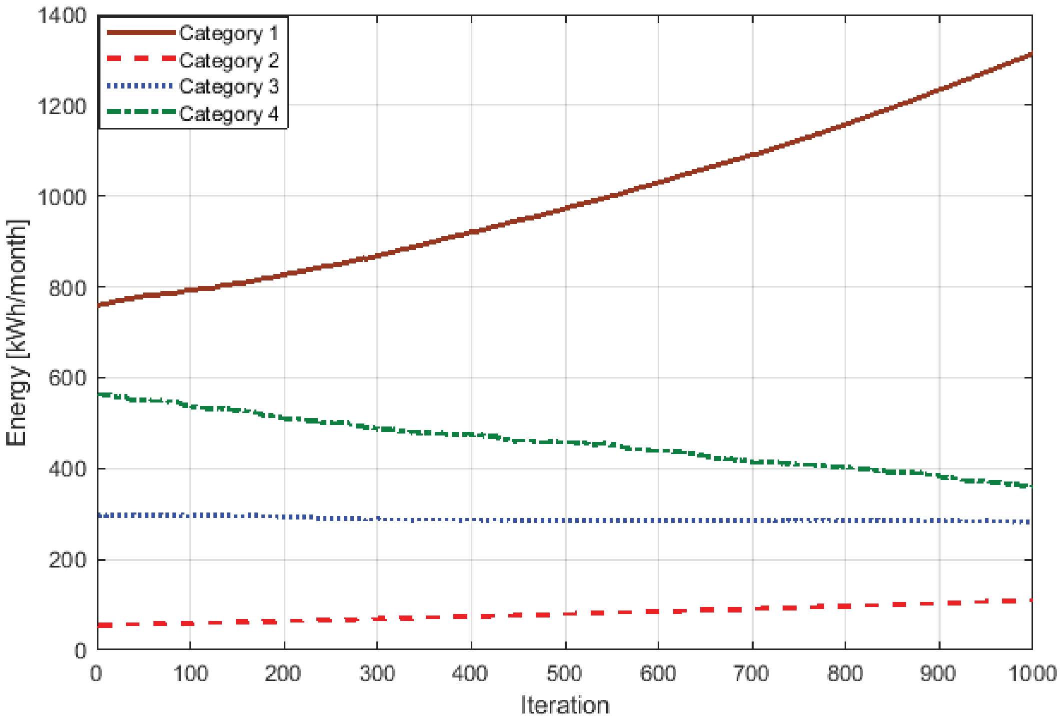
FIGURE 34 – AVERAGE MONTHLY ENERGY CONSUMPTION (SCENARIO 2)




SOURCE: The author (2019).

Categories one and two remained with a behavior a lot similar to the base case and scenario one, while categories three and four varied significantly, as can be perceived in FIGURE 35 and FIGURE 36. The average consumption of category three presented a small decrease throughout the entire simulation (a total variation of 16 kWh), while category four still presented a decreasing behavior (and not an increase as scenario one) but with a smaller slope, compared to the base case.

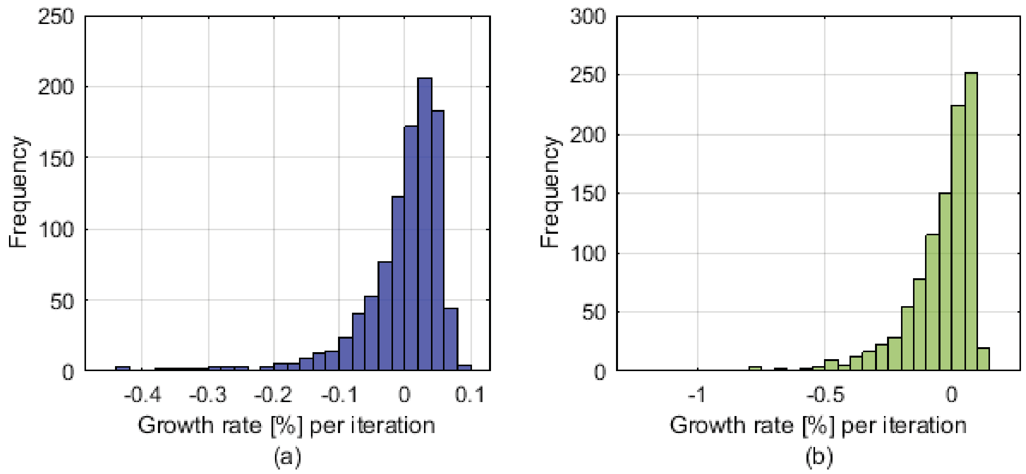
FIGURE 35 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR EACH CONSUMER CATEGORY (SCENARIO 2)




SOURCE: The author (2019).

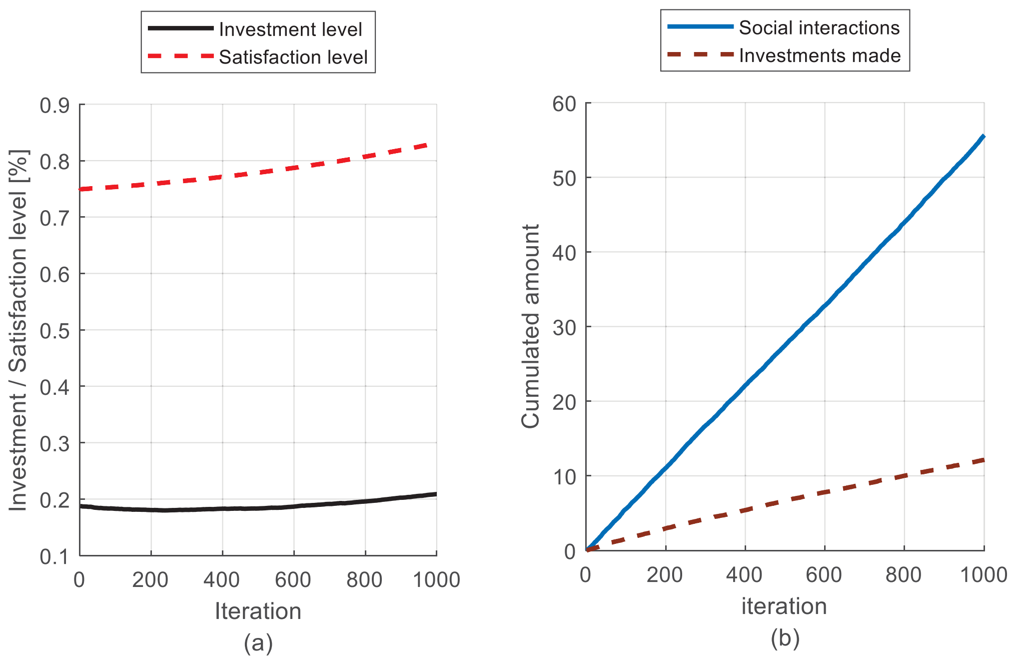
As shown in TABLE 10, the initial investment level of category two is 0%, resulting in an average initial level of 0.188 for scenario two (see FIGURE 37), which is a significantly lower level compared to the other scenarios. Satisfaction level reached higher values than the base case, as well as the total amount of investments made.

FIGURE 36 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION (SCENARIO 2): (A) CATEGORY 3; (B) CATEGORY 4.




SOURCE: The author (2019).

FIGURE 37 – EVOLUTION OF DIFFERENT VARIABLES (SCENARIO 2)

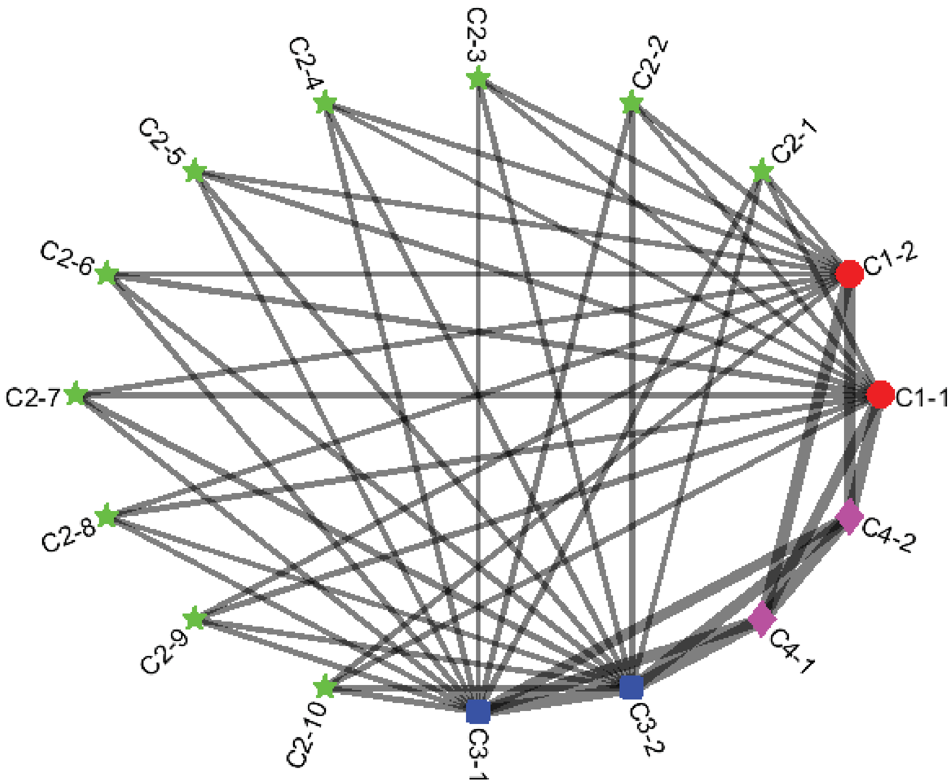



SOURCE: The author (2019).

FIGURE 38 presents the connected graph of the total amount of interactions among consumers. The graph although being fully connected, it is important to see the lack of interactions among customers of category two, for example, as defined by the social interaction scheme presented in TABLE 9.

Category two presents a degree value of four, followed by category four with five, category one with 12, and category three with 13. The total of interactions averaged 55.92. Although category two has the most agents (62.5%) on this scenario, nevertheless it contributed only with 33.26% of the interactions (18.6). Customers on category one contributed the most, with 46.24% (25.85 total of interactions).

FIGURE 38 – NETWORK OF SOCIAL INTERACTIONS (SCENARIO 2)



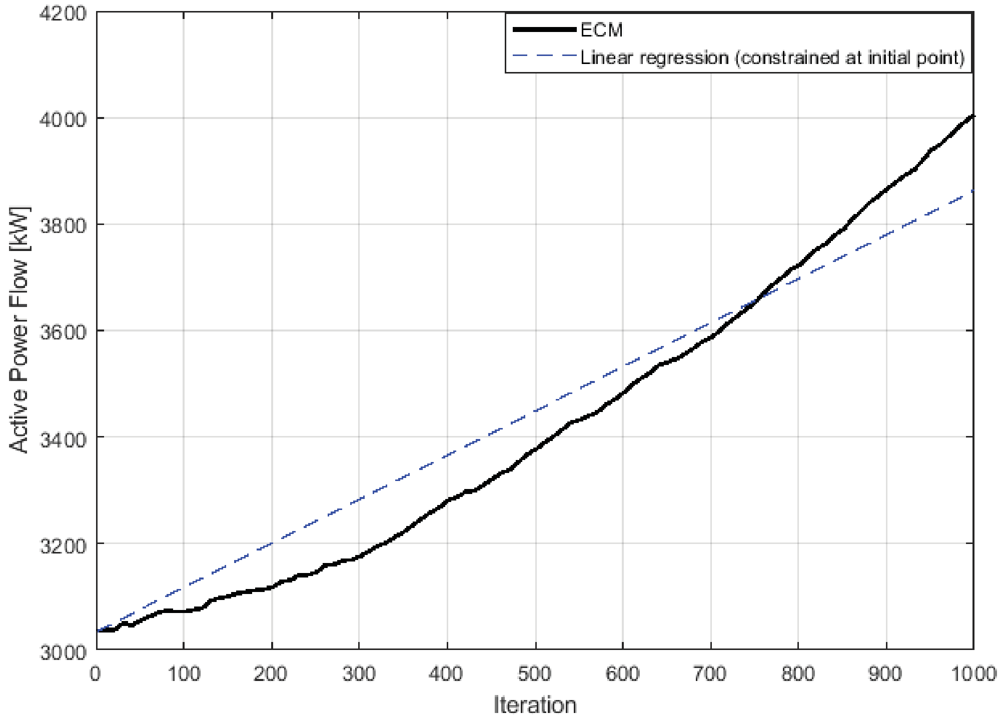

SOURCE: The author (2019).

### 5.4.3.2 Power analysis

The load flowing from the substation to the grid on the hour of maximum loading for scenario two is presented in FIGURE 39. As for the base case, initially the slope of the curve increases over the iterations and the output of the ECM starts lower than the linear regression and after around iteration 765, it shows a higher level.

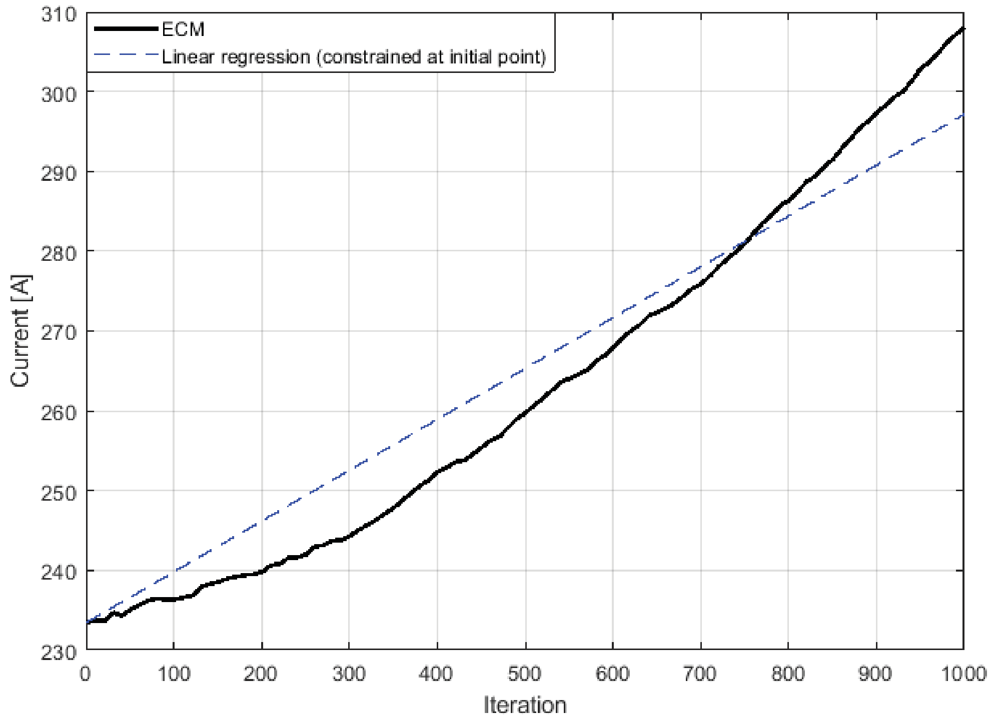
FIGURE 40 shows that the current values for this scenario did not trespass the theoretical limit of 350 A.

FIGURE 39 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (SCENARIO 2)




SOURCE: The author (2019).

FIGURE 40 – CURRENT FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (SCENARIO 2)




SOURCE: The author (2019)

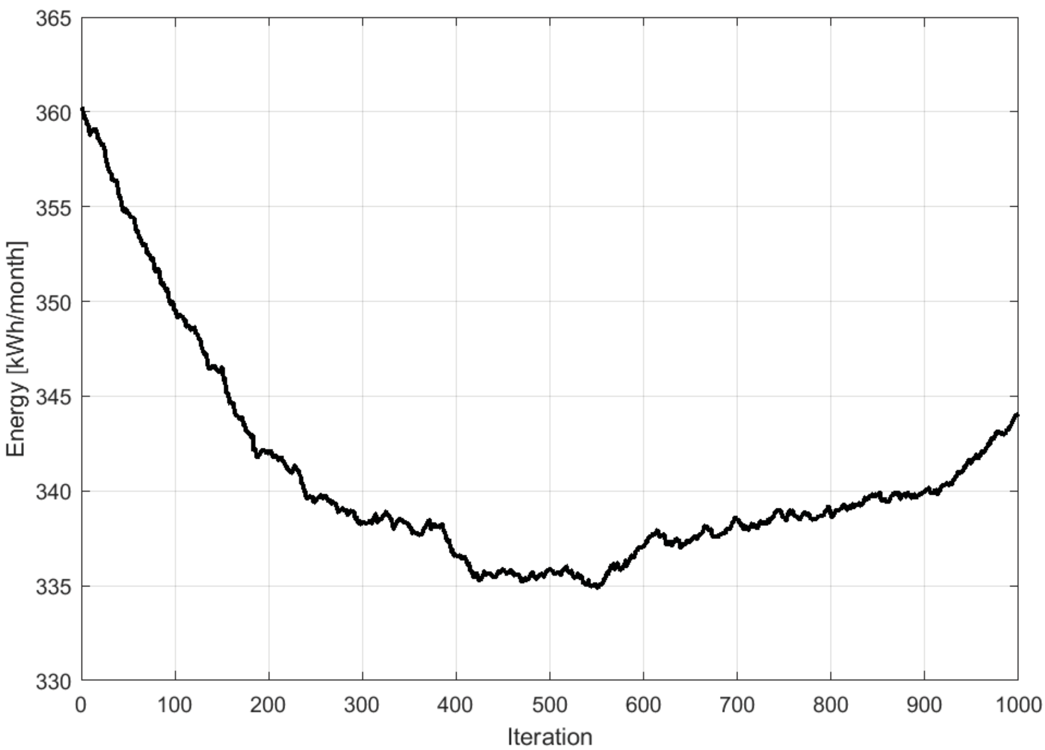
### 5.4.4 Scenario 3 (Focus on consumer category 3)

Scenario three considers category three with 4562 consumers (62.5%) and the remaining categories with 912 consumers each (12.5% each).

#### 5.4.4.1 Energy analysis

In scenario three, there was an initial tendency of a decrease in the average monthly energy consumption on the first 300 iterations (average of 2.08% for every 100 iterations), but remaining considerably constant after that, as illustrated in FIGURE 41 (average variation of 0.24% per 100 iterations from iteration 300 until iteration 1000). It is important to highlight the scales of the results of this scenario, while the base case presented a variation from the first compared to the last iteration of 93.8 kWh/month, scenario three varied 16.3 kWh/month.

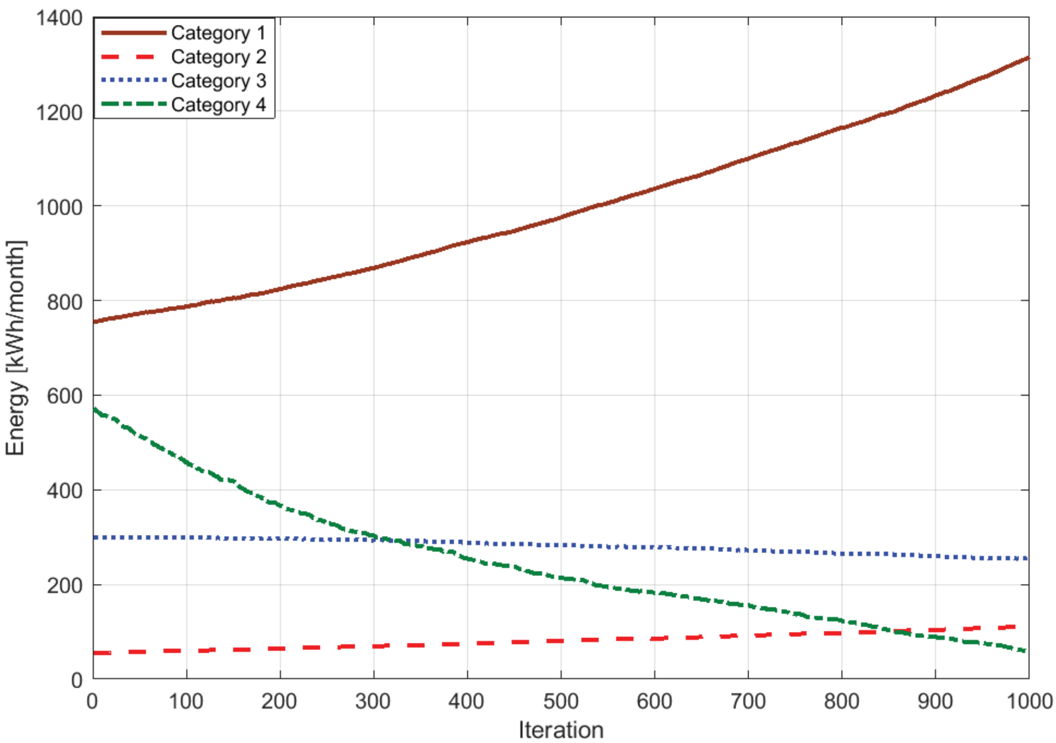
FIGURE 41 – AVERAGE MONTHLY ENERGY CONSUMPTION (SCENARIO 3)




SOURCE: The author (2019).

As for scenario two, categories one and two remained with a behavior a lot similar to the base case and scenario one, while categories three and four varied significantly, as can be perceived on FIGURE 42 and FIGURE 43. The average consumption of category three presented a decrease of 45.9 kWh throughout the entire simulation, while category four increased significantly the decreasing slope of the curve, compared to the base case. It is important to point out that category four reached a level with consumption even lower than category two. Following the tendency presented by the case, the prosumers on category four would still start to produce more energy than they consume on a monthly basis in some time.

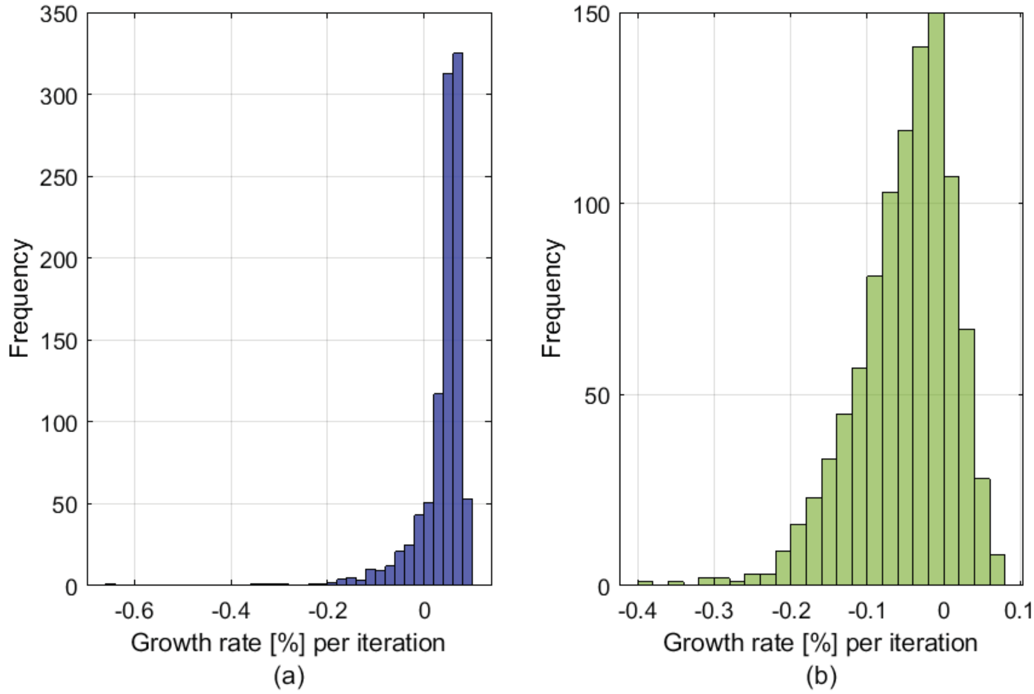
FIGURE 42 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR EACH CONSUMER CATEGORY (SCENARIO 3)




SOURCE: The author (2019).

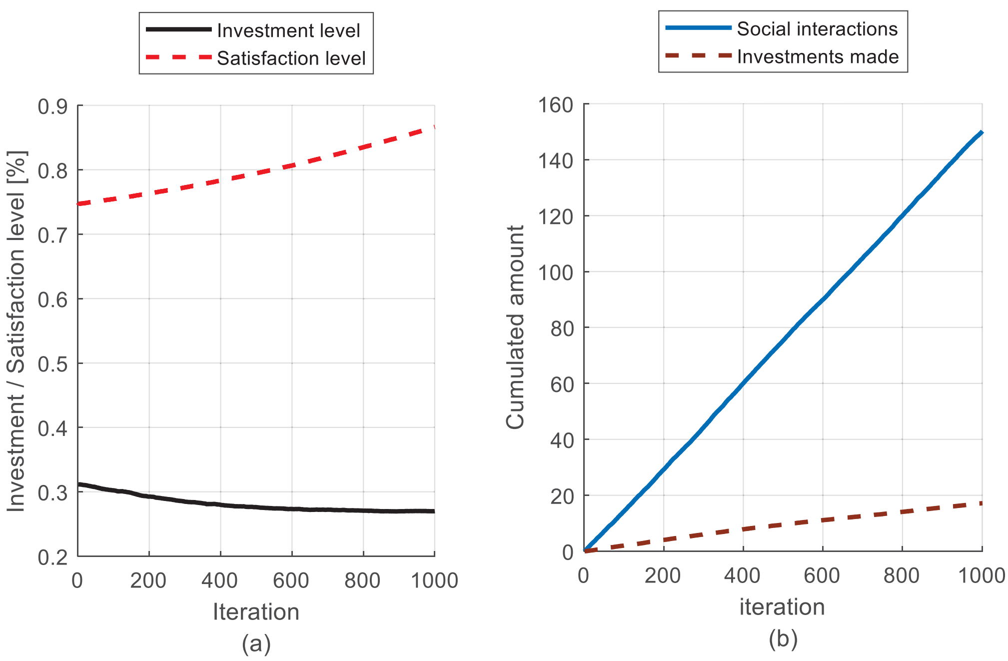
One factor that can be linked to this tendency of decreasing consumption of scenario three is social interactions. It totaled 151.38 on average, 42.23 more interactions than the base scenario, 82.26 more than scenario one, and 95.46 more than scenario two. Compared to scenario four, to be presented in the next section, the number of social interactions was 15.21 lower. It is important to notice that social

FIGURE 43 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION (SCENARIO 3): (A) CATEGORY 3; (B) CATEGORY 4




SOURCE: The author (2019).

FIGURE 44 – EVOLUTION OF DIFFERENT VARIABLES (SCENARIO 3)

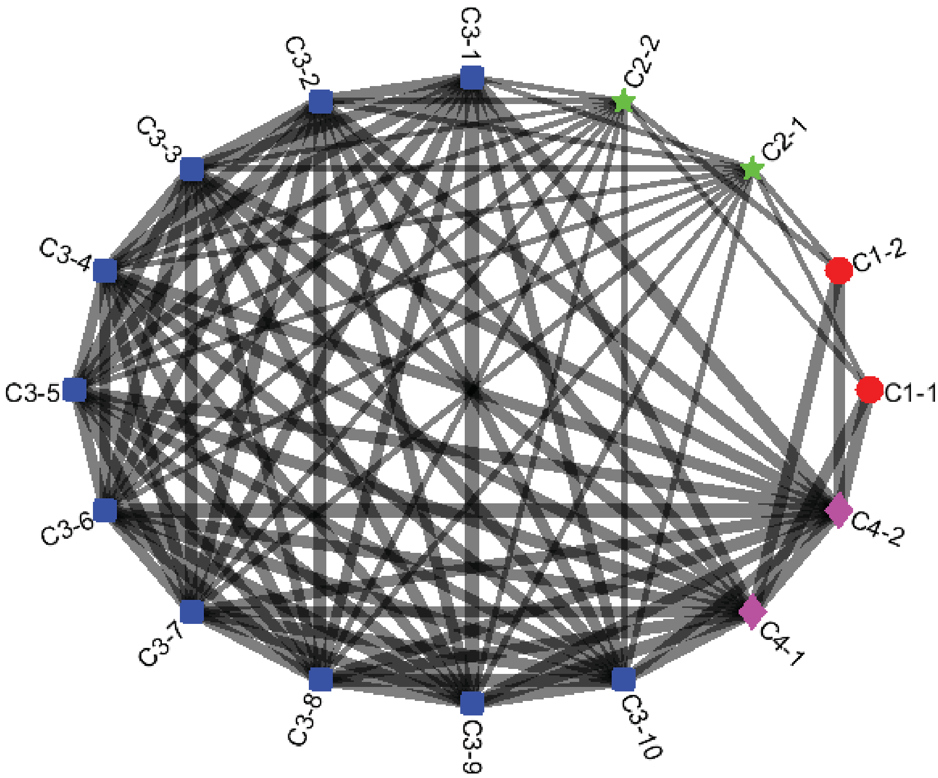



SOURCE: The author (2019).

interaction scheme proposed in TABLE 9, and the dynamics of the system shown on the CLD on FIGURE 11, consumers on category three present a strong tendency to decrease consumption when interacting. FIGURE 44 presents the evolution of some key variables of the model for scenario three.

FIGURE 45 presents the connected graph of the total amount of interactions among consumers. Category one presents a degree value of four, followed by category two with 12, and categories three and four with 13. Category three undertook 78.72% of all social interactions on this scenario.

FIGURE 45 – NETWORK OF SOCIAL INTERACTIONS (SCENARIO 3)

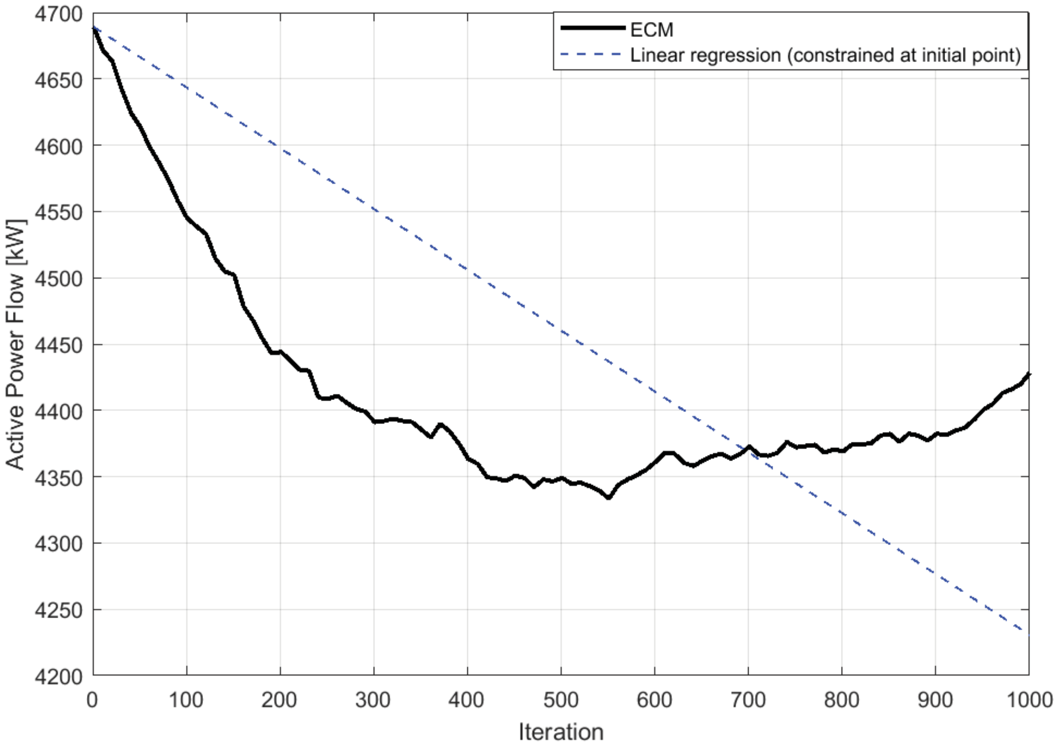



SOURCE: The author (2019).

### 5.4.4.2 Power analysis

The load flowing from the substation to the grid on the hour of maximum loading for scenario three is presented in FIGURE 46. As previously described on the curves for the base case, scenarios one and two, there is an overestimation of the linear regression model, when compared to the ECM, on a first phase, followed by an overestimation on a second phase. These differences are more accentuated on scenario three (but not on absolute levels), due to the strong non-linearity of the emergent behavior of the model under such assumptions.

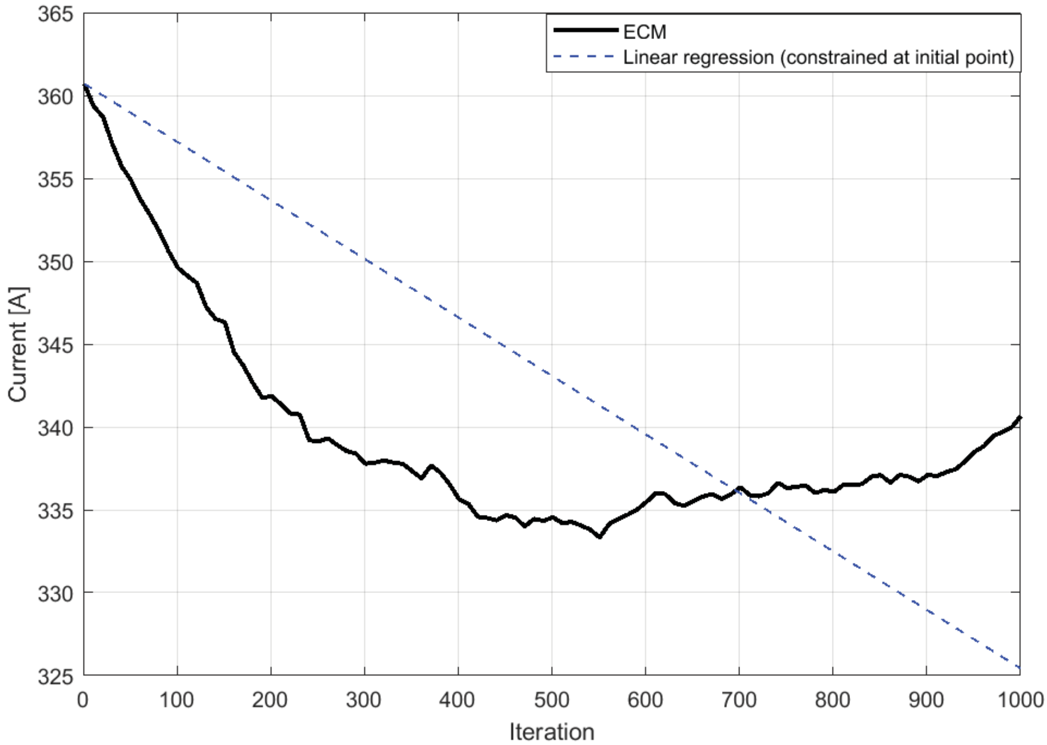
FIGURE 46 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (SCENARIO 3)




SOURCE: The author (2019).

FIGURE 47 presents the maximum current flowing from the substation at the time of maximal loading for scenario three. Consider that the current limit for the feeder is 325.3 A, as mentioned in section 5.1.1, the linear regression would assume that the system is operating at the time of the last iteration practically without overload. Considering the ECM, nevertheless, there is an overload of ca. 15 A.

FIGURE 47 – CURRENT FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (BASE CASE)




SOURCE: The author (2019).

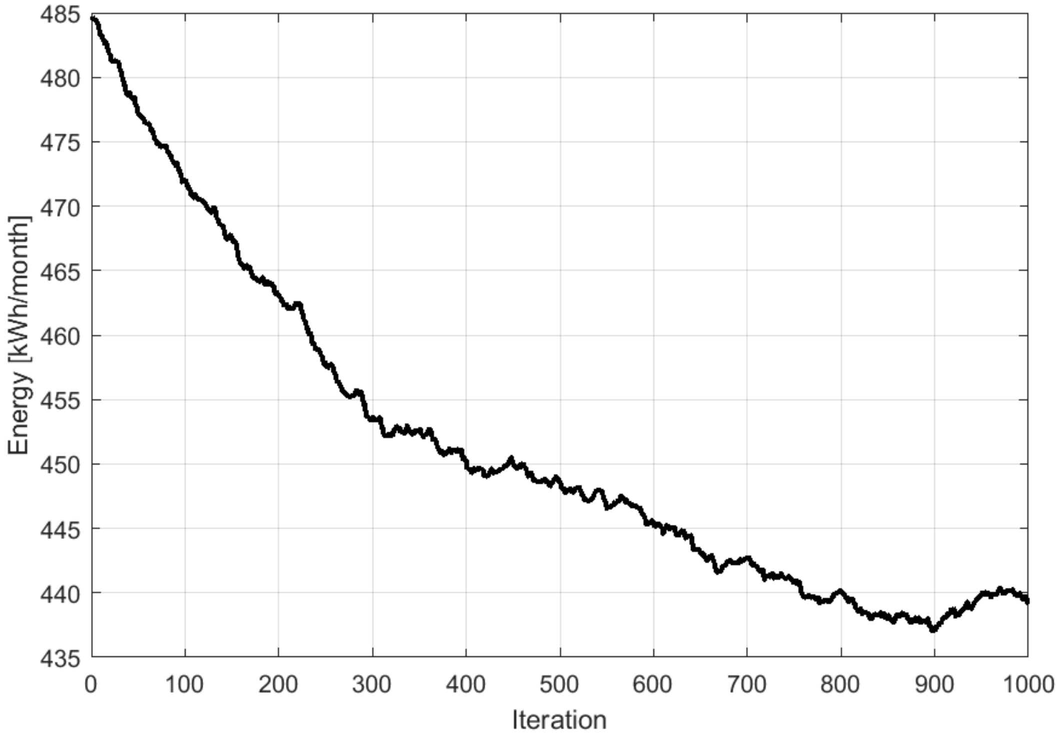
### 5.4.5 Scenario 4 (Focus on consumer category 4)

Scenario four considers category four with 4562 consumers (62.5) and the remaining categories with 912 consumers each (12.5% each).

#### 5.4.5.1 Energy analysis

The objective of scenario four is to highlight the behavior of consumers on category four, i.e. consumers inclined to strongly adopt new technologies and therefore invest in energy-efficient technologies, increasing their share on the agent counts. This scenario resulted in total energy consumption decreasing over the iterations, as presented in FIGURE 48.

FIGURE 48 – AVERAGE MONTHLY ENERGY CONSUMPTION (SCENARIO 4)

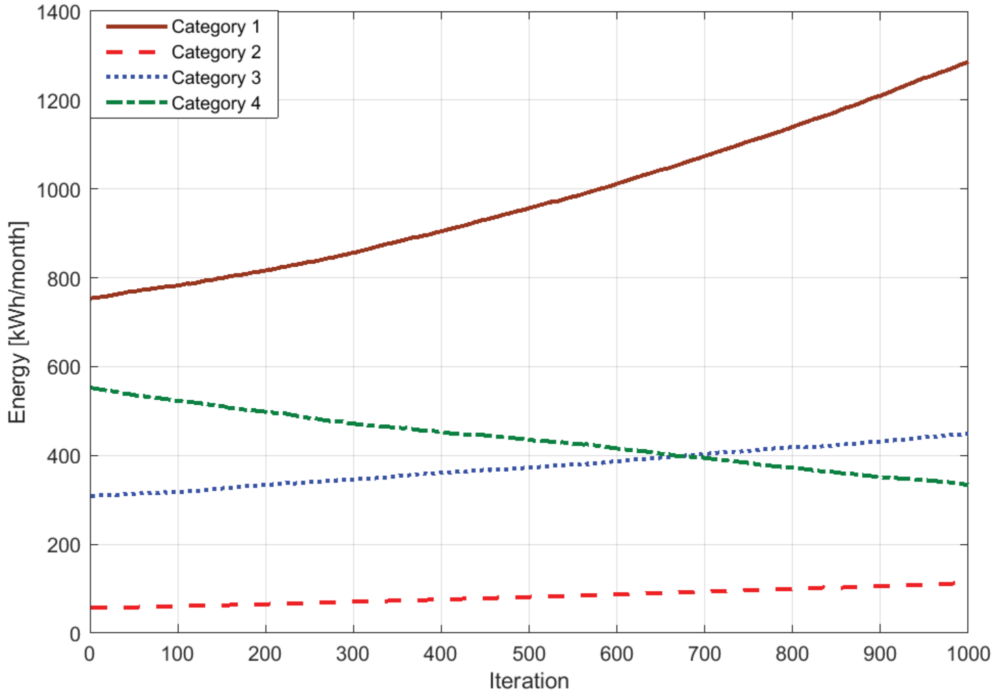



SOURCE: The author (2019).

As for scenarios two and three, categories one and two remained with a behavior a lot similar to the base case, while categories three and four varied significantly, as can be perceived on FIGURE 49 and FIGURE 50. Opposite to scenario three, the variation of consumers on category three was positive, in other words, to consume more throughout the simulations. From an initial average value of 308.8 to 449.4 kWh/month. Category four decrease their overall consumption level from 552.1 to 333.4 kWh/month.

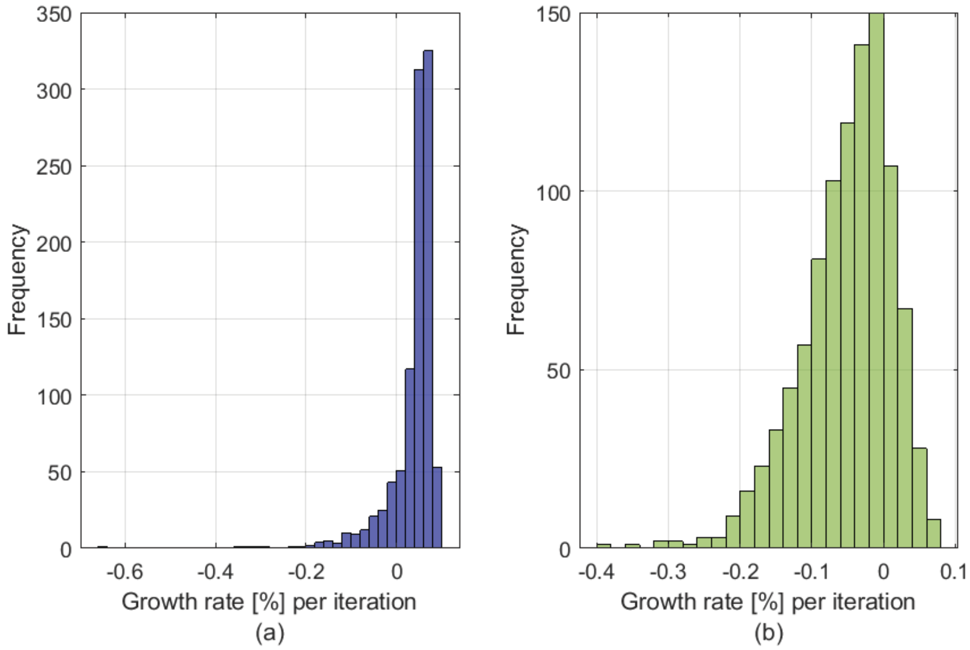
One of the possible reasons is the number of investments made. The investment level reached an average total value of 48.62, more than of any other scenario (four times more than scenario two, which presented fewer iterations, and 2.03 times more than the base case, which totaled 23.91 investments, the second higher value). FIGURE 51 presents the evolution of the investment level, total on investments made, and some other key variables of the model for scenario four.

FIGURE 49 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR EACH CONSUMER CATEGORY (SCENARIO 4)



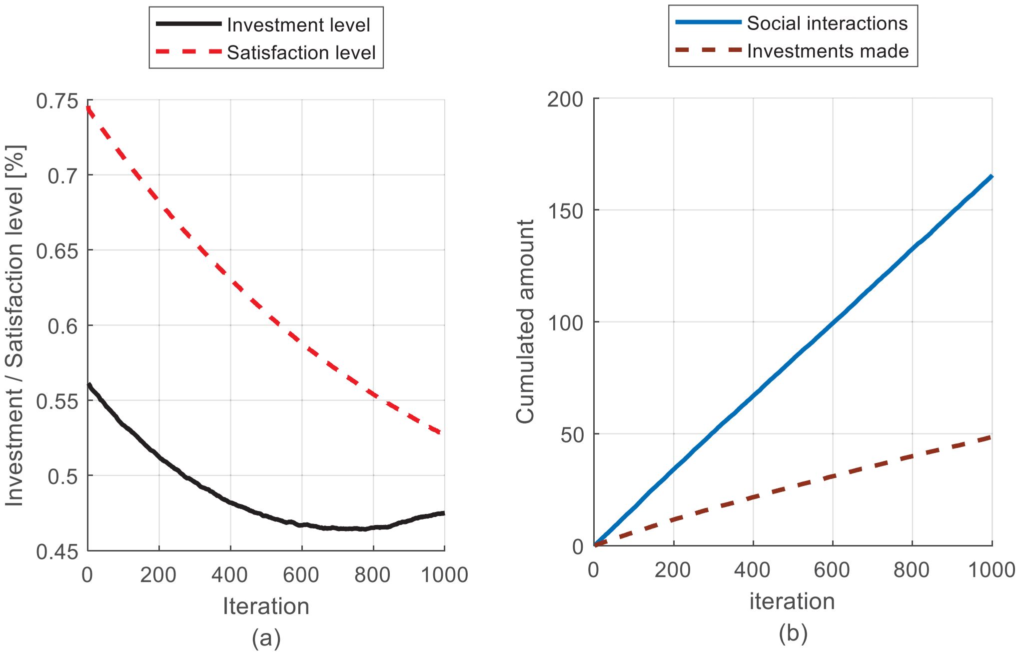

SOURCE: The author (2019).

FIGURE 50 – GROWTH RATE OF THE ENERGY CONSUMPTION PER ITERATION (SCENARIO 4): (A) CATEGORY 3; (B) CATEGORY 4.




SOURCE: The author (2019).

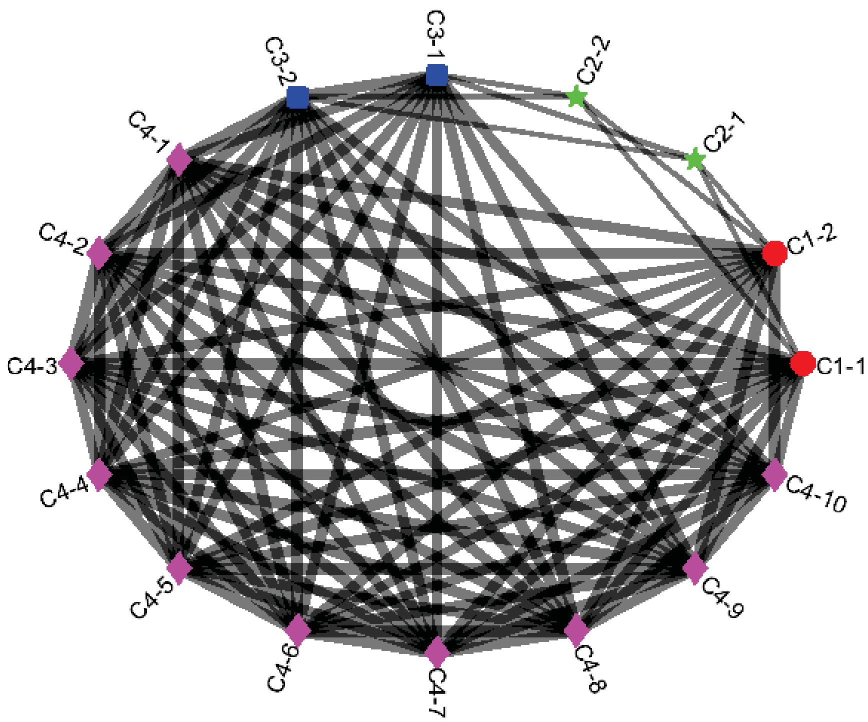
FIGURE 51 – EVOLUTION OF DIFFERENT VARIABLES (SCENARIO 4)




SOURCE: The author (2019).

FIGURE 52 presents the connected graph of the total amount of interactions among consumers.

FIGURE 52 – NETWORK OF SOCIAL INTERACTIONS (SCENARIO 4)



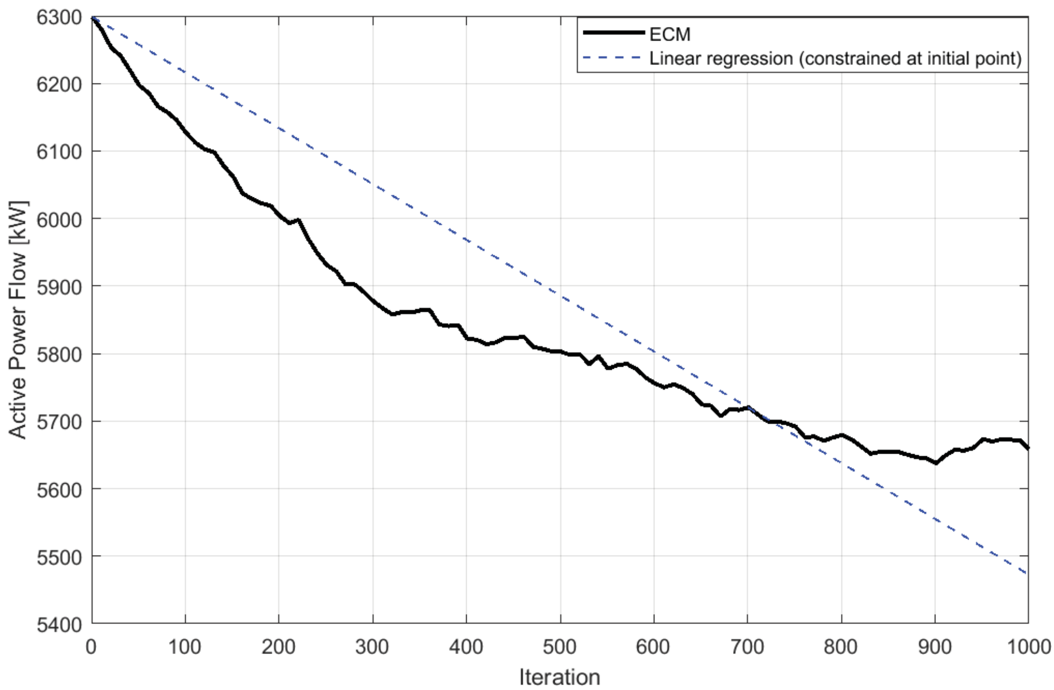

SOURCE: The author (2019).

Category one presents a degree value of four, followed by category one with 12, and categories three and four with 13. The total of interactions averaged 166.69, the largest amount among all scenarios. It was lead by the 83.08 interactions of consumers on category four, but also strongly influenced by the 40.6 interactions of category one and 39.21 of category three. Category two only presented an average value of 1.86 interactions (1.12% of the total of the scenario).

### 5.4.5.2 Power analysis

The load flowing from the substation to the grid on the hour of maximum loading for scenario four is presented in FIGURE 53.

FIGURE 53 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING (SCENARIO 4)




SOURCE: The author (2019).

### 5.4.6 COMPARATIVE ANALYSIS

Analyzing the results both in energy (FIGURE 16, FIGURE 27, FIGURE 34, FIGURE 41, and FIGURE 48) and power (FIGURE 23, FIGURE 32, FIGURE 39, FIGURE 46, and FIGURE 53) for all scenarios, it is possible to notice a recurring pattern, regardless of the tendency of the evolution to be of increase or decrease. This patter consists in initially the curves tending to have a slightly stronger descending slope, compared to their own average behavior, while on the last stage (roughly speaking, after iteration 900), this tendency inverts. In other words, the EMC's heuristics lead to an emergent property which leads to energy reduction on the next iterations and to increase on consumption on the last iterations, when set side by side with the average behavior of each category. This behavior may correlate to different parameters of the model such as satisfaction and investment levels, and interactions among consumers and with the utility, that input inertia to the model. Nevertheless, given the complexity of the model, it is not suitable to directly relate this behavior to a specific variable.

Regarding the energy analysis, specifically the average monthly energy consumption, TABLE 16 summarizes some of the main statistics for all scenarios.

TABLE 16 – STATISTICS ON TOTAL MONTHLY ENERGY CONSUMPTION FOR ALL SCENARIOS

| | Base case | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|---|
| **Initial consumption value** | 414,13 | 581,3 | 237,2 | 360,3 | 484,7 |
| **Consumption value at the last iteration** | 508,1 | 965,6 | 313 | 344 | 439,2 |
| **Percental variation** | ↑22,69% | ↑66,11% | ↑31,96% | ↓4,52% | ↓9,39% |
| **Minimum consumption value** | 411,10 | 581,30 | 237,00 | 334,90 | 437,00 |
| **Maximum consumption value** | 508,10 | 965,60 | 313,00 | 360,30 | 484,70 |

SOURCE: The author (2019).

The base case and scenarios one and two presented an increase in energy consumption. The scenario with the biggest percental variation is scenario one, with

66.11%. This variation is also the largest on absolute values (384.3 kWh/month). Given that the main characteristics of consumers on category one, which was prioritized on scenario one, are: to be insensitive to tariff changes; to invest in energy efficiency only when they find suitable, and; to only occasionally change habits due to social interaction; this behavior is as expected.

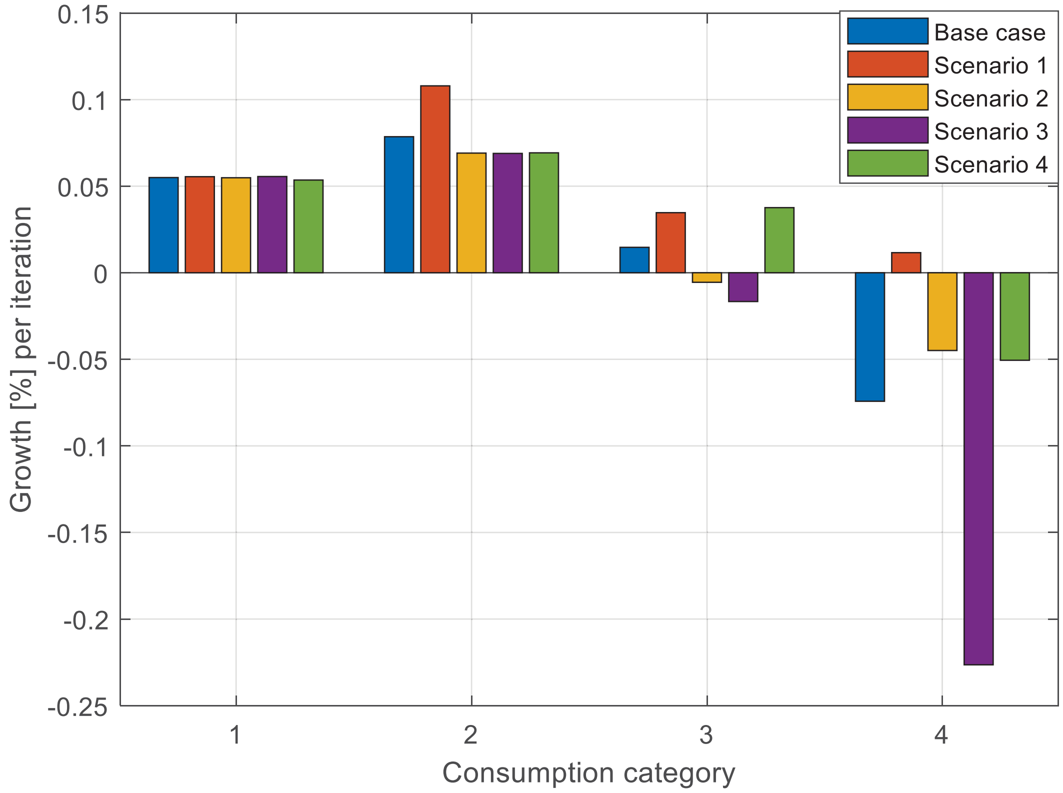
The scenario with the biggest decrease in energy consumption is scenario four, with – 9.39%, from 484.7 kWh/month to 439.2 kWh/month. It is important to highlight again that this behavior occurred contrary to the tendency of the model to increase energy consumption by 0.1% every iteration, calling attention to the effect of the modeled heuristics.

As illustrated by FIGURE 54, category one showed basically the same averages throughout all simulation scenarios, representing that this category is not influenced by the other agents in the environment. Category two showed a higher average growth rate on the scenario since customers on category two increase their consumption whenever they have social interactions with consumers on category one, the predominant agent on scenario one. For the other scenarios agents on category were not severely influenced.

Categories three and four presented a behavior with strong variations depending on the interaction with their peers. Category three presented average negative growth values for scenario two and three, and positive for the base case, scenario one, and scenario four. The highest average growth rate for category three was in scenario four (0.038%/iteration), and the most negative on scenario three (-0,017%/iteration). It can be traced to the fact that consumers on category three may decrease consumption when meeting with peers of the same consumption category, and that they increase their investment level when met consumers on category four (which leads to an increased likelihood of making investments in energy efficiency, in its turn, leading to a decrease in energy consumption).\

Category four only presented overall positive value for the growth in scenario one, which, on this case led to an increase in average energy consumption as presented in FIGURE 28. It happened because category four increase consumption when they interact with consumers on category one. Therefore, it can be considered that this result lead presents consistency with the tendency to average discussed on the theory of behavioral economics. In other words, even consumers that have a natural tendency

FIGURE 54 – AVERAGE GROWTH RATE FOR THE DIFFERENT CONSUMPTION CATEGORIES FOR ALL SCENARIOS




SOURCE: The author (2019).

to increase their efficiency with time can be influenced by their social environment and context they are inserted.

TABLE 17 presets selected statics on the power analysis. Regarding the coefficient of determination ($R^2$) for the maximum power flow level throughout the iterations, compared to the constrained linear regression, the most linear case is for scenario one, followed by scenario two. This result derives from two main reasons: consumers on category one and two interact less with other categories, and do not interact with their own category, as shown in TABLE 9; consumers on category two make few investments in energy efficiency.

TABLE 17 – STATISTICS ON THE POWER ANALYSIS FOR ALL SCENARIOS

| | Base case | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|---|
| **Coefficient of determination ($R^2$) between power flow and constrained linear regression** | 0.811 | 0.964 | 0.930 | -0.805 | 0.651 |
| **Slope of the constrained linear regression for the power flow** | 0,857 | 4,469 | 0,828 | -0,459 | -0,827 |
| **Maximum value of power flow [kW]** | 6495,448 | 12443,064 | 4006,698 | 4689,131 | 6298,297 |
| **Minimum voltage level [p.u.]** | 0,965 | 0,931 | 0,979 | 0,975 | 0,966 |
| **Maximum value of current [A]** | 499,650 | 957,159 | 308,208 | 360,702 | 484,484 |

SOURCE: The author (2019).

The base case presented an $R^2$ of 0.811, followed by scenario four with 0.651. As presented in FIGURE 53 for scenario four, the emergent result may be considered to have a strong non-linear component. Finally, scenario three presented an $R^2$ of -0.805. This negative value represents that the constrained linear regression fits the output of the EMC worse than a horizontal line on the mean values, not fitting the trend of the data. Therefore, a strong nonlinearity was found presumably in scenarios three and four, leading to the understanding that social interactions and investments play a big role in leading a system to nonlinearity and unpredictable complex behaviors.

The slopes of the linear regression are ranked, from the most positive to the most negative, as following: scenario one, base case, scenario two, scenario three, and scenario four. The absolute values of the slope have the same ranking as the percental variations of the electricity consumption showed in TABLE 16.

Moving on to basic indicators of power quality, the minimum voltage level, considered to be 0.95 p.u. for this analysis was only trespassed on scenario 1 (consider the base voltage level as 13,000 V). The current limit of 325.3 A has trespassed in all but scenario two. Nevertheless, given that the original loads on the feeder were replaced by the loads calculated by the EMC, these values should not be regarded as fixed operational limits, but only as a comparison basis among the scenarios.

Going into the variables of the model, TABLE 18 presents the final value (last iteration) of selected variables for all scenarios. The number of interactions with the utility was roughly constant for all scenarios since the same rules apply for all categories (if a given agent moves to a specific part of the simulation world in a given iteration they interact with the utility, regardless of their consumption class).

TABLE 18 – STATISTICS ON SELECTED VARIABLES OF THE ECM FOR ALL SCENARIOS

| | **Base case** | **Scenario 1** | **Scenario 2** | **Scenario 3** | **Scenario 4** |
|---|---|---|---|---|---|
| **Final value of interactions with the utility (DSM)** | 529.69 | 530.86 | 530.91 | 533.52 | 533.44 |
| **Final value on social interactions among consumers** | 109.15 | 69.12 | 55.92 | 151.38 | 166.59 |
| **Final value on investments made in energy efficiency** | 23,91 | 22,08 | 12,15 | 17,17 | 48,67 |

SOURCE: The author (2019).

On the total of social interactions, the biggest value occurred in scenario four, followed closely by scenario three. Since social interactions occur randomly on each iteration, respecting the scheme presented, it leads to an increase in nonlinearity, as previously verified. As previously mentioned, the model disregards social norms on class mixing, therefore the possibility of social interactions for all models is basically related to the number of consumers in the simulation. Nevertheless, as previously shown by TABLE 9, not all possibilities of social interaction become a social interaction, as it depends on the customer category.

Another event that has strong random influences in the investment in energy efficiency. As expected, scenario four, with most consumers from category four, presented the largest amount of investments in energy efficiency.

### 5.4.7 FINAL DISCUSSION

This chapter presented a case study to demonstrate the applicability of the proposed methodology. Initially, the materials were presented, followed by some specific parameters considered on the ECM, the computational platform used, and, finally the results and analysis for the base case and the four proposed analysis scenarios. The results and analysis were divided, for each scenario, in energy and power analysis, and a comparative analysis was proposed to complement the comprehension and analysis.

The results showed that the ECM may facilitate future comprehension of how behavior at the micro level (consumer behavior) may impact the macro level (in the present simulation, the electrical grid). Unfortunately, given the specificity of the case study and of the heuristics modeled, a direct quantitative comparison of the results with other works from the scientific community is not possible. Considering a more qualitative analysis of some of the specific points evaluated, Poghosyan et al. (2015) and Lee et al. (2014), also showed a high sensitivity for some of the parameters on different simulations scenarios. The first focused on the long term individual load forecast under different electrical vehicles uptake scenarios, trough an agent-based model that models the social influence of neighbors on the adoption of electric vehicles. A considerable higher adoption of electric vehicles was found when compared to conventional analysis that does not consider social influences. The second paper mentioned analyzes the actions of individual homeowners in a long-term domestic stock model, also using agent-based simulation. Householder individual decision making was modeled through the use of surveys. The developed model showed that current subsidies may not be enough to achieve the desired electricity consumption reduction in the UK by 2050, and a revision process should be undertaken. The high sensibility on parameters and the emergent complex behavior found on these studies are aligned with the results of this thesis. Nevertheless, although already mentioned, it is important to highlight once again that a direct comparison is not possible.

Regarding computational time the NETLOGO platform took approximately 4 minutes for each scenario. An increase on the amount of consumers increased exponentially the computational time for the ECM. The MATLAB platform 127.6 minutes for each scenario. Given a total of four scenario and the base case, the total simulation takes approximately 10.9 hours.

As aforementioned, all the discussions in this chapter did not mention any specific real-world time duration for each time step. It was done intentionally aiming not to confuse the reader on the main purpose of this simulation. Nevertheless, on this final discussion, some comments will be made on this matter, as an illustrative example of future applications. Considering a yearly growth rate of 1.1%, as indeed happened for the Brazilian residential sector from 2016 to 2017 (EPE), 2018b), some hypothesis could be undertaken:

- If the growth rate is only related to the fixed rate consumption level (0.1%/iteration), an increase (cumulative) of 1.1% would result that a year is related to approximately 11 iterations (precisely 11 iterations result in 1.1055%). 1000 iterations would, therefore, reflect around 90.9 years. This a rather unrealistic assumption, since many of the heuristics modeled on the ECM are not dependent on future scenarios and could already be considered as (partially) in place;
- Assuming that the growth rate of 1.1% relates to the EMC as a whole, considering all the modeled heuristics, it is possible to make discussions and evaluations for the base case, scenario one, and scenario two (scenarios three and four will not be discussed since they present an overall tendency to decrease electricity consumption):
    - For the base case, the average variation of electricity consumption per iteration 0.0205%, thus leading to approximately 54 iterations a year. The 1,000 iterations of the simulation, would then represent ~18.52 years;
    - For scenario one considering the average variation of 0.0508%/iteration, it would represent approximately 22 iterations a year, thus 1,000 iterations represent ~45 years;
    - Finally, on scenario two the average variation was 0.0277%/iteration, leading to approximately 40 iterations a year, thus 1,000 iterations representing 25 years.

The comments above are not supposed to be taken into account as a fixed variation of each iteration for the EMC, but only as an illustration of possible variations. To be able to achieve such a fixed variation, further investigations on the modeling of the heuristics, survey on consumer behavior, and more in-depth comparisons with historical data as well as forecast are necessary.

Although very hard to obtain, a relation between the iterations and a real-world time frame could lead to relevant opportunities for the planning on the power and energy sector. Instead of relying only on a fixed linear forecast, for instance, to be able to understand how nonlinearity plays a role for different groups of consumers may enable the utilities to build effective demand-side management plans targeting specific consumers, to expand their network accordingly, avoiding unnecessary expenses. To better understand how different consumers are evolving their consumption may also allow companies to understand the behavior of prosumers, their interaction with new emerging business models (such as peer-to-peer electricity trading), in time to take actions that would be aligned the companies strategical objectives.

Also, for the operational aspects of the power sector, an analysis that considers a more in-depth modeling of the consumer may enable flexibility operators to develop control strategies that could increase grid reliability and decrease operational costs. Further research is still necessary for such practical applications, nevertheless, the results and discussions presented showed that CST may be considered as a theoretical and modeling background for electricity consumption, and the necessity of models on electricity consumption that allow a better comprehension on human behavior.

# 6 FINAL REMARKS

## 6.1 CONCLUSION

The present work dealt with the application of CST to electrical energy systems, centering the analysis on the residential consumer and their behavior on electricity consumption. The main objective was to analyze complex emergent behaviors on electricity consumption and its impact on distribution networks, considering the electrical energy system as a complex system.

To reach it, five specific aims were designed. The first one focused on the study of CST and to understand its contributions to smart grid modeling and analysis. Chapter 2 presented a discussion on what complexity is, the main concepts involved in complexity science, and also why the electrical power system can be considered a complex system. This last claim was supported by a structured literature review and discussion on the state of the art of the most relevant applications.

The following aim dealt with the analysis and modeling of consumer behavior, focusing on behavioral economics and its applications to power systems. Chapter 3 presented an analysis of the factors related to consumer behavior regarding electricity consumption, followed by a definition of behavioral economics and its applicability to power systems.

One of the most relevant and challenging specific aims of this thesis was to build an agent-based simulation of the application of CST and behavioral economics to power systems. This was developed on the ECM, presented and discussed in chapter 4. Finally, the last two specific aims related to apply the simulation model to a case study and analyze the emerging patterns of the simulation scenarios. The fulfillment of this aim is demonstrated in chapter 5, and, together with the ECM, can be considered one of the major contributions of this work. The developed model is expected to serve as an inspiration and source of innovation on the use of agents with bounded rationality on modeling consumers of electricity, both by the development of new or changes on the functionalities of the ECM and by the development of new models.

The analysis of the simulation results on the emergent behavior of the heterogeneous agents modeled indicates how important it is to understand customer behavior. CST and agent-based simulation proved themselves useful for such analysis on the electricity domain since it does not demand complete mathematical modeling of all assumptions, allowing to represent behaviors of energy consumers and examine how the interaction of heterogeneous agents at the micro-level produce macro outcomes.

The heuristics modeled lead to a big diversity on the overall emergent electricity consumption pattern, given the specific groups of consumers to whom the analysis was focused on every scenario. These results are very relevant since it makes clear that customers should not be considered only as electric loads. According to their preferences, values, and behavior different short- and, long-term electricity patterns should be expected. To plan and operate the power system in this increasingly complex environment such patterns must be considered.

Indeed, to understand consumer behavior is of great importance on the planning and operation of electrical grids. Nowadays software and methodologies for electrical grid analysis focus mainly on modeling and detailing physical behavior of all the grid components, but few have been discussed on how to model and detail consumer behavior, and how this behavior may change over time. Many analyses rely on the assumption of linear demand growth, which is indeed a straightforward analysis that easily enables to extrapolate results and make projections for power systems planning. But the problem is that such a simplistic point of view many times do not reflect reality. Considering the complexity of such behaviors and interactions may significantly support power system analysis. Specifically, on problems related to the planning of power systems, the understanding of consumer behavior using an approach that does not implies global rationality may facilitate the analysis on the adoption of new technologies, markets, and their impacts to electricity consumption.

## 6.2 FUTURE RESEARCH

During the development of the present work, it was possible to highlight future research areas, in order to better understand and model future power systems and customer behavior. There is a need for developing methods and models that can capture the complexity of the power systems, considering advancements from different fields of science in a holistic approach. Even though this work presents contributions to the field, there is certainly several limitations that must be surpassed to allow proper applications to real-world systems. Future suggested works include:

- To advance the modeled heuristics to incorporate behaviors that relate with the impact of time variant tariffs, weather conditions, transportation (also considering electric vehicles), the presence of people in a household, other energy carriers, advance electricity markets such as P2P energy trading (which will definitely exponentially increase analysis and operation complexity), demand response programs (both price and incentive-based), among many other aspects;
- To develop methodologies and field projects to obtain heuristics that model customer behavior for a given context. This may also be undertaken, as in many works related to behavioral economics, in laboratory settings, or by applying advanced machine learning techniques to obtain such heuristics from pilot project historical data (including multiple other possible data sources such as social networks, weather forecasts, trends in search engines);
- To develop agent-based simulations using insight from CST to incorporate control actions such as self-healing systems, active grid management, and protection coordination, considering the smart grid as a SoS;
- To allow developed heuristics on consumer behavior to evolve and adapt through methods such as reinforcement learning, using behavioral economics concept to try to mimic people's behavior;
- To incorporate automated methods for demand response on the model to understand the impacts of such actions;
- To better model customer satisfaction in a more holistic approach, considering different aspects and their relationship to electricity consumption;
- To implement the case study on a geospatial system to be able to improve the heuristics to understand how geographical coordinates could influence social behaviors;
- To model consumers' values, so that such values could be derived to intentions and actions, therefore allowing adaptability of the modeled heuristics.

## 6.3 PUBLICATIONS

Throughout the development of this thesis, contributions to the scientific community in the form of publications were made. They are cited in the following two lists, which divide the publications into peer-reviewed journals and conference proceedings. The papers were related either to the present work as a whole or to one of the aspects involved.

### 6.3.1 Peer-reviewed journals

1. SIEBERT, L. C.; SBICCA, A.; AOKI, A. R.; LAMBERT-TORRES, G. A behavioral economics approach to residential electricity consumption. **Energies**, v. 10, n. 6, p. 1–18, 2017.
2. SIEBERT, L. C.; AOKI, A. R.; FERNANDES, T. S. P.; LAMBERT-TORRES, G. Customer targeting optimization system for price-based demand response programs. **International Transactions on Electrical Energy Systems**, e2709, 2018.
3. SIEBERT, L. C.; BIANCHI FILHO, J. F.; SILVA JÚNIOR; E. J.; YAMAKAWA, E. K.; CATAPAN, A. Predicting customer satisfaction for distribution companies using machine learning. **International Journal of Energy Sector Management.** Submitted (under the second round of the review process).

### 6.3.2 Conference Proceedings

1. TABATA, A. N.; AOKI, A. R.; SIEBERT, L. C. **Analysis of demand response program impact on prosumers**. In: SBSE 2018 - 7th Brazilian Electrical Systems Symposium, p. 1–6, 2018.
2. CATAPAN, A. M.; YAMAKAWA, E. K.; SIEBERT, L. C.; AOKI, A. R.; LIMA, E. P. DE. **Residential customer satisfaction performance assessment model for electricity Service for a Power Utility in Brazil**. In: Proceeding of the PICMET 2017 - Portland International Conference on Management of Engineering and Technology: Technology Management for the Interconnected World, p. 1–7, 2017.
3. SIEBERT, L. C.; YAMAKAWA, E. K. ; SILVA JR., E. J. ; MEDEIROS, L. ; CATAPAN, A. M. . **Data Mining on Technical and Customer Service Data of a Brazilian Disco to Increase Customer Satisfaction**. In: Proceedings of the 24th International Conference on Electricity Distribution (CIRED), 2017, Glasgow. 2017.

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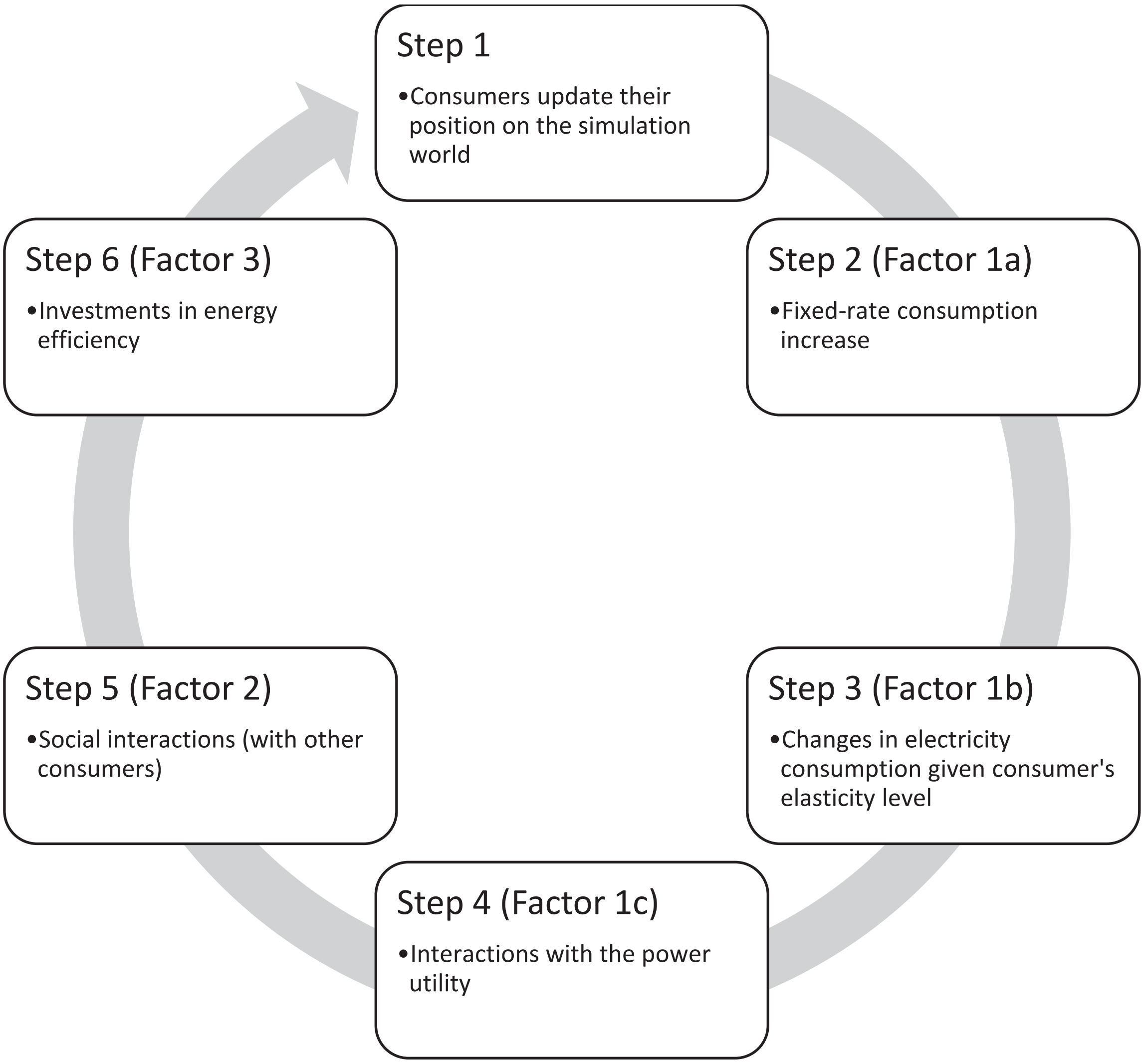
## APPENDIX 1 – PROCESSUAL DESCRIPTION OF AN ITERATION OF THE ECM

Section 0 presented the ECM using the ODD protocol (GRIMM et al., 2006). For clarity reasons, this appendix presents the internal process of update and the use of themodeled heuristics for each iteration. A general overview of the internal process of the ECM for each iteration is presented in FIGURE 55.

FIGURE 55 – SCHEMATIC OF THE INTERNAL PROCESS OF THE ECM FOR EACH ITERATION

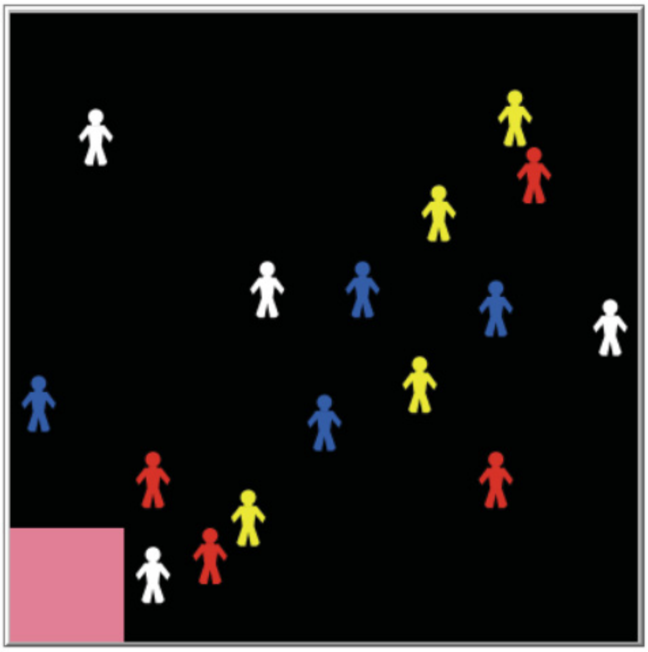



SOURCE: The author (2019)

Follows a more detailed description of these six steps that compose each iteration of the ECM:

- Step 1: The first step is an update of consumer’s special position, i.e. each consumer (agent) is moved to a randomized location (according to a uniform distribution) of the 2D map of the simulation world (FIGURE 56). If two agents share the same space after this update, interactions among them may happen, and, if this consumer is on the fixed area restricted for the power utility, they may interact with the company during the iteration;

FIGURE 56 – SIMULATION WORLD ON NETLOGO.



SOURCE: The author (2019)

- Step 2 (Factor 1a): A fixed-rate consumption increase occurs for all agents, regardless of the category, as a fixed percentual value (e.g. 0.1%/iteration);
- Step 3 (Factor 1b): Variation in consumption affected by customer's price elasticity of each consumer and, in some situations, their current satisfaction level. Variations occur according to (3), (4), (5), and TABLE 8.. After updating the consumption value this step also updates consumer's satisfaction according to (2) and TABLE 7;
- Step 4 (Factor 1c): If a given consumer is on the power utility area (given the spatial position update on step one), interactions with the company take place. This interaction aims to mimic possible consumer behavior when interacting with DSM or energy efficiency programs, resulting in a

decrease in electricity consumption and an increase in customer satisfaction;

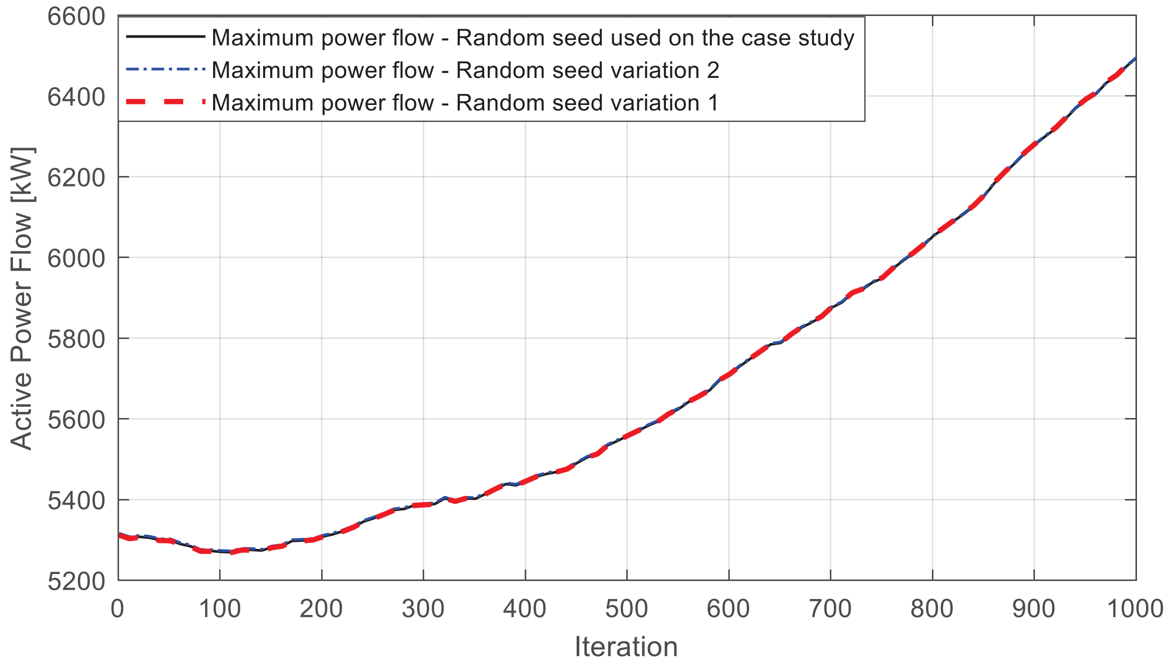
- Step 5 (Factor 2): If more than one consumer is at the same location (given the spatial position update on step one), Interactions with other consumers may take place, according to the heuristics modeled on TABLE 9;
- Step 6 (Factor 3): If a given consumer fulfills the condition specified in (6) they will make an investment in energy efficiency, which decrease electricity consumption. The willingness to invest in energy efficiency is also updated on this step, according to (7), (8), and TABLE 10.

## APPENDIX 2 –ANALYSIS ON THE PROCESS OF ALLOCATION OF CONSUMERS TO THE GRID

This appendix discusses the effect of the randomized process of allocating consumers on the electrical power grid for the base case of the case study discussed in section 5. As previously mentioned, after simulating the evolution of the electricity consumption (and therefore of the load curves) for each consumption class, these consumers are allocated to one of the 7299 specific connection points of the feeder, taken into account the proportion of each consumption category of the current scenario. FIGURE 57 presents the power flowing from the substation at the time of maximal loading considering the same random seed as in chapter 5 for the black line, while the two other lines represent other random seeds. SOURCE: The author (2019)

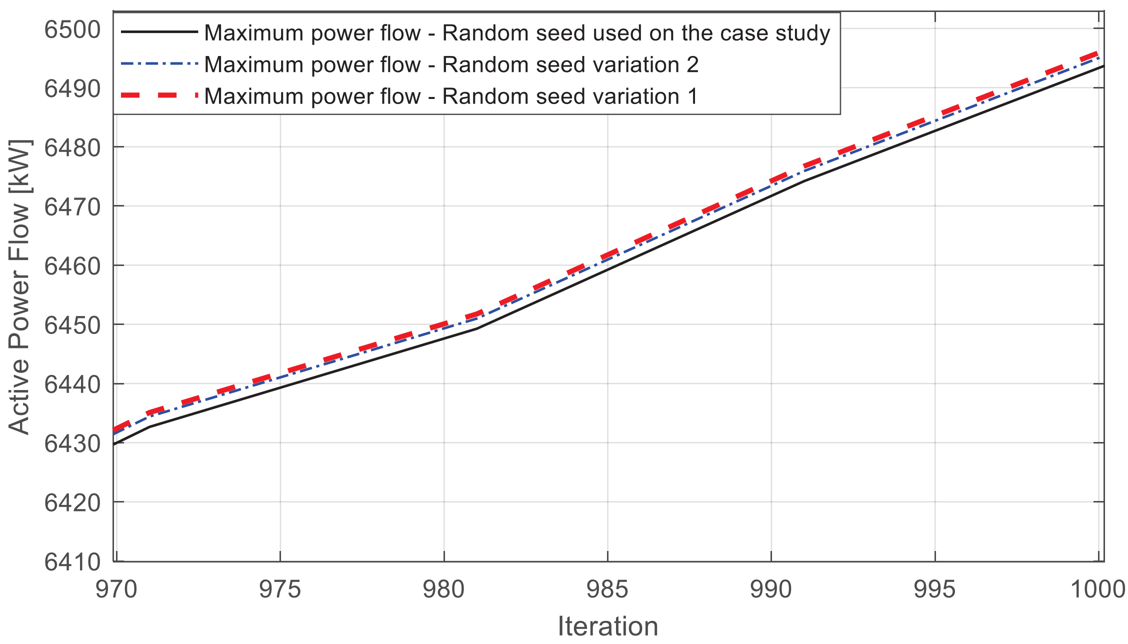
FIGURE 58 details this graph for iterations 970 to 1,000.

FIGURE 57 – POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING FOR THE ANALYSIS ON THE PROCESS OF ALLOCATING CONSUMERS TO THE GRID




SOURCE: The author (2019)

FIGURE 58 – DETAIL OF THE POWER FLOWING FROM THE SUBSTATION AT THE TIME OF MAXIMAL LOADING FOR THE ANALYSIS ON THE PROCESS OF ALLOCATING CONSUMERS TO THE GRID




SOURCE: The author (2019)

The analysis here performed is focused on the base case, i.e. the same number of consumers for each of the four consumption classes. It was concluded that only a very small variability of an average of 0.0318% was achieved due to this randomized simulation process, therefore allowing to the affirmation that it does not affect significantly any of the analysis performed in this work.

## APPENDIX 3 –SENSTIVITY ANALYSIS ON THE ELECTRICITY CONSUMPTION MODEL (ECM)

This appendix presents selected sensitivity analysis on the ECM, focusing on achieving a better comprehension on the dynamics of the model and how the uncertainty in its output can be related to different sources of uncertainty in its inputs. All analysis will be undertaken considering the base case. Specifically, three analysis will be performed:

1. Increase on risk aversion of the customers by decreasing by half the DRAI (Decrease Rate After an Investment);
2. Remove all social interactions of the model;
3. Double the fixed rate consumption increase for all categories.

### 1. Risk aversion

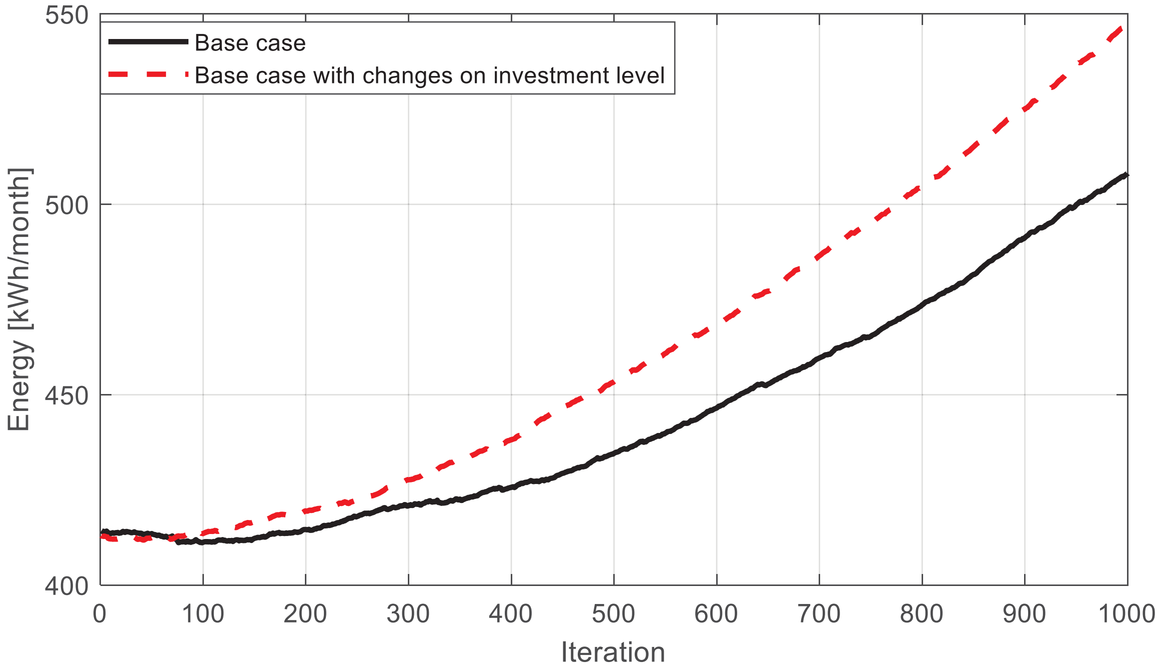
This analysis focuses on evaluating the impacts on electricity consumption by considering that people are more risk-averse than originally considered in the case study. Due to biases on intertemporal choices, investment in energy efficiency and distributed renewable energy are many times not considered an important investment. This was modeled by decreasing by half the DRAI, as shown in TABLE 19, relating to the description on TABLE 10.

TABLE 19 – ORIGINAL AND PROPOSED DRAI VALUE FOR THE ANALYSIS

| Consumption category | Original DRAI value | Proposed DRAI value |
|---|---|---|
| **1** | 0.4 | 0.2 |
| **2** | 0.2 | 0.1 |
| **3** | 0.4 | 0.2 |
| **4** | 0.8 | 0.4 |

The results, compared to the base case, showed that the overall electricity consumption increased, at the last iteration, in 7.80 %, from 508.1 kWh/month (base case) to 546.71 kWh/month (proposed sensitivity analysis), as presented in FIGURE 59. The difference between both curves increased proportionally with iterations. Nevertheless, it is not reasonable to argue that this change on investment level (DRAI) alone is accountable for all the changes between both curves since the model presents several feedbacks among the agents that can either increase or decrease the consumption increase led by the changes in the DRAI.

FIGURE 59 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR THE SENSITIVITY ANALYSIS ON DECREASING THE DRAI LEVEL (RISK AVERSION)



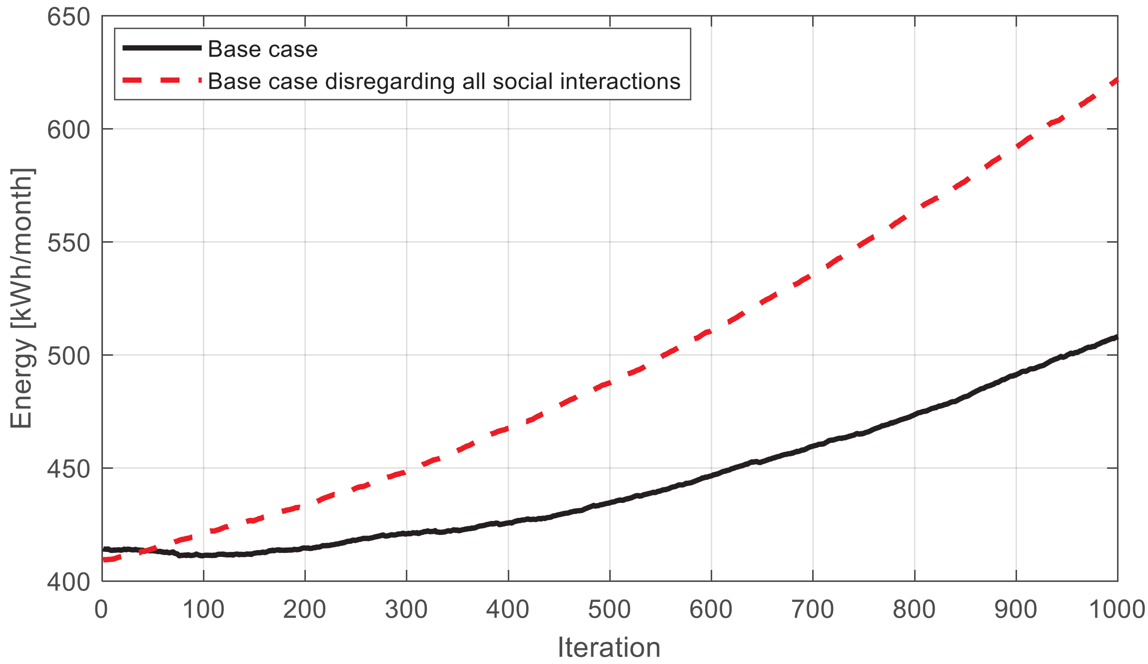

SOURCE: The author (2019)

**2. Disregard all social interactions**

This analysis disregarded all social interactions from the model, i.e. the interactions previously described in TABLE 9. FIGURE 60 presents the results for average monthly energy consumption for this analysis.

Social interactions occur when agents ‘meet’, while moving randomly on the ‘simulation world’. There is a strong non-linear component in these social interactions, hence the curve of the ‘base case disregarding all social interactions’ presented a more linear evolution throughout the iterations. Still, most social interactions modeled considering heuristics that lead to a decrease in energy consumption. Therefore, FIGURE 60 shows that disregarding social interaction lead to a final value at the last iteration of 621.9 kWh/month, instead of 508.1 kWh/month on the original base case.

FIGURE 60 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR THE SENSITIVITY ANALYSIS ON DISREGARDING ALL SOCIAL INTERACTIONS



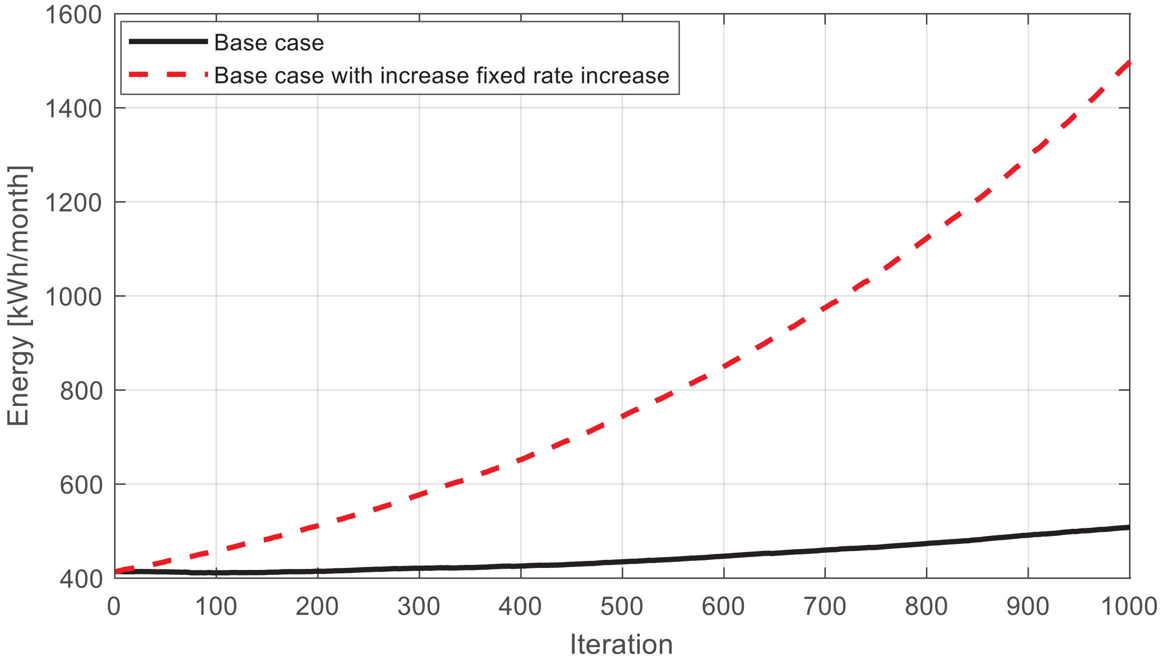

SOURCE: The author (2019)

### 3. Increase fixed rate consumption increase

Finally, this third analysis focused on evaluating the impact of a fixed rate consumption increase in the model, the rate that the energy consumption increase for every iteration, not considering any influence from all the other factors of the model. On the original base case it was considered a rate of 0.1%/iteration and, now, it is considered a rate of 0.2%/iteration. FIGURE 61 shows the evolution of the average monthly consumption for both conditions.

Since in a complex system many factors simultaneously affect the system, this two-fold increase did not lead to a two-fold increase in the result. This change led to a value of 1.498 kWh/month at the last iteration, compared to a value of 508.1 kWh/month for the original simulation presented. While the original simulation presented an increase of 22.64% comparing the first and last iteration, the doubled fixed rate analysis showed an increase of 262.10%.

FIGURE 61 – AVERAGE MONTHLY ENERGY CONSUMPTION FOR THE SENSITIVITY ANALYSIS ON INCREASED FIXED RATE CONSUMPTION INCREASE




SOURCE: The author (2019)