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A KNOWLEDGE-BASED MODEL TO HOUSE THERMAL PARAMETERS IDENTIFICATION FROM HEAT PUMPS CONSUMPTIONS IN A MULTI-ZONE SMART BUILDINGS CONTEXT

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Esta tese foi julgada adequada para a obtenção do Título de "Doutor", e aprovada em sua forma final pelo Programa de Pós Graduação em Engenharia e Gestão do Conhecimento da Universidade Federal de Santa Catarina e pelo Programa de Pós Graduação em Ciência da Computação da Sapienza University of Rome.

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To my Vivi and Alícia for their unconditional support

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I think therefore am!

Rene Descartes

RESUMO EXPANDIDO

Introdução

As emissões de dióxido de carbono (CO_2) são os principais contribuintes para a mudança climática. Essas emissões estão diretamente relacionadas ao aquecimento global. Portanto, ao reduzir emissões destes gases pode-se contribuir para a redução nas mudanças climáticas. As reduções nas emissões de CO_2 podem começar localmente nas regiões e, posteriormente, contribuir para o efeito de redução global. Isso implica que a redução do consumo de energia elétrica contribuirá diretamente para a redução de CO_2. O setor residencial foi responsável por cerca de 40% do consumo total de energia primária na União Europeia e é responsável por 36% das emissões totais de CO_2 nos últimos anos. Essa informação mostra que os estudos sobre o consumo de aquecimento são importantes uma vez que podem gerar impactos significativos na poupança de energia e, consequentemente, na redução das emissões de CO_2. No Brasil, o uso de bombas de calor para o aquecimento residencial não compõe um percentual tão significativo como ocorre em países europeus. Isso se dá especialmente pelo fato de que o Brasil é um país que possui uma situação climática em que períodos de inverno são menos rigorosos do que os países europeus, por exemplo. Como o escopo deste trabalho é estudar aquecimento em edifícios que usam bombas de calor, a questão problematizadora é: como reduzir o consumo de energia elétrica da bomba de calor devido ao aquecimento em ambientes multi-zona bem como a emissão de CO_2 para a atmosfera, considerando a garantia do conforto térmico de seus usuários?

Objetivos

O objetivo desta tese é propor um modelo que seja capaz de oferecer ao usuário final de um prédio inteligente um plano de temperatura interna para minimizar o custo de consumo de energia devido ao aquecimento de ambientes que usam bombas de calor, buscando garantir o conforto térmico de seus ocupantes. Esta pesquisa segue uma abordagem tecnológica e está organizada

nas seguintes etapas: (a) identificar na literatura os parâmetros que afetam o conforto térmico em edifícios multi-zonas; (b) propor um modelo capaz de reduzir o consumo de eletricidade e os custos financeiros no aquecimento residencial, bem como as emissões de CO_2 e (c) aplicar, testar e avaliar o modelo proposto.

Metodologia

O presente trabalho se enquadra como uma "pesquisa científica tecnológica" que busca propor um modelo. Esta pesquisa é caracterizada como sendo *experimental*, aplicando perspectivas tecnológicas. Trata-se de uma pesquisa *multidisciplinar* porque leva em consideração conhecimento e experiência de dois cursos de pós-graduação diferentes em duas universidades distintas: Ciência da Computação na Universidade Sapienza de Roma (Itália) e Engenharia e Gestão do Conhecimento na Universidade Federal de Santa Catarina (Brasil). Neste documento é proposto um modelo baseado em conhecimento para a identificação de parâmetros térmicos e para gerar um plano de temperatura interna em um contexto de prédios inteligentes (*Smart Building*). Tal temática é motivo de pesquisas em ambas as instituições. O modelo proposto utiliza-se de processos baseados em conhecimento para determinar a troca de estados entre os elementos nele constantes. No modelo a interação do usuário com o sistema comptuacional proposto a aquisição do conhecimento ocorre por meio de elicitação junto ao usuário de seu conhecimento e sobre sua residência. O conhecimento é representado e aplicado utilizando-se de grafos e a analogia eletro-térmica. Uma ontologia é proposta para a implementação do modelo no formato de repositório. Após processadas tais informações, os parâmetros térmicos (resistência, capacitância térmicas e coeficiente de performance) são calculados. Uma vez estimados, estes parâmetros são utilizados em um algoritmo de otimização que visa apresentar um plano de temperatura interna para as próximas 24h ao usuário. Em tais processos dão-se a descoberta e a visualização do conhecimento.

Resultados e Discussão

O modelo apresenta interação com o usuário em dois níveis: aquisição e visualização do conhecimento. Os dados e informações adquiridos do usuário doméstico foram relacionados à preferência de temperatura interna para o planejamento horário e plano assistido. Os dados obtidos com os usuários domésticos, dos sensores de temperatura (internos e externos), bem como o consumo de energia da bomba de calor instalados nas casas e os dados históricos foram utilizados para estimar os parâmetros térmicos. O estágio de identificação do parâmetro usa a analogia elétrica térmica e é responsável por estimar os valores médios de resistência térmica e capacitância. Nesta etapa, os valores para o coeficiente de desempenho das bombas de calor também foram calculados. Na segunda etapa, foi gerado um plano de temperatura interna. O algoritmo usou os parâmetros térmicos previamente identificados e um plano de temperatura interna foi proposto ao usuário doméstico. Tal plano levou em consideração as preferências de temperatura do usuário. Ao mesmo tempo, o plano buscou minimizar o consumo de energia para aquecer a casa, reduzindo o custo das emissões de CO_2. Na fase experimental, foi utilizado um conjunto de dados obtido de sete casas habitadas em um período de inverno, em uma situação real por um período de sete meses a partir do Projeto SmartHG. O modelo matemático utilizado na analogia térmico-elétrica e experimentos foi avaliado comparando os parâmetros obtidos e os dados reais da amostra, literatura de referência e informações do fabricante da bomba de calor. Objetivou-se reduzir o consumo de energia elétrica devido ao aquecimento de ambientes bem como a redução da emissão de CO_2. Neste contexto, buscou-se manter o conforto térmico, ou seja a temperatura interna calculada em relação à temperatura interna histórica. Os resultados experimentais mostraram que o algoritmo atingiu seus objetivos, mantendo os valores com uma variação máxima da temperatura interna em dois graus centígrados, estabelecida com o parâmetro no algoritmo de controle. No que diz respeito à economia de energia devido ao aquecimento, uma média de 59,92% para todas as simulações foi, onde os planos foram mais eficientes do que dados históricos. Quanto ao Coeficiente de Desempenho (COP), os resultados obtidos nas experiências de sete casas variaram de 1,03 a 3,07. Os valores de CO_2 mostraram um ganho comparado aos dados históricos. Embora representem um valor monetário aparentemente baixo, se tal cálculo puder ser escalado para um bairro inteiro ou uma cidade, tais números devem escalar proporcionalmente.

Considerações Finais

Esta tese apresenta um modelo que oferece uma interface gráfica interativa e amigável, na qual os usuários finais podem definir suas preferências e visualizar seu nível de consumo de energia, bem como os relatórios de consumo de energia. A principal vantagem deste trabalho é fornecer, sob o ponto de vista do usuário final, um modelo através do qual é possível identificar os parâmetros térmicos e propor um plano de temperatura interna para as seguintes 24 horas sem a necessidade de se conhecer as características físicas e materiais de composição da casa ou estrutura do edifício. Este modelo oferece uma ferramenta computacional, interativa e com uma interface amigável. O objetivo principal estabelecido para este trabalho foi alcançado. Um modelo computacional capaz de oferecer o usuário final de um Smart Building foi apresentado um plano de temperatura interna para as 24 horas seguintes. Este plano levou em consideração o conforto térmico, usando as preferências de temperatura interna do usuário doméstico. Experimentos foram realizados com base em dados históricos de um projeto europeu conhecido como SmartHG. Foram analisadas sete casas por um período de sete meses. O modelo proposto baseado no conhecimento ofereceu interação com o usuário final, o uso do conhecimento prévio por meio de dados históricos e calculou o parâmetro térmico dos ambientes. No modelo desta tese, um método para calcular os parâmetros térmicos em uma situação em que a casa inteira possui a mesma temperatura interna é proposto. Como um trabalho futuro, é sugerida a implementação de um modelo em que cada zona única

possa ter sua medição de temperatura interna individual considerada através de simulações. Uma proposta para futuro trabalho consiste na expansão da aplicação do repositório web usado por usuários domésticos do mesmo bairro (vizinhos). Esses dados podem ser aplicados em estudos comparativos nas áreas de Smart Cities e Smart Grids.

Palavras-chave: Ambientes Inteligentes. Estudos Energéticos. Modelo baseado em Conhecimento. Parâmetros Térmicos. Otimização de Consumo de Energia Elétrica

RESUMO

Tem crescido nos últimos anos o número de estudos acerca de ambientes inteligentes. Um dos fatores que mais geram gastos em um ambiente inteligente está relacionado com o condicionamento térmico destes espaços. Por esse motivo os estudos energéticos nos ambientes inteligentes se fazem importantes. Nesta tese é proposto um modelo baseado em conhecimento no contexto de ambientes inteligentes multi-zona. Esse modelo interage com o usuário final por meio de aquisição e visualização de conhecimento. O objeto central do modelo apresenta um algoritmo matemático que, por sua vez, busca identificar os parâmetros térmicos do ambiente para, posteriormente calcular um plano de temperatura interna para as 24 horas subsequentes. A identificação de parâmetros visa a, além de determinar a resistência e capacitância térmica do ambiente, também calcular o coeficiente de desempenho das bombas de calor. Já o plano de temperatura interna prevê a minimização dos custos de energia elétrica, a redução do valor gasto com a emissão de CO_2 e a manutenção do conforto térmico do ambiente. Os dados utiizados nos experimentos foram obtidos junto ao projeto SmartHG. Os resultados experimentais demonstraram que o algoritmo atingiu os objetivos, mantendo os valores com o máximo de variação de dois graus centígrados, estabelecidos como parâmetros no algoritmo central de controle. Em relação à economia de energia devido ao aquecimento, em média 59.92% dos planos foram mais eficientes do que os dados históricos. Os resultados do Coeficiente de Desempenho para sete casas ficaram entre 1.03 e 3.07. Os valores de CO_2 mostraram ganho comparado com os dados históricos.

Palavras-chave: Ambientes Inteligentes. Estudos Energéticos. Modelo baseado em Conhecimento. Parâmetros Térmicos. Otimização de Consumo de Energia Elétrica

ABSTRACT

The number of studies about intelligent environments has grown in recent years. One of the factors that generate more expenses on that is related to the thermal conditioning. For this reason energy studies in intelligent environments are important. This document presents a doctoral study that proposes a model based on knowledge in the context of multi-zone intelligent environments. This model interacts with the end user through acquisition and knowledge visualization. The central part of the model is a computer-mathematical algorithm which in turn seeks to identify the thermal parameters of the environment and then calculates a day-ahead internal temperature plan. The parameter identification aims to determine the thermal resistance and thermal capacitance of the environment as well as to calculate the coefficient of performance of heat pumps (heating). The internal temperature plan provides the minimizing of energy costs, the reduction in the amount spent on CO_2 emissions and maintenance of thermal comfort environment. The data used in the experiments were obtained from the SmartHG project. The experimental results showed that the algorithm met its restriction, maintaining the values with a maximum variation of two degrees centigrade, established with parameter in the control algorithm. With regard to energy savings due to heating, in the average, 59.92% of those plans have been more efficient than historical data. The Coefficient of Performance results, obtained in the experiments from seven houses, ranged from 1.03 to 3.07. The values of CO_2 showed a gain compared to historical data. Although they represent a seemingly low monetary value, if such a calculation can be scaled to an entire neighborhood or a city, such numbers should scale proportionately.

Keywords: Smart Buildings. Energy Studies. Knowledge-based Model. Thermal Parameters. Power Consumption Optimization

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LIST OF ABBREVIATIONS

AC	Alternating Current
AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Average
CIR	Circuit File
CO_2	Carbon Dioxide
COP	Coefficient of Performance
CS	Computer Science
CSV	Comma-separated Values
DC	Direct Current
EOF	End of File
EU	European Union
HDD	Heating Degree Days
HP	Heat Pump
HVAC	Heating, Ventilating, and Air Conditioning
IC	Initial Condition
ICT	Information and Communication Technology
IT	Information Technology
KDD	Knowledge-Discovery in Databases
KDT	Knowledge-Discovery in Text
KE	Knowledge Engineering
KEM	Knowledge Engineering and Management
KM	Knowledge Management
LEC	Levelized Energy Cost
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
ODE	Ordinary Differential Equation
Ph.D.	Doctor of Philosophy

PWL	Piecewise Linear Function
RC	Resistor Capacitor
RGB	Red, Green, Blue
SB	Smart Building
SC	Smart Cities
SE	Smart Energy
SG	Smart Grids
SH	Smart Homes
SQL	Structured Query Language
TOU	Time-of-Use
UFSC	Federal University of Santa Catarina

LIST OF SYMBOLS

a	Linear Function - Coefficient a
A	Convexity Variable
α	Internal Reference Temperature Tolerance
b	Linear Function - Coefficient b
β	Internal Temperature Tolerance
c_i	Cost of Power Electricity - Euro
C	Thermal Capacitance
$\overline{C}$	Average of Overall Thermal Capacitance
ΔT_{in}	Difference between $T_{in}(t+1)$ and $T_{in}(t)$
$\dot{Q}$	Heat Flow
e	Daily Consumed Energy
η_{max}	Heat Pump Coefficient of Performance Maximum
η	Heat Pump Coefficient of Performance
γ	Heat Pump Power Tolerance - W
I	Current Generator
J_e	Objective Minimization Function
$i(t)$	Current of Energy at time t
i	Current
MC_0	Marginal Cost of Producing Power - other expenses
MC_p	Marginal Cost of Producing Power
o_i	Cost of CO_2 Emissions - Euro
P	Power Consumption from the Heat Pump
ϕ	Heat Pump Power - ηP
$\dot{Q}$	Heat Flow
Q_h	Heat Energy Entering
R	Thermal Resistance
R_1	Thermal Resistance 1 - wall layer 1

R_2 Thermal Resistance 2 - wall layer 2

R_T Total Thermal Resistance - wall

$\overline{R}$ Average of Overall Thermal Resistance

$\overline{RC}$ Product o the Average of Overall Thermal Resistance and Average of Overall Thermal Capacitance

S Dynamic System

τ Unit of Time Interval in seconds $\frac{1}{3600}$

t Time

T_1 Temperature 1 - outside

T_2 Temperature 2 - inside

T_{bpt} Balance Point Temperature

TC_o Total Cost of Producing Power - other expenses

TC_p Total Cost of Producing Power

T_{in} Internal Temperature

T'_{in} Internal Temperature in time $t+1$

$\dot{T}_{in}$ Internal Temperature Calculated

T_{ort} Outdoor Reference Temperature

T_{out} Outdoor Temperature

T_{inref} Calculated Reference Internal Temperature

T_{ref} Reference Internal Temperature

$u(t)$ Dynamic System Input at time t

U or $U - value$ Thermal Transmittance

V Voltage

V_{in} Input Voltage

V_C Voltage across the Capacitor

V_R Voltage across the Resistor

W Work - Watt

$y(t)$ Dynamic System Output at time t

LIST OF ALGORITHMS

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1 INTRODUCTION

Emissions of Carbon Dioxide (CO_2) are the main contributors to climate change. These emissions are directly related to the global warming (FRIEDLINGSTEIN et al., 2010). Despite several initiatives held by international governments in order to reduce CO_2 emissions, researches, as Seneviratne et al. (2016) show that their goals are still far from being achieved.

Reductions in CO_2 emissions can start locally in regions and subsequently contribute to the overall reduction effect (SENEVIRATNE et al., 2016). This implies that reduction of power energy consumption will directly contribute to the CO_2 reduction.

Residential and services sectors are responsible for the growth in electricity usage. The consumption of electricity by sectors shows that electricity consumption in the service sector almost doubled within 1990 and 2014 (+83%), while electricity consumption in the residential sector increased by 29% during the same period, as presented by European Union (2016).

The residential sector was responsible for around 40% of the total consumption of primary energy in the EU and it is responsible for 36% of the EU's total CO_2 emissions. Energy-efficiency and low/zero-carbon energy technologies for heating and cooling in buildings will play a crucial role in the global and local strategies against the impacts of the greenhouse effect (DORER; WEBER, 2009).

Secondly U.S. Energy Information (2016), 41.5% of the energy consumption by end users in homes is used to space heating, 34.6% for appliances, electronics and lightings, 17.7% for water heating and 6.2% for air conditioning. This information shows that the studies about heating consumption are important once they can generate significant impact on saving energy and, consequently, on the reduction of CO_2 emissions.

The number of studies on themes as smart buildings, smart grids and smart cities has grown significantly in recent years. The key element in *smart* is its ability to gather data, analyze it and provide intelligent feedback (BUDDE, 2014), especially making conscious/better use of existing resources.

An important point of convergence among these three terms is the smart energy (PREISSLER, 2015) in which energy resources are applied in an innovative and sustainable way. Therefore, based on the relationships among those three areas and knowing that energy consumption is mainly based on the demand from the final consumers, it is necessary to lead the saving energy studies in intelligent homes or buildings.

Several studies related to the reduction in power consumption due to space heating have been published (BALAN et al., 2011b), (BENGEA et al., 2014), (CHEL; JANSSENS; PAEPE, 2015). In some of these works it is possible to distinguish studies of single-zone buildings (JAVED et al., 2015), (PARK et al., 2013) or multi-zone buildings (WEN et al., 2013), (ASCIONE et al., 2016), (BEKKOUCHE et al., 2013), (BENGEA et al., 2014), (BENHAMOU; BENNOUNA, 2013), (CHEL; JANSSENS; PAEPE, 2015). Few studies on multi-zone building take into account the calculation of heat flow between building zones (BUONOMANO et al., 2016).

The HVAC (Heating, Ventilating and Air Conditioning) systems studies in building environments are related to the maintenance of the air quality and thermal comfort of their occupants. By definition, thermal comfort is a situation in which a person feels satisfied with the temperature in the surrounding environment (ASHRAE, 2004). So, maintaining thermal comfort in a building depends not only on the physical characteristics of the environment and equipment but mainly on the desired temperature offered by the end user.

The HVAC-type problems are related to the reduction in the consumption of electric energy due to the thermal conditioning of environments, improvement of the thermal quality, reduction in the level of noise in the air conditioners, guarantee of the thermal comfort for users and others. One commonly found approach in the literature to solve HVAC-type related problems is the use of the electro thermal analogy (BEKKOUCHE et al., 2013), (THAVLOV; BINDNER, 2015), (BUONOMANO et al., 2016), (PARNIS; SPROUL, 2010). Such an analogy allows one to understand the thermal behavior of an environment by means of an RC (resistor-capacitor) circuit in a single or a multi-zone building representation. However, this understanding alone is not sufficient to reduce the power consumption that is necessary for conditioning environments;

The multi-zone environments can be represented through graph theory (GENC; SEHGAL, 2014). The association of methods such as: electro-thermal analogy and graph theory to represent multi-zone buildings is known in literature (GOYAL; LIAO; BAROOAH, 2011), (HAO et al., 2015), (MUKHERJEE; MISHRA; WEN, 2012). None of them, however, are used with the specific scope of air-to-air heat pumps. Such devices are responsible for using the external temperature as a source of heat which in turn is pumped into the internal environment. This heat comes from the air from the external environment. This is the reason why it is called air-to-air heat pumps.

As the scope of this work is to study heating in buildings where heat pumps are used, an important factor to be considered is the Coefficient of Performance (COP) (THAVLOV; BINDNER, 2015). The heat pump is responsible to *pumps* heat from the outside-temperature source to the indoor sink (KENT, 1997). The rest of energy that is necessary to produce the desired internal temperature is collected from the energy network. The COP represents the efficiency of a heat pump. So a higher value of COP reflects a higher heating efficiency (MIX, 2006).

Some studies use the heat pumps performance coefficient in their calculations (YOON; BALDICK; NOVOSELAC, 2014), (HU; KARAVA, 2014), (HAMDY; HASAN; SIREN, 2010). Nevertheless, they do so by obtaining values from the equipment manufacturers or even by assuming a fixed value for the whole calculation.

The heat pump HVAC studies use frequently forecasts (KNUDSEN; ROTGER, 2015), (AGHEB; TAN; TSANG, 2015), (BELTRAN; CERPA, 2014), (ROGERS et al., 2013) in order to predict consumptions or generate scenarios. These forecasts are basically divided into three types: power consumption (NGUYEN; NGUYEN; LE, 2013), (MUELLER et al., 2014), occupancy prediction (BELTRAN; CERPA, 2014) and internal temperature (ELLIS; HAZAS; SCOTT, 2013), (YANG et al., 2012). The majority of these studies generate forecasts for power consumption. Some of these studies act directly on heating devices (TSITSIMPELIS; TAYLOR, 2015), (SRIKANTHA; KESHAV; ROSENBERG, 2012), (ROGERS et al., 2013). None of them, however, is dedicated to offer the final user an internal temperature plan for the day after in the scope of this thesis.

Some HVAC studies take into consideration the preferences or the user profile (SRIKANTHA; KESHAV; ROSENBERG, 2012), (YOON; BALDICK; NOVOSELAC, 2014), (LAM; YUAN; WANG, 2014), (ZHAO et al., 2015), (WINKLER et al., 2016). Whether using direct, as in Lam, Yuan e Wang (2014) or indirect feedback. The user profile can be understood simply as the occupant routine in the environments of a house as well as the internal temperature preferences used for the calculation of thermal comfort (LAM; YUAN; WANG, 2014), (NGUYEN; NGUYEN; LE, 2013). Few of them, however offer a direct interaction tool with the end user (LAM; YUAN; WANG, 2014), (WINKLER et al., 2016), (ROGERS et al., 2013).

Some works propose design knowledge as presented by Wastell, Sauer e Schmeink (2006) or even knowledge visualization from Welge, Kujath e Opel (2010) in the HVAC-problem area. However, it was not possible to find in any of the researched cases the *knowledge visualization* been used by means of an user interface in which the household user could offer information about their residence or even receive data about their power consumption or savings, for example.

Having a prior knowledge (JAVED et al., 2015) of the structure of a building, the composition of the walls or even the behavior of its occupants, it is possible, for instance, to make forecasts (BELTRAN; CERPA, 2014), (DU; LU, 2011), (HU; KARAVA, 2014). If there is no such information, however it is necessary to collect or estimate it. This knowledge extraction process (VIEGAS et al., 2015) is known as thermal parameter identification (RADECKI; HENCEY, 2013), (PARK et al., 2013), (BEKKOUCHE et al., 2013), (GOETHALS; BREESCH; JANSSENS, 2011), (JASSAR; LIAO; ZHAO, 2009), (PARK et al., 2013), (BUONOMANO et al., 2016). The thermal parameter identification method offers an important contribution in the sense of extracting a set of information about the physical environment, but in itself does not represent a method of reduction in the power consumption due to the conditioning of environments.

Once the dynamics and composition of the thermal elements are known, it is possible to generate forecasts. The generation of forecasts for HVAC problems is commonly found in the literature as optimization problems. These problems are basically divided into three types, according to their objectives: guarantee of thermal comfort (ASCIONE et al., 2016), (BALAN et al., 2011b), (BEKKOUCHE et al., 2013), (BENGEA et al., 2014), (GOETHALS; BREESCH; JANSSENS, 2011), saving of electricity (GENC; SEHGAL, 2014), (WEN et al., 2013), (HAMDY; HASAN; SIREN, 2010), (XU et al., 2013) or reduction of CO_2 emissions (HAMDY; HASAN; SIREN, 2010), (SRIKANTHA; KESHAV; ROSENBERG, 2012), (PARISIO et al., 2013). Studies using the three arguments in the same optimization plan and that were, therefore, aligned with the scope of this work were not found, however.

Many works using the concept of HVAC optimization problems present the use of the external temperature and its variation for the thermal calculations (HU; KARAVA, 2013), (GOOD et al., 2015), (CONTRERAS-OCANA; SARKER; ORTEGA-VAZQUEZ, 2016), (AGHEB; TAN; TSANG, 2015), (MA et al., 2015), (LIAO; DEXTER, 2010). None of them, however, has identified the power consumption calculation based on the outdoor temperature and the internal temperature variation at the same time.

In the optimization process, weather forecasting (XU et al., 2013), (ZHUANG; LI; CHEN, 2007), (CONTRERAS-OCANA; SARKER; ORTEGA-VAZQUEZ, 2016), (BECKEL et al., 2015), (AGHEB; TAN; TSANG, 2015) and energy price forecasting (KNUDSEN; ROTGER, 2015) for the next hours or the next day are commonly used. The use of the weather forecast for a given region helps the optimizer to generate a more accurate future plan. This is because the external temperature, coming from a known external agent, can be used in the calculation. As well as some weather agencies offer their information on the Internet, some energy studies companies offer data on the expected expenditure on electricity for the next few hours or for the next few days. Such information, likewise, is useful for the optimizer that starts to make use of data offered by specialists. However, either, the use of external temperature, electric energy price and estimated value for the production of CO_2 were not found applied at the same time, in the optimization process aligned with the scope of this thesis.

Based on the above identified research opportunities, the following problematic question is proposed: how to reduce the heat pump power energy consumption due to the heating in multi-zone environments as well as CO_2 emissions, in order to guarantee the thermal comfort of their users?

1.2 GOALS

In this section both, the central objective of this thesis as well as the steps to achieve it are presented. Each specific objective has a deliverable which, in turn, refers to a specific chapter of this document.

1.2.1 Main Goal

This thesis' final goal is to propose a model which would be able to offer to the smart building's end user a day-ahead internal temperature plan in order to minimize the power consumption cost environments using heat pumps as well as guaranteeing the thermal comfort.

1.2.2 Specific Goals

This research follows a technological approach because it consists of the use and acquisition of the knowledge gained during the process for future practical application and it is organized along the following steps:

1. To analyze in the literature the parameters that affect thermal comfort in multi-zone buildings.
2. To identify methods and techniques of knowledge engineering, which can be applied in the Smart Buildings context.
3. To propose a model able to reduce electricity consumption and financial costs on residential heating as well as CO_2 emissions.
4. To demonstrate the usefulness of applying the proposed model.

1.2.3 Adherence to the Ph.D. Programs

This doctoral research was conducted in the form of a Joint Research agreement established between the postgraduate course in Knowledge Engineering and Management from the Federal University of Santa Catarina (Brazil) and the postgraduate course in Computer Science at the Sapienza University of Rome (Italy).

At UFSC this research was developed under the area of Knowledge Engineering, in line with research Theory and Practice in Knowledge Engineering, which focuses on studying the methodologies and techniques of this area and its relationship with Knowledge Management.

One of the first definitions for Knowledge Engineering was established by Feigenbaum and McCorduck when they explained that knowledge engineering is inseparably connected with solutions in the IT (Information Technology) area: “knowledge engineering involves integrating knowledge into computer systems in order to solve complex problems (...)” (FEIGENBAUM; MCCORDUCK, 1983), (JOOS et al., 2012). It was only in 1991, however, that Knowledge Management (KM) was introduced as a discipline that includes courses taught in the fields of business administration, information systems, management, and others (NONAKA, 2008).

It is possible, therefore, to state that from the early ’90s the two disciplines: “Knowledge Engineering” and “Knowledge Management” were able to merge and both formed a new branch of knowledge: “Knowledge Engineering and Management”. This, in turn, puts together the techniques of both its precursors and then formed a new area which is able to understand and study the problems related to business and business environment using the IT as support or means for managing.

The Knowledge Engineering (KE) is an area that can assist this process through a set of methods, techniques and tools that support the Knowledge Management (KM) to formalize and to make explicit the knowledge intensive tasks (SCHREIBER, 2000), (FEIGENBAUM; MCCORDUCK, 1983). Thus, the knowledge engineering provides a set of tools that gives support for knowledge management from the formalization and clarification of knowledge intensive activities in organizations (SCHREIBER, 2000).

The Knowledge Engineering is an area that aims to provide systems which are capable of affecting the explicitness and preservation of organizational knowledge. Initially treated as a subfield of artificial intelligence (AI) in building knowledge-based system for solving specific problems, the KE has transcended this vision by considering the whole organizational systemic context of knowledge intensive activities (LOPES; GONÇALVES; TODESCO, 2012), (SCHREIBER, 2000).

Although KEM and CS are two different doctoral programs, there are several common areas of study between them. Some of them are the studies of smart cities, smart homes and smart grids as the scope of this work.

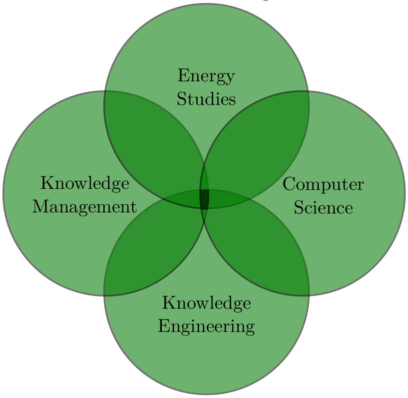
Another important point of convergence between these two postgraduate programs is the Information Technology. The KE, as a sub-area of KEM, is concerned to study IT as a tool for the KM. On the other hand, the CS is entirely concerned with IT studies. KE is an interdisciplinary studies area that uses both knowledge and IT in order to provide technological solutions (STUDER; BENJAMINS; FENSEL, 1998).

Assuming that the term "Smart" refers to the use of IT and considering that IT is also an important area of KEM studies, this work deals with IT as the main point of convergence between Smart Energy and KEM.

Both CS and KE are research areas capable of providing solutions to these kinds of problems. KE can be defined as the area of academic research to develop models, methods and basic technologies to represent and process knowledge and to build intelligent systems based on knowledge (KASABOV, 1996). The KE, provides all instrumental for modeling and development of knowledge-based systems that are able to explain, formalize and represent knowledge.

Energy management, the management of emission of toxic gases to the environment and the management of smart cities and smart grids are the KM objects of study. As it can be seen in Fig. 1, the central region of intersection among the related studied areas is objectively where this research fits. So, this is a study that seeks to solve a problem from the Knowledge Management area arising from the Energy Studies using techniques and tools from Knowledge Engineering and Computer Science.

Figure 1 – Intersection among the Studies Areas



Source: Author (2017)

This research still lays within the overall objectives of the KEM program (PPGEGC, 2014) in UFSC, where it is found that the KEM research goal refers to the macro processes of explicitness, management and dissemination of knowledge. These include creation of processes, discovery, acquisition, formalization/encoding, storage, use, sharing, transfer and evolution. Thus, the objective of the KEM postgraduate program is to investigate, design, develop and apply models, methods and techniques related to both processes, goods, services as their technical and scientific content (PPGEGC, 2014).

From the point of view of the didactic of postgraduate course in Computer Science department of Didattica Goals (2016), the CS Ph.D. students should be able to perform autonomously and coordinate activities of research within the academic or international research institutions worldwide, both, depending on their training, to design and manage systems development projects innovative information technology to address complex problems as well as using interdisciplinary.

Since this is a work that takes into account both the technological aspects and the interaction with the final user, which considers prior knowledge, usage profile and parameters obtained from the user, the multi and interdisciplinary bias research play a crucial role to obtain reliable results.

In both doctoral programs themes as smart cities and big data have been studied, as examples: in Klein (2015) and in (DEPINÉ, 2016) where the authors work with big data and open data for smart cities as well as creative class and intelligent human city, from UFSC and by Mancini et al. (2015) from Sapienza in a digital system design context.

Furthermore, in these programs a vast range of material has been produced on the theme of energy and power consumption like in *Strategic Guidelines for the Development of Communities of Practice in the Commercial Area of a Distribution Company or Electric Power Company* by Nunes (2012), *Management of Knowledge in the Electric Sector: Proposal for the Maintenance Sector of Transmission Lines of Eletrosul-Centrais Electricas SA.* by Lehmkuhl et al. (2008), *Perception of Materials by Users: Evaluation Model* by Dias et al. (2009), *Strategies in Knowledge Management for the Development of Wind Farms* by Silveira et al. (2010), *Mechanisms of Coordination and Practices of Knowledge Management in the Network of Outsourced Value: Study in the Electrical Sector* by Souza et al. (2011), *A Knowledge-oriented Reference Model for the Process of Planning Medium-voltage Distribution Systems* by Guembarovski et al. (2014), *The Psychological Profile and the Negotiation Style of the Electric Energy Negotiators in Brazil* by Teixeira et al. (2011), *SmartHG: Energy Demand Aware Open Services for Smart Grid Intelligent Automation* by Tronci et al. (2014) and *Residential Demand Management using Individualized Demand Aware Price Policies* by Hayes et al. (2015).

1.2.4 Originality

One of the main differences presented by this work is a model capable of identify the thermal parameters of the building without the need of knowledge on the structure physical environment. The central part of the model includes an algorithm to calculate these parameters based on the building's historical data as well as the end user preferences.

Another important contribution of this work relates to the fact that, in the step of thermal parameter identification, both, values for thermal resistance and thermal capacitance are calculated. These values are estimated based on the thermo-electrical analogy as it is presented in Sect. 4.4.1.

The calculus of the heat pump coefficient of performance presented in Sect. 5.4.5 is proposed in a different way from those found in the literature. In this study, the COP calculation is performed using intervals (ranges) based on the different outdoor temperatures.

As the heat pump coefficient of performance calculation part, inside of the optimization plan phase, a new method to estimate the heat pump power consumption as a function of outdoor temperature was used. In this case, for each range of outdoor temperature a different linear function that was used into the optimization files was calculated.

Another important contribution of this work concerns to the fact that the optimizer, at same time, seeks to minimize not only the difference between the calculated internal temperature and the one obtained from the household user, but also aims to calculate the amount spent on the purchase of electricity and the value of the emissions of CO_2 for the same period.

It is still an original proposal because it puts together in the same application: a graphical interface used for the acquisition and visualization of knowledge representation and application of knowledge into the database and automatic calculation of thermal parameters and internal temperature plan for the following 24 hours.

1.2.5 Contributions

The main research contributions can be cited as follows:

- mathematical-computer model able to identify thermal parameters of a smart building
- computational model optimization responsible for generating day-ahead internal temperature plans;
- calculation of the coefficient of performance of heat pumps depending on the outside temperature;
- weather forecasting, kWh price forecast and forecast the cost of CO_2 emissions for the next 24 hours used for generation of the internal temperature plans;
- knowledge representation using graph theory and thermo-electrical analogy;
- a graphical interface to be used for both knowledge acquisition and visualization.

Unlike other works found in the state-of-the-art section (Sect. 2.5), this thesis aims to contribute not only to the resolution of this problem and within the defined scope, but aims to present a contribution to the area with a model composed by knowledge-based processes. These knowledge-based processes are used to compose the proposal for a complete computational solution in which the Smart Building user can interact directly.

Despite its scope in the context of Smart Buildings, this study may have future application in the Smart Grids and/or Smart Cities contexts. This happens because the proposed model which will be operationalized by means of a web-based computer system, despite its private character to each household user, enables shared access. Such shared access concerns to offer visualization of their own reports as well as from their neighbors. There is therefore all the data organized in the same database, and the use of this information for Smart Grids and Smart Cities applications is made possible.

1.3 SCOPE

This study has established as a scope to study the heating of Smart Buildings, especially in winter periods. The study reviews take into account buildings which are heated by means of air-to-air electrical heat pumps.

The specific study on the materials involved in building the environment to be heated as well as the particular operational dynamics of each residence as opening doors and windows, use of other electric heaters, turn on and off lights are not part of this research scope. It will also not be considered in the scope of this study the industrial environments or buildings with continuous flow of equipment and personnel.

The proposed model, as a deliverable, provides the home user a table containing a schedule of internal temperature preference per hour range. Therefore this model does not act directly on heat pumps.

The model proposed in this thesis was developed based on studies of heating environments using heat pumps. In this way the proposed model does not apply to other cases.

Another limitation of this work is related to the absence of historical data for the calculation of thermal parameters. That is, if a Smart Building does not yet have historical data on temperature and power consumption, the end result of the model may not result in accurate values for using default values and not necessarily the environmental data. This refers to the initial period of execution of the newly implanted model.

1.4 THESIS STRUCTURE

This thesis is organized in seven chapters as it is specified below: Chapter one provides the introduction, identifying the problems and objectives of this work. In chapter two the theoretical basis is presented for the development of work, especially with regard to thermal parameter identification and internal temperature plan optimization. Chapter three presents the methodology used to perform each step of the present work. In Chapter four and five the proposed model is presented and detailed as well as its implementation process. Chapter six shows the carried out experiments and evaluation results. Chapter seven concludes the work presenting the final remarks, followed by the references and appendix.

2 LITERATURE REVIEW

This chapter presents the main concepts to be used throughout this thesis work as well as the state of the art. The definition of the main general terms is presented in Section 2.1. The model proposed in this thesis is divided into two distinct stages: thermal parameters identification and internal temperature plan generation. The definitions of the concepts used in such steps are presented respectively in Sections 2.2 and 2.3. The state of the art is presented in Section 2.5. This review describes the related works to the studied topic as well as their interrelationship.

2.1 SMART ENERGY STUDIES

Energy Studies are, frequently, related to the mitigation of climate change by means of the use of renewable energy strategies (wind, solar, wave and biomass). Energy savings on the demand side can causes significant impact on the sustainable development, which is one of the goals of smart energy studies.

Smart technologies have been extensively studied in the last years, especially those (PREISSLER, 2015) ones referring to the Smart Energy. This is due to the possibility of using Information Technology (IT) to support energy management processes. In that case, the term “smart” refers to the use of Information Technologies (IT) for automation processes as energy thermal controllers.

Such systems have contributed to both the representation of residential and non-residential environments and to their behavior in relation to the heating and/or cooling dynamics. Smart Energy is a term that can be used in order to refer to the intersection area between the major areas of study: Smart Grids, Smart Cities and Smart Homes or Buildings (PREISSLER, 2015).

2.1.1 Smart Grids

The term Smart Grid may be understood as the overlaying of a unified communication and control system on the existing power delivery infrastructure to provide the right information to the right entity (...) at the right time to take the right action. It is a system that optimizes power supply and delivery, minimizes losses, is self-healing, and enables next-generation energy efficiency and demand response applications (ALTO, 2008). Smart Grid is designed to integrate advanced communication and networking technologies into electrical power grids to make them "smarter" (GAO et al., 2012). Objectively this term refers to the application of Information Technology to power systems.

Lund et al. (2012) aims to explain why Smart Grids should not be seen apart from the other energy sectors and what the integration of the other sectors means for the identification of proper solutions to the integration problem. For this author the converging point between the other areas of the power sector and the Smart Grid is the "renewable energy power".

2.1.2 Smart Cities

Notwithstanding the term "Smart Cities" (or Smarter City) is largely used nowadays, there is still not a clear and consistent understanding of its concept among practitioners and academia (CHOURABI et al., 2012). Nevertheless, an important meaning was given by the World Foundation for Smart Communities, which combines digital cities to intelligent growth, a type of development based on information and communication technologies. "A Smart Community is a community that has made a conscious effort to use information technology to transform the lives and work within its territory significantly and fundamentally, instead of following an incremental way" (NAM; PARDO, 2011).

A SC can be defined as a community that has made a conscious effort to use information technology to transform, significantly and fundamentally, the live and work within its territory, instead of following an incremental way (COMMUNITIES, 2001). Its concept can be categorized into several areas such as planning and management, human and infrastructure and many sub-areas as government and agency administration, public safety, social programs, health-care, education, transportation and water energy, environmental and smarter buildings and urban planning (ANTTIROIKO, 2006). For this study, though, the focus lies on those related to the energy sector (BATTY et al., 2012), (TOWNSEND et al., 2010).

2.1.3 Smart Buildings

The Smart Homes (SH) and Smart Building (SB) terms share some functional and technical commonalities. The term SH, however, is mainly used to describe residential homes while SB refers to tertiary buildings (office buildings, industrial premises, hospitals, schools, etc.) (MARTINS et al., 2012).

One SB can be defined as a building equipped with computing and information technology which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security and entertainment through the management of technology within the home and connections to the world beyond (ALDRICH, 2013). Smart Buildings has applications that allow homeowners to improved energy efficiency, frequently based on HVAC and thermal comfort studies.

In this case the concept of *smart* applies to buildings that have some sort of automation and where there is an interactive technology with the final user. This intelligent automation principle arises from the need for families to have a better control over their lives. So it can provide better home life experience to residents with intuitive user interfaces without overpowering them with complex technologies. For this study the home automation areas which are related to the consumption and production of electricity will be taken into consideration.

Smart homes such as “habitat control” or “intelligent home” type networks are equipped with devices that possess an amount of integrated intelligence required to manage and exchange data. Smart home functions include: entertainment, communications, energy and climate control, security, alternative energy and energy neutral applications, lighting and robotics (BUDDE, 2014). This work focuses on energy and climate control functions, specifically heating using heat pumps.

Several scientific works refer to the use of building representation in order to understand the thermal dynamics (WETTER, 2006), (GOUDA; DANAHER; UNDERWOOD, 2000). Such pieces of work are divided into studies in single-room or multi-zone building representation. Both of them use thermal engineering principles as part of their methods.

Thermal engineering is an important area of studies of the process of heating or cooling spaces, equipments or enclosed environments. Two of the subareas involved are the Thermodynamics and Heat Transfer.

A thermal dynamic model for a multi-zone building is presented by Goyal, Liao e Barooah (2011). In that study authors use graph theory to represent the entire house. They represent nodes as the temperatures in zones and edges as models of dynamic interaction between the thermal variables connected by the edges. Such approach is close to this work’s purpose. However, thermal parameter identification was solved by mathematical equations starting from the electrical laws (ROBERTSON; GROSS, 1958) derive from the thermodynamics laws.

Furthermore Mukherjee, Mishra e Wen (2012) propose a passivity based control strategy in a multi-zone building using thermal resistance and capacitance analogy. They used indirect graph to represent a house focused on building thermal control.

A practical approach for parameter identification with limited information is proposed by Zeni et al. (2014) using genetic algorithms and circuits. Instead, in Yang et al. (2012) is proposed what the authors call an efficient evolutionary approach to parameter identification in a building thermal model. In this last work the authors also use also genetic algorithms to find the thermal parameters.

Studies related to multi-zone buildings are more complex when compared to single-zone buildings because they need to consider aspects such as connection between zones, the interference between them and a larger overall size of the buildings. This work has as its scope the studies in multi-zone buildings.

2.2 THERMAL PARAMETERS AND COEFFICIENT OF PERFORMANCE IDENTIFICATION

Thermodynamics and Heat Transfer as subareas of Thermal Engineering are concentrated in study problems related with heat and temperature as well as their relation to work and energy as the Heat Transfer regards to thermal energy, physical systems depending on the temperature and pressure.

From the thermodynamics, the heat can be transferred from one place to another in three different ways: conduction, convection and radiation. The conduction takes place when heat transfer occurs between substances that are in direct contact with each other; convection happens when warmer areas of a liquid or gas rise to cooler areas in the liquid or gas; and radiation happen when the heat transfer does not rely upon any contact between the areas.

2.2.1 Thermal Parameters

For several decades, many researchers have been studying the identification of building parameters such as thermal conductivity, heat capacity and convective heat transfer coefficient. These parameters can be determined by measurements (in laboratory or on site) and computational estimations (PARK et al., 2011). In thermodynamics and heat transfer areas, some insulation parameters are often studied, such as:

- *Thermal capacitance* C is related to the ratio of the amount of heat energy transferred (added to or removed from an envelope) resulting in a temperature change. The C value can express, in thermodynamics the ration in which a space is heated in a function of time.

- The *thermal resistance* is represented by R which is the ratio of the temperature difference across an insulator and heat flux. It is the heat property of an object or material to resist to a heat flow. The R value is often used to represent thermal resistances, that always exist between two distinct temperatures.

- The *U-value* or *thermal transmittance* is the overall heat transfer coefficient that describes how well an element conducts heat. It quantifies the thermal conductance of a structure along with heat transfer due to convection and radiation process. *U-value* is the inverse of R.

There are also other parameters and concepts as the *thermal conductance* that is the quantity of heat that passes in unit time through a particular area and thickness when its opposite faces differ in temperature by one kelvin.

Thermal-electrical analogy is a commonly used method to identify thermal parameters. In that case, identifying thermal parameters means that they are unknown and will be estimated using the analogy between the electrical and thermal study fields.

2.2.2 Thermal-Electrical Analogy

The use of the electrical analogy dates back to before the 1950s when physical electric circuits were used to model thermal properties of phenomena such as walls, enclosures and heat pump processes (PARK et al., 2011). This method use the analogy between thermal and electrical study fields by means of representation of a heat behavior in a room, for example, using a RC circuit.

Several scientific studies have been published using Thermal Electrical Analogy to solving problems related to space heating. Parnis e Sproul (2010) cites Paschkis in 1942 as the first publication describing how the electrical analogy could be used to analyses and quantify thermal behavior in buildings (PARNIS; SPROUL, 2010). In this direction, Robertson e Gross (1958) published in 1958, suggest an electronic instrument which provides a solution for transient heat-flow problems by the use of direct analogy to electrical networks.

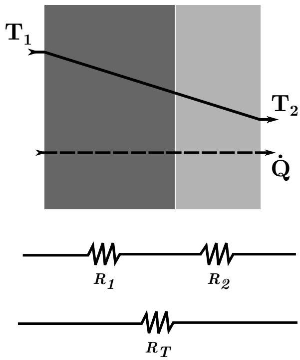
Moreover, parameter identification using Thermal Analogy can be found in Balan et al. (2011b) that presents solutions in modeling, parameter identification and control of the thermal energy in a house. Moreover, Park et al. (2013) study a model of a building system in order to predict thermal behavior within a building and its energy consumption. It uses RC thermal network based on the thermal-electrical analogy. The parameters of the parametric models are obtained by the least square approach.

Several studies use electrical-thermal analogy through RC circuits simulations (PARNIS; SPROUL, 2010) as an important approach to solve the proposed problem. Some of the works that make temperature control, use transient analysis with a SPICE-like language (MUKHERJEE; MISHRA; WEN, 2012), (MITRANI et al., 2009). This computational language and tool is able to reproduce electrical circuits behavior by means of simulations. Few of them, use transient analysis (ROBERTSON; GROSS, 1958) in order to understand the heat behavior or to collect thermal parameters.

2.2.2.1 Thermal Resistance

The thermal resistance is the ability of a material to resist the changes between two temperatures. It is also known as thermal insulation (SCHAGRIN, 1963), (BS, 2014). Fig. 2 shows an hypothetical case of a wall having two layers, with two temperatures T_1 and T_2, where $\dot{Q}$ is the heat flow. Each of the layers constructed of different material, has a distinct resistance value to the wall R_1 and R_2. The sum of the two resistances can be represented by a single resistor, using the thermal-electrical analogy as R_T.

Figure 2 – Thermal Resistance in a Double-Wall case

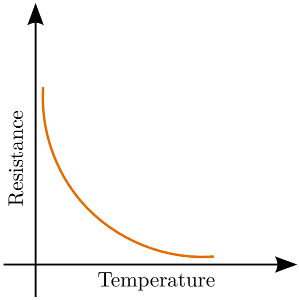


Source: Author (2017)

The heat flow through the resistance is proportional to the temperature difference and it is inversely proportional to the value of the resistance. A thermal resistance exists between two separate temperatures, one on each side (CHEEVER, 2013). In Fig. 3 this relational concept between temperature and thermal resistance can be seen.

Therefore the sum of all thermal resistances of a room or house can be designed as *overall resistance*, which is used in this present study. Once the thermal resistance is directly related to

Figure 3 – Relationship between Thermal Resistance and Temperature



Source: Author (2017)

the changes in temperatures and the behavior of the inhabitants of a house, such as opening doors and windows, in this study the overall average resistance $\overline{R}$ is used.

2.2.2.2 Thermal Capacitance

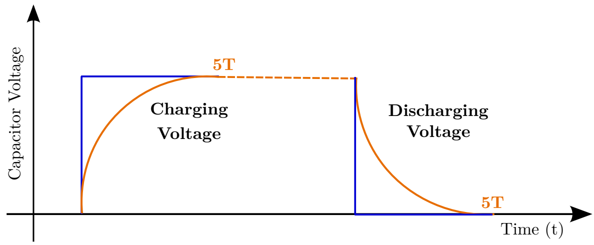
The thermal capacitance of an object is a measure of how much heat it can store. The rate of change of temperature of a thermal capacitance is proportional to the heat flow into it and it is inversely proportional to the its value (CHEEVER, 2013).

Fig. 4 presents on the same graph the two possible waveforms in a capacitor or in this case the thermal capacitance: charging and discharging.

Both, the capacitor charge and capacitor discharge varies with respect to time. The charging equation of a capacitor can be expressed as $V(1-e^{\frac{-t}{RC}})$ and discharge as $V(e^{\frac{-t}{RC}})$ (CHEEVER, 2013). Where V is Voltage and t time.

As thermal resistance, the thermal capacitance calculated in this thesis is the average of overall thermal capacitance $\overline{C}$. Which is obtained from the calculated overall average resistance

Figure 4 – Capacitor Charging and Discharging Waveforms



Source: Author (2017)

$\overline{R}$ and the overall average relation between thermal resistance and capacitance $\overline{RC}$.

2.2.2.3 Computing the Thermal Transmittance - *U-value*

The *U-value* or *U-factor* is the inverse of the total thermal resistance (ANDERSON, 2002) of the envelope and it represents the coefficient of overall heat lost in watts through $1m^2$ $[W/m^2\ °C]$. The heat pump power is represented by $\Phi_P = \eta P$ and it is considered as the coefficient of overall lost heat.

The *U-value* describes how well a building element conducts heat. For instance, a well-insulated building has a low thermal transmittance whereas poorly insulated parts of a building have a high thermal transmittance (BS, 2014).

Considering *U-value* as the coefficient [W/m^2-°C] overall heat loss and is been the reciprocal of R, the Eq. 2.1 can be presented as:

$$\overline{U} = \frac{1}{\overline{R}} \tag{2.1}$$

The *U-value* has been widely used by the construction industry and the building standards from the materials industry (BS, 2014).

2.2.2.4 Unit of Measures Equivalence Table

The analogy between thermal and electrical systems is used to represent thermal systems dynamics by means of electronic circuits (lumped parameter circuit), as can be seen in Tab. 1. In this sense, it is also possible to use thermodynamics and electricity laws such as Newton and Ohm's laws in an analogous way.

Scientific papers related to the use of representation of envelopes or buildings through electrical circuits (PREISSLER, 2016) have been published (MUKHERJEE; MISHRA; WEN, 2012), (PARK et al., 2013). The majority of these works, however, starts directly from the electrical circuit representation (ROBERTSON; GROSS, 1958).

To develop a mathematical model of a thermal system the concept of an energy balance is used. The energy balance equation states that at any given location, or node, in a system, the heat into that node is equal to the heat out of the node plus any heat that is stored (heat is stored as increased temperature in thermal capacitances) (CHEEVER, 2013).

$$Heat\ in = Heat\ out + Heat\ stored$$

The heat balance equation which is applied to the thermal electrical analogy, presented by Park et al. (2011) can be seen on Eq.2.2. It is described from the first principle of thermodynamics for a well-insulated single room with a heater.

$$C\frac{dT_{in}(t)}{dt} = P(t) - \frac{1}{R}(T_{in}(t) - T_{out}(t)) \tag{2.2}$$

Table 1 – Analog Elements Between Thermal and Electrical Systems

Thermal			Electrical		
Property	Symbol	Unit	Property	Symbol	Unit
Temperature	θ	$^{\circ}C$	Voltage	v	volt
Time	t_t	second	Time	t_e	second
Heat-flow rate	$\frac{\partial Q}{\partial t_t}$	watt	Current	i	micro-ampere
Heat capacity	C	joule/cm^3/$^{\circ}C$	Capacitance	C	micro-farad/cm^3
Resistance	R	$^{\circ}C$/watt	Resistance	R	Ohm's[Ω]
Conductivity	k	watt/cm^3/$^{\circ}C$	Conductivity	$1/r$	1/mega-ohm cm
Length	x_t	cm	Length	x_e	cm
Temperature gradient	$\frac{\partial \theta}{\partial x_t}$	$^{\circ}C$/cm	Voltage gradient	$\frac{\partial v}{\partial x_e}$	volt/cm
Rate of temperature rise	$\frac{\partial \theta}{\partial t_t}$	$^{\circ}C$/second	Rate of voltage rise	$\frac{\partial \theta}{\partial t_e}$	volt/second

Source: Robertson e Gross (1958)

This equation which is obtained from the electrical-thermal analogy and which is represented by a zone as an RC circuit determines that: the thermal capacitance C of the internal environment is derived from the change of internal temperature T_{in} over the time t, and it directly depends on the energy generated by heater P and the difference between external T_{out} and internal temperature as well as the thermal resistance R between these two temperatures.

This heat balance equation is an alternative to be used in order to identify the thermal parameters. In addition to identifying these thermal parameters the heating coefficient of performance - in this particular case heat pumps - was also calculated.

2.2.2.5 η-max and Balance Point Temperature

In order to calculate the maximum value of the coefficient of performance it is possible to use the outdoor reference temperature T_{ort} which calculates the balance point temperature T_{bpt}. The building balance point temperature is the outdoor air temperature required for the indoor temperature to be comfortable without the use of any mechanical heating or cooling (KEELER; BURKE, 2013). T_{bpt} can be found using Eq. 2.3

$$T_{bpt} = max(T_{out}(t) \mid s.t.\ P(t) \neq 0) \tag{2.3}$$

In order to obtain T_{ort} it is possible to use Eq. 2.4. It is assumed that when the T_{out} is greater or equal to T_{ort} then η is at maximum value η_{max}.

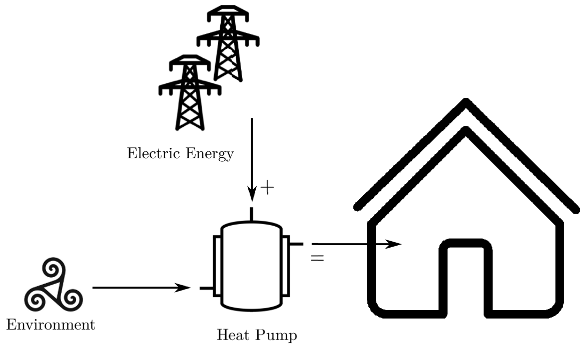
$$T_{ort} = \lfloor T_{bpt} \rfloor - 1 \tag{2.4}$$

In order to check the consistence of the found values for this procedure, it is possible to obtain η_{max} values from the technical specifications for each heat pump equipment manufacturer and make evaluations can be made.

2.2.3 Heat Pumps

Heat pump is a device which receives low-grade heat from a low-temperature source and it provides higher-grade energy to a high-temperature sink (NAVE, 2016). It seemingly "pumps" heat from the low-temperature source (at or near ambient temperature) to the high-temperature sink (KENT, 1997). The rest of the energy needed to produce heat inside the building is then obtained from the electrical network and it is shown in Fig. 5.

Figure 5 – A Heat Pump Schema



Source: Author (2017)

Current heat pumps can reduce the electricity use for heating by approximately 50% compared to electric resistance heating such as furnaces and baseboard heaters (ENERGY, 2016).

There are basically three types of heat pumps: those that absorb external temperature from the underground (geothermal), from the water (water source) and from the external air (air-to-air). In this study the most commonly (ENERGY, 2016) heat pumps that use air from the external environment to heat the envelope, that is *air-to-air*, are used.

2.2.3.1 Heat Pump Coefficient of Performance

The Coefficient of Performance (COP), here represented by η, is a dimensionless value defined as the energy produced by a heat pump. The energy *produced* by a heat pump (in watts) divided by the energy *consumed* by the heat pump (in watts). COP represents the efficiency of a heat pump while in the heating mode. A higher value of COP reflects a higher heating efficiency (MIX, 2006).

By Carnot's theorem and from the second law of thermodynamics any heat engine efficiency can be measured by heat introduced to the system divided by the work (URIELI, 2010). Eq. 2.5 shows this theorem where Q_h is the heat energy entering the system and W represents the work [Watt].

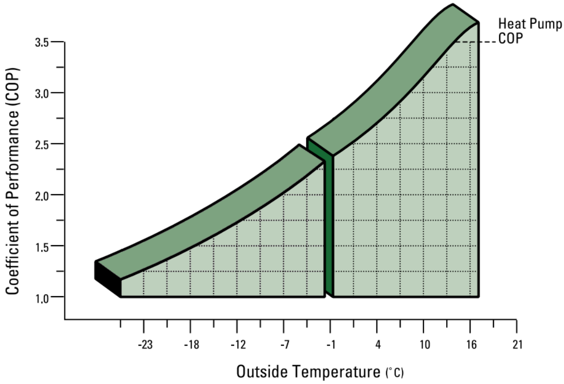
$$COP = \frac{Q_h}{W} \tag{2.5}$$

A heat pump Coefficient of Performance (COP) is a ratio of heating provided to the envelope. When the COP is high it implies low operating costs and higher heating efficiency (HEPBASLI; KALINCI, 2009). A heat pump COP can starts in one (indicating 100% efficiency) and it can be greater than one because these devices pump heat from external sources. So it is dependent on the outdoor temperature (BERTSCH; GROLL, 2008).

Second the Natural Resources Canada Office of Energy Efficiency (ENERGUIDE, 2004), at $10^0 \circ$C, the coefficient of performance of air-source heat pumps is typically about 3.3, at -8.3°C the COP is typically 2.3 and even when the temperature falls to -15°C the COP is 1.0 as it is presented by Fig. 6.

Applying the same concept to study heat pumps dynamics (KENT, 1997) investigates the performance of a compact air-to-air heat pump for residential heating. The author shows a real case using data from an office room at Istanbul Technical University. The coefficient of performance and heating capacity of the system are measured and presented as a function of

Figure 6 – Typical COP values per Outdoor Temperature



Source: EnerGuide (2004)

outdoor-air temperature but in a way which is different from what is proposed in this study.

In Tahersima (2012) it is investigated how the heat pumps work focused on optimization of the system performance in terms of energy efficiency. In the section of future discussions and conclusions the results were presented. In the discussion, the author states that controlling a heat pump is not a trivial task, and he also mentions that another factor to be concerned about is the electricity supply instability by the power companies.

Heading to Tahersima (2012) conclusions, the present study proposes the generation of future scenarios in order to reduce the consumption of electricity, due to space heating. This output concerns in the generation of an internal temperature plan for the following 24 hours.

2.3 INTERNAL TEMPERATURE PLAN

This section present some elements found in the literature. These elements are used to forecast electricity consumption in the generation of future scenarios as well as other characteristics taken into account in these studies.

The generation of future scenarios for reducing energy consumption usually acts directly on the devices and it is called controllers. These control algorithms often are called *forecasts*, as they aim at making predictions of future consumption based on future situations.

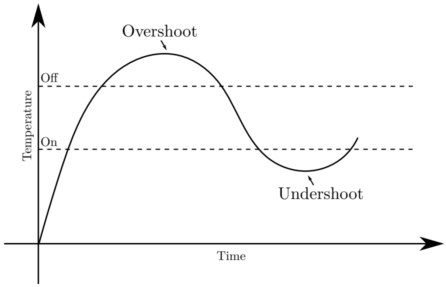
In Suganthi e Samuel (2012), while doing a review about energy models for demand forecasting, the authors present the results of more than 360 scientific papers. According to the authors, genetic algorithms, fuzzy logic, support vector regression and operational research (VANDERBEI, 2001) are emerging techniques in forecasting commercial and renewable energy sources.

Lara et al. (2013) presents a predictive controller based on the thermal model of a hotel, and in his Thesis, Kämpf e Robinson (2007), focused on how to use a computational implementation of one model. Both of them present problems related to technological models applied to the the energy consumption.

One of the internal temperature plan goals is to reduce the over and undershoots. The cycling between heat pump turned *On* and *Off* limits occur due to the thermal inertia of buildings. An hypothetical example of Internal Temperature Response Curve is presented in Fig. 7.

The term Model Predictive Control (MPC) is frequently used as a control methodology that can use predictions to improve building thermal comfort, decreasing peak demand, and reducing the total energy costs (MA et al., 2012). Building controls design, however, can become challenging as they move beyond standard heuristic controls approaches and seek to incorporate predictions of weather, occupancy, renewable energy

Figure 7 – Internal Temperature Response Curve



Source: Author (2017)

availability, and energy price signals (MA et al., 2012).

2.3.1 Thermal Comfort

The reduction in energy consumption in residential and non-residential places is also directly related the amount of money that is saved by their owners. The reduction in energy consumption for heating these environments, however, should take into account the degree of thermal comfort (ASHRAE, 2004) to its households users.

The forecasts of occupancy profiles represent an input of the optimization problem (ASCIONE et al., 2016). Other studies working on multi-zone building, with lumped heat transfer model based on thermal resistance and capacitance for system analysis based on the occupant feedback (WEN et al., 2013), has shown that the calculation of the internal temperature based on the participation of domestic users has significant importance not only for the accuracy of the models but also for the use of support systems for these same users.

A building is in its entirety a complex network of heterogeneous and inter-connected subsystems. The occupants of a building constitute an important subsystem, whose comfort level must be accounted for, in optimizing energy usage in a building (GUPTA et al., 2014). Using a lumped heat transfer model based on thermal resistance and capacitance for system analysis can be a complete tool applied to thermal models.

The main goals of HVAC systems studies in building environments are based on providing indoor thermal comfort for its occupants. Furthermore, they expect to provide acceptable air quality and understanding thermal comfort as a situation where a person feels satisfied with the temperature of the surrounding environment (ASHRAE, 2004).

One solution for thermal modeling of a house includes experimental identification of the model's parameters. Identifying the parameters of a thermal model of the house can help to reduce the energy consumption (BALAN et al., 2011a).

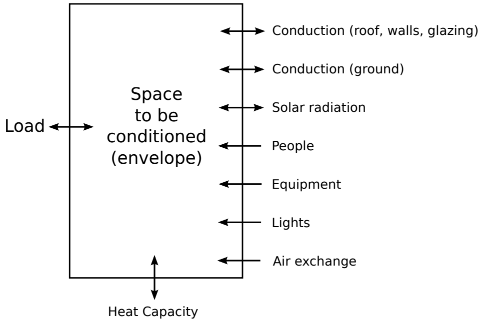
Thermal models of buildings are often used to identify energy savings within a building. This requires an understanding of the thermal dynamics of the building, which is often obtained from physical thermal models (YANG et al., 2012). Predictive models of building thermal dynamics and energy costs of control actuators allow computation of the optimal inputs to each actuator in order to deliver the desired energy profile (MA et al., 2012).

2.3.1.1 Heat Balance Representation

The principal terms of heat gain/losses of one envelope to be conditioned, according to the American Society of Heating (ASHRAE, 2004) is represented in Fig 8. In this heat balance representation is possible to understand a building as a dynamic system.

It is understood that the heat exchange in an environment is due to several factors. Considering that the percentage of heat load components in one envelope are distributed as follow (ASHRAE, 2004): $77-85\%$ due to outdoor temperature and

Figure 8 – Heat Balance Envelope System



Source: Ashrae (2004)

electrical equipment, 5 – 8% infiltration, 4 – 8% lighting, 3 – 7% solar transmission and 3% from people corporal heating.

In order to understand the dynamics of an environment heat exchange, it is firstly necessary to estimate the thermal parameters of each environment. Once knowing these parameters it is possible to set plans for the heating process or for the cooling zones..

2.3.2 Weather Forecast

The control strategy of heating systems using the forecasts of occupancy profiles and weather conditions have demonstrated important results related to save power consumption (ASCIONE et al., 2016).

Energy studies of predictive controls using the weather forecast to estimate the outdoor temperature have shown results in energy savings of 70% on average during the heating season (BENGEA et al., 2014). Other studies show that despite the use of the data source in hourly weather (FRANCES; ESCRIVA; OJER, 2014) may cause slowdowns in the general calculations consumption forecast, it improves the accuracy of the results.

Therefore the use of weather forecast for the energy consumption estimate or the generation of future scenarios is an important tool that provides great accuracy to algorithms (GENC; SEHGAL, 2014). Such statements make it possible to perform more accurate calculations on the forecasts and this accuracy is directly related to the quality of the source of weather information.

One method that is used for calculations related to the effect of outdoor temperature on smart buildings energy consumption is called the degree days. In the heating period it is called HDD (Heating Degree Days) (ALLEN, 1976). HDD is a measure of how many degrees and how many days the outdoor temperature was lower than a specific base temperature, (BENGEA et al., 2014).

2.3.3 Energy Price

Another important component used in predicting energy consumption is the price of electricity. Specifically price forecast this value for the next days or hours. Pricing forecast (GENC; SEHGAL, 2014) is an important tool and the prediction algorithms are based to estimate the total amount that will be spent in a house or in a building in the next few hours or the next day.

For household electricity demands forecasting, there is a benchmarking state-of-the-art methods by Veit et al. (2014). They applied a number of forecasting methods including Autoregressive Integrated Moving Average (ARIMA), neural networks, and exponential smoothening using several strategies for training data selection, in particular day type and sliding window based strategies. The results indicate that forecasting accuracy varies significantly depending on the choice of forecasting methods/strategy and the parameter configuration.

Sevlian e Rajagopal (2014) presents experimental simulations on forecasting for the energy consumption, and Veit et al. (2014) presents the state-of-the-art methods for forecasting electricity demand on the household level. Both articles report that when the forecasting models are applied to real cases the results may change. Furthermore, it is necessary to take into account the absence of some data when in real cases.

In Ziekow et al. (2013) it is possible to find discussions on the potential of smart home sensors in forecasting household electricity demand. This work studied three houses. For this reason at the end of their article, the authors state that an interesting way to extend that research would be to analyze the required computational resources to make forecasts for large numbers of households in detail, because the complexity increases.

2.3.3.1 The Energy Prices Policies

Nowadays, many power companies have a schedule of prices that depends on the quantity taken during a given time period. The electricity demand for final users can changes day to day, hour to hour, minute to minute. This kind of pricing is called time-of-use(TOU) (CHEN; LEIWU; FU, 2012).

To better understand the prices policies, the follow model (MOORE, 1970) can be used. This model considers a firm that sells only to residential customers: j is the time period (hour) $j = 1, 2, ...L$ P_i is the price charged in the ith step of the rate schedule $i = 1, 2, ...n$. TC_p and MC_p are the total cost and marginal cost of producing power. TC_o and MC_o are the total cost and marginal cost of other expenses. $TC = TC_p + TC_o$ and $MC = MC_p + MC_o$ and $MC_j = MC_{pj} + MC_{oj}$; q_j is the total amount taken at the jth time. $Q = \sum_j q_j$ is the total quantity taken. $q_{pj} = q_j + q_{lj}$ where q_{pj} is the amount produced at the jth time and q_{lj} is the amount lost in transmission and distribution, so $Q_p = \sum_j q_{pj}$.

$$\pi = \sum_j Pq_j - \sum_j TC_j \tag{2.6}$$

The total revenue that is generated during the jth hour is equal to the price, P, times q_j and so total revenue for the year is $\sum_j Pq_j$. Profit, π, can be expressed as Eq.2.6:

2.3.3.2 Levelized Energy Cost

The Levelized Energy Cost (LEC) is the price at which electricity must be generated from a specific source to break even over the lifetime of a project (AGENCY, 2005 Update). It is an economic assessment of the cost of the energy-generating system including all the costs over its lifetime: initial investment, operations and maintenance, cost of fuel, cost of capital, and it is very useful in calculating the costs of generation from different sources. It can be defined in a single formula as Agency (2005 Update):

$$\mathrm{LEC} = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{2.7}$$

Where

LEC = Average lifetime levelized electricity generation cost

I_t = Investment expenditures in the year t

M_t = Operations and maintenance expenditures in the year t

F_t = Fuel expenditures in the year t

E_t = Electricity generation in the year t

r = Discount rate

n = Life of the system

These models and methods are widely used by companies which are providers of electricity. Such calculations are applied both for actual consumption situations (this) and to forecast (future scenarios) prices.

2.3.4 CO_2 Emissions

Energy for heating and cooling is the main reasons for the associated CO_2 emissions. In order to reduce such emissions, investment has to be made, in terms of better features of the building envelope and heating, ventilation and air conditioning system type and components (HAMDY; HASAN; SIREN, 2010).

Petersdorff et al. (2005) presents European Union Climate Policy, CO_2 emissions, energy costs and others. Herein may be perceived the environmental impacts in reducing energy consumption and also trends for European policies in order to reduce CO_2 emissions.

Several scientific papers in the area of planning future spending on energy and other forecasting this area mainly take into account the user thermal comfort and seek to reduce the amount of consumption of electric power. Few of them, thought, consider the reduction of CO_2 emissions in the optimization process.

Maintaining low CO_2 levels in the atmosphere (ASHRAE, 2004) is the duty and obligation of every citizen. In this work the reduction of CO_2 gases is taken into account.

2.4 KNOWLEDGE-BASED PROCESS

As presented in Sect. 1.2.3, the KE is part of the KEM and and it has origins from the Artificial Intelligence area. The KE, since its inception, focused on the use of methodologies and formal techniques to develop knowledge-based systems in a systematic and controlled manner (STUDER; BENJAMINS; FENSEL, 1998). It is a discipline that aims to build knowledge systems, supporting in methodologies, techniques, languages and tools for extracting, encoding, representing and using of knowledge (RAUTENBERG et al., 2010), (SCHREIBER, 2000), with special emphasis on intensive-knowledge tasks.

In this thesis, five important knowledge processes (NONAKA, 2008) are used to describe and apply the proposed model. They are Knowledge Acquisition presented in Sect. 2.4.1, Knowledge Representation in Sect. 2.4.2, Knowledge Application in Sect. 2.4.3, Knowledge Discovery in Sect. 2.4.4 and Knowledge Visualization in Sect. 2.4.5.

2.4.1 Knowledge Acquisition

The first studies on the acquisition of knowledge date from 1980, when Edward Feigenbaum (FEIGENBAUM; MCCORDUCK, 1983), developing the first expert systems have his technology adopted by the US business community. Those expert systems were first developed in artificial intelligence laboratories as an attempt to understand complex human decision making.

The knowledge *elicitation* (STUDER; BENJAMINS; FENSEL, 1998) can be part of the of the acquisition process. Commonly used in software engineering to define the requirements of an information system or application, this technique aims to promote the interaction between user and system. The purpose of this interaction with the actors is to obtain information about a process or a procedure that one wishes to know. Once all the necessary information to build the desired knowledge in an information system is acquired, it becomes necessary to perform the representation of this knowledge.

2.4.2 Knowledge Representation

Knowledge representation is a branch from Artificial Intelligence (AI) and that goes beyond the mathematical representation of knowledge, seeking automated reasoning. The language of classical logic that is most widely used in the theory of knowledge representation is the language of first-order (predicate) formulas (VANHARMELEN; LIFSCHITZ; PORTER, 2008).

The use of methodologies, methods and techniques aimed at modeling systems has significant importance in the knowledge representation (STUDER; BENJAMINS; FENSEL, 1998), especially when applied to the knowledge-based systems (LOPES; GONÇALVES; TODESCO, 2012), (YANG, 2007).

The knowledge representation is a way to turn data and information into a new or existing explicit format (BRACHMAN; LEVESQUE; REITER, 1992). In this thesis, the knowledge representation makes use of two techniques: graph theory and thermo-electric analogy.

2.4.2.1 Knowledge Representation using Graph Theory

The theory of graphs is a branch of mathematics that studies the relations among the objects of a given set. The structures called graphs are used, where V is a non-empty set of objects called vertices and A is a set of unordered pairs of V, called edges (LAI; LEINWAND, 1988).

Several studies have been carried out on representing environments through graph theory (KIM; KIM, 2003). These representations were, at the same time, used to understand the thermal dynamics environment (WETTER, 2006), (GOUDA; DANAHER; UNDERWOOD, 2000).

Roth e Hashimshony (1988) depicts some work on developing models based on graph theory to solve problems in architectural design. Authors show how the graph decomposition can be used in order to simplify complex problems by removing edges as well as applying algorithms to transform graphs into rectangular dimensions plan.

A study using graphs in order to draw floor plans is presented by reference Alvarez et al. (2004). In this work, algorithms are used to place exterior and interior rooms on a technique consisting of a heuristic search with respect to depth.

An algorithm for designing floor plans using planar triangulated graphs was proposed by reference Gogoi e Kalita

(2012). This algorithm consists of several steps as finding out the exterior face, placing these nodes as a floor plan room representation, finding out the interior rooms, finding the connection among the exterior and interior environments and representing all the building connections and rooms in a floor plan draw representation.

2.4.2.2 Knowledge Representation using Thermal Analogy

The analogy between thermal and electrical systems is used to represent thermal dynamics by means of electronic circuits. In this sense, it is also possible to use these two systems in an analogous way, replacing the electricity laws by the thermodynamics laws.

Building representation using both electrical circuits and thermal analogy are presented by several scientific works (MUKHERJEE; MISHRA; WEN, 2012), (PARK et al., 2013), (RAMIREZ; SAGUES; LLORENTE, 2014). They are also used in order to help in the understanding of their thermal dynamics (WETTER, 2006), (GOUDA; DANAHER; UNDERWOOD, 2000).

2.4.3 Knowledge Application

Knowledge application, or utilization is used in different ways as an *instrumental* use of knowledge and it involves acting on research results in specific and direct ways. *Conceptual* use involves using research results for general enlightenment and *symbolic* use that involves using research results to legitimate and sustain predetermined positions (BEYER; TRICE, 1982). The application of knowledge in this thesis is understood as an intermediary process between the knowledge representation and the knowledge discovery.

2.4.4 Knowledge Discovery

The concept of knowledge discovery and its processes emerged, in the 90's from the need for a more detailed analysis of the information generated. The knowledge discovery can be divided into two parts: KDD (Knowledge-Discovery in Databases) and KDT (Knowledge-Discovery in Text). This division is based on the content that will be analyzed, that if content was previously organized and structured discovery process will be used in the KDD. If the content found was dispersed in textual documents the process to be used will be the KDT (GONÇALVES et al., 2000).

In the present thesis, the identification of thermal parameters and the generation of internal temperature plans for the day ahead is part of the process of discovery of knowledge. In this process a computational algorithm and a data repository are used.

2.4.5 Knowledge Visualization

The field of knowledge visualization examines the use of visual representations to improve the *creation*, *use* and *transfer* of knowledge (EPPLER; BURKHARD, 2004). Inside the knowledge visualization field there is another important definition that is aligned with this thesis. It is the *information visualization.* Information visualization can be defined as the use of computer-supported, interactive, visual representation of abstract data to amplify cognition (EPPLER; BURKHARD, 2004).

Studies have shown that smart energy system users tend to use and enjoy the user support system when they can view and compare their performance with the neighbors (AMATO et al., 2014). Other approaches such as *gamification* (LUCA; CASTRI, 2014) and social interaction are excellent alternatives to stimulate energy consumption reduction and CO_2 emission from a collaborative point of view.

2.5 STATE OF THE ART

This section presents the result of a systematic review made on the studied subject. It is also possible to identify the positioning of this work in relation to related works as well as its contributions (first row).

In order to identify research gaps in related works, four systematic reviews were performed. The first of them, Preissler (2015) presented on the "III International Congress on Energy Efficiency - Climate Innovation and Sustainable Development Systems" with the title *How has does the Knowledge Engineering contributed for Smart Energy Technologies?*.

Two other reviews were published. They are: *Knowledge Engineering and Management Contributions for Scientific Research in the Thermal Smart Energy Context* in "International Journal of Recent Scientific Researchl" and *Knowledge Engineering and Management in Thermal Multi-zone Building Studies: a Systematic Review* published by the "IJKEM International Journal of Knowledge Engineering and Management".

The last systematic review will be presented within the paper *House Thermal Parameters Identification from Heat Pumps Consumption.* When this thesis was written, the paper was under review to be submitted.

Regarding to the choice of the model, the first paper had a generalist character, once at that stage the goals of this research were still being defined. In the second and third reviews, the focus was on locating intersections between Energy Studies and Knowledge Engineering and Management as well as including elements aligned to the current scope of this work.

In the sequence a table that composes the main studies that have been identified as being in line with the scope of this research is presented. Such a table is derived from the last systematic review based on previous research.

		Scope			Parameter Identi cation					Optimization					
										Features			Constraints		
Id	References	Heating	Heat Pumps Air-to-Air	Multi-zone Buildings	Electrical-Thermal An.	Calculate Params	Uses Prior Knowledge	T_out as Input	Calculates COP	Occupancy Pro les	Makes Predictions	Weather Forecast	CO_2 Emissions	Thermal Comfort	Energy Price
	This work	●	●	●	●	●	●	●	●	●	●	●	●	●	●
01	Agheb, Tan and Tsang (2015)	●						●		●	●	●		●	●
02	Anvari-Moghaddam, Monsef and Rahimi-Kian (2015)	●				●					●			●	●
03	Ascionand et al. (2016)	●		●			●			●	●	●		●	
04	Balan et al. (2011b)	●				●								●	
05	Beckel et al. (2015)	●						●				●			●
06	Bekkouchand et al. (2013)			●	●	●								●	
07	Beltran and Cerpa (2014)	●		●	●		●	●			●			●	●
08	Bengea et al. (2014)	●		●						●	●	●		●	
09	Benhamou and Bennouna (2013)			●										●	
10	Buonomano et al. (2016)			●	●	●								●	
11	Chel, Janssens and Dand Paepand (2015)	●		●											
12	Contreras-Ocana, Sarker and Ortega-Vazquez (2016)	●						●		●		●		●	●
13	Du and Lu (2011)	●				●	●			●	●			●	●
14	Ellis, Hazas and Scott (2013)	●		●							●	●		●	
15	Ferdyn-Grygierek (2014)	●		●										●	
16	Frances, Escriva and Ojer (2014)	●		●		●						●			
17	Genc and Sehgal (2014)			●		●				●	●	●		●	●
18	Goethals, Breesch and Janssens (2011)			●		●					●			●	
19	Good et al. (2015)	●						●		●	●			●	●
20	Goyal, Liao and Barooah (2011)	●		●	●	●	●				●			●	
21	Gupta et al. (2014)	●		●	●	●				●	●			●	●
22	Hamdy, Hasan and Siren (2010)	●		●			●						●		●
23	Hao et al. (2015)	●		●	●						●			●	
24	Hu and Karava (2013)			●	●	●		●		●	●	●		●	
25	Hu and Karava (2014)			●	●			●			●	●		●	
26	Huang et al. (2013)	●		●		●					●			●	
27	Huang, Chen and Hu (2015)	●		●		●					●			●	
28	Jassar, Liao and Zhao (2009)			●		●					●			●	
29	Kent (1997)	●	●					●	●						
30	Knudsen and Rotger-Griful (2015)										●	●			●
31	Lam, Yuan and Wang (2014)	●		●				●		●				●	
32	Lee, Horesh and Liberti (2015)	●		●				●						●	●
33	Liao and Dexter (2010)	●		●		●		●			●			●	
34	Ma et al. (2012)			●						●	●				●
35	Ma et al. (2015)	●						●							●
36	Morosan et al. (2011a)	●		●			●			●				●	
37	Morosan et al. (2011b)	●		●						●				●	
38	Mueller et al. (2014)	●									●				●
39	Mukherjee, Mishra and Wen (2012)	●		●	●		●				●			●	
40	Nassif and Moujaes (2008)			●		●	●							●	
41	Nguyen, Nguyen and Land (2013)										●			●	●
42	Nguyen and Land (2014)	●				●						●		●	●
43	Nguyen, Nguyen and Land (2015)	●												●	●
44	Okuyama and Onishi (2012)	●		●		●	●							●	
45	Parisio et al. (2013)	●			●			●		●		●	●	●	
46	Park et al. (2013)	●			●	●		●			●				
47	Parnis and Sproul ("2010")	●			●	●									
48	Radecki and Hencey (2013)	●		●	●	●					●				
49	Ramirez-Laboreo, Sagues and Llorentand (2014)				●	●									
50	Rogers et al. (2013)	●						●			●	●		●	●
51	Sobhy, Brakez and Benhamou (2014)	●		●		●	●							●	
52	Srikantha, Keshav and Rosenberg (2012)	●								●			●	●	
53	Thavlov and Bindner (2015)	●			●	●				●				●	
54	Tsitsimpelis and Taylor (2015)			●		●	●								
55	Wen et al. (2013)			●	●	●					●			●	●
56	Winkler et al. (2016)	●		●				●		●				●	●
57	Xu et al. (2013)	●		●						●		●		●	●
58	Yang et al. (2012)	●		●		●					●				
59	Yoon, Baldick and Novoselac (2014)	●		●			●			●				●	●
60	Zeng, Zhang and Kusiak (2015)			●			●				●			●	
61	Zhang et al. (2013)			●		●								●	
62	Zhao et al. (2015)			●						●	●			●	
63	Zhuang, Li and Chen (2007)	●		●		●						●		●	
	Quantity	45	1	42	16	29	13	16	1	20	31	16	3	48	23
	Percent of Total	71,4%	1,6%	66,7%	25,4%	46,0%	20,6%	25,4%	1,6%	31,7%	49,2%	25,4%	4,8%	76,2%	36,5%

The bibliographic research was divided into three major classification groups: in relation to the scope, in relation to the techniques for the calculation of the thermal parameters and on the optimization, its features and its constraints.

The classes are: about the scope, if it fits as a heating study, if it is applied to the heat pump air-to-air devices and if the environment is related to multizone buildings.

About the parameter identification, the studies were classified if they use electrical thermal analogy, if they calculate or estimate parameters, if use prior knowledge (historical data) to estimate thermal parameters, use external temperature (T_{out}) as input and if they calculate/estimate COP.

In the optimization processes the specific paper was classified if it takes into account the occupancy profiles as their preferences for example. If it makes some kind of predictions or forecasts as well as if it uses weather forecast for it. In relation to the constraint into the optimization processes the paper was classified if it uses CO_2 as a parameter, if it uses thermal comfort as a constraint and/or uses energy price into the optimization phase.

Several scientific studies have been published using thermal-electrical analogy to solving problems related to space heating. Paschkis in 1942 was the first publication describing how the electrical analogy could be used to analyses and quantify thermal behavior in buildings (PARNIS; SPROUL, 2010).

In this direction, reference Robertson e Gross (1958), suggests an electronic instrument which permits solution of transient heat-flow problems by use of direct analogy to electrical networks. In that work it was used an analogy between electrical and thermal circuits directly in order to allow building control using equivalent measurements.

Moreover, parameter identification using Thermal Analogy could be found in Balan et al. (2011b) that presents solutions in modeling, parameter identification and control of the thermal energy in a house. As well Park et al. (2013) study a model of a building system in order to predict thermal behavior within a building and its energy consumption. It uses an RC thermal network based on the thermal-electrical analogy. The parameters of the parametric models are obtained by the least square approach.

One method to build grey-box thermal models based on electrical equivalent circuits is presented in Ramirez, Sagues e Llorente (2014). The unknown parameters are identified using temperature measurements and applying nonlinear optimization techniques. Other approach to parameter identification in a building thermal model is proposed by Yang et al. (2012). In that model they use fitness function which quantifies the difference between the energy-consumption.

Furthermore, Mukherjee, Mishra e Wen (2012) propose a passivity based control strategy in a multi-zone building using thermal resistance and capacitance analogy. They use an indirect graph to represent a house focused on building thermal control.

The main goal of HVAC (Heating, Ventilating and Air Conditioning) systems studies, in building environments, is to provide indoor thermal comfort for its occupants. Furthermore, it aims to provide acceptable air quality and understanding thermal comfort as a situation where a person feels satisfied with the temperature of the surrounding environment (ASHRAE, 2004) is not a trivial task.

Smart homes or buildings are equipped with devices that possess an amount of integrated intelligence required to manage and exchange data. These functions include: entertainment, communications, energy and climate control, security, alternative energy and energy neutral applications, lighting and robotics (BUDDE, 2014). This paper focuses on energy and climate control functions, specifically heating using heat pumps.

However, such studies do not present an approach in which the preferences of the home user are applied in the algorithms not even calculating the coefficient of performance of heat pumps based on the outside temperature changes. Studies in which the thermal parameters identification was used to generate an internal temperature plan for the next 24 hours were not located, either.

Only one work, Kent (1997) in which the COP is calculated and it is based on the external temperature was identified. However, this is a technical proposal for the calculation of the COP and does not result in plans for saving electric energy or maintaining thermal comfort.

From these works, 76,2% use thermal comfort as the main constraint into the optimization process. Only 13 works from 63 use some kind of prior knowledge in order to estimate the thermal parameters and 31,7% use occupancy profile as internal temperature preference as a reference.

3 METODOLOGY

The present work fits as being a *technological research* that aims to suggest a model. A *model* is a logic representation, a set of physical or virtual mechanisms which allows the knowledge or product representation as presented by Creswell (2013). This model was used to represent the real physics system, enabling the simulation, analysis and the optimization in laboratory.

This research is characterized as been *experimental* by applying technological perspectives (CRESWELL, 2013). It is a *multidisciplinary* research because it takes into account knowledge and expertise from two different postgraduate courses in two different universities: Computer Science at Sapienza University of Rome (Italy) and Knowledge Engineering and Management at Federal University of Santa Catarina (Brazil).

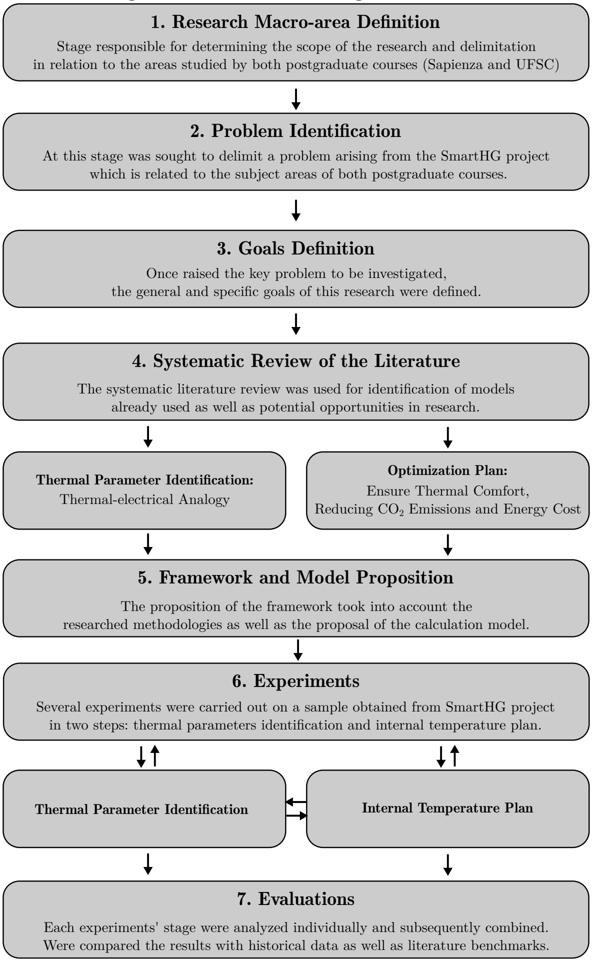
3.1 THE METHODOLOGICAL PROCESS

Fig. 9 presents the sequence of stages that were implemented for the development of this research. In the first and second stages the research object was defined between both universities, seeking to find convergences areas of study between courses. Moreover, it was expected to apply the study into a current research project.

Step three took into account the previous steps as well as the expertise of both postgraduate programs and the academic. The systematic reviews accounted for result in the choice of the thermo-electrical analogy in the parameters identification stage as well as the choice to propose an optimizer responsible for: ensuring the thermal comfort by reducing energy consumption and CO_2 emissions.

In step five scripts and algorithms based on thermal-electrical analogy to identify the thermal parameters of the stu-

Figure 9 – Methodological Process



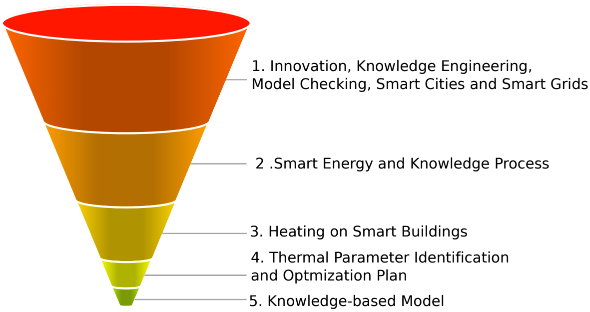
Source: Author (2017)

died houses were developed. For the analysis of the mathematical model a mathematical software was used.

In steps six and seven several tests were performed as well as experiments using the the proposed model. The experiments were performed based on real historical data.

The stages one to five were of paramount importance for determining and for proposing the model. Fig. 10 shows a graphical representation of a funnel using key words.

Figure 10 – Funnel of the Methodological Process 1-5



Source: Author (2017)

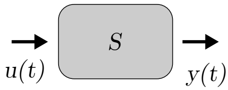
In this funnel it is possible to identify the steps that the ideation of the proposal passed, reducing the search area and result into the model proposed in this document. Sect. 3.2 presents the approach used to develop the mathematical model as well as the algorithm.

3.2 PROBLEM CLASSIFICATION AND METHODS

The present studied problem is classified as a physical *dynamic system*. The type of dynamic system problem studied in this thesis is characterized as *system identification* and it can be solved by the *gray-box* method. In this section such concepts are discussed.

The heating of a room can be considered as a dynamic system because it has varying with respect to time having inputs and outputs (GHOSH et al., 2015). A dynamical system can be described as a system in which the current output value depends not only on the current external stimuli but also on their earlier values (LJUNG, 1987).

Figure 11 – Representation of a Dynamic System



Source: Author (2017)

Fig. 11 represents an arbitrary system S that has inputs $u(t)$ and outputs $y(t)$. There are three general problems of dynamics and control systems (SONTAG, 2013):

1. **Simulation Problem - given $u(t)$ and S - find $y(t)$**: if the inputs and the system dynamics are known so it is possible to figure out the system outputs trough simulations and it can predict how the system will behave by playing the input through the system.

2. **Control Problems - given $y(t)$ and S - find $u(t)$**: if the system is known and depending on how one wants to the outputs to behave then it can determine the appropriate inputs through the various control methods. This is the typical method where it is possible to change the inputs in order to determine how the outputs behave.

3. **System Identification - given $u(t)$ and $y(t)$ - find S**: knowing the inputs and the outputs then it is possible to determine how the system looks like through a process called system identification.

Since the mathematical model, for this thesis, that expresses the heating behavior of a given room in a house is unknown and it is classified with a dynamic system, the technique of *system identification* is applied. This is a technique for finding a mathematical model by analysis of input-output characteristic of an unknown system (AZMI et al., 2015).

It can be described as a science of building mathematical models of dynamic systems from observed input-output data. It can be seen as the interface between the real world of applications and the mathematical world of control theory and model abstractions (LJUNG, 2010).

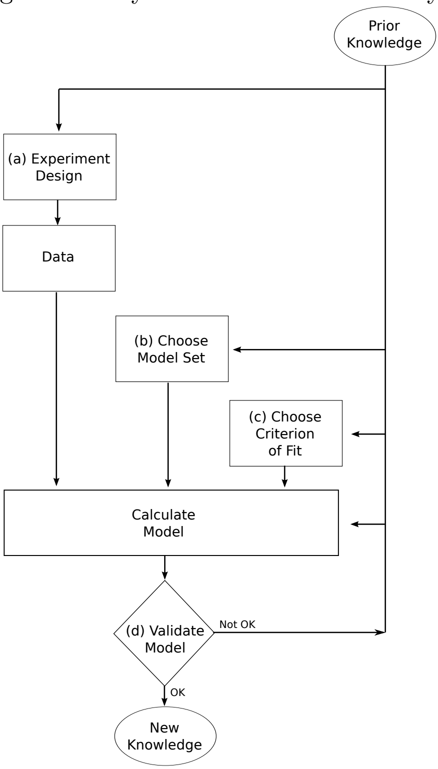
System identification is used by Holland et al. (2014) with an experimental methodology that was developed for a thermal system or heated space. It uses mathematical models and collected temperature data to estimate the network thermal resistance and capacitance. Other scientific study in this way conducted by Parnis e Sproul (2010) who present an approach to building thermal modeling using electric circuits. It uses an electric circuit simulator program where results are interpreted in terms of thermal quantities and energy.

The four main steps of the system identification process are generally described as Azmi et al. (2015): (a) *collection of experimental data*, (b) *selection and structuring of the model*, (c) *approximation of parameters of the model* and (d) *validation of the mathematical model.*

Fig. 12 shows the system identification flow that was used. The idea is to apply the *Prior Knowledge* from the systematic reviews and related works and then design (a) a model that will be used on the historical data, then the model is calculated. If the found thermal parameters are compatible with the literature then a model is validated and it can be used into the model. Otherwise another *Model Set* (other parameters within the model) can be selected or even adjusted to the *Criterion Fit* (actual parameters within the model). The loop insists until the model can be validated. In this model's case the *new knowledge* is the *mathematical model* used to identify the thermal parameters.

Such method of system identification applied to this particular problem aims to act as a lifecycle for implementation and validation of the mathematical model. This model is presented

Figure 12 – System Identification Lifecycle



Source: Author (2017) based on Azmi et al. (2015)

in Fig. 12. In step (b) the model used is proposed (according to Sect. 4.4) and not simply chosen.

The system identification goal is to identify the unknown parameters of the system and to provide a new knowledge based on the thermal parameters estimated by the model. This new knowledge is related to the environment heating behavior. That process can be understood as a Problem-Solving Methods which is a branch of the Knowledge Engineering discipline (VANHARMELEN; LIFSCHITZ; PORTER, 2008). This discipline provides knowledge-presentation techniques for solving particular problems (STUDER; BENJAMINS; FENSEL, 1998).

To step (a), the *experiment design*, a data from a specific house is gathered. This data will be used on the next steps.

Step (b), *choose model set* proposes a mathematical model which is based on the thermal-electrical analogy. This model is presented in Sect. 4.4.

For step (c), *choose criterion of fit*, a parameter identification method (PARK et al., 2013) was used. This method allowed the adjustment of the mathematical model based on the thermal-electrical analogy and the prior knowledge.

Finally, in step (d), *validate model*, the *gray-box approach* (ARPACI-DUSSEAU; ARPACI-DUSSEAU, 2001) was used. Therefore, even without full knowledge of the system behavior or all parameters, simulations results can be compared with the collected data.

The gray-box is one of these three methods that can be used to solve System Identification Problems. There are some differences among them as follows:

1. **Black-box method**: it can be applied in a situation in which there is a hypothetical box that is so dark that its inside cannot be observed, that is the system S. According to this method, if the inputs $u(t)$ and outputs $y(t)$ are known, it can be inferred that the system is using the data from the inputs and outputs as well as it is aware of the relationship between them.

2. **White-box method**: in this case, the box is so transparent that it is possible to see inside it. The components of system S can also be seen and it is possible to directly write the differential equations about this system.

3. **Gray-box method**: that is the middle term between black and white-box in which not all components of the system S are known. Thus, these components may be simulated.

The models are usually obtained based on a full description of the building features (white-box), based on an identification process (black-box) or combination of the two (gray-box) (BALAN et al., 2011b). For more advanced applications, it may be necessary to use models that describe the relationships among the system variables in terms of mathematical expressions like difference or differential equations (LJUNG, 1987).

Basically, a model has to be constructed from observed data. A model sets with adjustable parameters with physical interpretation may be called gray boxes (PARK et al., 2013).

It is possible to identify the thermal parameters using the thermal-electrical analogy to build gray-box thermal models based on electrical equivalent circuits (RAMIREZ; SAGUES; LLORENTE, 2014). The unknown parameters can be identified by using temperature measurements and applying nonlinear optimization techniques (YANG et al., 2012).

4 THE PROPOSED MODEL

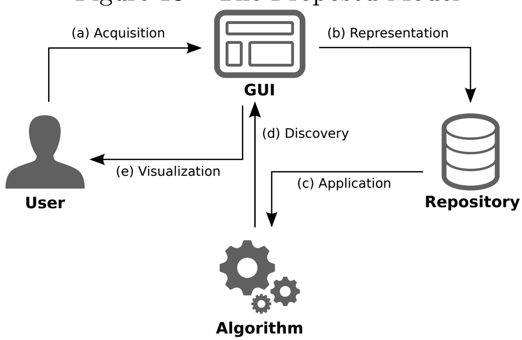
This chapter aims to present the model proposed in this thesis. A graphical representation of this model is shown in Fig. 13.

The central component of the model is the algorithm. It is the implementation of the mathematical solution proposed throughout this thesis.

The user represents the person of the residence or building who is responsible for performing the interactions with the proposed computer system. The interactions will be given by an interface, here represented as the GUI (Graphical User Interface).

Each building has a data repository. The historical data of the sensor readings, estimated thermal parameters and any other necessary information for the complete operation of the proposed model should be stored in this repository. That will be presented throughout this document.

Figure 13 – The Proposed Model



Source: Author (2017)

The interactions among the components of the model are presented in the form of knowledge-based process. The processes are discussed in the following sections: (a) Knowledge *Acquisition* in Sect. 4.1, (b) Knowledge *Representation* in Sect. 4.2, (c) Knowledge *Application* in Sect. 4.3, (d) Knowledge *Discovery* in Sect. 4.4 and (e) Knowledge *Visualization* in Sect. 4.5.

4.1 KNOWLEDGE ACQUISITION

The knowledge acquisition is the first knowledge-based process proposed in this model. This process intends to provide end user the access to an interactive environment. This access must be easy to use and able to ensure to the next processes the necessary information and knowledge about the building.

In this process of elicitation the goal is to collect the residential user internal temperature preferences (Sec. 4.1.1), building floor composition (Sec. 4.1.2), the sensors measurements as well as the visualization of its reports. The knowledge *visualization* process is presented in more details in Sect. 4.5.

4.1.1 Temperature Preferences

The internal temperature preferences are collected as part of the knowledge acquisition process from the home users. This is done only once, but it can be changed at any time and it is stored in a repository.

In this first interaction, the user must inform to the system, for each hourly slot, the desired internal temperature. These data will then be used to calculate the *thermal comfort*. This is the generation of the day-ahead *internal temperature* plan proposed to the household user at the end of the whole model.

4.1.2 Building Floor Plan

The building floor plan composes an essential information to this model. This is what justifies the need for an user interaction interface. This is essential because from the information about the position of the rooms in a building, the walls between them, the positioning of the sensors and the heat pumps as well as the existence of solar gain in certain rooms, the thermal parameters of these environments will later be calculated. So, this process assists the thermal parameter identification process by providing all building features.

Having acquired the knowledge necessary to proceed with the aim of this model it is necessary to represent this knowledge as it is presented in Sect. 4.2.

4.2 KNOWLEDGE REPRESENTATION

The knowledge representation process is understood as the *explicitation* of the knowledge collected from the home user. It occurs by transforming the collected knowledge into a standard format to be used in the following steps of this model, that is, the thermal parameter identification stage.

4.2.1 Representing Zone Features

The first stage of the representation is to differentiate each zone of a building and its features. To this end, a method using different colors is proposed in this work.

The colors help the process of identifying and checking the features of each zone. This stage generates important information for the later stages as: the existence of heat pumps, temperature sensors and solar influence in the rooms.

4.2.2 Representing the Relationship Between Zones

Having the graphical representation of the rooms in the building and its features, everything was duly verified by visual means. After that, the stage of graph-knowledge-representation was started. The purpose of it is to interpret the floor plan into a graph.

In this proposed representation, each zone in the building is being interpreted as a graph node that can be applied in a programming language as an *object*. Each node can establish a relationship with the others (internal walls).

After representing the building into a graph, it is suggested that such information must be stored into a repository. This procedure is presented in Sect. 4.2.3.

4.2.3 Representing Nodes into a Repository

In the last step of the knowledge representation process, it is proposed the representation by graphs that can be stored into a database. The repository should contain information about the features of the rooms informed by the users, the relationships between the rooms of the house and the users preferences.

This repository should enable recording of sensor measurements and results obtained in the thermal parameter estimation steps. Such a repository can also be used for the expansion of this model in collaborative networks, estimation of consumption and user profile by district as well as reuse of data by the same user in different buildings. These possibilities are dealt with in Sec. 7.2.

4.3 KNOWLEDGE APPLICATION

At this stage, the knowledge application is proposed as a symbolic use of data and information that is captured and represented in the earlier stages of the model in order to provide subsidies for the next step of knowledge discovery.

In this thesis, the knowledge application is used to refer to the electrical-thermal analogy where the knowledge is applied in order to obtain the thermal parameters of a building. This analogy allows representing a house heating behavior using electrical circuits.

The output data is sent to the repository, and from this process, the measurements from sensors must have the same time interval among them. Once the thermal parameters were identified, it is possible to move to the next step: knowledge discovery (Sect. 4.4).

4.4 KNOWLEDGE DISCOVERY

The process of knowledge discovery blending KDD and computational mathematical model as it is proposed in this work is represented in the model as an *algorithm*.

The knowledge discovery process proposed in this model is divided into two parts. The first Section 4.4.1 concerns to estimate the thermal parameters in the house. These parameters are stored into the repository and then will later be used, in the second step, to generate the day-ahead internal temperature plan as it is presented in Sect. 4.4.2).

4.4.1 Thermal Parameter Identification

Identification of thermal parameters is important for this model because it provides significant elements for understanding the heating behavior of each house individually. The parameters identified in this model are thermal resistance $\boldsymbol{R}$ and thermal capacitance $\boldsymbol{C}$. Besides these parameters also the heat pumps coefficient performance - COP (η) as well as the *U-value* are calculated.

4.4.2 Internal Temperature Plan Generation

The main purpose of the day-ahead temperature plan is to offer to the end user a schedule table for the next day internal temperature. The purpose of this generation of internal temperatures table is to provide to the end user a non-invasive method. That is, the intent of the model is not acting directly on heat pumps, as controllers, but suggesting economic use profiles.

The plan generation takes into account the weather forecast for the day ahead, the estimated cost of CO_2 emissions and the estimated the electricity cost. All of those forecasts are obtained by the same time slot and for the specific district where the analyzed house is located.

The generated plan focuses on maintaining the *thermal comfort* reducing the consumption of electricity. Thermal comfort is calculated based on the values of internal temperature which were obtained from the household user in the knowledge acquisition process.

4.5 KNOWLEDGE VISUALIZATION

This last phase of the model, known as the Knowledge Visualization, aims to provide information to the end users in order to give them greater knowledge about the dynamics of their own house. The main objective of this process is to provide, in the same interface used as knowledge acquisition process (a), visualization of the results generated by the algorithms as well as other graph analysis.

There will basically be three types of information: the day-ahead *internal temperature plan*, *performance analysis* and *comparative graphs* with the performance of the neighbors. They are presented in the next sections.

4.5.1 Internal Temperature Plan

The internal temperature plan consists in a schedule table on which the user will find the exact value of internal temperature that must be programmed in the heating device for each hour of the next day.

4.5.2 Individual Performance

In this set of graphics the household users can find relevant information only from their personal consumption or savings, i.e. only their homes. Graphics and its features are described below:

1. *Individual Daily Power Consumption:* it shows the typical daily profile of the heat pump power consumption. In particular, it shows average (standard deviation), minimum and maximum values on the whole period for each day of the selected period.

2. *Individual Hourly Power Consumption:* it shows the typical hourly profile of the heat pump power consumption. In particular, it shows average (standard deviation), minimum and maximum values on the whole period for each time-slot of the day.

3. *Individual Energy Cost:* it shows the typical monthly profile of the energy cost. In particular, it shows the values on the whole period for each day in a selected month as well as the average during the selected month.

4.5.3 Comparative Performance

In this another set of graphics, the household users can check the data on their own consumption as well as from their neighbors in a comparative way. The purpose of these graphs, in a future work, is to provide an environment in which the users are encouraged to use the internal temperature suggested plan and to generate feedback performance or potential problems to developers. The proposed graphs and reports are:

1. *Comparative Daily Power Consumption:* it shows the typical daily profile of the heat pump power consumption for each user, highlighting the household user consumption. In particular, it shows average (standard deviation), minimum and maximum values on the whole period for each day of the selected period.

2. *Comparative Hourly Power Consumption:* it shows the typical hourly profile of the heat pump power consumption for each user, highlighting the household user data. In particular, it shows average (standard deviation), minimum and maximum values on the whole period for each time-slot of the day.

3. *Comparative Energy Savings by Period:* it shows the typical monthly profile of the energy cost for each user, highlighting the household user data. In particular, it shows the values on the whole period for each day and for each user in a selected month as well as the average during the selected month of all household users.

To be able to offer this graphics class, it will be required that the model can be expanded. That is, it will would allow an external connection between the private databases of users. For this, the household users will have a configuration option in their web environment where they can set whether or not to share their information with the neighbors.

Once selected this option to share data with the neighbors, the home users will be informed about the treatment of political and security of their information. The other household users, the neighbors, will not be identified as a matter of privacy of information. This process is presented by Preissler, Gonçalves e Fernandes (2016).

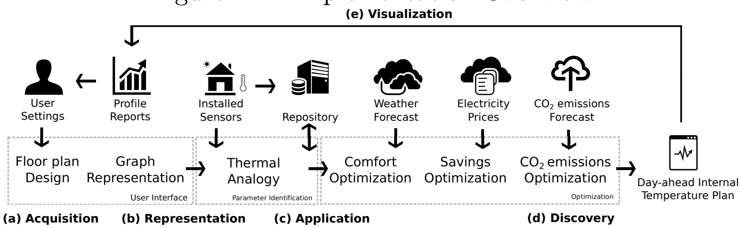
5 MODELING AND IMPLEMENTATION

In this thesis the proposed model is implemented as a computational tool. In this chapter implementation and modeling of GUI, algorithm and repository are detailed.

This chapter establishes, as a main goal, presenting propositions for the implementation of the model and how it was modeled. Still in this chapter the development of the mathematical model proposed for the identification of the thermal parameters as well as the generation of the internal temperature plane will be presented.

The model implementation overview is presented in Fig. 14. In the image it is possible to identify the knowledge-based process in each stage of the model. Throughout this chapter this figure will be explained in detail using as reference the knowledge-based processes from *(a)* to *(e)*.

Figure 14 – Implementation Overview



Source: Author (2017)

The knowledge *acquisition* occurs with the first interaction with the home users, which in turn informs the system the composition of their home, through an interactive floor plan. Later this knowledge is represented by means of graphs and it is stored in the database of the user.

The knowledge *representation* also occurs when using the electro-thermal analogy for the identification of thermal parameters. The identification of the thermal parameters is based on the historical data of each building coming from the sensors installed in them.

Once the thermal parameters are identified, the knowledge is *applied* to the subsequent process of knowledge *discovery*, where the mathematical model, through a computational algorithm generates the internal temperature plan for the building.

The data is sent to the same interface in which the home users can *view* this generated information as well as they can access the graphs related to their energy consumption profile.

5.1 KNOWLEDGE ACQUISITION

The objective of the implementation in this process is to offer to the final users an intuitive and functional environment as well as a reliable and personal web-based application system that aims to collect their preferences and building features. The process is assisted by means of a "step-by-step" system in which a wizard helps the user with *questions-to-action*.

In this process two types of information are requested from the household users: the internal temperature preferences by hourly range and the composition of the floor plan of their building containing its respective features. Other information such as: internal temperature, external temperature and consumption of heat pumps are collected through sensors previously installed in the building.

5.1.1 Internal Temperature Plan

In this first interaction, the user must inform to the system, for each hourly slot, the desired internal temperature. An hypothetical example of the Internal Temperature Preferences can be seen in Tab. 2.

Table 2 – Example of an Internal Temperature Preferences

Hour	Temperature
00:00	23.0
01:00	23.0
02:00	23.0
⋮	⋮
21:00	24.0
22:00	24.0
23:00	25.0

Source: Author (2017)

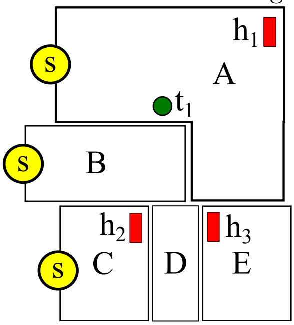
5.1.2 Building Floor Plan

This information is gathered, from the household user by means of a system, to make the process of representing floor plans intuitive and interactive using a responsive design. Both the collection of information about internal temperature preferences as well as the composition of the floor plan can be reported not necessarily by the home user but by another agent, such as an installation technician.

At this stage, the end user must inform, using a web-based system, for instance, in which there is the possibility of drawing the floor plan of the house through a *drag and drop* web application. The *drag and drop* is a proposition in that it makes designing the floor plan faster, intuitive and pleasing to the end user. However, as a proposition within the model one can choose to use another method. The important about this knowledge-based process is to collect the data presented in Fig. 15

In this hypothetical example of a multi-zone building, the letters *A, B, C, D* and *E* represent the zones of a building. Those rooms which have external solar influence, (sunlight) are signed by a yellow circle (S). In this building representation, the heat pumps are represented by h_1, h_2 and h_3 whereas the temperature sensor is represented by t_1.

Figure 15 – Multi-zone Building Example



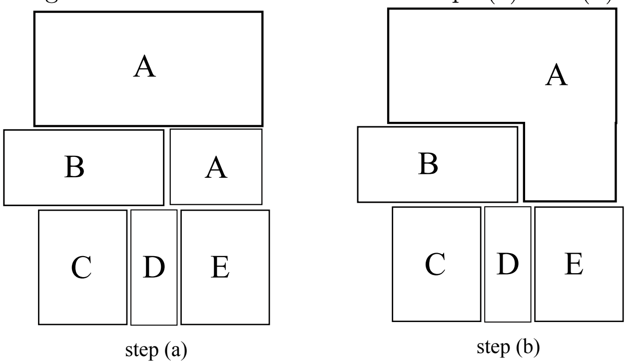
Source: Preissler, Gonçalves e Fernandes (2016)

In the step-by-step process of knowledge acquisition, the household users are invited to draw their own house or building, by means a web-based system. To draw the floor plan, an interface in which the user can draw simple frames (squares) into the screen, as exampled in Fig. 16 step (a) is proposed. In this first process, the household user needs to inform the quantity of rooms and their intersections will be labeled automatically by the system.

Once the squares are drawn into the interface, the user needs to inform which frames are included in the same space, here referred to as *open spaces*, rooms in which there are no walls between them. One example can be observed on Fig. 16 step *(b)*. Through the image it is possible to identify when comparing with *(a)*, that the room A is, actually an open-space room. It is proposed that the process of *connection* between squares, which intends to generate open-spaces areas occurs by a simple sequence of *clicks* on the squares.

After informing the floor plan composition and the open-spaces areas, the user is invited to inform the features of each

Figure 16 – Floor Plan Features - steps (a) and (b)



Source: Preissler, Gonçalves e Fernandes (2016)

room. These features are related to the existence of heat pumps, *heaters* and/or temperature sensors *thermostats* as well as the rooms receive solar influence - *sunlight*.

At the end of this process, the household is asked to check all the features and if all squares are well placed, especially the walls (connections) between them.

5.2 KNOWLEDGE REPRESENTATION

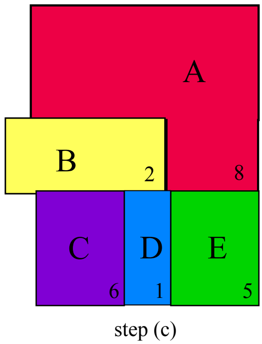
In this thesis three types of knowledge representation are proposed. The first of them is the visual representation of the floor plan of the house using colors that aims to facilitate the final check of the information offered by the home user. The second uses the graph theory to establish relationships between the rooms of the house. The latter aims to represent the information collected in the format of an ontology which in turn can be applied to a data repository. All these types are presented in the following sections.

5.2.1 Representing Zone Features

In order to offer an intuitive and *friendly* interface the use of a set of colors is proposed in order to distinguish the different features of each room. This is achieved by using different RGB (Red, Green, Blue) color patterns, which were selected due to their good visual contrast, as can be seen in Tab. 3.

In Fig. 17 step (c) it is possible to verify the application of the proposed color pattern following the precedent example. That is, depending on the features each room presets a different color. The numbers are related to the *Id.* column from Table 3.

Figure 17 – Floor Plan Features - step (c)



Source: Preissler, Gonçalves e Fernandes (2016)

Table 3 presents the proposed structure of colors for each possible zone features. In column *RGB* an Red, Green, Blue codes of system of colors (Co) is proposed for each possible combination of *Heater* (He), *Thermostat* (Th) and *Solar gain* (SG). The numbers 0 and 1, respectively, stand for “not having” and “having”.

Table 3 – Proposed Classification by Zone Features

Id.	**RGB**	**Co**	**He**	**Th**	**SG**
1	(000,132,255)		0	0	0
2	(255,255,092)		0	0	1
3	(172,147,147)		0	1	0
4	(128,132,000)		0	1	1
5	(000,212,000)		1	0	0
6	(128,000,212)		1	0	1
7	(000,128,128)		1	1	0
8	(237,000,069)		1	1	1

Source: Preissler, Gonçalves e Fernandes (2016)

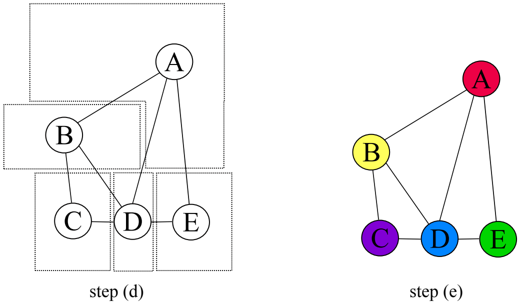
5.2.2 Representing the Relationship between Zones

An undirected graph $G = (V, E)$ describes the thermal relationship among building zones in terms of a node set $V = \{1, ..., n\}$ and edge set $E \subset \{V \times V\}$ (GOYAL; LIAO; BAROOAH, 2011).

In this representation each node in the set V corresponds to a variable which must be represented by a zone. In a situation where the nodes u and v have thermal connection between them as, for instance, a wall, it can be assumed that there is an edge between u and v: $(u, v) \in E$. The edges represent the heat transfer through the walls, between the zones (nodes).

In Fig. 18 step (d) it is possible to verify the hypothetical example of a building using graph representation. In step (e), the graph is represented also using the set of color patterns proposed. This method offers a different alternative for visual checking the information provided by the user. The colors codes are the same used in Fig. 17.

Figure 18 – Floor Plan Features - steps (d) and (e)



Source: Preissler, Gonçalves e Fernandes (2016)

5.2.3 Representing Nodes into a Repository

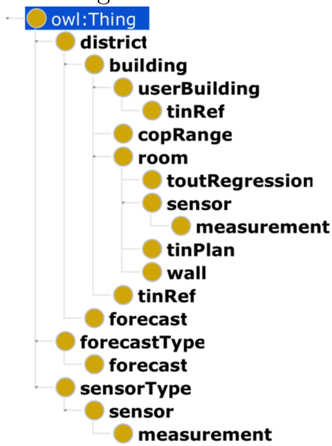
At this stage it is suggested to use a repository to perform all information collected and generated. All the information and data which are necessary for the operation of this model are proposed in this section in the form of an ontology by means of representational primitives. The classes are presented in Fig. 19.

The attributes, as object and data properties are presented in Fig. 21 and Fig.22 respectively. The relationships, that is, the relations among class members are presented by Fig. 20. For the ontology representation Web Ontology Language (OWL) in Protégé software v.5.2.0 (MUSEN, 2015) was used .

The *building* class is contained in a *district*, which in turn may have several buildings. This district information is important so that the weather *forecast* (external temperature), classified by types (*forecastType*) can be obtained, for example by regions as well as it can allow comparative analysis of performance by neighborhood.

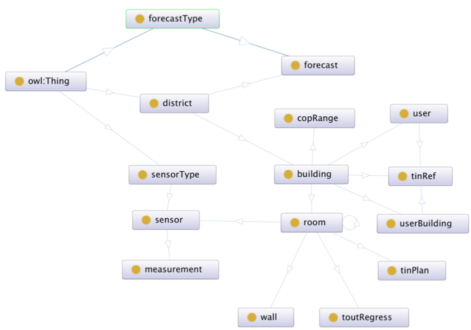
The *userBuilding* class refers to the home users who can manage more than one building. In this case the buildings in-

Figure 19 – Classes



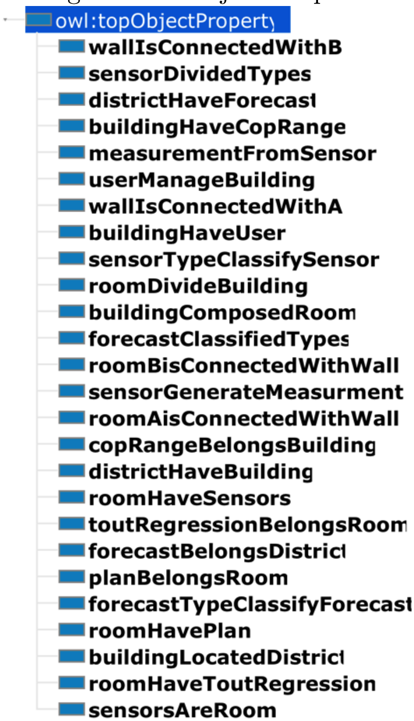
Source: Author (2017):

Figure 20 – Classes Relationship



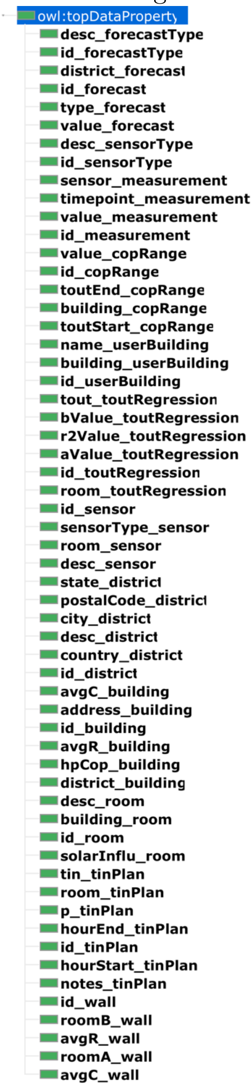
Source: Author (2017):

Figure 21 – Object Properties



Source: Author (2017):

Figure 22 – Data Properties



Source: Author (2017):

ternal temperature preferences (*tinRef*) are also related to it.

Each building may have one or more rooms. These, in turn may be related to each other (*walls*). For each room the thermal parameters are estimated as well as the relation between the COP and the external temperature (*toutRegression*).

For each room one or more sensors (*sensor* class), classified by types (*sensorType*) may be installed and in turn generate *measurements*. For each room containing a heat pump it is possible to have, for each day, an internal temperature plane (*tinRef*).

5.3 KNOWLEDGE APPLICATION

The following sections offer an explanation on how the electro-thermal analogy is applied in this work as well as the use of this analogy in a multi-zone building context. More details on such analogy in multi-zone environments can be found in Appendix 8.1 and Fig. 58.

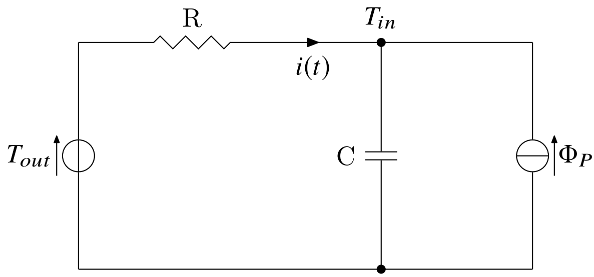
5.3.1 Thermal Electrical Circuit

In order to understand the dynamics of heating a dwelling is necessary, before identifying the heating parameters. In this thesis it refers specifically to Thermal Resistance R and Thermal Capacitance C. Such a step is called thermal parameter identification.

The parameter identification uses thermal-electrical analogy, according to which a room to be heated can be represented by a RC (resistor-capacitor) electronic circuit. By using this analogy it is possible to estimate R and C.

In order to analyze the thermal behavior of a residence and to analyze the mathematical functions used in the circuit, it is first necessary to analyze a single zone. The proposed RC electrical circuit is presented in Fig. 23 and it shows the equivalent model of one specific room. It is assumed that the total amount of necessary energy to heat this room is from T_{out} and also from the power Φ_P.

Figure 23 – Circuit House Thermal Model for One Room



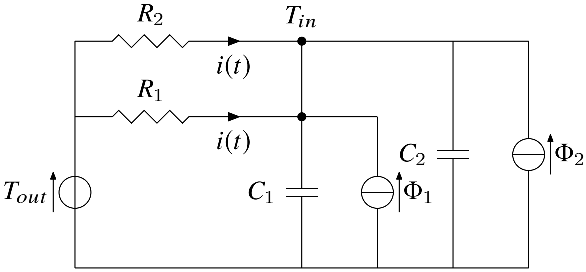
Source: Author (2017)

For this thesis the overall thermal resistance of the house envelope is represented by R, the overall thermal capacitance is represented by C, internal and outdoor temperatures are T_{in} and T_{out} and the heat pump power is P. The terms, definitions, symbols and units used in this thesis follow the standards from ISO 9869-1:2014 (BS, 2014).

Fig. 24 shows a proposed RC representation for a situation in which is possible to identify two zones in a house. In this case, the total heat generated inside the house comes from two heat pumps (Φ_1 and Φ_2) and from the outdoor temperature T_{out}.

Using the electrical-thermal analogy, an RC circuit representation is proposed based on the graph representation. Each zone i connected through a wall with another room j is associated with one Capacitor C_{ij} and one Resistor R_{ij}. A Current Source I_i is included in each room i which has a heater. The same way, a Voltage Source V_j is included in each room j which has sunlight. Similarly, each room i with a thermostat is associated to a Voltage "point" T_i next to the corresponding capacitor for that room C_i. The thermal behavior of the building can be

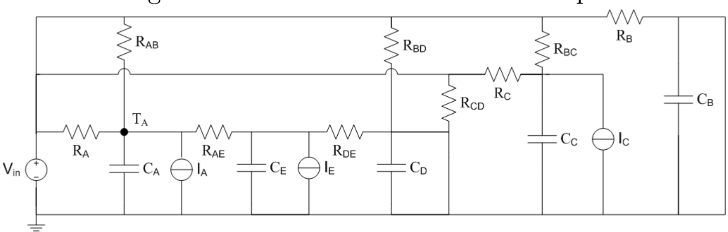
Figure 24 – Circuit House Thermal Model for Two Rooms



Source: Author (2017)

inferred from the behavior of the electrical circuit using the same parameters. Fig. 25 shows an RC circuit based on the example of Fig. 15.

Figure 25 – Thermal RC Circuit Example



Source: Preissler, Gonçalves e Fernandes (2016)

Once the thermal electrical analogy is modeled, it is necessary to obtain the data for the thermal parameter estimation. The data obtained from the sensors often have different reading ranges between measurements. This can occur because they are from different manufacturers or, as is the case with the experiments of this thesis, obtained from a pre-existing database, here called historical data. For cases like this, Sect. 5.3.2 presents a proposition for the normalization of this data.

5.3.2 Data Normalization

It is important to note that the calculation of thermal parameters is given primarily on the basis of historical data measurements. That is, the building should have had sensors installed for internal and outdoor temperature as well as for heat pump power consumption. The data should be stored in a repository over time. Often, such readings generated by the sensors do not have a single standard and even the interval between readings is not constant. For this reason there must be a process of *data normalization*. The proposition is that the measurements obtained from each sensor have the following format:

$Timepoint, Value$
$DD/MM/YYYYHH : MM : SS, 0.00$

The main objective of this normalization is that it could apply an *interpolation* among the data points grouping in a repository record all measurements taken at the same *timepoint*. It is needed to maintain a constant interval *timepoints* in the repository records. This interpolation occurs on the historical data of measurements of each house.

The proposed Interpolation Algorithm 5.1 is responsible for reading the repository file, interpolates *timepoints* T at time t, internal and outdoor temperatures $T_{in}(t)$ and $T_{out}(t)$. The Heat Pump Power $P(t)$ is also used here.

Algorithm 5.1 calculates the time difference m between $(t+1)$ and (t). After that, the rate between the values P, T_{in}, T_{out} and m is calculated and added to the values at time $(t+i)$. The interpolated output data format file is presented below:

$Timepoint, Power, Tin, Tout$
$DD/MM/YYYYHH : MM : SS, 0.00, 0.00, 0.00$

Algorithm 5.1 Interpolation Algorithm

Require: $repository\_file(P, T_{in}, T_{out})$

read $T(t)$ and $T(t+1)$
read $P(t)$ and $P(t+1)$
read $T_{in}(t)$ and $T_{in}(t+1)$
read $T_{out}(t)$ and $T_{out}(t+1)$
$m\,(\leftarrow T(t+1) - T(t))$
read $r_P \leftarrow (P(t+1) - P(t))\,/m$
read $r_{Ti} \leftarrow (T_{in}(t+1) - T_{in}(t))\,/m$
read $r_{To} \leftarrow (T_{out}(t+1) - T_{out}(t))\,/m$
for i =1 to m **do**
    $T(i) += T(t+i)$
    $T_{in}(i) += r_{Ti}$
    $T_{out}(i) += r_{To}$
    $P(i) += r_P$
    return $T(i), P(i), T_{in}(i), T_{out}(i)$
end for

5.4 KNOWLEDGE DISCOVERY

Once the measurements of the sensors have been obtained and normalized, having the data of the composition of the floor plan of the building it is possible to begin the process of discovery of knowledge. In this thesis such process is related to the identification of the thermal parameters and with the generation of day-ahead internal temperature plan.

5.4.1 Computing Thermal Parameters

The parameter identification values are given based on the thermal-electrical analogy. Therefore the obtained analog electric circuit equations are applied to calculate the parameters. In this section it is described how the equations obtained from the RC circuit Ordinary Differential Equations (ODEs) from the thermal electrical analogy were applied.

Starting from the room model circuit (Fig. 23), applying the thermal-electrical analogy and Kirchhoff's Oldham (2008) circuit laws it is possible to obtain the Eq. 5.1 where V_{in} represents the total voltage as result of the sum of voltage across the resistor V_R and the voltage across the capacitor V_C.

$$V_{in} = V_R + V_C \tag{5.1}$$

After that, the Ohm's law (SCHAGRIN, 1963) was used. That means the current through a conductor between two points is directly proportional to the voltage across the two points (MILLIKAN; BISHOP, 1917). Applying this law in Eq. 5.1, it was obtained Eq. 5.2.

$$V_{in} = Ri + V_C \tag{5.2}$$

Understanding that the current through the capacitor is equal to the derivative of the voltage which passes through itself over time, Eq. 5.3 is obtained.

$$V_{in} = RC\frac{dV_C}{dt} + V_C \tag{5.3}$$

Where V_{in}, V_R and V_C are respectively voltages (analog) from: outdoor temperature T_{out}, through resistor $i(t)$ and through capacitor T_{in}. So Eq. 5.4 is presented.

$$T_{out} = Ri(t) + T_{in}(t) \tag{5.4}$$

Starting from Eq. 5.4, and isolating the derivative of T_{in} it is possible to obtain Eq. 5.5.

$$\frac{dT_{in}}{dt} = \underbrace{-\frac{1}{RC}}_{\alpha} T_{in}(t) + \underbrace{\frac{T_{out}}{RC} + \frac{\eta P}{C}}_{u(t)} \tag{5.5}$$

Being this a differential equation containing one or more functions of one independent variable and its derivatives the Ordinary Differential Equation (ODE) α and $u(t)$, from Eq. 5.5 where used to solve it.

$$\frac{dT_{in}}{dt} = \alpha T_{in}(t) + u(t) \tag{5.6}$$

To solve ODE it was assumed that $T_{in}(t)$ has the following form:

$$T_{in}(t) = Ae^{\alpha t} + B \tag{5.7}$$

Thus,

$$\frac{dT_{in}(t)}{dt} = A\alpha e^{\alpha t} \tag{5.8}$$

By substituting Eqs. 5.7 and 5.8 in Eq. 5.6 it is possible to obtain:

$$A\alpha e^{\alpha t} = \alpha \left(Ae^{\alpha t} + B\right) + u(t) \tag{5.9}$$

Therefore, from Eq. 5.9 it possible to B as Eq. 5.10:

$$B = -\frac{u(t)}{\alpha} \tag{5.10}$$

Once B is obtained, A could be found (substituting Eq. 5.10 in Eq. 5.7):

$$A = T_{in}(0) + \frac{u(0)}{\alpha} \tag{5.11}$$

Coming back to Eq. 5.7 and substituting A and B found in Eqs. 5.11 and 5.10, $T_{in}(t)$ can be presented as Eq. 5.12.

$$T_{in}(t) = \left(T_{in}(0) + \frac{u(0)}{\alpha}\right) e^{\alpha t} - \frac{u(t)}{\alpha} \tag{5.12}$$

By expanding back $u(t)$ and α (defined in Eq. 5.5), $T_{in}(t)$ can be defined as Eq. 5.13.

$$T_{in}(t) = T_{out}(t) + [T_{in}(0) - T_{out}(0)]\, e^{-\frac{t}{RC}} + R\eta \left[P(t) - P(0)e^{-\frac{t}{RC}} \right] \tag{5.13}$$

Moving the notation with *present* and *next state* variables, where next state variables are primed, the Eq. 5.14 is obtained. In one interval $[0, t]$ that it is considered (of length τ), $P(t)$ and $T_{out}(t)$ will be constant and equal to $P(0)$ and $T_{out}(0)$ respectively. In that case the Eq. 5.14 expresses the final equation to obtain $T_{in}(t + 1)$.

$$T'_{in} = T_{out} + [T_{in} - T_{out}]\, e^{-\frac{t}{RC}} + R\eta \left[P - Pe^{-\frac{t}{RC}} \right] \tag{5.14}$$

From Eq. 5.14 it is possible to find the unknown components, here called *thermal parameters* such as: resistance (R), capacitance (C) and Coefficient of Performance - COP (η).

In order to compute R and C separately, the model starts estimating product of $\overline{RC}$ presented in Sect. 5.4.2. After that it is possible to compute R (Sect. 5.4.3) and C (Sect. 5.4.4) separately. Further η and *U-value* can be obtained as it is presented in Sections 5.4.5 and 2.2.2.3.

The computation process starts taking into account that τ is the time step fixed to one minute, i.e. $\tau = \frac{60}{3600} = \frac{1}{60}$ secs as well as T_{in}, T_{out}, and P are obtained from historical measurements.

5.4.2 Computing the Resistance and Capacitance Average Product - $\overline{RC}$

Assuming that the Heat Pump is turned off ($P = 0$), the product RC is estimated in the whole one minute interval. So Eq. 5.14 can be present as Eq. 5.15

$$T'_{in} = T_{out} + [T_{in} - T_{out}]\, e^{-\frac{t}{RC}} \tag{5.15}$$

Starting from Eq. 5.15 and assuming $T_{in} - T_{out} \neq 0$, RC can be obtained as Eq. 5.16.

$$RC = \frac{\tau}{\ln\left(\frac{T_{in}-T_{out}}{T'_{in}-T_{out}}\right)} \tag{5.16}$$

The product RC is estimated for all N available intervals and then their average is calculated. By denoting with $T_{in}(i)$ the internal temperature at i-th interval and with $T_{in}(i+1)$ the internal temperature at $i+1$-th interval, that is T'_{in}, Eq. 5.17 can be used:

$$\overline{RC} = \tau \frac{1}{N} \sum_{i=1}^{N-1} \frac{1}{\ln\left(\frac{T_{in}(i)-T_{out}(i)}{T_{in}(i+1)-T_{out}(i)}\right)} \tag{5.17}$$

Since the value of $\overline{RC}$ is known then it is possible to estimate the value of R. The calculation process for this step is shown in Sect. 5.4.3.

5.4.3 Computing the Thermal Resistance - *R*

For this thesis, the average of overall thermal resistance of the house envelope is represented by $\overline{R}$. In this work, the R value comprises the sum of all possible resistances existing within the envelope (internal and external air resistance, layers of the walls, objects, etc.).

To compute R it was necessary to establish T_{in} in *steady-state*, simulating in this way a constant R value. It is presented in condition (a) where $\beta = 0.002[\circ\mathrm{C}]$ was used in this study. Considering η as the coefficient of performance of a heat pump and, beyond the amount of the electric power applied, it pumps external heat to the envelope. It can be considered, in condition (b), that when the outside temperature is less than or equal to zero then the heat from outer space is not being pumped. Therefore the heat pump is working at 100% capacity, ie $\eta = 1$.

Conditions to calculate R:

a) $\{T_{in} \in T_{in}(0, \ldots, t-1) \mid$
$(|T_{in}(t) - T_{in}(t+1)| < \beta) \wedge$
$(|T_{in}(t) - T_{in}(t-1)| < \beta)\}$

b) $\{\eta = 1 \mid T_{out} \leq 0\}$

Starting from Eq. (5.14) and using $\overline{RC}$ it is possible to compute R as Eq. 5.18 when T_{in} is in a *steady-state* and $\eta = 1$ with $T_{out} \leq 0$:

$$R = \frac{T'_{in} - T_{out} + [T_{out} - T_{in}]\, e^{-\frac{\tau}{\overline{RC}}}}{\eta\left[P - Pe^{-\frac{\tau}{\overline{RC}}}\right]} \tag{5.18}$$

After that it is possible to compute R for all N available intervals and then average on them thus obtaining Eq. 5.19.

$$\overline{R} = \frac{1}{\eta}\frac{1}{N}\sum_{i=1}^{N-1} * \left(\frac{T_{in}(i+1) - T_{out}(i) + [T_{out}(i) - T_{in}(i)]\, e^{-\frac{\tau}{\overline{RC}}}}{\left(P(i) - P(i)e^{-\frac{\tau}{\overline{RC}}}\right)}\right) \tag{5.19}$$

Since the value of $\overline{RC}$ and $\overline{R}$ is known then it is possible to estimate the value of C. The process to obtain C is presented in Sect. 5.4.4.

5.4.4 Computing the Thermal Capacitance - *C*

Thermal capacitance is related to the ratio of the amount of heat energy transferred, that is added to or removed from an envelope, resulting in a temperature change. In the present study, the average of overall thermal capacitance is represented by $\overline{C}$.

Since turning on a heat pump, the environment does not reach the desired temperature immediately but rather in a function of time, the C value expresses this physical property.

The thermal average capacitance $\overline{C}$ can be obtained from $\overline{RC}$ (Eq. 5.17) and from $\overline{R}$ (Eq. 5.19).

$$\overline{C} = \frac{\overline{RC}}{\overline{R}} \tag{5.20}$$

Once the values for $\overline{RC}$, $\overline{R}$ and $\overline{C}$ are found, it is possible to estimate the value of the heat pump coefficient of performance. The process for calculating the COP is shown in Sect. 5.4.5.

5.4.5 Computing the Coefficient of Performance - η

The Heat Pump Coefficient of Performance η can be obtained starting from Eq. 5.14:

$$\eta = \frac{T'_{in} - T_{out} - (T_{in} - T_{out})\, e^{-\frac{\tau}{\overline{\overline{RC}}}}}{\overline{R}\left(P - Pe^{-\frac{\tau}{\overline{\overline{RC}}}}\right)} \tag{5.21}$$

Having the general η equation (Eq. 5.21) it is proposed in this thesis that η should be calculated through the use of ranges. These twelve ranges are defined in relation to the outdoor temperature T_{out} and they can be expressed by the following cases:

1) $T_{out} < 0$

2–11) $\forall\ To \in \{0, \ldots, 9\}$: $To \leq T_{out} < To + 1$

12) $T_{out} \geq 10$

For each one of the twelve cases above the formula in

Eq. (5.21) was applied only to those time points where the corresponding formula holds. Algorithm 5.2 shows the steps used in the $\overline{\eta}$ calculation.

Algorithm 5.2 Compute $\eta(T_{out})$

Require: P, T_{in} and T_{out} have N time-slots, from 0 to $N-1$ {ranges are as described in 5.4.5}

1: **for** $r \leftarrow 0$ to 11 **do**
2:     $C(r) \leftarrow 0$
3:     $\eta(r) \leftarrow 0$
4:     **for** $t \leftarrow 1$ to $N-2$ **do**
5:         **if** $(P(t-1) > 0$ and $P(t) > 0$ and $P(t+1) > 0$ and $|P(t) - P(t+1)| \leq \gamma$ and $|P(t) - P(t-1)| \leq \gamma)$ **then**
6:             $x \leftarrow \frac{T_{in}(t+1) - T_{out}(t) - (T_{in}(t) - T_{out}(t))e^{-\frac{\tau}{RC}}}{R\left(P - Pe^{-\frac{\tau}{RC}}\right)}$
            {let r be index of range where T_{out} falls}
7:             $C(r) + +$
8:             $\eta(r) \leftarrow \frac{x}{C(r)} + \eta(r)\frac{C(r)-1}{C(r)}$
9:         **end if**
10:     **end for**
11: **end for**
12: **return** η;

Line 1 starts the loop that will calculate the η for the twelve ranges. Subsequently, in line 4, the calculation of Î· is started for each time-slot. It is possible to verify in line 5 the conditions for the calculation that are: P positive and in state-steady. Such conditions being met it is then possible to calculate the partial η which is stored in x. At the end of the procedure, the moving average of η for each range is calculated and returned.

$$\begin{aligned} \{P \in P(0, \ldots, t-1) \mid \ & (|P(t) - P(t+1)| < \gamma) \wedge \\ & (|P(t) - P(t-1)| < \gamma)\} \end{aligned} \tag{5.22}$$

In that procedure, η represents the set of coefficient of performance for each r-th range of outdoor temperature T_{out}. The η value was calculated in a P *steady-state* as it is presented in the constraint on Eq. 5.22 where $\gamma = 0.1$[W] was defined.

5.4.6 Internal Temperature Plan

Once the thermal parameters and the coefficient of performance have been calculated, it is suggested in this thesis to create a day-ahead internal temperature plan. This plan aims to offer the end user, basically, a table of internal temperatures to be configured in their heat pumps by hourly range. In this process, reducing the amount of power consumption and ensuring thermal comfort are the prime goals.

Thermal comfort is guaranteed based on user informed internal temperature (T_{ref}) preferences. In order to allow the optimization algorithm to be more flexible in the search for results, a tolerance value *apha* was used. Doing that, it was possible to generates the upper and lower limits for the desired internal temperature. This procedure is also intended to reduce the upper and lower bounds between heat pump power on and off as shown in Fig. 7.

So, assuming the reference temperature obtained from the household user is $T_{ref}(t)$ for each time slot of the day $t \in \{0..23\}$, than the internal temperature calculated $\dot{T}_{in}(t)$ should be inside the tube between $T_{ref}(t) - \alpha$ and $T_{ref}(t) + \alpha$, as it is presented in Eq. 5.23:

$$T_{ref}(t) - \alpha \leq \dot{T}_{in}(t) \leq T_{ref}(t) + \alpha \tag{5.23}$$

The application of thermal comfort rule will be presented in Sect. 5.4.6.2

5.4.6.1 Power Consumption as a function of T_{out}

It is assumed that the heat generated by a heat pump comes from the sum of electric power and power generated from the external environment. It is also considered that the energy generated from the external environment is directly related to the outdoor temperature T_{out}. Finally, it is assumed that for each unit of external temperature there is a specific function for the internal temperature.

In order to figure this function out, it was necessary to calculate the ΔT_{in}. The ΔT_{in} is obtained from historical data of consumption from each house. This is the difference between the average of the next and the current internal temperature from the historical data grouped by T_{out} and the average energy consumption.

After obtaining the ΔT_{in} and its average energy consumption for each house as well as each external temperature, it is finally possible to calculate the linear regression for each house and each value of T_{out}. This calculation step is responsible for returning the values of a and b as it is shown in Eq. 5.24. In the equation it is possible to identify X as the ΔT_{in}.

$$y(T_{out}) = aX + b \tag{5.24}$$

The values of a and b are stored in the data repository and they are subsequently used in the optimization process in order to adjust the internal temperature behavior curves in relation to the external temperature oscillation. The optimization plan process is presented in Sect. 5.4.6.2

5.4.6.2 Optimization Plan

In the optimization process a preprocessing of data was made. Its purpose is to group for each house the data necessary to optimize the day-ahead internal temperature plan. In this preprocessing, information such as times of day, weather forecast (T_{out}), price of kWh per time slot, cost of CO_2 emissions for that particular time of day, values of R, C, η, T_{ref} and values for a and b is gathered.

With the information which was obtained in the preprocessing it was then possible to generate the MILP (Mixed Integer Linear Programming) files to be sent to the optimizer. For these implementation it was decided to use IBM CPLEX optimization software (CPLEX, 2009). Such decision is based on its wide use by researchers as well as the existence of license of use for the Sapienza University of Rome. In addition CPLEX is widely known for its accuracy in solving quadratic problems.

The objective function given by Eq. 5.25 is proposed to be used to optimize the internal temperature plan. Where c_i is the cost of electricity while o_i is the cost of CO_2 emissions. These values are expressed in the same unit of currency (Euro) per unit time i (hourly) $i \in \{0..23\}$.

$$\begin{gathered} Min\ J_e = A \sum_{i=0}^{23} (c_i + o_i) P_i + \\ (1 - A) \sum_{i=0}^{23} (T_{inref}(i) - T_{in}(i))^2 \end{gathered} \tag{5.25}$$

Subject to

$$\begin{aligned} T_{in}(i+1) = T_{out}(i+1) + [T_{in}(i) - T_{out}(i+1)]\, e^{-\frac{\tau}{RC}} + \\ R\eta \left[P(i) - P(i) e^{-\frac{\tau}{RC}} \right] \end{aligned} \tag{5.26}$$

$$\begin{gathered} (T_{in}(i+1) - T_{in}(i)a + b) - \\ \beta \le P(i) \le (T_{in}(i+1) - T_{in}(i)a + b) + \beta \end{gathered} \tag{5.27}$$

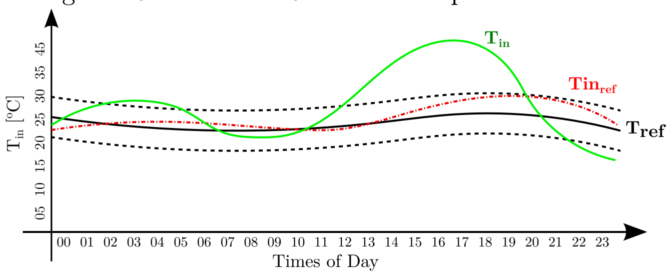
Bounds

$$T_{ref}(i) - \alpha \leq T_{inref}(i) \leq T_{ref}(i) + \alpha \tag{5.28}$$

As it is expressed by the Eq. 5.28, T_{inref} was inserted, one variable that represents a soft-constraint for the optimizer. It has the goal of ensure the thermal comfort.

As it can be seen in Fig. 26, as an hypothetical example, the soft-constraint seeks to reduce the difference between the real internal temperature and the estimated internal temperature. It gives flexibility to the optimizer which in turn aims to reduce the cost of the power consumption as a hard-constraint (Eq. 5.27).

Figure 26 – Internal Reference Temperature Bounds



Source: Author (2017)

In this graph T_{in} represents the real internal temperature that can vary its amplitude and frequency throughout the hours of a day in different unit of degrees Celsius. The T_{ref} represents the temperature reported by the user that is contained within a tube, defined by $T_{ref} + \alpha$ and $T_{ref} - \alpha$. This area comprises the possible values that T_{inref}, calculated by the optimizer, may contain.

The knowledge visualization proposed by this model essentially consists of the proposition to the end-user of the day-ahead internal temperature plan as well as the access to reports and graphs. This is proposed to be done in a simple and intuitive understanding shape.

The visualization occurs through a designed system interface. The interfaces are presented in Appendix 8.2.

5.5.1 Internal Temperature Plan

Based on the premise of non-invasiveness proposed in this thesis, there will be no direct action in the heat pumps thus guaranteeing the privacy of choice of the end users. This is the reason why it is proposed to present the day-ahead internal temperature plan by means of an interface.

Table 4 – Example of an Day-ahead Internal Temperature Plan

Hour	**Temperature**
00:00	23.0
01:00	24.5
02:00	24.0
⋮	⋮
21:00	25.0
22:00	24.0
23:00	23.0

Source: Author (2017)

In this proposition, the plan is offered in the form of a table containing the calculated temperatures for each hour of the following day. One reduced example of this output can be seen in Tab.4.

5.5.2 Reports and Charts

As part of the system interfaces in which the home user can monitor their individual performance as well as in comparison to consumers belonging to the same category of consumption were designed. The charts and reports are thus divided into- **Individual Performance** and **Comparative Performance**.

Once the knowledge-based processes and their respective modeling for implementation are discussed, Sect. 5.6 presents the modeling for the support system, the GUI component of the proposed model. This section is intended to complement the information in this chapter.

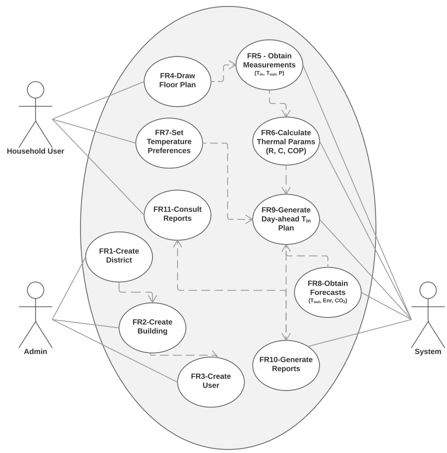
5.6 SYSTEM MODELING

The actors who must interact with the proposed computer system are the *administrator* and the *household user*. There is also the figure of actor as being the *system* itself because it performs actions for itself. In Fig. 27 it is possible to identify the actors and the actions (arrows) over the requirements (circles).

The functional requirements identified in the diagram can be further detailed in Table 5. In the table can be seen the first column as the identifier for each distinct functional requirement (FR ID). The second column shows the dependency relation between the requirements, ie if the FR01 requirement is not met, it is not possible to execute the FR02 requirement, for example. The descriptions of the requirements are related to the actions that can be executed by the actor, the actors enabled to execute each requirement are presented in the use case diagram.

The description of the requirements that are part of the system environment, that is, its suggested functionalities, is related to Non-functional Requirements (NFR) as interface and other requirements not necessarily essential for its execution are presented in the Table 6. These are propositions presented only

Figure 27 – Use Case Model



Source: Author (2017)

Table 5 – Functional Requirements

FR ID.	Dependent	Description
FR01		Create District
FR02	FR01	Create Building
FR03	FR02	Create User
FR04		Draw Floor Plan
FR05	FR04	Obtain Measurements
FR06	FR05	Calculate Thermal Params
FR07		Set Temperature Preferences
FR08		Obtain Forecasts
FR09	FR06, FR07, FR08	Generate day-ahead T_{in} Plan
FR10	FR09	Generate Reports
FR11	FR10	Consult Reports

for the present implementation, and it can be changed when a model of different form is implemented.

Table 6 – Non-functional Requirements

NFR ID.	Description
NFR01	Have an interactive and easy to use interface
NFR02	Have a responsive design
NFR03	Must store the data in local repository for security
NFR04	Should send measurements data to a remote server
NFR05	The floor plan should use the *drag-and-drop* concept

Table 7 presents the business rules (BR) associated with the functional requirements of the second column (FR). These rules are used in the creation of the ontological model of the application, later transposed to a case of relational database, proposed for this application. The rules also define the behavior of the computational system which in turn must be checked at the end of the development of the proposed support tool.

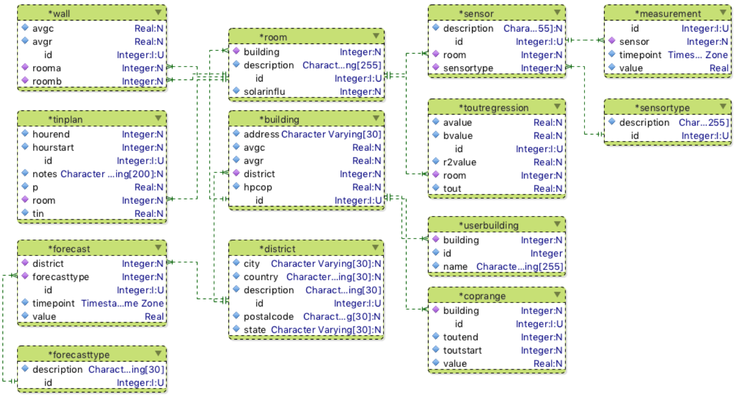
The relational database presented by Fig. 28 is proposed

Table 7 – Business Rules

BR ID.	**FR ID.**	**Description**
BR01	FR01	Each district may have one or more houses.
BR02	FR01	Each district should have a postal code (used to temperature forecast).
BR03	FR02	Each building must be associated with at least one district.
BR04	FR03	Each building must have a primary user.
BR05	FR04	The floor plan should allow the connection between rooms of the house.
BR06	FR04	Each room of the floor plan may have one or more: heaters, internal and external temperature sensors as well as the solar influence.
BR07	FR04	The connection between the rooms and the existence of elements inside or outside them must be safe in a repository using the concept of graphs.
BR08	FR05	Every minute the system must store the data of: internal and external temperature as well as the power of energy used by the heat pumps.
BR09	FR06	On a daily basis, the system must recalculate the thermal parameters: Thermal Resistance, Capacitance and Heat Pump Coefficient of Performance based on historical data.
BR10	FR07	The user can configure their internal temperature preferences based on an easy-to-use interface that will suggest the internal temperature of 24 degrees for the day's slots.
BR11	FR08	For each hourly range of the following day, the system should, through web services, search for forecasts of: hourly electricity, CO_2 emission cost and external temperature.
BR12	FR09	The system should generate a time plan (interval of one hour) of internal temperature for the following day as well as suggest it to the user.
BR13	FR10	Daily, the system should generate reports of user consumption (with the possibility of daily, monthly or annual viewing) as well as forecast of consumption for the next day.
BR14	FR11	Through a friendly interface the user can view the reports as well as access the settings and approve the consumption plan for the next day.

for the present implementation and it was obtained based on the ontological model previously presented in this thesis. Such a database model was designed to enable the application developed in order to allow the storage of experimental data in a centralized repository.

Figure 28 – Relational Database Model



Source: Author (2017)

Appendix 8.2 presents a set of *screenshot* available from the web application developed in order to interact with the final user. This process is assisted by the system through a step-by-step wizard.

6 EXPERIMENTS AND EVALUATIONS

In this chapter the experiments and evaluation results are presented. The mathematical model was developed in the form of computational algorithms with knowledge discovery bias. Such algorithms aims to estimate the thermal parameters and calculate the day-ahead internal temperature plan.

6.1 EVALUATION CRITERIA

Table 8 presents the Evaluation Criteria used in this thesis. The first column depicts to *What* is being evaluated. The second column explains *Where* positioning the evaluation criteria inside two classes: *TPI* as Thermal Parameters Identification and *ITP* as Day-ahead Internal Temperature Preferences. The third and fourth columns present the comparative object as well as the applied methods and tools. The last column (*Sect.*) references which section of this chapter the evaluation is presented.

Table 8 – Evaluation Criteria

What	**Where**	**Comparative**	**Method and Tools**	**Sect.**
R and C values	TPI	Benchmarks	NGSpice and OpenModelica	6.4.1
η values	TPI	Manufacturer and Literature	Calc. Using T_{out} Intervals	6.4.1.1
Thermal Comfort	ITP	Preferences and Historical Data	CPLEX, min. T_{inref} and T_{ref}	6.4.2.1
Energy Cost	ITP	Historical Data	CPLEX, min. Energy Costs	6.4.2.5
CO_2 Emission Cost	ITP	Historical Data	CPLEX, min. CO_2 Emission Costs	6.4.2.6

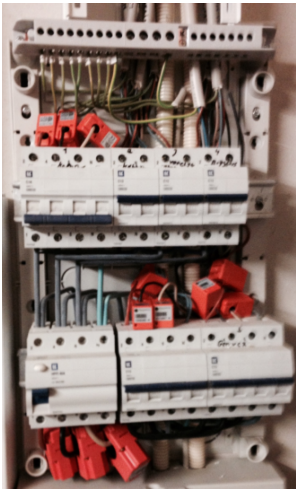
The experiments performed in this thesis are given based on historical data of measurements from sensors installed in seven homes in a period of seven months (March-October 2015) of SmartHG project. Such project is supported by the European Union's Seventh model Programme (FP7/2007-2013) under grant agreement n^o 317761 (CORDIS, 2014).

The SmartHG project goal is to develop a suite of integrated software services (the SmartHG Platform) aiming at steering residential users energy demand in order to: keep operating conditions of the electrical grid within the given healthy bounds, minimizing energy costs and CO_2 emissions. This is achieved by exploiting knowledge (demand awareness) of electrical energy consumption of residential users as gained from SmartHG sensing and communication infrastructure (ALIMGUZHIN et al., 2015).

The SmartHg project has three testbeds: Kalundborg (Denmark), Central District (Israel) and Minsk (Belarus). The Kalundborg testbed was selected to be used in this present work. This test bed consists of 98 homes several of which equipped with photovoltaic panels or a heat pump. In total there are 134 such installations connected to the substation whose transformer has a primary voltage of 10 kV, a secondary voltage of 400 V, and a nominal power of 400 kVA (TRONCI et al., 2014). Sensors, smart meters and communication devices have been deployed in 25 houses in Svebølle (Kalundborg test-bed). See Fig. 29 for an example of installed sensors (ALIMGUZHIN et al., 2015).

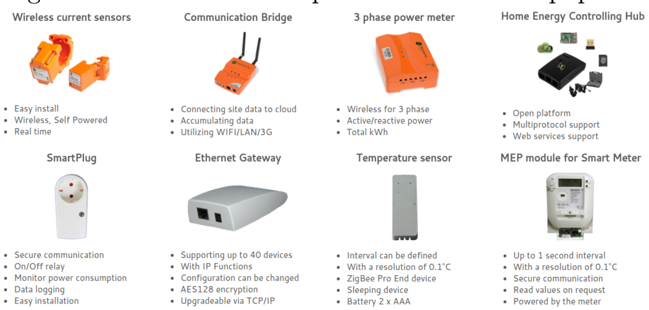
All houses in the Svebølle test-bed have sensors measuring instantaneous values for voltage and current at the main meter as well as sensors measuring inside temperatures and energy consumption for relevant appliances such as heat pump, electric oven, laundry machine, dishwasher, etc (ALIMGUZHIN et al., 2015). Fig. 30 presents the description of the sensors and equipments installed in 44 houses from the SmartHG project.

Figure 29 – Installed Sensors in Svebølle



Source: Alimguzhin et al. (2015)

Figure 30 – SmartHG compliant sensors and equipment



Source: Alimguzhin et al. (2015)

In this project, the measurements from the sensors and smart meters were sent to a repository. For the experiments, in this thesis, the internal and external temperature measurements and power consumption of the heat pumps are used.

All analyzed houses belong to the same district and have the same type of devices installed comprising sensors and heat pumps. These air-to-air heat pumps use external temperature coupled with the power energy to generate heat inside the houses.

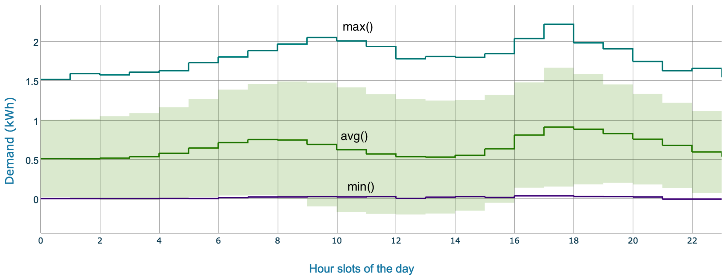
In this thesis, the measurement values used were T_{in}, T_{out} and P. Such information was available in not-standardized fixed intervals. Therefore, it was necessary to perform an interpolation process of these data in order to obtain a constant time interval. For all experiments τ is expressed in time step fixed to one minute, i.e. $\tau = \frac{60}{3600} = \frac{1}{60}$ secs.

The SmartHG users' typically daily average demand profile is presented in Fig. 31. In this context, *demand* means consumption (loads) minus production (photo-voltaic in the test-beds), both at substation and at residential level. More on definitions: *aggregated* means the sum at substation level of all single demands or consumption, while average simply means averaging on all householders connected to a substation at each hour.

This plot shows the typical daily profile of the average demand of users connected to the substation. In particular, it shows average (+/− standard deviation), minimum and maximum user average demand on the whole period for each time-slots of the day. For example, average(0) shows the average of user average demand on the whole period within the time-slot 0 of the day.

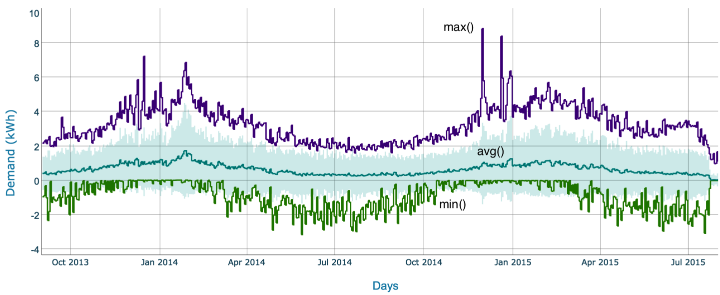
Fig. 32 shows the average demand profile, on the substation level. The chart is related to the whole period of the SmartHG project.

Figure 31 – Typically Daily Average Demand Profile



Source: CORDIS (2014)

Figure 32 – Average Demand Profile

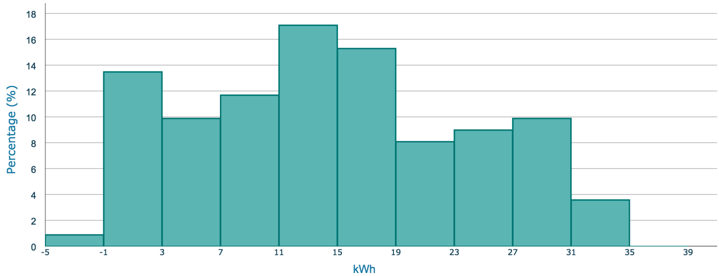


Source: CORDIS (2014)

The bar chart (Fig. 33) shows the distribution of users as for the average daily demand on the whole period. In particular, each bar represents the percentage of residential users whose average daily demand falls within a certain range of kWh. It represents the whole period.

Fig. 34 shows the distribution of users as for the annual

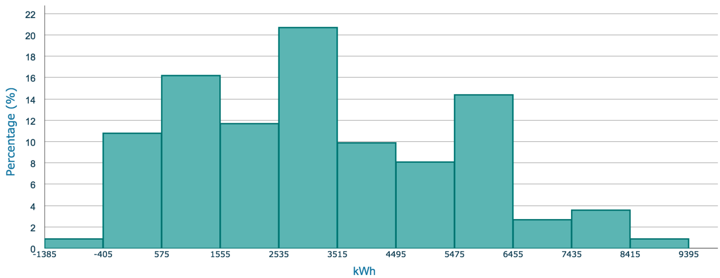
Figure 33 – Distribution of Users for Average Daily Profile



Source: CORDIS (2014)

demand. In particular, each bar represents the percentage of residential users whose annual demand falls within a certain range of kWh. it is related to the year 2015. Negative values can occur due to the production of energy by the residence (via photovoltaic panels) and that in turn, stops consuming of the substation.

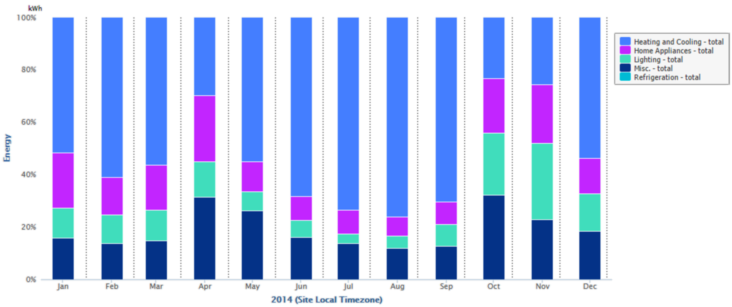
Figure 34 – Distribution of Users for Annual Energy Demand



Source: CORDIS (2014)

In Fig. 35 it is possible to identify the distribution of the annual energy usage for the SmartHG Project. The energy usage is distributed in categories like: heating and cooling (blue and superior class bar), home applications (magenta and second class bar), Miscellaneous (Misc) represented by color green and the third class bar. It is related to other devices which were not traced by the research. The last one is Refrigeration (color blue and the last class bar).

Figure 35 – Annual Usage Analysis by Category



In this chart it is visually evident that within winter and summer months the energy consumption for heating and cooling is higher than the sum of the others. In certain months of the year as from December to February and from May to September this figure exceeds 50%.

6.3 GENERAL SETUP AND TOOLS

The experiments were performed using the following portable equipment: Intel(*R*) Celeron(*R*) CPU 1005M 1.90GHz, operational system Ubuntu 14.04 64bits with 4GB of RAM.

For the mathematical model analysis, the Matlab software and Mathematica 10 were used. For the development of scripts and algorithms C++ and Python were chosen as development and script languages.

The proposed ontology in this model was implemented into a relational database system using PostgreSQL in the experiments stage. For the development and generation of internal temperature of plans the IBM CPLEX (CPLEX, 2009) optimizer was used. At the experiments stage, the Open Modelica (TILLER, 2014) software and NGSpice (NGSPICE, 2011) simulator were also used.

The motivations for choosing such technologies relied on the following criteria: volume of use by the scientific community; Ease of use and learning; Availability of use license for educational institutions and adherence to the thesis proposal.

It was decided to start implementations using NGSpice and Open Modelica. Subsequently the proposed model was fully developed in Phyton script language integrated with CPLEX. It was only in the last step that the user interface was implemented taking advantage of the functionalities already developed. The experimental results were compared with historical data obtained from the SmartHG project as well as other benchmarks from the literature.

A data set of seven houses in the same region (district) of Denmark was gathered from the SmartHG Project. The data collection period occurred within March and October 2015. The collected data is outdoor temperature T_{out}, heat pump power P, internal temperature T_{in} and Coefficient of Performance maximum value η_{max}. The η_{max} was obtained from the information of the manufacturers of heat pumps. The data was normalized using the same time-point as a reference and it was then interpolated in order to obtain a one-minute step time-point.

6.3.1 Organization of Experiment Data

In order to organize all data obtained with SmartHG project, a local database for the experiments was implemented. This database contains all the information about the houses which were studied in the experiments and it was developed based on the ontology proposed in this thesis.

6.3.2 Data Interpolation

Since the data stored did not have a fixed time interval, it was necessary to perform a data interleaving in order to develop the experiments. That is, keeping the values using the same *timepoint* intervals. Algorithm 5.1 is responsible for the reading of the database file. It interpolates in *timepoints* T at time t, internal and outdoor temperatures $T_{in}(t)$ and $T_{out}(t)$. The Heat Pump Power $P(t)$ is also used at this stage.

The presented algorithm calculates the time difference m between $(t + 1)$ and (t). The rate between P, T_{in}, T_{out} and m is calculated and added to the values at time $(t+i)$. Once the data is interpolated, a CSV file is generated as it is presented below:

Timepoint, Power, Tin, Tout
DD/MM/YYYY HH:MM:SS, 0.00, 0.00, 0.00

This CSV file is then ready to be used as the main simulation data source as well as it is saved into the database. These data will be used by the main algorithm (Alg.6.2).

6.4 EVALUATIONS

The evaluation process occurred in two distinct stages: *thermal parameter identification* (TPI) and *internal temperature plan* (ITP). In the first verification step the found parameters were compared to the historical data, benchmarks in the literature as well as values obtained from the heat pump manufacturer. In the second stage, to generate plans of internal temperature for the following 24 hours, the results obtained for the of generated plan, day by day, were compared with historical data.

For simulation purposes, the internal temperature of the user preferences was obtained from historical data by the average daily temperature by time slots. Therefore, for simulation purposes the weather forecast for the outside temperature, the forecast for energy prices and the cost of CO_2 emissions were obtained with historical data for the same period found in the historical data.

6.4.1 Thermal Parameters Evaluation

The evaluations were made using machine *processing time* as a measurement, comparatives with historical data values, with pieces of informations obtained from heat pump devices manufacturers, as well as from the literature (PARK et al., 2011) (RAMIREZ; SAGUES; LLORENTE, 2014) related to the used approach.

In this section the procedures used in the thermal parameters identification experiments as well as the final results are presented. Methods and results for obtaining COP are also presented in this section.

Once the equations based on electrical circuits were defined and developed, it was necessary to verify their correctness. For this purpose, the Mathematica (WOLFRAM, 2003) software was used.

After the mathematical equations were validated, the thermal parameters discovery process was started. The first attempt to discover thermal parameters was made using the electrical circuit simulation system known as NGSpice.

Thermal Parameter Identification Using NGSpice

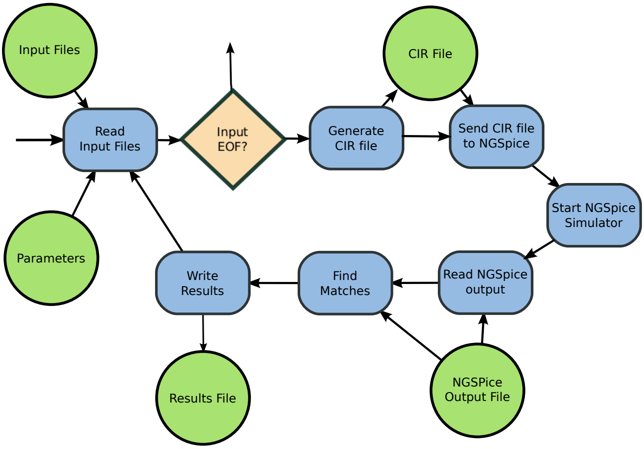
NGSspice is a mixed-level/mixed-signal circuit simulator (NENZI; VOGT, 2011). Through this software it is possible to carry out transient analysis in circuits. Transient analysis is an extension of DC analysis to the time domain. A transient analysis begins by obtaining a *DC* solution to provide a point of departure for simulating time-varying behavior (NENZI; VOGT, 2011).

The initial goal of the use of this simulator was to identify the values for thermal resistance R and thermal capacitance C using Transient Analysis. Since the values for heat pump power consumption P, outdoor temperature T_{out} and internal temperature T_{in} were known, a set of algorithms were developed. These algorithms are responsible to read the measurements from the database and then created files to be interpreted by the NGSpice simulator. After the simulation, the algorithms read the results and sought to compare if the simulated internal temperature was the same as the internal temperature obtained from the measurements (historical data).

Once no value was known neither for R nor for C, the algorithm was however engaged in performing a *brute-force* test. That is, it has sent sequentially values for C, within a range informed as a parameter, searching for answers of R. At the end, the simulation in which the combination of values for R and C and calculated internal temperature approximates the real internal temperature, were chosen as ideal values. The next subsections explain how the simulations occurred.

To better understand the proposed simulation process with NGSpice, the state-space diagram is presented in Fig. 36. In the picture, the rectangular blue blocks depict the process steps while the circular green blocks portray the *external files.*

Figure 36 – State-Space Diagram



Source: Author (2017)

The process starts with a *parameter file* and a *database file*. After reading these files, the algorithm checks, on each loop, asking to the input file whether it is the end-of-file (EOF) or not. Once it is affirmative, the process is terminated and if the answer is negative, a *circuit file*(CIR), in a SPICE-like format is created. This file is sent to the NGSpice simulator. Then, NGSpice is started and it generates an output file with the simulation results. All these steps are presented as it follows.

A *parameter file* was used in order to allow running a sequence of simulations in NGSpice in an sequential way. Algorithm 6.2 is responsible for providing reference values to the main algorithm. This file assists the main algorithm, providing the execution ranges and main values for the simulation variables. An hypothetical example of a parameter file is presented below:

$paramFixed[C = 1/R = 2/Both = 3] = 2$
$rValueFixed = 0.024334$

$cValueFixed = 0$
$rValueFrom = 0$
$rValueTo = 0$
$cValueFrom = 1000$
$cValueTo = 99999$
$loopStep = 10$
$marginError = 0.1$

The $paramFixed \in \{1, 2, 3\}$, where, $paramFixed \leftarrow 1$ for instance, means that the main algorithm needs to keep the capacitance value as $C \leftarrow cValueFixed$, 2 means that the algorithm needs to keep values for $R \leftarrow rValueFixed$ and 3 stands for parameters C or R which are not steady. The loop range is initiated, in all cases in $paramFrom$ and it will be finished when it reaches $paramTo$ value. A time interval $loopStep$ Ls[sec] is used as all over the PWL (Piecewise Linear Function) and finally $marginError$ Me is used to evaluate how big is the difference between the measured Internal Temperature T_{in} and Internal Temperature calculated $\dot{T}_{in}$.

In addition to creating a parameter file, an algorithm (Alg. 6.1) capable of reading the parameter file and calling the main algorithm (Alg. 6.2, here called *sweeper*) based on parameter settings was created. This algorithm takes into account the simulations to R and/or C, where C_{fv} and R_{fv} stands for the capacitance and resistance fixed values, R_f and C_f are the R and C reference numbers *from*, while R_t and C_t are R and C reference values *to*. The parameters Ls and Me represent the *loop step* and the *margin of error* values. Depending on the read parameters, the main *sweeper*-algorithm is called dynamically.

Once the parameters for the simulation are obtained, it is possible to generate the files to be sent to the simulator. The *CIR files* have a standard layout as it is presented in Alg. 6.4.1. In this example it can be seen that the Initial Condition (IC) will have the T_{in} value. That is, in order to simulate a house where the internal temperature starts with the first value for

Algorithm 6.1 Parameter Algorithm

Require: $paramFile$

if $paramFixed == 1$ **then**
  $sweeper\left(C_{fv}, R_f, R_t, Ls, Me\right)$
else
  if $paramFixed == 2$ **then**
    $sweeper(R_{fv}, C_f, C_t, Ls, Me)$
  else
    if $paramFixed == 3$ **then**
      $sweeper(Ls, Me)$
    else
      return "$paramFixed$ error"
    end if
  end if
end if

T_{in}, so that $IC = T_{in}(0)$. In this *CIR file*, N stands for number of *timepoints* T.

```
House X - CIR script
Vin 1 0 PWL(1s 0.00, 2s 0.00, 3s 0.00...)
R 1 2 0.00;
C 0 2 0.00 IC=0.00;
I 0 2 PWL(1s 0.00, 2s 0.00, 3s 0.00...)
.tran 1s Ns Lss uic;
.print tran v(b);
```

In order to do a Transient Analysis, the time of each instance is considered in *seconds* and it complies with the values which are obtained in the parameter file for Ls. In this hypothetical example, Vin represents T_{out}, R stands for the thermal resistance, C the thermal capacitance, I depicts the heat pump power and the result $v(b)$ illustrates the calculated internal temperature $\dot{T}_{in}$.

Algorithm 6.2 presents the main algorithm used to perform experiments using NGSpice as a solver. Each simulation S is sent to the NGSpice. It uses the parameter file and the parameter algorithm, creates the *CIR file*, sends it to the NGSpice simulator, reads the results and at the end writes the results into an output file.

Algorithm 6.2 Sweeper Main Algorithm

Require: $inputFile$ and $paramFile$

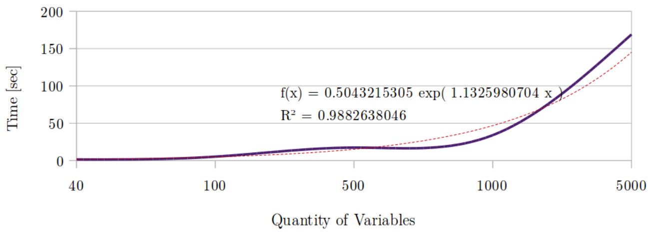
```
sweeperParamAlgorithm()
for EACH S ← paramFrom to paramTo do
    create CIR file
    send CIR file to NGSpice
    read NGSpice outputFile
    if | (T_in − Ṫ_in) | ≤ Me then
        return resultFile (T, R, C, T_in, Ṫ_in, (Ṫ_in − T_in))
    end if
end for
```

As it was presented before, the intention is to read and compare each row from the NGSpice simulator results, in order to find out if T_{in} value taken into account if it is equals/close to $\dot{T}_{in}$ for $\dot{T}_{in} \leftarrow v(b)$, using ($Me$) a margin of error and, when matches are found between them, the entire row is copied to a *output file* and the process starts again.

Two assays were conducted in NGSpice, in order to establish a performance analysis from SPICE-like files. In the first one, an input file with 10 records (Fig. 37) was used.

In Fig. 37 it is possible to observe the calculated red trend line (dotted) and its function plus R^2 value. In statistics, R^2 is related to the fraction of variance, that is, as closer it is to 1 the better fit between the calculated with the trend line is. In this case, it is perceived that the adjustment is very close to an exponential behavior. The processing of 5,000 variables took about two and a half minute to be completed.

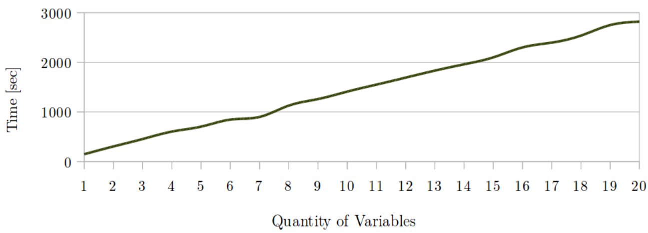
Figure 37 – NGSpice Simulations Performance - Assay 1



Source: Preissler, Gonçalves e Fernandes (2016)

The second assay was conducted as a sample space of 24181 records (Fig. 38). This value is equivalent to measurements of a house in 16 days interval of one minute. In both tests, R as $fixedValue$, $Ls \leftarrow 10$ and $Me \leftarrow 0.01$ were used. In a visual analysis, it can be seen that the behavior of the graph has a linear tendency.

Figure 38 – NGSpice Simulations Performance - Assay 2



Source: Preissler, Gonçalves e Fernandes (2016)

In the first experiment, records by *timepoints* in order of tens and thousands were used (here called variables). As a consequence, a single simulation occurred almost instantaneously.

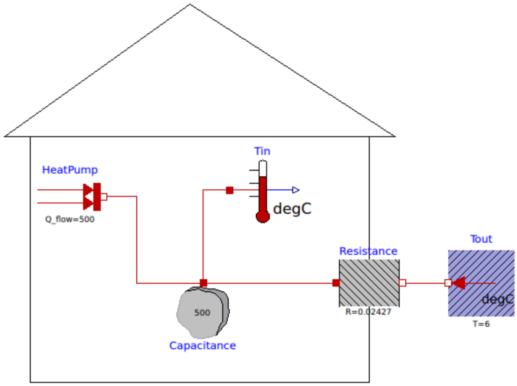
A whole hour was necessary to simulate 25 variables in the second experiment that took about two minutes for each simulation. It was verified that within these two minutes, approximately 25 seconds were used by the algorithms while the remaining time was used by the NGSpice simulator in a transient analysis mode.

These tests represent that with a large parameter combination applied to a small number of records, the response time is very brief. However when the amount of measurements and consequently of days increases, the processing response time, even with a small or low combination of variables, may become infeasible for an real (commercial) application.

Thermal Parameter Identification Using OpenModelica

In order to evaluate the results obtained with the simulations in NGSpice, the same tests and simulations were performed using the OpenModelica (TILLER, 2014) *thermal library* (PREISSLER, 2016). The same RC circuit was applied as can be observed in Fig. 39. In the figure it is possible to observe the visual elements that represent the outdoor temperature, the wall of the house (resistance), the thermal capacitance of the environment as well as the heat pump and the internal temperature.

Figure 39 – Modelica Thermal Library for a Single-Room



Source: Preissler (2016)

Using OpenModelica the results for the two assays were generated respectively in ten minutes for the first assay and nine and a half minutes for each simulation in the second one. Nevertheless, the algorithm kept on using 25 seconds for data preparation (pre-processing).

The overall mean values for $\overline{C}$ and $\overline{R}$ were obtained through simple arithmetic average of all values of C and R found in a given period of time t. Those values are presented in Tab. 9. In this table values obtained by $\overline{R}$ calculation presented by the Related Work* (CHEN; FU; XU, 2015) are also depicted. The proposal presented by (CHEN; FU; XU, 2015) was implemented as suggested by the mentioned literature. For these simulations the same randomly fixed value for $\overline{C}$ was set for 6500.

Table 9 – $\overline{R}$ values using different approaches

	Experiment 1	**Experiment 2**
NGSpice	0.02472	0.02987
OpenModelica	0.02798	0.02966
Related Work*	0.02568	0.02605

Source: Preissler, Gonçalves e Fernandes (2016)

The percentage of error in the first experiment which was taken with simulations using NGSpice and OpenModelica for $\overline{R}$ calculation was 13.19%. When (CHEN; FU; XU, 2015) are considered as a reference, this percentage is 3.88%. For the second experiment, the error percentage was 0.7% when compared to OpenModelica and 12.79% if compared to related work by (CHEN; FU; XU, 2015).

The carried out experiments took into account the simulation of the thermal resistance calculation of a house, using real measurements of a period of 16 days. The results of the two experiments demonstrated that the use of the NGSpice or OpenModelica simulators, in relation to the related work (CHEN; FU; XU, 2015), are close, even when the number of variables in the experiments increases.

Even having found satisfactory the results, as it is presented in this section it was sought to reduce the computational time spent in the simulations. This is the reason why it was chosen to develop the equations, as presented in Sect. 4.4.1, implement an algorithm in order to solve it integrated with CPLEX optimizer as well as perform experiments in order to evaluate the results, presented as follow.

Thermal Parameters Identification Using the Proposed Model

This subsection provides the process of evaluation of thermal parameters for each house, as it was presented in Sect. 4.4.1. In this experiment, a computational algorithm was developed to calculate the thermal parameters, following the steps of the proposed model based on the historical data of each residence.

This algorithm takes into account the fact that assuming that C comes from the relationship between R and C as Eq. 5.20 and having values for $\overline{RC}$ as shown in Sect. 5.4.2 it can therefore evaluate either R or C to verify that the results comply. For that case, it was decided to evaluate the values for R, understanding that once found the value for R and having the values for $\overline{RC}$ been already established, it is possible then to find the values for C.

Table 10 shows the simulation results for all studied houses. It is possible to observe the averages for $\overline{R}$ and $\overline{C}$ which were obtained from the thermal parameter identification. The last column lists the calculated values for $\overline{R}^*$ according to the method proposed by Park et al. (2013). These values were calculated each step, with a τ interval. Their average was performed later.

Table 10 – Result Simulations for R and C

	$\overline{R}$	$\overline{C}$	$\overline{R}^*$
House 1	0.034871	2144.962708	0.039455
House 2	0.027445	2145.083158	0.026414
House 3	0.011865	2554.082026	0.010117
House 4	0.018565	3857.414424	0.019849
House 5	0.027030	1074.227824	0.028974
House 6	0.031118	3096.822475	0.029878
House 7	0.024334	2847.673077	0.023145

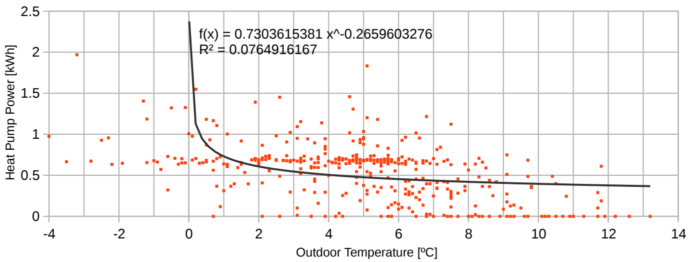
Source: Author (2017)

The experiments were performed using historical data for T_{in}, T_{out} and P and developed using Python script language to calculate $\overline{R}$, $\overline{C}$ as well as $\overline{R}^*$. The average time spent by the algorithm to calculate the three thermal parameters was about (average) 1.17543 seconds.

6.4.1.1 Heat Pump COP Analysis

Since the COP (η) calculation, proposed in this model, must occur based on the variation of the outdoor temperature and in time intervals (ranges), the Fig. 40 was generated. This happens because, observing the graph one can perceive the relationship between heat pump power and outdoor temperature. The graph is shown only for house 1 because the objective is to demonstrate the relationship between P and T_{out}. The behavior that comes from this relationship is also found, in a similar way in the other studied houses.

Figure 40 – Relation between P and T_{out} - *house 1*



Source: Author (2017)

A trend line presents the cloud points behavior to the rise in temperature. It is also possible to see the trend line equation and its coefficient of determination (R^2). Moreover it shows that a superficial analysis of the relationship between these two variables is not enough to establish an expected liner positive function (ENERGUIDE, 2004) between them.

In order to calculate the COP, based on the proposed model the Algorithm 5.2 was developed. In the sequence, the steps followed to calculate $\overline{\eta}$ are presented.

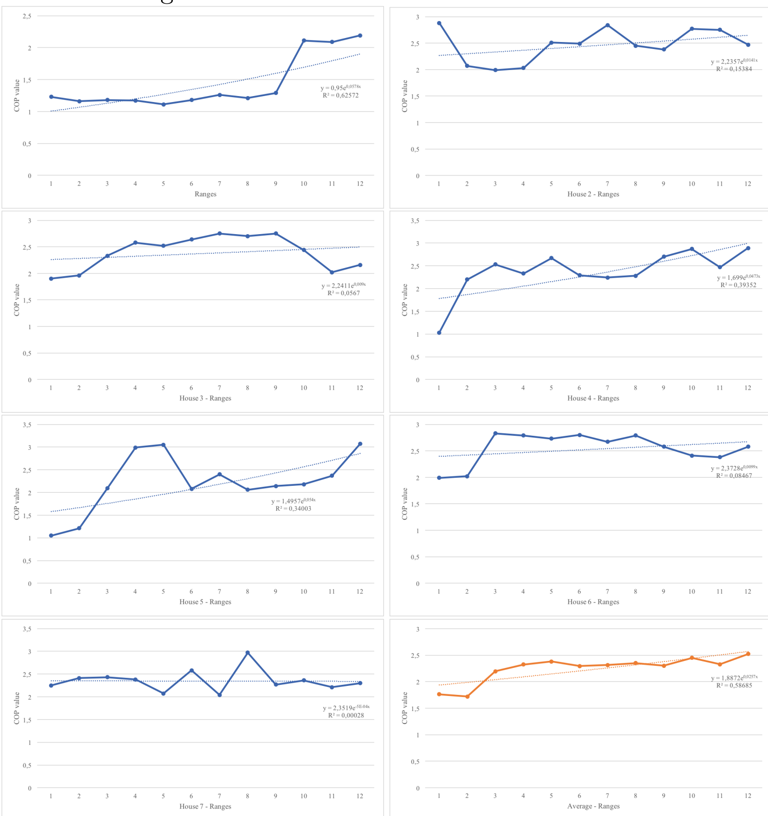
The η simulation results can be seen on Table 11. That table shows the summary data obtained from all simulated houses. The means using the original η formula have considered P in a *steady-state*.

Table 11 – Average COP values Simulation Results per Ranges

Ranges	House 1	House 2	House 3	House 4	House 5	House 6	House 7
$[-\infty\ to\ 0)$	1.23	2,88	1,90	1,03	1,05	1,99	2,25
$[0\ to\ 1)$	1.16	2,07	1,96	2,20	1,21	2,02	2,41
$[1\ to\ 2)$	1.18	1,99	2,33	2,53	2,09	2,83	2,43
$[2\ to\ 3)$	1.17	2,03	2,58	2,33	2,99	2,79	2,38
$[3\ to\ 4)$	1.11	2,51	2,52	2,67	3,05	2,73	2,07
$[4\ to\ 5)$	1.18	2,49	2,64	2,29	2,08	2,80	2,58
$[5\ to\ 6)$	1.26	2,84	2,75	2,24	2,40	2,67	2,04
$[6\ to\ 7)$	1.21	2,45	2,70	2,28	2,06	2,79	2,97
$[7\ to\ 8)$	1.29	2,38	2,75	2,70	2,14	2,58	2,27
$[8\ to\ 9)$	2.11	2,77	2,44	2,87	2,18	2,41	2,36
$[9\ to\ 10)$	2.09	2,75	2,02	2,47	2,37	2,38	2,21
$[10\ to\ +\infty)$	2.19	2,47	2,16	2,89	3,07	2,58	2,30

Fig. 41 shows the relationship between the COP ranges calculated (by Algorithm 5.2) and the Outdoor Temperature T_{out} for each house and the average (the last one). It is also possible to observe the trend exponential line among the found points (dotted line).

Figure 41 – COP Results for All Houses



Source: Author (2017)

The main line represents the calculated COP by range.

The dotted line shows the calculated trend between the points. Even without having a value for R^2 close to or equal to one, was chosen that the exponential function would be used as the basis for the studies, following the surveys of EnerGuide (2004).

The highest value of R^2 relative to the linear regression of all houses was found in house one, where the value corresponds to 0.62. The lowest correction value R^2 was detected in house seven, represented by 0.0002.

The last chart (orange) represents the average COP calculated for all households. The overall mean of all households has a value of R^2 of 0.58 in relation to linear regression. This means that the relation between the COP value of the houses studied is not strongly related. This factor may be due to the behavior of heat exchanges that each house presents individually.

Due to this factor of low correction between the regression of the points and the value R^2, it was decided to first find the values of COP for each external temperature and later to calculate the exponential function between these points. Such a function is in the future used in the algorithm to estimate the value of COP in the phase of experiments. So, in the following steps, the COP values are obtained first by the calculation in ranges and then, based on these values, the exponential function of the COPs is obtained.

6.4.2 Internal Temperature Plan Evaluation

This section describes the analysis performed on the generation of the day-ahead internal temperature plans. The average time spent by the optimizer to generate the internal temperature plans was 0.000116 seconds.

In the optimization stage, values for c_i, the cost of electricity and o_i, the cost of CO_2 emissions were expressed in the same unit of currency in this experiment in Euro(€).

6.4.2.1 Thermal Comfort

In the experiments part, the thermal comfort was calculated based on the historical of internal temperatures by calculating the average for each time slot of the day and for each house individually.

This internal temperature average is called T_{ref}. To this value a tolerance alpha (α) was added for optimization purposes, generating the upper ($T_{ref}+\alpha$) and lower ($T_{ref}-\alpha$) limits for the desired internal temperature. The alpha (α) value is provided as a parameter to the main model, thus offering flexibility to the optimizer(CPLEX) in the search for solutions.

6.4.2.2 Adjusting the Convexity

Taking into account that the experiment was dealing with a multiple objective function, i.e integrating by two arguments in the same objective function such those have different dimensions, it was necessary to insert a factor A to adjust the convexity of these two arguments as it is presented in Eq. 5.25 in Sect. 4.4.2. This adjustment factor is required in order to obtain a balanced function in which these two arguments can be comparable.

The adjustment process for A is given as follows. For each house a consumption plan was generated. Each generated plan used a different value for A; the results obtained for calculated P and T_{in} were compared with real P and T_{in} from the historical data. At the end of the simulations the average A value for the entire period and for each house was obtained.

6.4.2.3 Cases of Internal Temperature Plan

In Figs. 42, 43, 44, 45, 46, 47 and 48 it is possible to identify an aleatory sample of cases of daily internal temperature plan simulated for all houses. The results of the simulations are compared with historical data.

On the left side, the red line (dots) indicates the calculated P while the blue line indicates the actual P obtained from the historical database. On the right side, for the same simulation, the red line indicates the calculated T_{in} while the blue line (dots) indicates the actual T_{in}.

In all these cases, it can be seen that the algorithm generated values close to the real data and that they are, on average, below the real average values. Such accuracy is analyzed in Sect.6.4.2.5.

6.4.2.4 Daily and Hourly Analysis

In order to graphically demonstrate the performance of the algorithm against the historical data, a series of eight graphs, which follows, are presented. Two houses (2 and 7) were chosen in random periods. All these analyzes were performed with the mean data grouped by hourly or daily slots.

Fig. 49 shows the relationship between the calculated T_{in} and real/historical T_{in} taken from historical data for *house 2* in an hourly composition. The green line shows the calculated T_{in} while the blue line shows the real T_{in} (from the database).

The relation between the estimated and historical temperature for *house 7* is shown in figure Fig. 50. In both cases, especially for *house 7*, it can be seen that the calculated internal temperature and the real temperature have a similar oscillatory behavior. Few peaks are found, especially in *house 2*.

This difference between the estimated P and the historical P is mainly due to the fact that the main variable that has the greatest freedom in the optimization process and into the algorithm is P. This does not occur for T_{in} because it is contained in a constraint within the optimizer and has freedom of valuation controlled by parameters.

The relationship between the hourly calculated P and real

Figure 42 – Samples of T_{in} Plans - Houses 01 and 02

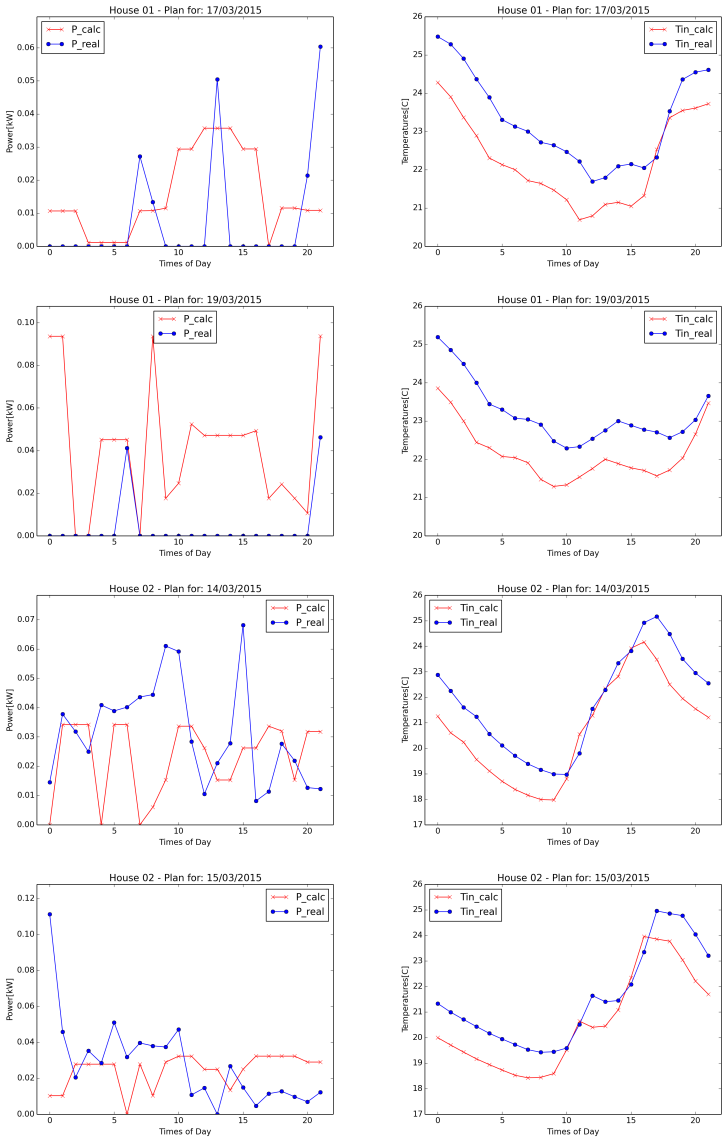


Figure 43 – Samples of T_{in} Plans - Houses 02 and 03

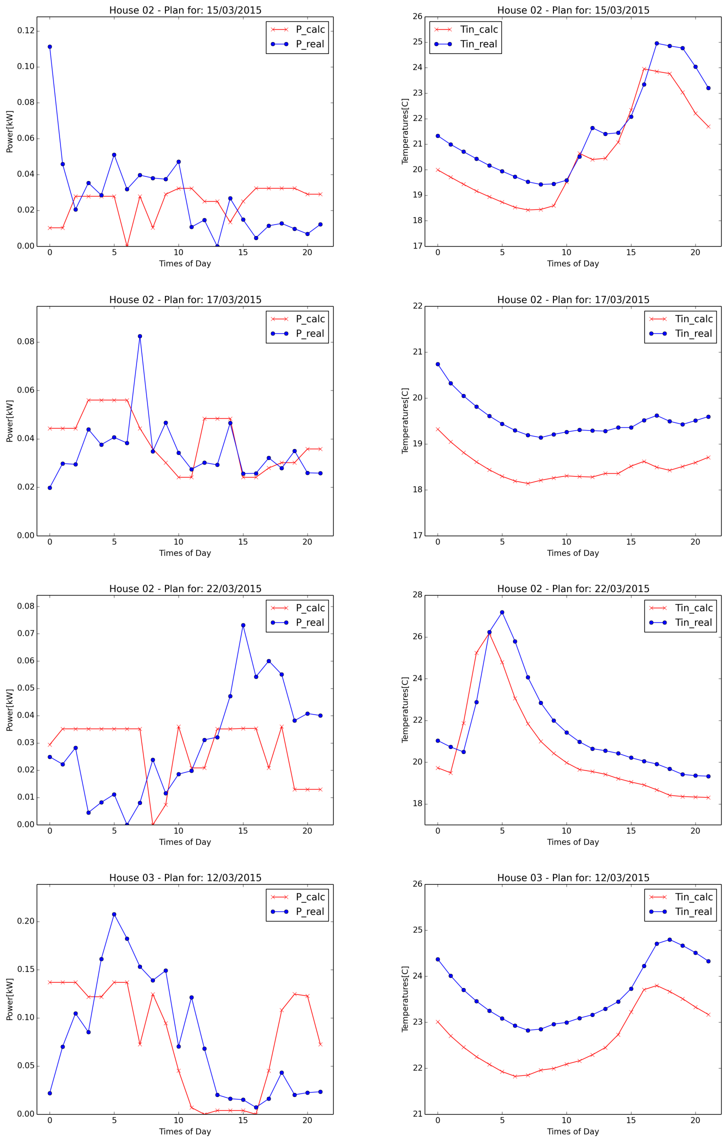


Figure 44 – Samples of T_{in} Plans - Houses 03 and 04

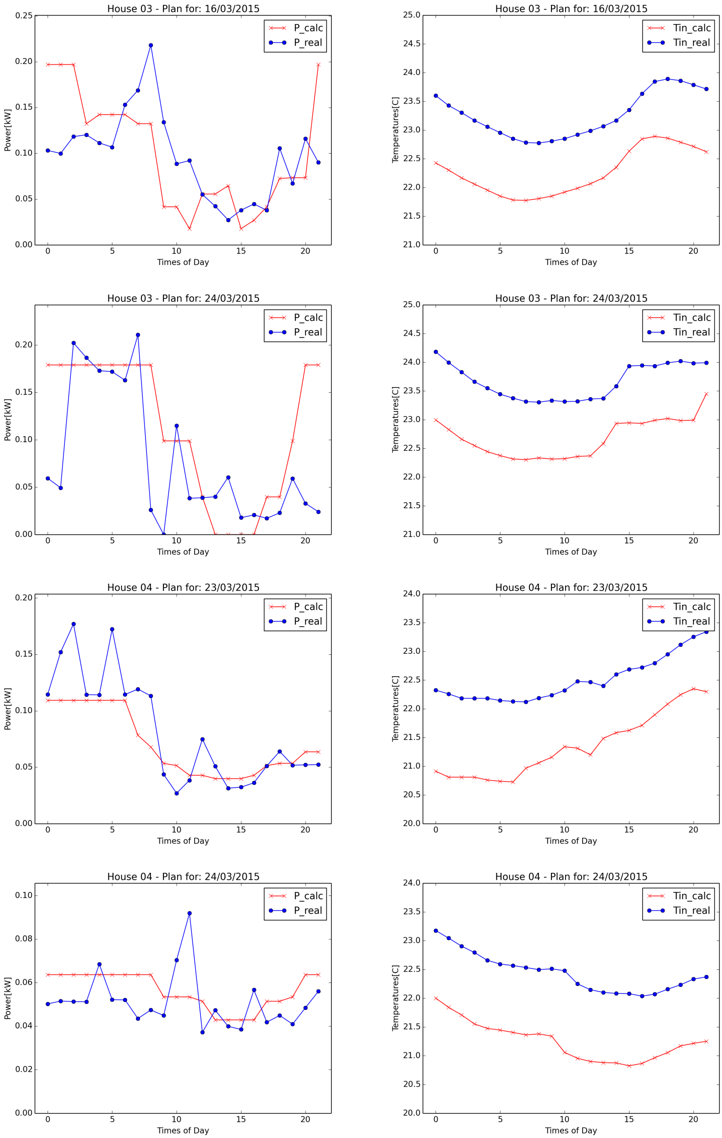


Figure 45 – Samples of T_{in} Plans - Houses 04 and 05

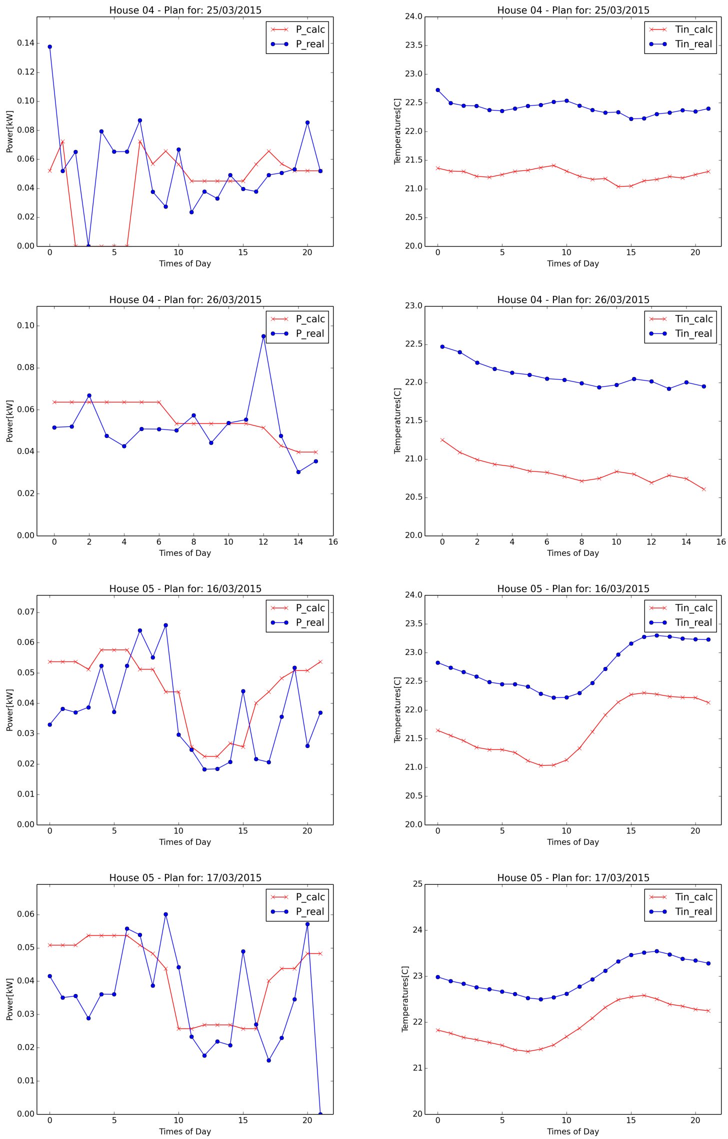


Figure 46 – Samples of T_{in} Plans - Houses 05 and 06

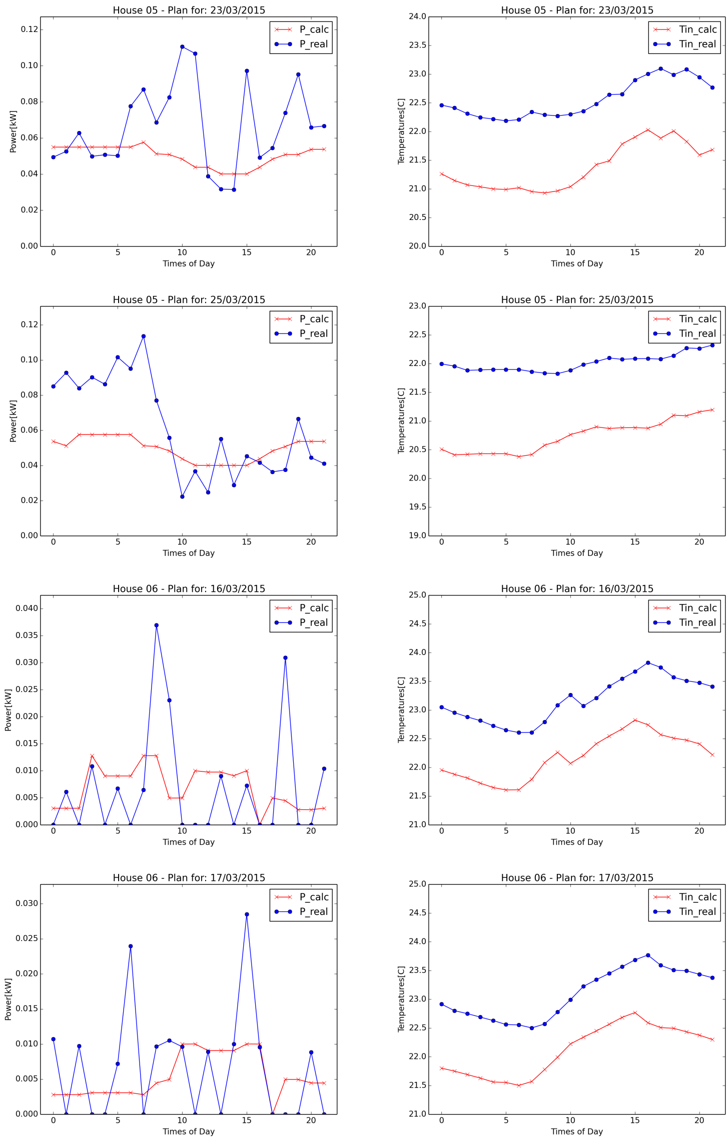


Figure 47 – Samples of T_{in} Plans - Houses 06 and 07

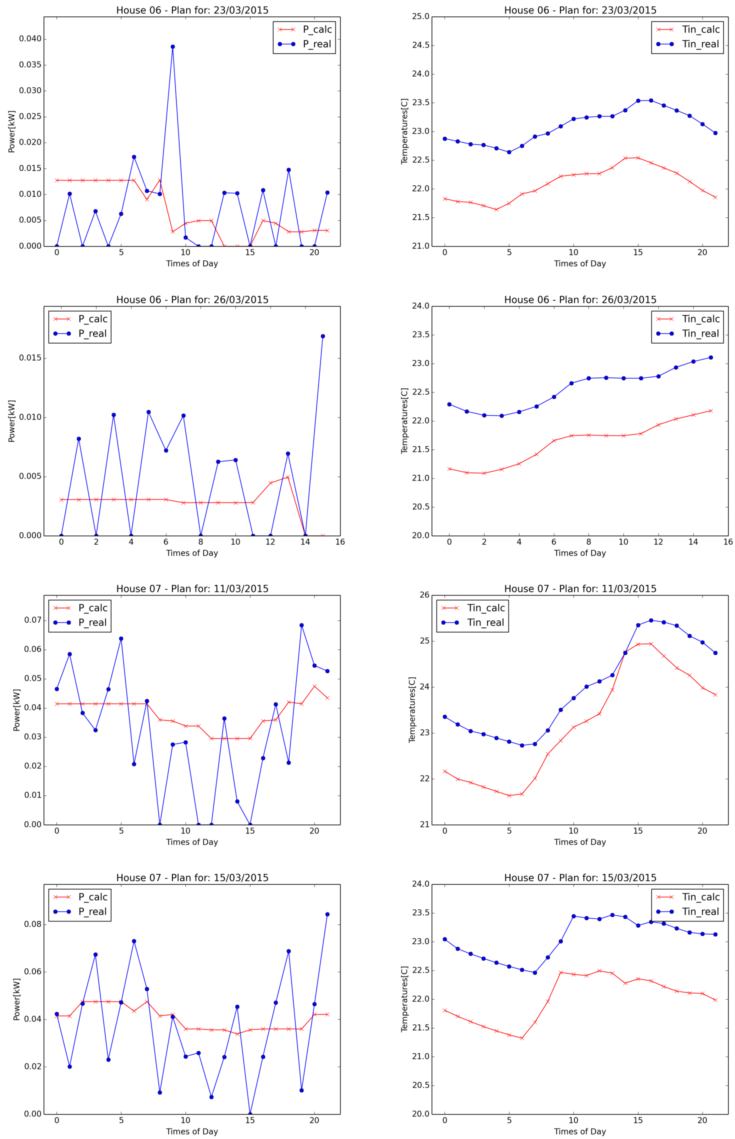


Figure 48 – Samples of T_{in} Plans - House 07

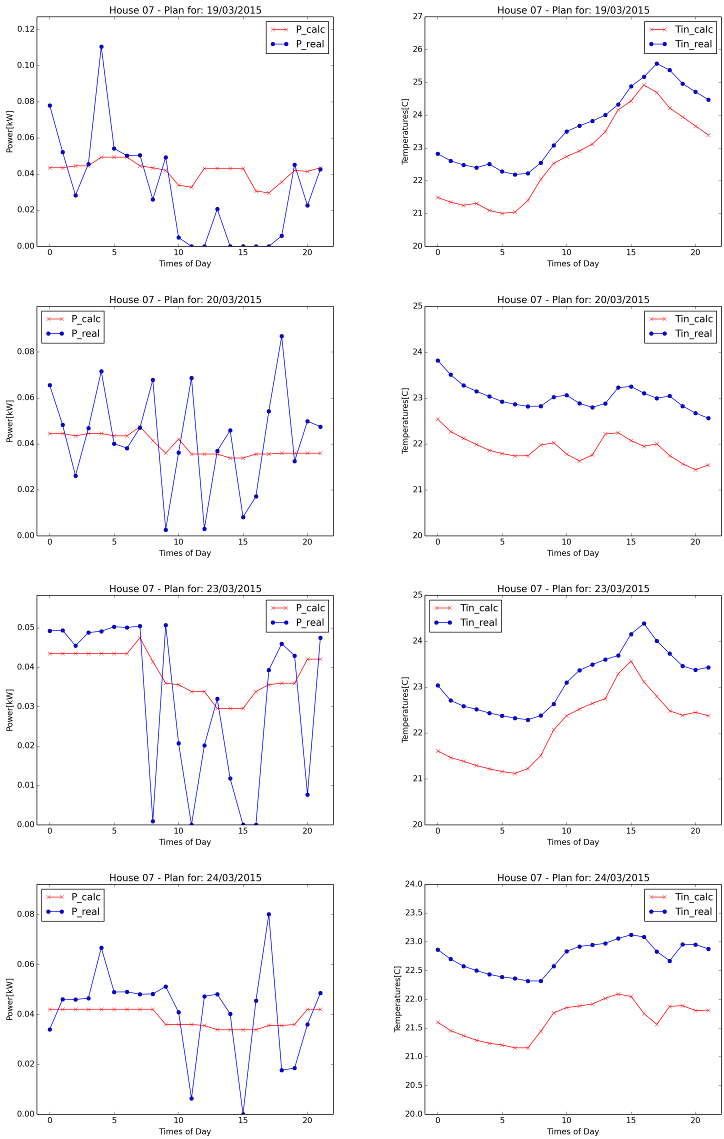
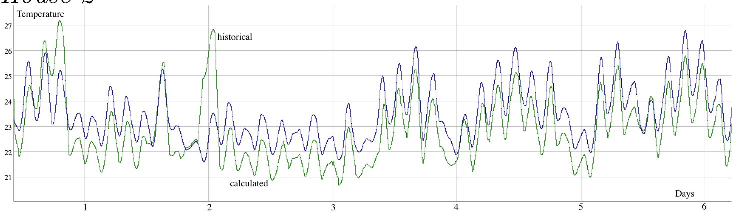
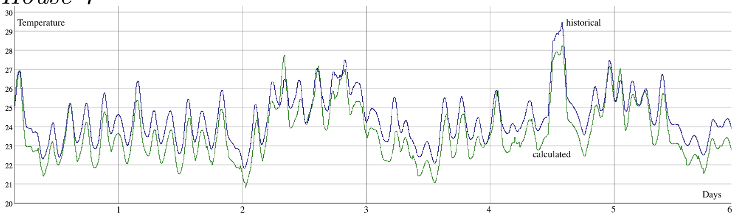


Figure 49 – Hourly Internal Temperature Averaging Deviation - *House 2*



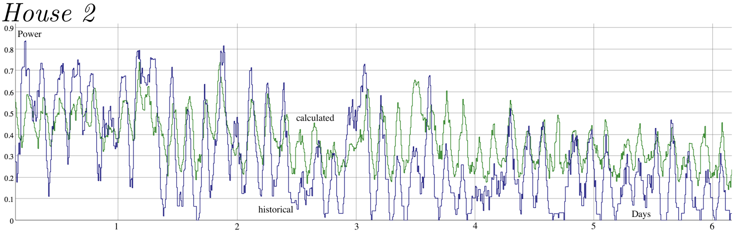
Source: Author (2017)

Figure 50 – Hourly Internal Temperature Averaging Deviation - *House 7*



Source: Author (2017)

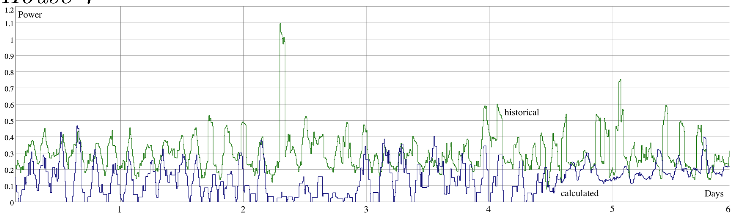
Figure 51 – Hourly Average Power Consumption Deviation- *House 2*



Source: Author (2017)

P from historical data for *house 2* is presented (in a specific range) by Fig. 51. The green line shows the calculated *P* while the blue line shows the real *P*.

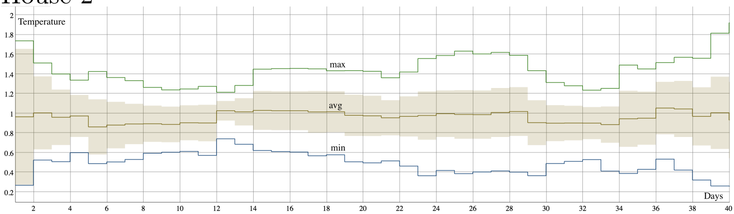
Figure 52 – Hourly Average Power Consumption Deviation-*House 7*



Source: Author (2017)

Fig. 52 shows the relation between the calculated versus the historical power. For *house 2* one perceives a wave behavior close to each other. However, for *house 7* positive peaks are identified, mainly from historical data, which suggests that the algorithm is resulting in a reduction in energy consumption.

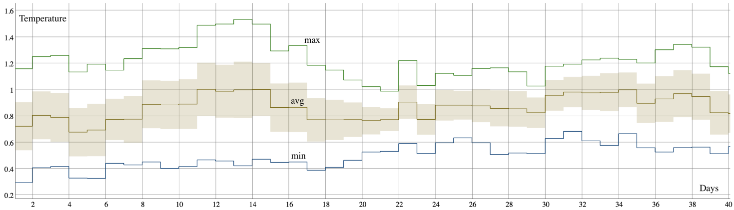
Figure 53 – Daily Internal Temperature Average Deviation - House 2



Source: Author (2017)

The daily Internal Temperature average deviation for *house 2* is presented in Fig. 53. It also shows the maximum (green line) and minimum values (blue line), the standard deviation (hatched area) and the average error (brown line). It is related to the calculated T_{in} analysis for this particular house.

Figure 54 – Daily Internal Temperature Average Deviation - House 7



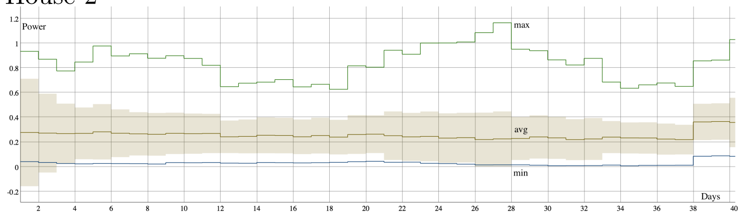
Source: Author (2017)

Fig. 54 shows a sample of estimated temperatures behavior for *house 7*. For *house 2*, it is identified by the scale of the graph, that the maximum positive peak for the analyzed period reached two degrees Celsius and that the average kept floating near one degree. For *house 7* this maximum variation was lower, of 1.5 degrees and the average between 0.5 and one degree Celsius. In most of the analyzed time slots, the standard deviation demonstrates that there was no great variation of the estimated values in relation to the general mean.

Fig. 55 presents the maximum (green line) and minimum values (blue line), the standard deviation (hatched area) and the average error (brown line) for the *house 2* in relation to the calculated P . All these values are depicted in a daily composition.

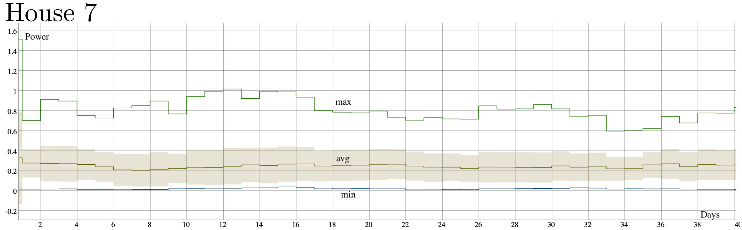
A sample of calculated P for *house 7* analysis is shown in Fig. 56. For *house 2* and for *house 7* the minimum value obtained averaged fluctuated within the value zero. The maximum mean obtained for *house 2* varied between 0.6 and 1.2 kW and in *house 7* the maximum value did not exceed 1kW in average. In both cases the overall mean fluctuated close to 0.4kW

Figure 55 – Daily Average Power Consumption Deviation - House 2



Source: Author (2017)

Figure 56 – Daily Average Power Consumption Deviation - House 7



Source: Author (2017)

6.4.2.5 Energy Cost

In order to measure the accuracy of the model the absolute daily difference e_d between the sum of the electricity from the historical data used to heat the residence $e(t)$, where $t \in 0, \ldots, 23$ represents the 24 hours of the day, and the estimated energy for the same period $e^*(t)$ was estimated using Eq. 6.1.

$$e_d = |\sum_{t=0}^{23} e(t) - \sum_{t=0}^{23} e^*(t)| \tag{6.1}$$

Once having the e_d values the following values were then obtained: average value $\overline{e}$ of e_d, $\lfloor e \rfloor$ min from e_d, maximum $\lceil e \rceil$ value of e_d and the standard deviation $\sigma(e)$ for e_d. In these estimates it was also calculated the percentage (*% accur.*) that represents how small is the sum of the calculated daily amount of energy e when compared to the sum of real daily energy e^*. Such information is presented in Tab. 12.

Table 12 – Difference between Calculated and Real Energy

	$\overline{e}$	$\lfloor e \rfloor$	$\lceil e \rceil$	$\sigma(e)$	*% accur.*
House 1	1.4665	0.0001	5.2978	1.2600	52.58%
House 2	1.9742	0.0001	5.3524	1.3713	53.01%
House 3	2.3089	0.1487	6.4917	1.4834	64.35%
House 4	1.5012	0.0928	3.4998	0.9470	57.14%
House 5	1.2509	0.0000	4.3573	1.2001	58.33%
House 6	0.7167	0.0039	4.3103	0.5830	61.02%
House 7	0.2610	0.0351	1.1152	0.1120	73.04%
Avg()	1.5766	0.0369	5.2323	1.2025	59.92%

Source: Author (2017)

The results obtained from the generations of the plans, which in turn make use of the thermal parameters obtained through this model, show that in 59.92% of the average of generated calculations, the projected energy consumption is lower than the real energy consumption. It also shows that the maximum error between the calculated energy and the actual energy is 5.2323 kW, that the minimum error is 0.0369 kW in a day, the error average is 1.5766 and, finally, that the standard deviation average is 1.2025.

6.4.2.6 CO_2 Emission Cost

Historical values for the price of electric energy and for the value of the emission of CO_2 into the atmosphere, both in euro currency were obtained from the following companies: NordPool, available on `www.nordpoolspot.com` and from EnerginetDK, available on `www.energinet.dk` a non-profit enterprise owned by the Danish Climate and Energy Ministry.

A period of 100 days was chosen by sampling to demonstrate the efficiency of the optimization algorithm for those seven houses. Since the cost of CO_2 is included in the minimization function of the optimization problem, the algorithm aims to reduce the CO_2 value designed for the timeslice being calculated.

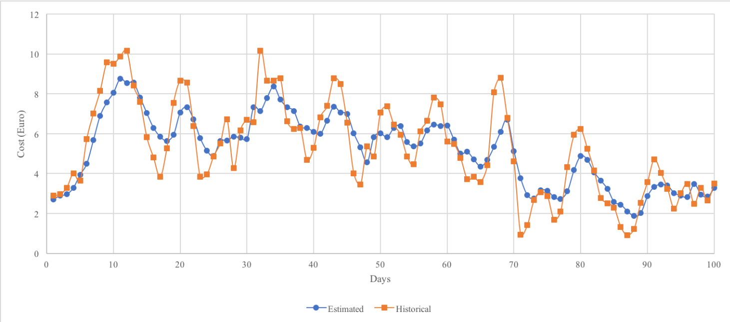
Fig. 57 shows the relation between the historical value in orange (squares) and the value of CO_2 calculated after the experiments, in blue (circles). The average simulation for 100 days was a saving of 1.71% over historical data.

The y-axis represents the value in Euros of the cost of CO_2 emission into the atmosphere. This value is relative to the sum of kWh saved daily for simulated houses. This means that for the 12th day the cost of emission of CO_2 into the atmosphere was 10.15799217 and with the use of the proposed model this value was reduced to 8.53084.

6.5 EXPERIMENTS DISCUSSION

The initial experiments generated to estimate the thermal parameters $\boldsymbol{R}$ and $\boldsymbol{C}$ using NGSpice showed good results in

Figure 57 – Sample of CO_2 saved (average)



Source: Author (2017)

relation to the benchmarks, but the method used to search was the association between brute force and circuit simulator. Such a combination generated a high computational time in these experiments.

In order to prove the circuit modeling, experiments were performed with OpenModelica. In this software, the same circuit was implemented. The methodology proposed by the tool in question and which positively resulted in equal values for the same simulations was the used one, though. Thus verifying the correctness of the model. It was also identified an improvement in the computational time velocity used in the resolution of experiments in OpenModelica in relation to NGSpice.

Based on the high computational times offered by the simulators using NGSpice as well as OpenModelica, it was decided to develop the mathematical model of the simulated circuits and to propose a calculation model for the thermal parameters, for the performance co-efficient of the heat pumps in script language.

As a second step, after the identification of the thermal parameters, we opted to use the CPLEX optimization tool. This tool was chosen because it is widely used by the scientific community. Moreover, the fact that there is availability of license of this software for the institution was also taken into account. A third reason to be considered in this choice was the ability to solve problems of quadratic order of this tool.

Once the optimization models were developed and sent to the optimizer, the results were read and compared with the historical data available for the simulated houses. Regarding the maintenance of the thermal comfort, the algorithm was excellent because as the internal reference temperature was treated as a strong constraint, the standards of comfort established by the user were respected.

In relation to the energy saving due to the heating, many cases proved to remain within the average, but for the majority 59.92% the plans generated were more efficient than the historical data. The maximum error in the energy calculation was 6.4917 for house 3, but for house 7 this value was 1.1152.

The CO_2 values also showed a gain in relation to historical data. Although they represent a seemingly low monetary value, if such a calculation would been scaled to a whole district or a city, such numbers should scale proportionally.

Different values were found for all houses. Both the thermal parameters and the calculated P and T_{in} values. Such differences are due to the unique behavior of each residence and the relation of use of its members. Internal and external factors can directly contribute to the change in thermal parameters such as lighting a set of lamps, opening a window, more people inside a house, etc. Longer periods of absence of users, in which occupants leave their homes for a short or long period of time, also influence these thermal behaviors.

7 FINAL CONSIDERATIONS

In this document a knowledge-based model for thermal parameters identification and for generating a day-ahead internal temperature plan in a Smart Building context was presented.

The model presents user interaction on two levels: knowledge acquisition and visualization. The data and information acquired from the household user were related to the internal temperature preference for hourly time slot and floor plan assisted design.

Data obtained from the household users from the temperature sensors (internal and outdoor) as well as the heat pump power consumption installed in the houses and the historical data were used to estimate the thermal parameters. A large amount of data was analyzed. About three months were spent cleaning and organizing the database. This was primarily due to the fact that different sensors were used in the experiments. Each sensor performed readings in different time slots. Time slots needed to be standardized, which was called data normalization in this thesis.

The parameter identification stage uses the electrical thermal analogy and it is responsible for estimating the average values for thermal resistance and capacitance. In this step the values for the coefficient of performance of heat pumps were also calculated.

In the second stage, an internal temperature plan was generated. The algorithm used the thermal parameters previously identified and a day-ahead internal temperature plan was proposed to the household user. This plan took into account the thermal comfort and the user temperature preferences. At the same time, the plan sought to minimize the energy consumption for heating the house, reducing the cost of CO_2 emissions.

In the experimental stage a data set obtained from seven inhabited houses in a winter period, in a real situation for a period of seven months from the SmartHG Project was used. The mathematical model made use of the thermal-electrical analogy and experiments were evaluated comparing the parameters obtained and the actual sample data, benchmark literature and information from the heat pump manufacturer.

This study is also important because it may help Smart Building's users to save energy and money. It also contributes to the energy efficiency of these buildings, potentially to Smart Grids and Cities. This work provides a model to calculate the thermal parameters of an environment based only on the historical data without the need for knowledge of the physical characteristics.

Household Energy Consumption depends on the thermal insulation and the individual characteristics of each residence. For this reason, it is important to perform the thermal parameters identification of a smart home or building before offering an internal temperature plan.

The internal temperature plan for the following 24 hours is generated through an optimizer that seeks to minimize spending on electricity as well as to minimize the amount spent on CO_2 emissions. This optimizer also takes into account the thermal comfort, aiming to minimize the distance between the planned temperature and the desired temperature.

This study presents a knowledge-based model which aims to offer to the household user a day-ahead plan of internal temperature. The goal is to maintain thermal comfort while reducing energy consumption as well as CO_2 emissions. The scope of this research is to study heating of multi-zone buildings that use air-to-air heat pumps.

It was decided to carry out a study in multi-zone environments because they are closer to the reality of a residence or commercial building that in turn is composed of several spaces. In the present study, it was chosen to use the electro-thermal analogy as an effective and recurring method applied in the literature to identify the thermal parameters of environments such as resistance and thermal capacitance. By means of this analogy it is possible to represent the knowledge about the physical and thermal structure of a residence from the identified and calculated parameters. For this reason, in the proposed model the term *knowledge representation* is adopted. This term, therefore, is used, firstly to identify the thermal parameters and then, later used to represent each connection between the rooms in a building.

It is proposed that specifically problems related to heating of environments due to the use of air-to-air heat pumps should also be studied in order to reduce the consumption of electric energy and CO_2 emission while maintaining thermal comfort. The present study proposes an internal temperature plan for the successive day (next 24 hours) without acting on the heating devices. Thereby, the method becomes non-intrusive, as it does not act direct on the devices as well as it offers to the end user the possibility of choosing between setting up the suggested plan in his equipment or not.

In this sense, the present study aims to contribute by offering a computational tool capable of *acquiring knowledge* about the composition of the home from the household user as well as to offer information about his power consumption and savings as a *knowledge visualization* tool.

In order to generate forecasts of internal temperature or power consumption it is understood that it is necessary to know the building characteristics firstly. Calculating the dynamics of heating or cooling a building can become an arduous task. This is due to the fact that simply opening a door or window can completely change the building's thermal dynamic values, for example.

This study aims to present a model in which no previous knowledge about the composition of the building is necessary. This gives to the model an applicability in which can be used by any household user without the need of knowledge about the walls structure and values for resistance or thermal capacitance of the building, for example. This tends to impact positively in the use of this model in real situations, since prior knowledge about the thermal resistance and thermal capacitance values of the walls of a building, for example, are hardly known by the home user. For this reason, it was decided to carry out the thermal parameters identification.

Another novel contribution lays on the fact that the COP is calculated in intervals of variation of the external temperature. That is, a value for COP is generated for each interval of a degree variation of the outdoor temperature in the calculation.

Once the thermal parameters of the building and the heat pump COP are known, it is possible to generate future scenarios.

For this reason, the joint use of the three elements in the same optimization plan: thermal comfort guarantee as well as the reduction of costs of power consumption and CO_2 emissions is justified as an important contribution of the present study.

The present study makes use of weather forecast for the generation of the internal temperature plan for the next 24 hours as well as of the energy price forecast. Therefore, another important contribution of this work is to make use not only of the predictions that have already been mentioned but also of the forecast of the costs of CO_2 emissions (LUCKOW et al., 2016), offered by specialized agencies.

In this study, a function of power consumption based on external temperature is proposed and it is used in the process of plans optimization. So, as it was presented before, it is identified the need to develop a knowledge-based model for thermal parameter identification and generating future scenarios for internal temperature for the following 24 hours. Having as scope the heating using air-to-air heat pumps in multi-zone smart buildings and considering the user's knowledge.

This work presents a model that offers an interactive and user-friendly, graphical interface in which the end users are able to set their preferences and view their energy consumption level as well as the power consumption reports.

At the end, the main advantage of this work is to provide, under the end user's point of view, a model through which is possible to identify the thermal parameters and propose an internal temperature plan for the following 24 hours without knowing the physical characteristics and composition materials of the house or building's structure. This model could offer a computational tool, that should be interactive, easy to use and with a friendly interface.

7.1 RESPONDING GOALS

The main goal established for this work was achieved. That is, a computational model able to offer the Smart Building's end user a day-ahead internal temperature plan was presented. This plan took into account the thermal comfort, using the internal temperature preferences from the household user.

The proposed knowledge-based model offered interaction with the end user, the use of prior knowledge through historical data and calculated the thermal parameter of the environments. The specific goals were achieved, because:

1. An exploratory and descriptive systematic review on the literature in order to identify the state-of-the- art on the subject was made.

2. A technological knowledge-based model which is able to estimate thermal parameters of a Smart Building was modeled, projected and applied. It was also suggested the development of an internal temperature plan in order to reduce not only the electricity consumption but also the financial costs on residential heating and the CO_2 emissions.

3. The stage of model test and evaluation has been completed comparing results with benchmarks and especially with historical data from the SmartHG project.

The electrical-thermal representation and the final object of this thesis can be used not only to detect the parameters of an envelope but also to understand heating or cooling behaviors of an environment. This application contributes to related studies at a higher level such as Smart Cities and Smart Grids, reducing energy consumption, pricing policy studies Mancini et al. (2015) and reducing CO_2 emissions from electricity production.

In this model a method to calculate the thermal parameters in a situation which the whole house has the same internal temperature is proposed. As a future work it is suggested to implement a model where each single zone can have its individual internal temperature measurement considered through simulations.

After the data normalization process, was chosen to use the seven-month experiments for seven houses. Such choice was mainly due to the fact that this was the period when the amount of data for these houses was sufficient for the experiments. In this sense, it is suggested that the present research can be expanded to a larger number of houses in larger periods so that there can be a comparison over the years.

Due to the large amount of data to be analyzed, it is suggested that Advanced Analytics concepts be used to organize and display such information. It is also suggested that future research on this subject may deal with the proposal of a protocol for communication and data acquisition by and between sensors.

It is suggested that the sensor readings occur in a grouped manner by residence and with time slots fixed and previously defined. The readings may also consider the absence of people in the house, which would generate a new verifying element in the experiments.

A proposition for future work concerns about expanding the application of web database used by household users of the same district (neighbors). Such data can be applied to studies in the areas of Smart Cities and Smart Grids.

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8 APPENDIX

8.1 SINGLE AND MULTI-ZONE BUILDING REPRESENTATION

Figure 58 shows two representations where RC circuits can be used as electro-thermal analogy. In the image it can be seen that a single room (a) can be represented by a simple RC (b) circuit.

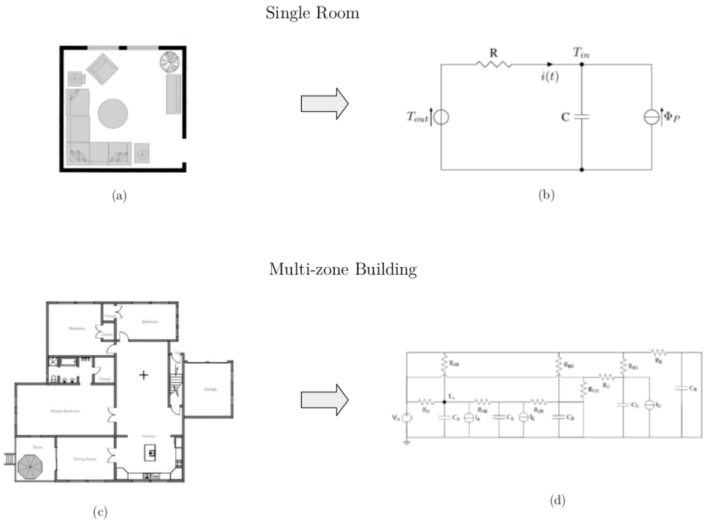
On the other hand, a multi-zone environment (c) must be represented by an electronic circuit (d) more complex than the first, but using the same concept of an RC circuit.

The complexity of the representation of a multi-zone environment lies in the fact that between the rooms there are walls that separate them and this must be interpreted by means of an electric resistance $\boldsymbol{R}$ in the circuit. Each room in the house must still contain a capacitor $\boldsymbol{C}$, which represents the thermal capacitance of that room.

Another two factors that make up a thermal circuit for a multi-zone environment is the influence of the external temperature T_{out}, in this case represented by an initial voltage V as well as the existence of heat pumps in each room, represented by the current generator I.

Finally the existence of temperature sensors in the rooms is indicated by T_{in}, which is represented by the electric point immediately above the capacitor of each room.

Figure 58 – Single and Multi-zone Electrical Representation



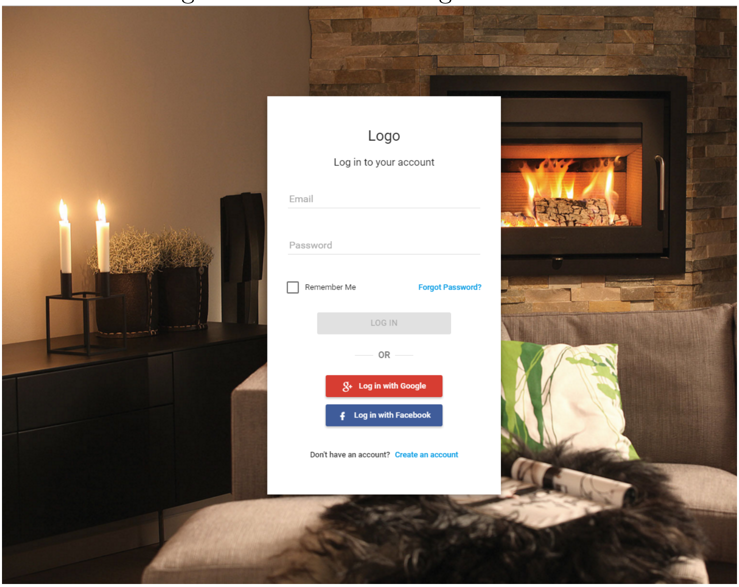
Source: Author (2017)

8.2 INTERFACES

This section is responsible for presenting some screen shots available and in final phase of development for this model.

Fig. 59 presents the login interface through which the household user can have access to the web-based system. It is proposed to be used in a web-browsers, smartphones and tablets.

Figure 59 – Interface: login interface

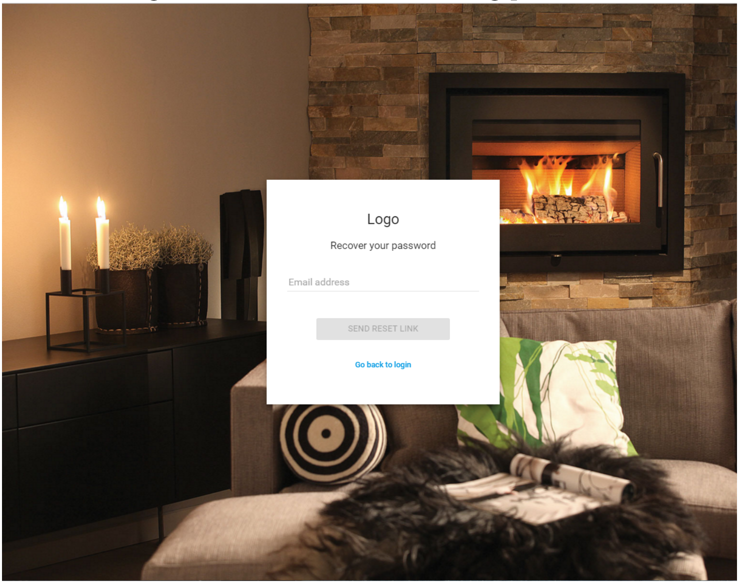


Source: Author (2017)

If the user selects the option *Forgot Password?*, he/she is directed to the interface presented by Fig. 60. With this process it is possible to recover the password by using the instructions received via email.

To create an account the user needs to inform only his

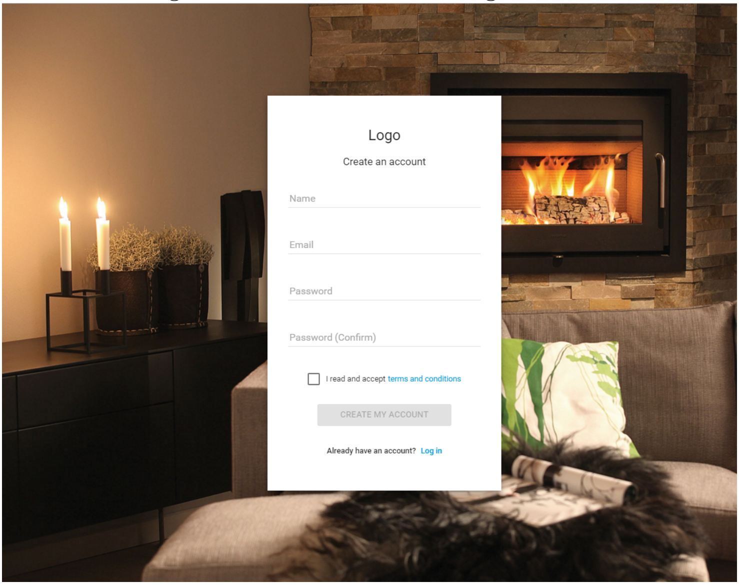
Figure 60 – Interface: recovering password



Source: Author (2017)

name, email address (used to recover password an as a login name) and a password as it is presented in Fig. 61.

Figure 61 – Interface: creating account



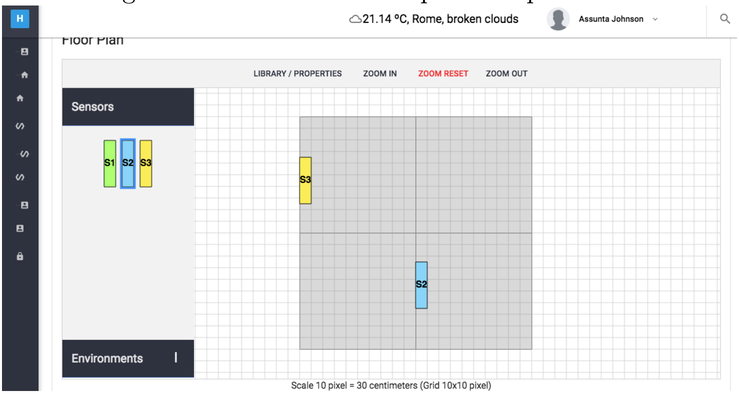
Source: Author (2017)

Fig. 62 presents a screen to the floor plan wizard. In this stage the user have already informed his floor plan composition and a multi-zone picture of his house is showed in order to check the informed features.

Fig. 63 presents an example of the implemented version of the prototype. In this picture it is possible to identify the floor plan composition and its features.

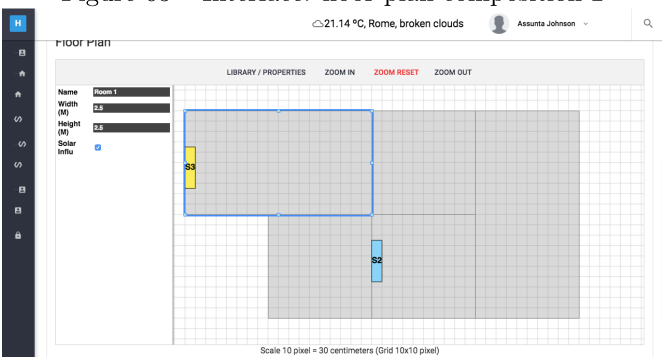
Fig. 64 presents a mobile interface in which the final users can select their preferences about the Internal Temperature. This interface was implemented based on the Tab. 2 but in

Figure 62 – Interface: floor plan composition 1



Source: Author (2017)

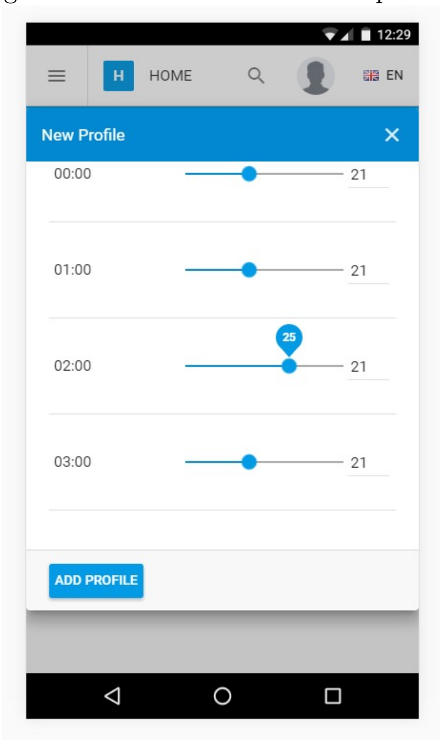
Figure 63 – Interface: floor plan composition 2



Source: Author (2017)

an intuitive way.

Figure 64 – Interface: desired temperature



Source: Author (2017)

8.3 SCIENTIFIC PRODUCTION OVER PH.D.

This section presents the scientific production carried out during the PhD course. The subsections that follow show the results achieved to date as well as papers in submission process.

8.3.1 Books and Chapters

- Preissler Jr., Sigmundo. *Organization, Systems and Methods.* ISBN 978-85-66237-40-5. Balneário Camboriú(SC): Avantis, 2015.

8.3.2 Proceedings in Congress

- Preissler Jr., Sigmundo. *How has does the Knowledge Engineering contributed for Smart Energy Technologies?* in: 3rd International Conference Energy Efficiency, Climate Innovation, Systems and Sustainable Development Conference. Florianópolis/SC(Brazil): UFSC, 2015.

- Preissler Jr., Sigmundo. *A model for thermal building parameter identification and simulation* in: 2016 International Multidisciplinary Conference on Computer and Energy Science (SpliTech). DOI 10.1109/SpliTech 2016 7555920. Split. Croatia: IEEE, 2016.

- Preissler Jr., Sigmundo and Gonçalves, Alexandre L. Reis, William F. *A model for Multi-zone Building Thermal Electrical Representation* in: 12th International Conference on Intelligent Environments. IE'16 IEEE International Environments. DOI 10.1109/IE.2016.36. London(United Kingdom): IEEE, 2016.

- Preissler Jr., Sigmundo. *A model for thermal parameter identification in a smart buildings context* in: International Smart Cities Conference (ISC2). DOI 10.1109 / ISC2 2016. 7580782. Trento(Italy): IEEE, 2016.

- Preissler Jr., Sigmundo. Reis, William F. *Interface to Reduce the Power Consumption due to the Heating Environments* in: IV International Conference Energy Efficiency, Climate Innovation, Systems and Sustainable Development Conference. Florianópolis/SC(Brazil): UFSC, 2016.

8.3.3 Papers in Journals

- Preissler Jr., Sigmundo. Gonçalves and Alexandre L. Knowledge Engineering and Management Contributions for Scientific Research in the Thermal Smart Energy Context. *International Journal of Recent Scientific Research.* Vol. 8, Issue, 4, pp. 16367-16372, April, 2017 DOI: http://dx.doi.org/10.24327/ijrsr.2017.0804.0138

- Preissler Jr., Sigmundo. Gonçalves and Alexandre L. Knowledge Engineering and Management in Thermal Multizone Building Studies: a Systematic Review. *IJKEM International Journal of Knowledge Engineering and Management.* v.6, n.15, 120-141, 2017.

8.3.4 In Submission Process

- Preissler Jr., Sigmundo. Tronci, Enrico. Mari, Federico. Mancini, Toni. Salvo, Ivano and Mellati, Igor. *House Thermal Parameters Identification from Heat Pumps Consumptions.* Target Journal: IEEE Transactions on Smart Grid Journal.