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MSc in ICT for Smart Societies Engineering

Design and Development of a Data Driven Model for Autonomous Heating System Management by IoT technologies and data analysis to reduce losses and improve comfort

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A mia madre e a mio padre,
che mi hanno sostenuto in ogni mia scelta.

Abstract

Energy consumption has a huge impact in companies budget and environment. Its monthly budget is affected by waste and losses and consequently the final product or service increases its price, becoming less competitive into the market. Heating systems represent the higher component of energy cost in most automotive plants, but its use is necessary to guarantee thermal comfort to employees and it may be regulated by government laws, such as in Italy and in most countries. Industry 4.0 technologies era with interconnected systems starts new autonomous heating system design to reduce losses.
Aim of this work is to present a temperature data-driven and scalable model, which does not require specific building characteristics to predict internal temperatures trend and be the basis of an efficient automatic control system. IoT devices and weather forecast are used to collect temperatures data and Unscented Kalman Filter to compute firstly building parameters and then internal temperature trend prediction The final solution aims to a base tool for Model Predict Controller which can use it to reduce waste and losses.

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Chapter 1

Introduction

Energy efficiency in buildings attracts interest of companies and governments because of its costs and environmental impact. In EU households, heating and hot water alone account for 79% of total final energy use . Currently, about 35% of the EU's buildings are over 50 years old. By improving the energy efficiency of buildings, we could reduce total EU energy consumption by 5-6% and lower CO2 emissions by about 5%[8]. The European Commission [1] set its own energy savings target to 20% in 2020 and to growth up to 30% in 2030[7]. Great investments in researches to develop more efficient energy source and innovative systems are allocated, because of industrial countries willingness to reach higher efficiency targets, using challenging policies, they invest and force investment of companies. An inefficient energy system affects companies' monthly energy cost because of waste and losses and consequently the final product or service increases its price, becoming less competitive into the market.

International Energy Agency [2] asserts that global investment in energy efficiency continued to grow in 2016, increasing by 9% to $231 billion. Buildings still dominate energy efficiency investment, accounting for 58% of the world total in 2016, with most investment in that sector going to building envelopes, appliances and lighting[1]. In Figure 1.1 is shown a pie chart of energy efficiency investments, as we previously said *Building* is predominant compared to *Transport* and *Industry*, but it is interesting to look at 2 particular pie slides: **HVAC** (Heating, Ventilation and Air Conditioning) and Envelope. Considering an existing building or plant such as in our case study, improvements in HVAC management systems reduce energy waste and losses, but it does

[1] European Commission website: energy topics, https://ec.europa.eu/energy/en/topics

[2] International Energy Agency website:,https://www.iea.org

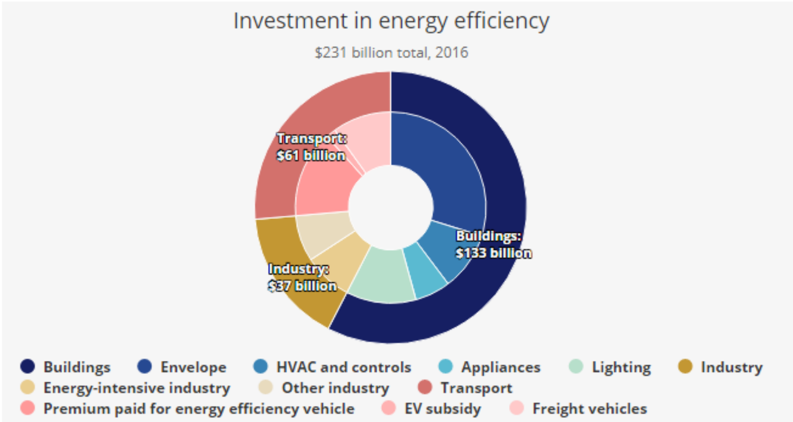


Figure 1.1: Global investment in energy efficiency.

not require the high cost in term of money, time and intrusiveness that a structural intervention demands.

Furthermore, considering the case of an industrial plant, an envelope intervention may interrupt the normal activities and may be a not feasible solution. On the other hand, there is a growing number of environmental performance building analysis programmes on the market, such as Integrated Environmental Solutions © IES <VE>, Autodesk © Revit, Ecotect, Vasari and Green Building Studio, Graphisoft © EcoDesigner STAR, EDSL © TAS Building Designer, EDR California © eQuest, U.S. Department of Energy © Energy Plus etc[5]. At the same time, **BIM** (Building Information Modelling) is a growing phenomena. BIM gives the opportunity to create a virtual model in which the information of the physical model, such as materials, subsystems, usage etc. is preserved[10]. Figure 1.2 shows the great interest on BIM in the recent past. The use of BIM in Energy Plus for thermal simulations is what is known as *white model*. Energy Plus [3] is free, open-source, and cross-platform, used to model both energy consumption—for heating, cooling, ventilation, lighting and plug and process loads—and water use in buildings. Performs building's simulations analyzing energy consumption aspects taking into account the before mentioned aspects. Throws Energy Plus and BIM models accurate energy simulation may be performed, having the possibility to set preferred internal temperatures threshold. But this software simulations may be not reliable if something is missed in the virtual model or not properly set on simulation software, internet have a key role to overcome this problem.

[3]Energy Plus website:https://energyplus.net/

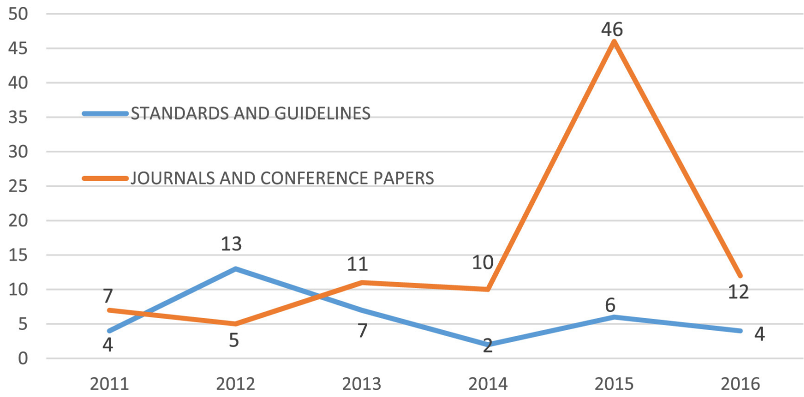


Figure 1.2: BIM standards and guidelines; and Academic publications[5].

The Internet revolution allowed people to interconnect with others independent of their geographical location through the Internet infrastructure. The current challenge of the Internet revolution is to connect objects and put them in the global network to make them available, with their data if they have them, to one user or more, who can not only read the data that means knowledge about the environment in which the sensors are located, but also acts and interacts using actuators. Due to the Internet revolution, in particular referred to **Internet of Things** (IoT), it is possible to connect, then collect data from objects, *sensors*, and/or give input throw *actuators*. This opens a new building scenario, in which every object is connected: **Internet of Everything** (IoE). Real-time information that IoT enables, accessible from everywhere if shared on cloud, Performsmakes it possible to work with simulation models which use a virtual representation of reality, benefit from real data of the physical environment that represents physical proof.

Furthermore, IoT will affect all the behaviours and services of each individual, because IoT context provides a huge device [1] [1] connected system that is able to control different services, starting by monitoring the traffic trend, cars, bicycles, parking etc. passing to monitor air quality or a surveillance system to arrive to touch every aspect of a “smart citizen”: health, transportation, home consumptions, security. IoT pervasiveness and ability to collect and analyse data that can be converted into information have motivated a plethora of IoT applications in the main fields showed in in : Smart Home, Smart City, Industry 4.0, connected vehicles School, Market, Transportation, Healthcare, Agriculture.[4]

The use of IoT can also change data model and energy modelling. It enables online systems and it can be used to give direct measures of the physical environment. In an ideal *Building Automation System*[4] (**BAS**), a predictive controller would understand everything related to thermal conditions and dynamics: occupant usage, weather predictions, and typical disturbances. This way opens to save energy, but at the same time improves occupant comfort.

Clearly, for this aim the model which takes charge of these different factors plays a key role and represents the main difficulty. To implement *Model Predictive Controller* (**MPC**) for HVAC in buildings is main research issue[18] . Moreover, for real-time control the model needs to be as simple as possible to reduce computational time, but at the same time modeling inconsistency can cause MPC performance deterioration. Nowadays, it is hard to find scalable and data-driven methods for cost saving to throw an optimal control. The root cause is in the buildings' diversity in their HVAC equipment, construction, years and use. To summarize, a long-term usable model requires a low-cost scalable method which has to learn both the dynamics and the disturbance patterns quickly, provide stable extrapolation, be adaptable to future changes in building structure or use, and use existing available data[25].
The work made by Xiwang Li and Jin Wen [18] gives a global overview of the current energy modelling state of art. There essentially three different kind of approach, each one has its pro and cons:

1. white box: it uses detailed physical models even if they may reach better accuracy, its computational demand is might be too high for on-line building operation, because they deal with huge number of parameters and iterations. They are not robust to changes, and take extensive engineering or research effort to be build;

2. black box: these models use statistics, this allows on-line building operation because calculation speed is faster; on the other side, they require huge amount of data for training, including building operation. In situation in which there is a lack of data, such in our case, they need an important collection time to operative.

3. gray box: these simplified physical models are better for practical building model based operation application. They have less parameters to determine and need shorter computation time, which has huge potential in building energy model for energy and cost saving

[4]A building management system (BMS) or building automation system (BAS), is a computer-based control system installed in buildings that controls and monitors the building's mechanical and electrical equipment such as ventilation, lighting, power systems, fire systems, and security systems. A BMS consists of software and hardware.

Radecki and Hencey demonstred that utilizing building topology plus online temperature and weather data with gray-box methods in [26], may give a low-cost, scalable way to learn passive thermal models from measured data. A resistor-capacitor (RC) network is used to model the conduction, convection, and mass transfer thermal dynamics occurring in the building. But also other gray-box models show potential as a scalable option for data-driven model, in which may not have previous data collection or database[24][11].

1.1 This Master Thesis

This Master Thesis has been developed from October 2017 to March 2018 in the **World Class Manufacturing** (WCM) office of **Fiat Chrysler Automobiles** (FCA) under the supervision of Ing. Francesco Canuto, in collaboration with Politecnico di Torino, under the supervision of Prof. Andrea Acquaviva and Dott. Lorenzo Bottaccioli. This Thesis represents the Final Project of the Master Degree in ICT for Smart Societies, and it covers several topics studied within this degree, together with the author's personal background and experience. Among the subjects associated with this work, the main ones are: Internet of Things, Information Communication Technologies, Networks Architectures and Protocols, Programming Languages, Software Design and Development, Statistics and Computer Science. Besides, also some Energetic and CAD Modelling issues have been addressed.

1.1.1 Main Objectives and Results

The main objective of this Master Thesis is the study and development of Data-Driven Model for building temperatures and thermal condition prediction. Clearly, several topics have been encountered, studied and discussed. Going in details, the following fields have a dominance importance: Data Model, Energy Modelling for buildings and the application of Data Model on Energy Modelling, to achieve a data-driven and scalable model for internal temperatures prediction that can be a first brick for an advanced autonomous HVAC management system. For the proposed solution a real case study has been used as reference: Body Shop area in Mirafiori Plant, Torino. The approach was to first design a Wireless Sensor Network to install in plant and get a dense amount of temperature data, including technology standard for exchanging data over short distances and board selection. Simultaneously, Data Model and Data Model for Energy prediction have been studied. Then an application has been implemented, making use of Unscendent Kalman filter and RC circuit to model the layout of the building.

The strategy implemented can be divided in the following steps:

1. First, the Wireless Sensor Network (WSN) has been designed, choosing the physical techonogy for packet transmission among sensors. In fact the WSN in use does not fit the current data model information density demand.

2. Second, a literature research to discover the current data model in use has been made. In particular, in the case study of reference (Mirafiori plant), there was lack of temperature data, it was necessary to adopt a Data Driven model for energy efficiency improvements purpose, in which no previous information was available to give as input to the model.

3. Third, a modular application has been implemented, considering one cube exchanging heat with the external environment. This model has been reproduced in Design Builder, then passed to Energy Plus to obtain the temperature internal trend. This data were necessary to validate the model. A temperatures simulator to compensate for data scarcity has been implemented.

The project has led to useful results in terms of buildings parameters estimation and model potentialities. The main Thesis outcomes can be summarized as follows:

- The data model works starting from no previous information or dataset, but receiving as input just the circuit model.

- The parameter estimation has showed excellent results on simulated data and it is currently at the center of some further developments, aimed at improving its usability, in order to integrate it with a multi-room model.

- The modular case study application has been successfully realized and it can now be integrated with more features.

1.1.2 Outline

This Subsection presents the Thesis organization, which has been structured in the following seven Chapters.

Chapter 1 (this Chapter). It provides an introduction to this Master Thesis, presenting a brief discussion of the main topics addressed during the project development: Energy Efficiency, Internet of Things, HVAC and data-driven model. Besides, it provides a description of the work done, highlighting the main results achieved.

Chapter 2. It contains an overview of **WCM** (World Class Manufacturing). The Chapter aim is to provide the main theoretical concepts to understand the WCM view. Moreover, a link between Industry 4.0 idea and WCM philosophy is proposed.

Chapter 3. A general and brief analysis of both to IoT and sensor's Communication Technologies is presented, necessary to design the wireless sensor network to guarantee radio channel coverage for the case study, which is the main work developed in the first part of this Thesis.

Chapter 4. The data-driven model developed is explained in details. Not only the theoretical concepts behind it are presented, but also a step-by-step description of the implementation process is provided.

Chapter 5. The actual case studies with the possible solution is addressed. Moreover the reasons why data-driven model may outperform the BIM strategy in some conditions is highlited.

Chapter 6. A conclusion to this Master Thesis is presented, including open issues, possible future developments and achieved results.

Chapter 2

Background

This thesis is the outcome of an internship experience in the World Class Manufacturing office of Fiat Chrysler Automobiles Group Turin. It is only right to discuss about why World Class Manufacturing was born, which is the current implementation of World Class Manufacturing inside FCA Group. Moreover, the current industry context needs to be introduced, well known as Industry 4.0, characterizes by innovative Information Communication Technologies applications can radically change not just production technologies but above all the entire Factory management. Factory is the matchmaker between WCM and Industry 4.0, these apparently parallel worlds work together to build the ideal concept of Smart Factory in different ways, the first one hands on whole production chain management, the second one bringing new technologies in industrial plant.

2.1 World Class Manufacturing

Manufacturing companies research continuously the competitive advantage, that purpose brings companies to make innovation in production systems and adopt more efficient methodologies. Profit margins are usually small in the car mass-market manufacturing industry, manufacturing efficiency is a must to be competitive in term of price in the market. Japanese car manufacturers started to develop several methods to optimize manufacturing processes after the World War II the most famous, is Toyota Production System. Toyota managed to became the world reference for manufacturing efficiency thanks to its Production System. Lean Manufacturing, Just In Time, Total Productive Maintenance and Total Quality Management are some of the concepts birth with TPS.

WCM was born in the 90s: the over mentioned themes were implemented in United States with the Cost Deployment, which classify in order different problems, underlying priorities.This leads the World Class Manufacturing: a different set of concepts, principles, policies and techniques for managing and operating a manufacturing company. WCM is a renovation program based on excellent standards that govern the whole logistic-productivity cycle and aims to improve performances and techniques adopted by top companies.

Finally in 2005 Fiat and Chrysler adopted World Class Manufacturing program both in vehicle and powertrain production, which resulted in resources and energies to be addressed at the program. This great innovation required the creation of a training system in order to develop the required competences at every level: for this reason several WCM Academies were born in the following years, starting from Cassino plant one in 2009.

World Class Manufacturing is method to be applied every day and has not an end point, because its program of continuous improvement leads at the optimization of every productive and logistic process eliminating all wastes and losses. The final target is to achieve the "zero": zero scraps, zero defects produced in the manufacturing process, zero breakdowns, zero stock thanks to an efficient logistic system, zero injuries all at the lowest cost. Clearly, these objective act directly on production site in which they have to be reached, creating better conditions to: product quality, working conditions, higher profitability, higher efficiency, lower risks and eventually the establishment of continuous improvement culture.

Total Industrial Engineering, Total Quality Control, Total Productive Maintenance and Just In Time are part of WCM philosophy, but it distinguishes from the previous systems because it is an integrated model that determines the priority of action by means of the identification and analysis of wastes and losses in the production process. Cost Deployment is the tool to give these priorities: it guides the WCM process and assure main issues intervent and solution. The output of Cost Deployment is the identification of model areas. Morever, WCM differs from other systems in the introduction of specific methodologies, the application and diffusion of specific tools, a significant change in people skills and behaviors.

2.1.1 WCM structure

In 2.1 WCM pillars are shown. WCM transverse to all processes and affects all the company activities by means of a pillar structure: indeed the program targets are achieved using and implementing the methodologies included in ten technical pillars and ten managerial pillars.

Technical pillars are focused on the development of a WCM methodology for the optimization of

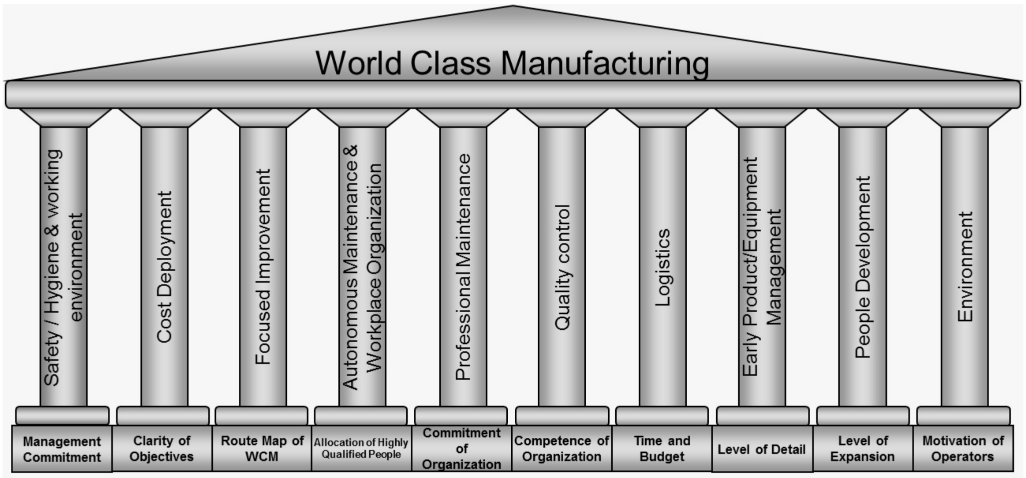


Figure 2.1: WCM pillars: technical (colums) and managerial (floor).

the ten major aspects of production: Safety, Cost Deployment, Focused Improvement, Autonomous Activities that are Workplace Organization and Autonomous Maintenance, Professional Maintenance, Quality Control, Logistics and Customer Service, Early Equipment Management, People Development, Environment.

Managerial pillars support the technical pillars and aim at people and leadership development. Moreover, they are needed to inform the management and the entire organization of the WCM benefits. This will ensure the availability of resources and the commitment for the WCM program. The pillars have a step by step structure: indeed each pillar is composed of 7 steps. Each step has a gradual structure of in smaller steps. The whole process starts from the identification of a model area for the implementation of the steps. At the end of each step, the results are measured with proper indicators that are divided in Key Activities Indicators (KAI) and Key Performance Indicators (KPI). These seven steps are needed to achieve the target in several phases. During the implementation of the pillar steps the problem solving approach changes from a reactive to a preventive and then a proactive approach.

Firstly the reactive approach is used during the first steps and it solves the problems simply reacting to them, without searching and eliminating the root cause. Secondly, a preventive approach is adopted and the work is carried on in dorder to eliminate problem sources. At the end, During the last steps the approach becomes proactive and the effort are addressed at eliminate the possibility of future problems already in the design phase.

When improvement activities have been carried out in the model area and the results have been checked, the process continues with the standardization and implementation of the solutions in the so called expansion areas, which can benefit from the improvements applied in the model area. Once the method has been spread in all the expansion areas, the improvements are implemented in the whole plant.

An audit system has been implemented in order to evaluate WCM performances of the plants. To obtain a comprehensive total score, to each pillar a partial score from 0 to 5 points is assigned according to the level of WCM implementation for that pillar.The total score is the sum of the partial ones and vary from 0 to 100 points: according to the total score the plants are divided in four levels. The minimum award level is Bronze and starts from 50 points, the following level is Silver and starts from 60 points, then there Gold level starts from 70 points and finally the World Class level starts from 85 points. It is clear that this audit system is aimed at the creation of a competitive and exiting environment that encourage the continuous improvement culture, which is perhaps the most important concept of World Class Manufacturing.

2.2 Industry 4.0

The Internet revolution as previously said in Introduction touches not only our city of the future, but it's also changing our Industry and its design. The first industrial revolution introduced the mechanization of production using steam power; the second industrial revolution then mobilised mass production with the help of electric power. The third industrial revolution began in the half of the 20th century through the electrical and information technology to achieve automated manufacturing2.2.

Industry 4.0 is used to identify the new industrial revolution; its core is on Internet plus Manufacturing. This term was used for the first time by a German government project which aimed to computerizes at high-level technologies of manufacturing[2][6]. The essence is represented by "cyber-physical systems", but the Industry 4.0 includes Internet of Things and cloud computing. Cyber physical system carry out the main task, it must translate the real system in a virtual system machines-friendly in which them can work interacting with the real world and humans. This virtual world adds the storage, computation, communication and control in order to be able to create

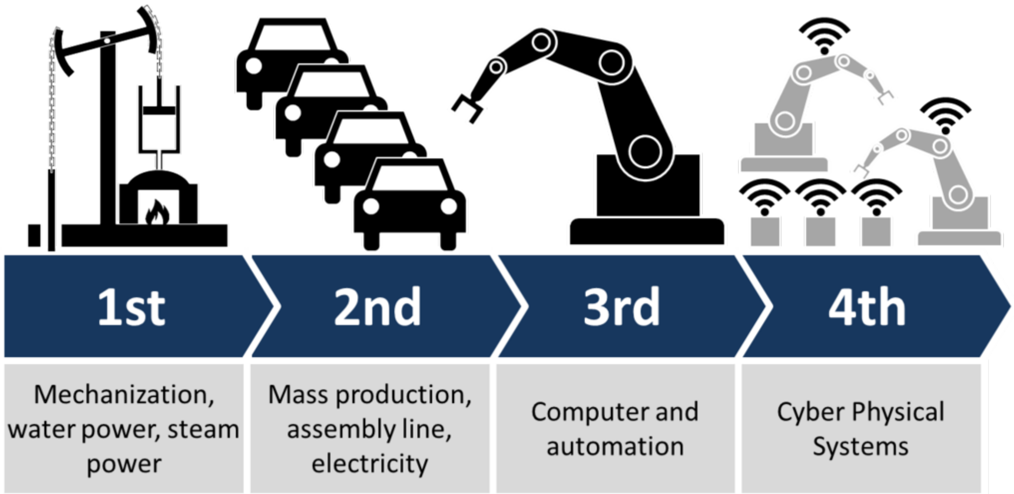


Figure 2.2: Industrial revolutions. Courteously contribution by Christopher Roser[27].

reliable system, with real-time interactions in the real world collecting feedback by it in order to take next decisions[6]. Industry 4.0 aims to improve automation using data exchange in manufacturing technologies. Its nine pillars are: virtual reality, artificial intelligence, industrial internet, industrial big data, industrial robot, 3D printing, cloud computing, knowledge work automation and industrial network security. Industry 4.0 refers to the strong customization of products under the conditions of highly flexible (mass-) production. Its principles are defined by:

1. **Interoperability**
2. **Information transparency**
3. **Technical assistance**
4. **Decentralized decision**

All these characteristics are strictly correlated to the concepts of interconnected, data, integrated and innovation. To achieve Interoperability it is necessary the ability of machines, devices, sensors, and people to connect and communicate with each other (Interconnected), this is possible with IoT. Information transparency requires high data meaning and understand their connections in the context to augment the capacity to work with them. The previous mandatory concepts and features allow to perform decentralized decision, the cyber physical systems can make decisions autonomously and to perform their tasks as autonomously as possible [20][22]. In the future, the production processes of intelligent factory will be highly transparent. They will use intelligent production to obtain smart products. Nowadays a lot of countries are investing in the intelligent manufacturing, but for this objective a unique communications method is required to obtain a common language knew by everybody. In this way it'll be possible to interconnect completely all the players in the intelligent factory. For this aim, there are different projects in different countries working to create the new standards, in Germany "i40", in the United States "Internet of things", in China "Made in China 2025". All of them want to enhance the current level of the manufactory using the new technologies in term of information and energy consumptions. This process of standardization and prototype of Industry 4.0 will the foothold of the next generation of manufactory “Intelligent manufacturing”

2.3 Smart Factory

Smart Factory is an ideal production plant where Industry 4.0 fundamentals, concepts are implemented in production solutions. It represents the center in which Internet of Things, augmented reality, Big data analytic, additive manufacturing, autonomous robot, simulation, cyber-security, vertical and horizontal integration and cloud, working together realize a smart production environment. Client demand, supplier availability, production status, product process and many other parameters may be easly accessible with current technologies, factories become smarter, more efficient, safer and more environmentally sustainable, thanks to the combination and integration of all the previous shared information, plus innovative technologies which support technical and managerial operation.

Radio-Frequency Identification (RFID) is the most known technology[28]. It supports the monitoring and the scheduling of production procces, increasing traciability and bringing new solutions for logistic. RFID like IoT case make objects smart, they 'talk' with machines in the line, giving them the possibility to take decisions depending on product characteristics. Sensors and RFID are key features of the fourth industrial revolution, not only for the basic monitoring that they may give, but for the ralation with a virtual world they can build, creating huge opportunity for simulations and oprimizations.

Common examples of Smart Factory application are related with flexibility and re-configurability of production line, because customers researches customizes products, but the cost they are willing to pay its still the one available by mass market production. Cost efficiency is a must to satisfy customer needs and remain competitive, inter-operable and flexible lines allow companies to save money, but at the same time responce to single customer's custom demand.

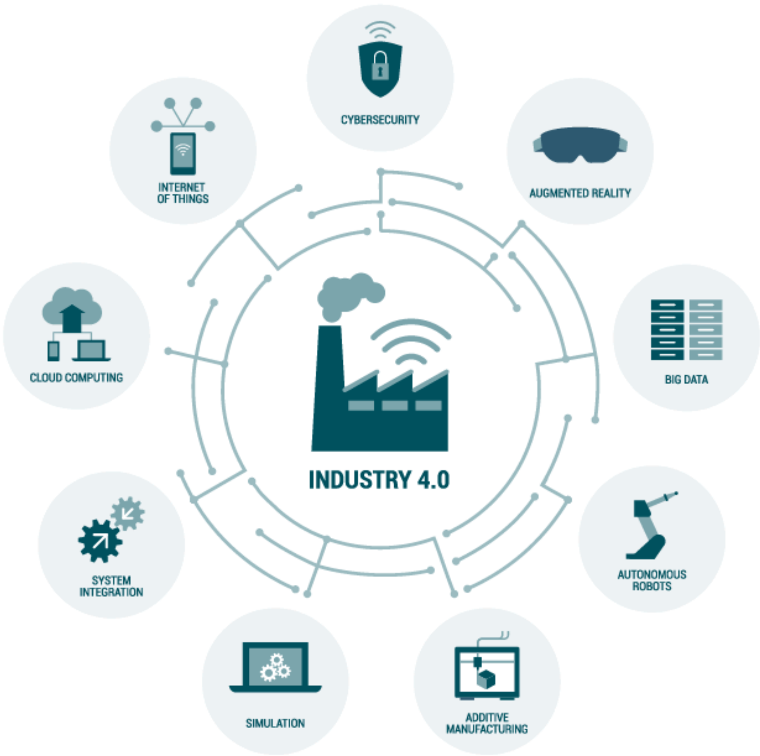


Figure 2.3: Smart Factory and main concepts (Picture by https://www.i-scoop.eu/industry-4-0/).

Industry 4.0, in particular the Smart Factory, aims to bring inside industrial environment an efficiency which has been researched by World Class Manufacturing since the begging. All these new technologies with the Information Communication Technologies gives opportunity to improve WCM attack on waste and losses.

Boston Consulting Group stands that The factory of the future is a vision for how manufacturers should enhance production by making improvements in three dimensions: plant structure, plant digitization, and plant processes[12]. In WCM Academy applications on these dimensions have been already deployed and available to test for employees, in 2.4 an augmented reality application. On the other hand, cutting-edge technology requires great investment budget, especially if they imply plant renovation like the case of automotive sector. Moreover, cutting-edge technology does not assure better performances. For this reason the WCM' technical and managerial vision with help of Cost Deployment tool assure right intervention and real benefit on 'short term' investment.

Figure 2.4: Augmented reality in WCM Academy.

Information and Communication systems, data and services in network infrastructures. For example, in a Smart Factory f. Other examples include the implementation of the Internet of Things (IoT) technologies in the Smart factory: e.g. sensors and artificial intelligence drive smart maintenance; mobile and augmented reality devices empower workers to increase the efficiency and agility of their operations with processing of information in real time; and cloud computing systems allow storing data in a network-based sharing environment. Altogether, the implemented technologies allow for the use of resources in an efficient way, making sustainability a key feature of Smart Factories.

Smart manufacturing is a broad category of manufacturing with the goal of optimizing concept generation, production, and product transaction. While manufacturing can be defined as the multi-phase process of creating a product out of raw materials, smart manufacturing is a subset that employs computer control and high levels of adaptability. Smart manufacturing aims to take advantage of advanced information and manufacturing technologies to enable flexibility in physical processes to address a dynamic and global market. There is increased workforce training for such flexibility and use of the technology rather than specific tasks as is customary in traditional manufacturing. Smart Manufacturing both leads and respond to a dramatic and fundamental business Computers and Chemical Engineering 47 (2012) 145–156 transformation toward demand-dynamic economics, performancebased enterprises, demand-driven supply chain services and broad-based workforce involvement and innovation. This intensification of 'manufacturing intelligence' comprises the real-time understanding, reasoning, planning and management of all aspects of the enterprise manufacturing process and is facilitated by the pervasive use of advanced sensor-based data analytics, modeling, and simulation ([9]

Chapter 3

Internet of Thing: protocols and technologies for Industry

This part of the thesis has been developed during the second semester of abroad studies in Barcelona at *Universitat Politècnica de la Catalunya* [1]. This chapter offers a general overview on current Internet of Things protocols and technologies from physical to network layers of Open Systems Interconnection model (OSI model).

The IoT deals with a lot of challenges emerged to connect objects to Internet. The normal architectures have been discussed and changed to be applied in IoT network, TCP/IP protocol stack played a fundamental role in the communication evolution, but its application in the Internet of things concept cannot be taken as obvious, since working in Wireless Sensors Network (WSN) means to deal with tiny objects, small computing power which characterizes these devices. Then it was necessary to find new architectures and protocols suitable for this case. Some architectures and protocols for WSNs are explained to consider their pros and cons.

The work made by [15] introduce IoT general architecture and dived it in five levels as showed in 3.1 (The IoT generic architecture). The Perception layer corresponds to the Physical layer in the standard ISO OSI. Its purpose is the identification and collection of specific information by each type of sensor devices. This physical layer consists of the different types of sensor (i.e. RFID, Zigbee, QR code, Infrared, etc.) devices and environmental elements. This layer includes sensors and actuators to perform different functionalities such as querying location, temperature, weight,

[1] Universitat Politècnica de la Catalunya currently referred to as BarcelonaTech and commonly named just as UPC, is the largest engineering university in Catalonia, Spain

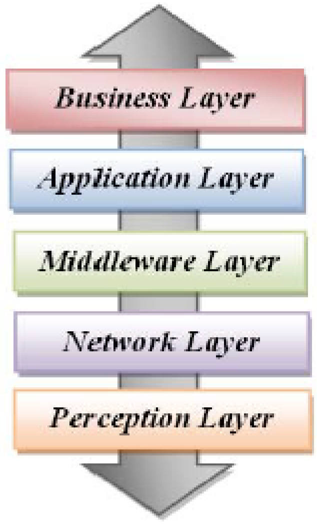


Figure 3.1: Generic architecture. Courtesy of [15]

motion, vibration, acceleration, humidity, etc. The perception layer sometimes referred as Objects Layer digitizes and transfers data to the Object Abstraction layer through secure channels. The big data created by the IoT are initiated at this layer.

The Network or Object Abstraction layer plays an important role in securely transfers and keeps the sensitive information confidential from sensor devices to the central information processing system. Data can be transferred through various technologies such as RFID, 3G, GSM, UMTS, WiFi, Bluetooth, LowEnergy, infrared, ZigBee, etc. Furthermore, other functions like cloud computing and data management processes are handled at this layer.

Middleware or Service Management layer includes service management and store the lower layer information into database, this layer has capability to retrieve, process, compute information, and then automatically decide based on the computational results.

The application layer provides the services requested by customers layer, is responsible for inclusive applications management based on the processed information in the Middleware layer. It has the ability to provide high-quality smart services to meet customers' needs. The application layer covers numerous commercial market such as smart home, healthcare, transportation, industrial automation etc. Business layer deals with IoT applications and services management. Depending on the amount of data and their quality that lower layer sends to it and effective data analysis process, it can create from those, graphics solutions that helps decision making and presentation, such as graphs, business models, flow chart, executive report.

3.1 Protocols and standards

World Wide Web Consortium (W3C), Internet Engineering Task Force (IETF), EPCglobal, Institute of Electrical and Electronics Engineers (IEEE) and the European Telecommunications Standards Institute (ETSI) are some of the groups that are working to build protocols and standards for IoT applications. Those are necessary to help programmers to develop IoT networks and clarify a common way to work depending on the requirements of a specific applications. 3.2 shows some of the current protocols and standards used in WSNs and in general for IoT application. In this section some of the protocols showed are discussed.

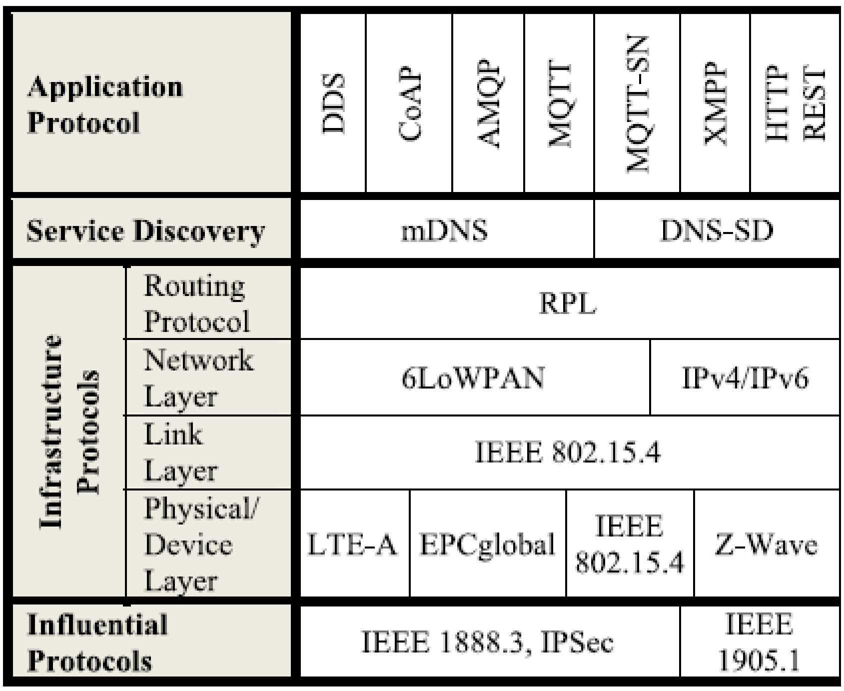


Figure 3.2: Partial overview of main protocols used in IoT.

3.1.1 IEEE 802.15.14

The main objective of this protocol is to define low-rate wireless personal area networks (LR-WPANs) operations. It specifies the physical layer and media access control for LR-WPAN. It is used in IoT, Machine-to-Machine (M2M) and WSNs, because it presents low power consumption, low data rate, low cost, and high message throughput. It is the basis for the ZigBee and many other property and not protocols in which upper layers are provided, because they extend this standard developing upper layers that are not defined by IEEE 802.15.14.

IEEE 802.15.4 PHYs only supports frames of up to 127 bytes so an adaptation layer protocol provides fragmentation schemes to support larger network layer packets, that is the case of 6LoWPAN that also relay on this standard. The IEEE 802.15.4 protocol was created to specify a sub-layer for Medium Access Control (MAC) and a physical layer (PHY) for low-rate wireless private area networks(LR-WPAN) as showed in 3.3

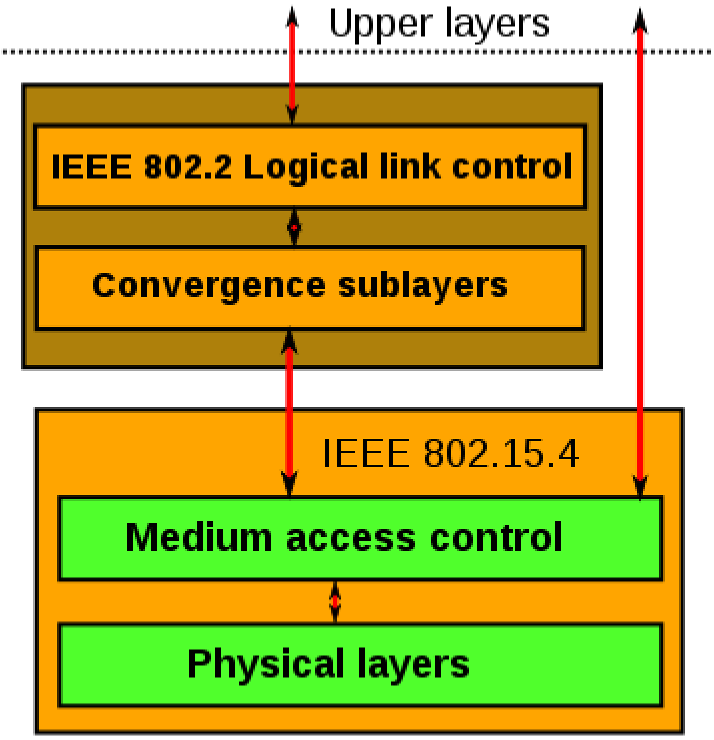


Figure 3.3: IEEE 802.15.4 protocol stack.

IEEE 802.15.4-conformant devices may use one of three unlicensed frequencies bands for operation (868/915/2450 MHz): 250 kbps at 2.4 GHz, 40 kbps at 915 MHz, and 20 kbps at 868 MHz.

In upper frequencies it is possible to have bigger transmission rate, but the choice depends on the distances covered. Higher frequencies and wider bands provide high throughput and low latency whereas lower frequencies provide better sensitivity and cover larger distances. IEEE 802.15.4 utilizes the CSMA/CA protocol to reduce and avoid the collisions.

It provides a reliable communication, operability on different platforms, and can handle a large number of nodes (about 65 k). It also provides a high level of security, encryption and authentication services. However, it does not provide QoS guarantees. IEEE 802.15.4 defines two types of node: full-function device (FFD) and reduced-function devices (RFD). FFD can store a routing table within their memory and implement a full MAC. It can serve as a personal area network (PAN) coordinator: responsible for creation, control and maintenance of the network. FFDs. They also can communicate with any other devices and act as a normal node. RFD are extremely simple devices with a low amount of resource and communication requirements, for this reason they can just communicate with FFDs and they cannot be or act as a coordinator in the network.

The IEEE 802.15.4 standard support three types of topologies: star, peer-to-peer, cluster tree. In the star topology the PAN coordinator (that also means one FFD must be present) has to be the central node who communicates with the different devices both FFDs and RFDs. The peer-to-peer topology is a generic topology in which there is a PAN coordinator and the FFDs communicate each other and with RFDs. The cluster three is a particular case of the peer-to-peer topology in which the RFDs are leaves.

3.1.2 Z-Wave

Z-Wave is a wireless communications protocol used primarily for Home Automation Networks (HANs). Zen-Sys firstly developed Z-Wave, then it has been acquired by Alliance. This protocol is designed to provide reliable, low-latency transmission of small data packets.

Wi-Fi and other IEEE 802.11-based wireless LAN are designed for high-data rates, then they can't be suitable for sensors applications. Z-Wave s operates in ISM bands around 900 MHz depending by the country, due to its throughput equal to 40kbit/s and data rates up to 100kbit/, Z-Wave is preferred in IoT and M2M context. More precisely, this protocol aims to home and office automation market, in fact it has been applied in smart home, control lighting, HVAC , security systems, home cinema, automated window treatments, swimming pool and spa controls,

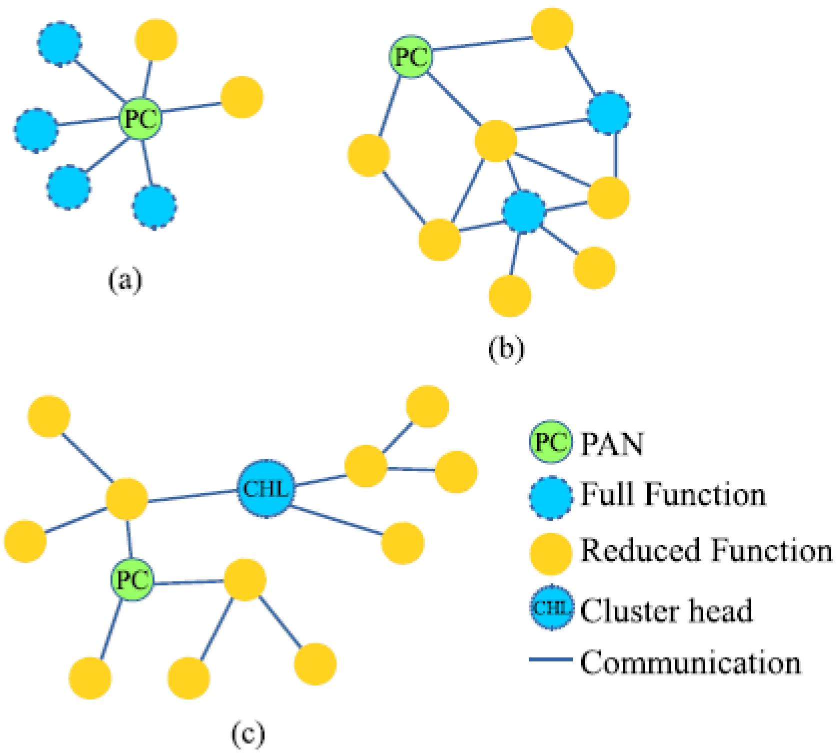


Figure 3.4: IEEE 802.15.4 topologies: (a)Star. (b)Peer-to-peer. (c) Cluster-tree.

and garage and home access controls.

The network covers distance between two nodes about 30 meters. Each network is identified by a Network ID with a length of 4 bytes, and also each device has its own ID, a device is identified by a Node ID of 1 byte and must be unique in its network. The Network ID (also called Home ID) is the identification of all nodes belonging to one logical network. When the device is "included" into the Network receives the Network ID by the primary controller. Nodes with different Network IDs cannot communicate with each other.

Z-Wave uses a source-routed mesh network architecture, its network can consist of up to 232 devices, with the option of bridging networks if more devices are required. Two types of nodes compose its network: controllers and controlled devices. The controllers devices are able to store a routing table and pass the information to the controlled devices. A controlled device could be a sensor which is able to get temperature, humidity, turn on/ off light, open/close a window etc. In 3.5 Z-Wave stack is showed. The lower layers, MAC and PHY, are described by ITU-T G.9959.

At MAC layer it uses CSMA/CA.

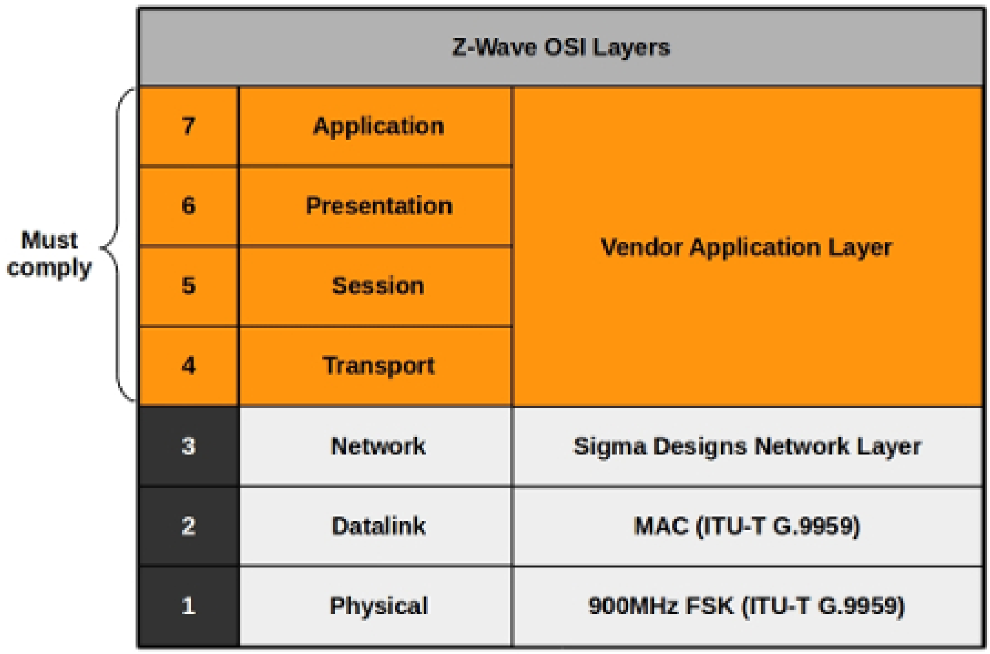


Figure 3.5: Z-Wave: protocol stack

3.1.3 Bluetooth Low Energy

Bluetooth Special Interest Group developed Bluetooth Smart better known as Bluetooth Low Energy (BLE). It is a wireless personal area network technology which aims to be applied in health care and home entertainment applications market, in general it can be used in low power and energy technology, in fact it is used also in fitness, wearable sensors etc. The main difference with its predecessor is in the battery consumption that ensure a longer device's battery life. It is already adopted and native supported by almost all smartphone companies.The Bluetooth 4.0 specification permits devices to implement either or both LE and Classic systems, so the new version is fully compatible with its predecessor.

BLE's network stack 3.6 work in this way: In the lowest level of BLE's stack there is a Physical (PHY) Layer which transmits and receives bits, its spectrum range is 2.400–2.4835 GHz ISM band as Classic Bluetooth technology, but it uses a different set of channels. Then there is the Link Layer services including medium access, connection establishment, error control, and low control are provided. Over the last one, the Logical Link Control and Adaptation Protocol (L2CAP) provides multiplexing for data channels, fragmentation and reassembly of larger packets. The other upper layers are Generic Attribute protocol (GATT) which provides efficient data collection from sensors, and Generic Access Profile (GAP) that allows the application for configuration and operation in different modes such as advertising or scanning, and connection initiation and management.

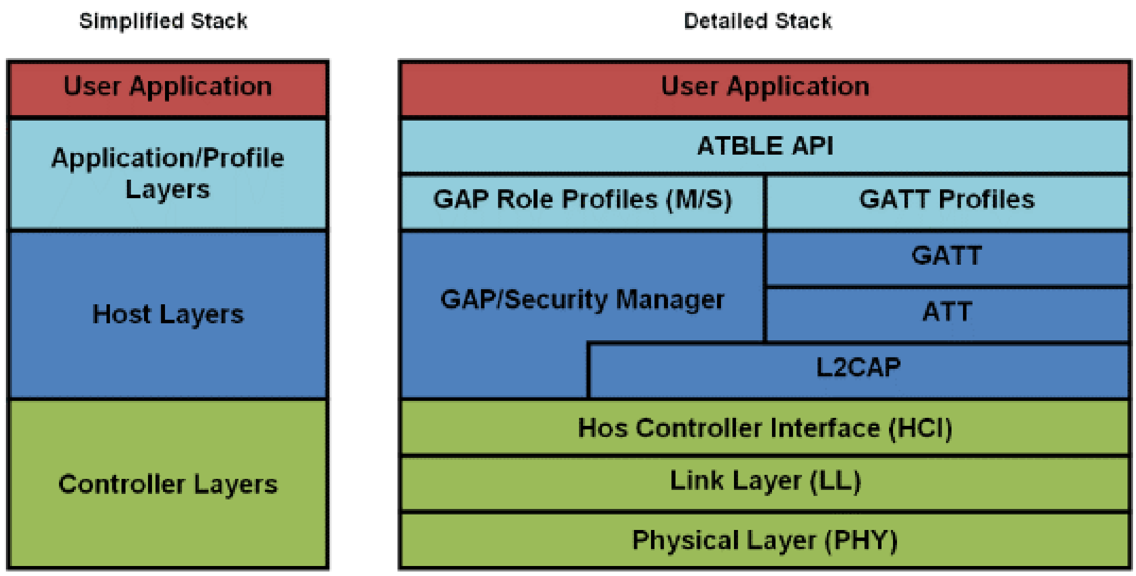


Figure 3.6: BLE's stack

BLE presents a bigger cover area compared with the classical one and furthermore it has a shorter latency time with a slightly reduced power consumption. BLE adopts a star topology in which allows devices to operate as masters or slaves. For the discovery mechanism, slaves send advertisements over one or more of dedicated advertisement channels. To be discovered as a slave, the master scans these channels. Except for the time when two devices are exchanging data, they are in sleep mode for the rest of the time.

3.1.4 6LoWPAN

In the Internet of things, the Identification of the objects it's the first step to obtain a network in which the objects are able to communicate. First of all the problem is dived in objects ID and addressing. An object ID is its identification code in the network, for instance it could be "H2" for a humidity sensor in the network, but it is necessarily addressed at each resource with a unique name that can't be found in another object. There are several ways to address objects in WSNs such as electronic product codes (EPC) and ubiquitous codes (uCode).

In addition to address objects over Internet it's necessary to use IP protocols: IPv4 and IPv6. Since they require a big amount of data in headers, these protocols are not suitable to WSNs. Adopting IP addresses allows to connect the WSNs devices with all the internet dispositive, so it represents a big advantage. 6LoWPAN (IPv6 over Low power Wireless Personal Area Networks) is used to make IPv6 addressable objects with power constraints. 6LoWPAN is an open standard defined in RFC 6282 by the Internet Engineering Task Force (IETF).

Using IP to connect dispositive It's possible to connect them within all the other IP networks, because 6LoWPAN only specifies operation of IPv6 over the IEEE 802.15.4 standard, edge routers may also support IPv6 transition mechanisms to connect 6LoWPAN networks to IPv4 networks. It provides a compression mechanism over IPv6 headers. 6LoWPAN is located in OSI layers model between the data link layer and the Network layer, IP in this case. 6LoWPAN is adopted over IEEE 802.15.4 because it allows IPv6 packets to be carried efficiently within small link layer frames, such as those defined by IEEE 802.15.4. However, it is now being adapted and used over other networking media: Sub-1 GHz low-power RF (IEEE 802.15.4g), Bluetooth Smart, power line control (PLC) and low-power Wi-Fi. In 6loWPAN both Physical and MAC are defined by IEEE 802.15.4 (even if other technologies are starting to use it as mentioned above). Then 6loWPAN works in the middle of the data link layer and the IP network layer. Over that there is the transportation layers with its two protocols: TCP and UDP. UDP is more interesting for low power consumption systems (such WSNs context), because it has a lighter header and does not required a permanent connection. On top of it there is the application layer responsible of data formatting

The 6LoWPAN network is connected to the IPv6 network through an edge router which is responsible of three actions: the data exchange between 6LoWPAN devices and the Internet, local data exchange between devices inside the 6LoWPAN, the generation and maintenance of the 6LoWPAN network. In the 6loWPAN Network there are routers and hosts. Routers are able route data inside the 6loWPAN network to other devices that compose this subnet. Hosts are end devices such as sensors, controllers, etc. cannot route data in the network. In order to obtain a low power consumption and as consequence a huge energy saved, hosts can work as sleepy device. The host in sleepy mode has to wake up periodically and ask to its parent (a router) to retrieve

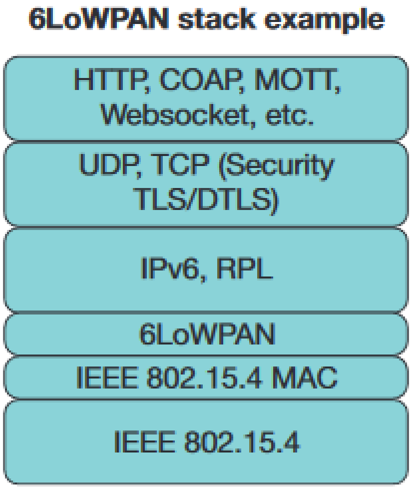


Figure 3.7: Example of the 6LoWPAN stack.

the data.

Chapter 4

Data-Driven Model

The adopted method described in this chapter is the result of consideration problems which fit the final objective of project between FCA and PoliTo: a scalable and data-driven solution. IoT technologies are still not implemented in most industrial plant in Italy and in the world. Temperatures sensor may not be collected or worst, monitored. In the solution's development this consideration drove to the final model characterization. A case in which no previous data were available had to be our benchmark. A part of the other specific problematic better explained in the next paragraph that both white-box and black-box brings with them, a gray-box model adoption is the most reasonable way to solve HVAC management inefficiency in industrial plants.In this chapter, after a brief remind about possible model solution, the focus will be moved to the specific model developed and tools used during this thesis work.

Energy efficiency margins in buildings' heating , ventilating, and air conditioning (HVAC) systems are important. Advanced control systems have a key role to reach such profits [3]. But most solutions are specific solutions for each building, scalability and cost effective solutions are necessary to develop a MPC which may adapt with different buildings and its characteristics.

In particular a Building Automation System (BAS) should have a complete knowledge about all the aspects which affects the building thermal balance: weather temperature, internal temperature, occupancy and loads. Through an MPC, BAS changes temperature set points and loads, to answer to real-time demand and work to near-optimal condition, bringing savings both in energy and money. However, the huge complexity and unavailable information of buildings parameter does not help in the constraction of such a scalable and accurate model.

Inspired by the model and work developed by Peter Paul Radecki, the solution developed uses the Unscented Kalman Filter (UKF) to build an on-line gray-box data-driven to estimate the building parameters, thermal dynamics and time varying thermal loads. This probabilistic model also uses simple physics laws plus real-time data, in this way it adapts time by time, in continuous improving parameters and thermal dynamic estimation. This probabilistic estimation method may overcome specialized solutions, because white-box model does not adapt to changes and black-box method needs great amount of data, from 6 months to 1 year, moreover Artificial Neural Network are sensitive to data quality, because they build a statistical model which is not directly correlated to the physical one. Gray-box model performances in other studies support their quality over time. Because they give short term solution, while continuing to learn and adjust thermal load estimation.

The proposed solution aims are:

- test UKF estimation performances and gray-box data-driven model on simulated 2 zone network:
  - RC parameter estimation,
  - known thermal load estimation,
  - week prediction performances evaluation,
- compare UKF estimation performances and gray-box data-driven model on Virtual Model 2 zone network Energy Plus output:
  - RC parameter estimation,
  - solar radiation disturbance estimation,

This work is a first brick to start working on a multi-zones and multi-mode UKF data-driven model which can be the basis for an MPC used by a BAS.

The model developed in this thesis is a grey-box model. The major issue to implement a Model Predictive Control (MPC) for HVAC, is to acquire a model of thermal dynamics and disturbances that characterize the building [2], [16]. The model has to be as simple as possible when real-time control has to be performed. But it is also true that modeling inaccuracy may generate MPC bad performance.

Gray-box models are a kind of model in which both a virtual model and sensor's data are used. Compared with white box model, the latter requires a detailed virtual model, then a energy simulation software uses to evaluate the performances of the building by means of energy exchange formulas. This approach can reach more accurate evaluation but it requires a huge computational time if we consider an online application. Another possible solution is the use of black-box model, in this case a virtual model is non necessary and performances are fast enough for an online application. But it is also true that it requires time and data that covers entire HVAC usage to train the model, before being able to use it. In our specific case study because of lack of previous and current data, a model which does not require huge amount of data was needed.

4.0.1 Thermal Model Formulation

The model formulation and implementation brings the result quality. The model adopts an RC circuit which represents buildings rooms parameters in term of resistance and capacitance, then an Unscented Kalman filter computes buildings' parameter (Resistance and Capacity) values by using a mathematical energy exchange equation and real time temperatures data from sensor's and external temperature by forecast. Once the parameters are estimated it is possible to use the model to predict next temperature trends.

The model state s is function of the state x (temperatures), u_1 known or measured input, u_2 unmeasured, inputs, p are selected uncertain model parameters, and z is the measured output.

$$s = f(x, u_1, u_2, p) \tag{4.1}$$

$$z = h(x, u_1) \tag{4.2}$$

The energy exchange between different zones of the building, including the external environment is regulated by the formula 4.4. The temperature rate change $\dot{T}_i$ ($\frac{degree}{second}$) between zone i and adjacent zones j is directly proportional to the temperatures differences ($degree$)and it is inversely proportional to the product of resistance ($\frac{degree}{watt}$) and capacitance $\frac{Joule}{degree}$ between zone i and j, plus an additional component b_i (watts) which represent disturbances.

$$\dot{T}_i = \sum_i \left(\frac{T_j - T_i}{R_i j C_i} \right) + \frac{b_i}{C_i} \tag{4.3}$$

The product of the temperature rate change $\dot{T}_i$ (degree/second) with capacitance (Joule/ degree) is equal tot eh heat flux q_i (watt).

$$C_i \dot{T}_i = q_i \tag{4.4}$$

From 4.4, the convection, mass transfer and conduction heat flux (watt) is directly expressed.

$$q_i = \sum_i \left(\frac{T_j - T_i}{R_i j} \right) + b_i \tag{4.5}$$

The representation of temperature rate change in 4.3 is analogous to the voltage change due to current flow. For this reason it is possible to model the building plant as a Resistor Capacitance network. Considering a two node network it is possible to express a state space representation, in which the temperatures vector $T\bar{(t)}$ multiplies the RC matrix A and the vector $b(t)$ of additive, time-dependent, disturbances are added.

$$\begin{aligned}
\dot{\bar{T}_i} &= A(RC)\bar{T}_i(t) + \bar{b}(t) \\
A &= \begin{bmatrix} \frac{1}{R_{12}C_1} & \frac{-1}{R_{12}C_1} \\ \frac{1}{R_{12}C_2} & \frac{-1}{R_{12}C_2} \end{bmatrix} \\
b\bar{(t)} &= \begin{bmatrix} \frac{b_1(t)}{C_1} \\ \frac{b_2(t)}{C_2} \end{bmatrix}
\end{aligned}$$

4.1 Estimation Process

In this section the procedure adopted to estimates parameter is explained. The UKF performers model parameters estimation in different steps, each one aims to characterize specific parameters to build a solid model time by time. The steps are essentially three:

1. thermal dynamics parameters (RC) are evaluated during low disturbance period, in which the solar radiation is minimum and RC is the main heat flux contributor;

2. once RC has a low variance, solar radiation contribution is evaluated and modelled;

3. at the end, input thermal loads are included in the model.

Thermal dynamics parameters (Resistance and Capacitance) are the most easily parameters to isolate. For this reason these are the first ones to be estimated during the estimation procedure. During low solar radiation disturbance period and no thermal load action, it is possible to address temperatures change to RC. In this way a good approximation can be obtained. Typically, during the night, thermal input are off and solar radiation has its minimum value. Then, a night-estimation period for RC is a reasoning consideration, in real application does not disturb normal activities.

Once these first circuit network parameters have low variance, their values can be considered nearly constant. Then, the UKF can be augumented in order to track unknown disturbances, at the same time, its dynamics model is constantly evaluated and estimated, enabling a time-adaptation of the filter where a co-variance quality metric is mantaneid and controlled. This adjusts parameter estimates just in case incoming data provides different and new thermal information. Disturbances significantly impact buildingsdynamics, it is hard model them most of the time, because of their complexity.

For what it concerns solar gain it was firstly estimated and then modeled as day-by-day constant. The filter treated it as an unmodeled external disturbance. This simplification limits the solution accuracy, but it still provides good results. To better perform thermal elevation, external weather file with global solar gain contribution was used. Solar gain affects prediction quality, a bad solar modelling is characterized by good descendent slope in thermal trend due to a good estimation of RC, but a too high or too low slope going up during solar exposition hours. Modelling of direct and indirect sunlight, shading, and night sky radiation temperature, are cut off by means of this simplification.

The state space update at each 10 minute time-steps interval. The UKF firstly predicts next values and then it updates its estimation and variable variance, integrating measured information. The full discrete-time stochastic system is:

$$
\begin{aligned}
\bar{T}(k+1) &= A(p(k))\bar{T}(k) + \bar{b}(k) + \bar{q}_1(k) \\
\bar{p}(k+1) &= \bar{p}(k) + \bar{q}_2(k) \\
\bar{b}(k+1) &= \bar{b}(k) + \bar{q}_3(k) \\
\bar{z}(k) &= \bar{T}(k) + \bar{r}(k)
\end{aligned}
$$

where $\bar{q}_1(k)$ is the process noise, $\bar{q}_2(k)$ represents estimation uncertainty in RC parameters, $\bar{q}_3(k)$ refers to disturbances' process noise, and $\bar{r}(k)$ represents measurement noise. In the developed solution, temperature state has a process noise level which depends on the time stamp adopted. This assumption came from an empiric observation, the more time passes between two measures, the more uncertain temperature prediction can be made. Instead, RC disturbance process noise changes by time, at begging without any previous assumption, a big noise allows it to rapidly change in time and avoid filter divergences. Then, meanwhile the filter keeps on estimating parameters, the noise becomes smaller and smaller. This way can be adopted only with RC, because it can be considered nearly constant. About the measurement noise, it is equal to its technological limit which characterizes the sensor accuracy, telling how much the user can be confident on detected values. It is declared by sensor companies with its technical performances.

The noise term value affects the estimation process. This artificial process noise for the constant parameters is a strategy that makes the filter able to converge on the parameter value, it allows the filter to change its estimate through time and allows the filter to track the true time varying disturbance. Increasing the process noise means that there is an inability of the model when it tries to describe the process evolution. Every parameter has a noise linked, its level for any parameter disturbances is an index of uncertainty. Consequently the model is not able to track the process.

Dealing with disturbance bias, it cannot be decreased time by time, because its value changes over time. Then the iterative approach adopted for RC decreasing its process noise can't be adopted. Consequently, the noise level for RC parameters has to be smaller than the one of disturbances. Highlighting process noise behaviour, a big value allows the filter to rapidly change and adapt to the new value, fitting the solution at every update step of UKF. But this also means big uncertainty and during the prediction step brings bad result. On the other hand, a small value does not let the filter adapt to the value easily and brings the filter to diverge. For this reason an iterative approach has been adopted, we will discuss it in details. It is right to highlight that every noise terms are assumed zero mean, Gaussian, white, and stationary.

The multiplication of several factor included in this representation, clearly exposes the problem of non linearity. In fact the temperatures are divided by the product of resistance and capacity which are both estimated parameters through the dynamics function. To minimize the non-linearity of the estimation, RC products are estimated together. On the other hand,this multiplicative combinations starts extra parameters. To avoid such a problem a network algorithm is necessary to avoid estimation of parameter that are linearly dependent, which could introduce problems about inversion of covariance matrix. This algorithm has to avoid cycle in the RC network, which is sign of dependent parameters. In particular nodes are independent when they do not share a Resistance, this means no conduction and convection. Their edge connects them in the circuit just with thermal linked node. The ones forming loop will be evaluated, then one will be cut from it, since from the other two, it can be computed.

In our case study, we deal with a two nodes circuit (one internal and one external), in this case the RC products directly compose the minimal parameters set representation of the system. The external node capacity is treated as an infinite capacity, this allows to pass the external temperature as an external distrurbe.

4.2 Unscented Kalman Filter

In this seciton the Unscendent Kalman Filter algorithm is presented, for the formulation and explanation details we refer to [14][16].

4.2.1 Predict Step

In the predict step, the UKF computes the priorby mean of the process model $f()$. $f()$ is supposed to be nonlinear, then we generate sigma points $\mathcal{X}$ and their related weights W^m, W^c according to some function:

$$\boldsymbol{\chi} = \text{sigma-function}(\mathbf{x}, \mathbf{P})$$

$$W^m, W^c = \text{weight-function}(\mathtt{n}, \mathtt{parameters})$$

We pass each sigma point through $f(\mathbf{x}, \Delta t)$. This projects the sigma points forward in time according to the process model, forming the new prior, which is a set of sigma points we name $\boldsymbol{\mathcal{Y}}$:

$$\boldsymbol{\mathcal{Y}} = f(\boldsymbol{\chi}, \Delta t)$$

We compute the mean and covariance of the prior using the *unscented transform* on the transformed sigma points.

$$\bar{\mathbf{x}}, \bar{\mathbf{P}} = UT(\mathcal{Y}, w_m, w_c, \mathbf{Q})$$

These are the equations for the unscented transform:

$$\bar{\mathbf{x}} = \sum_{i=0}^{2n} w_i^m \boldsymbol{\mathcal{Y}}_i$$
$$\bar{\mathbf{P}} = \sum_{i=0}^{2n} w_i^c (\boldsymbol{\mathcal{Y}}_i - \bar{\mathbf{x}})(\boldsymbol{\mathcal{Y}}_i - \bar{\mathbf{x}})^\mathsf{T} + \mathbf{Q}$$

This table compares the linear Kalman filter with the Unscented Kalman Filter equations. I've dropped the subscript i for readability.

Kalman	Unscented
	$\boldsymbol{\mathcal{Y}} = f(\boldsymbol{\chi})$
$\bar{\mathbf{x}} = \mathbf{F}\mathbf{x}$	$\bar{\mathbf{x}} = \sum w^m \boldsymbol{\mathcal{Y}}$
$\bar{\mathbf{P}} = \mathbf{F}\mathbf{P}\mathbf{F}^\mathsf{T} + \mathbf{Q}$	$\bar{\mathbf{P}} = \sum w^c (\boldsymbol{\mathcal{Y}} - \bar{\mathbf{x}})(\boldsymbol{\mathcal{Y}} - \bar{\mathbf{x}})^\mathsf{T} + \mathbf{Q}$

4.2.2 Update Step

Kalman filters perform the update in measurement space. Thus we must convert the sigma points of the prior into measurements using a measurement function $h(x)$ that you define.

$$\boldsymbol{\mathcal{Z}} = h(\boldsymbol{\mathcal{Y}})$$

We compute the mean and covariance of these points using the unscented transform. The z subscript denotes that these are the mean and covariance of the measurement sigma points.

$$\boldsymbol{\mu}_z, \mathbf{P}_z = UT(\boldsymbol{\mathcal{Z}}, w_m, w_c, \mathbf{R})$$
$$\boldsymbol{\mu}_z = \sum_{i=0}^{2n} w_i^m \boldsymbol{\mathcal{Z}}_i$$
$$\mathbf{P}_z = \sum_{i=0}^{2n} w_i^c (\boldsymbol{\mathcal{Z}}_i - \boldsymbol{\mu}_z)(\boldsymbol{\mathcal{Z}}_i - \boldsymbol{\mu}_z)^\mathsf{T} + \mathbf{R}$$

Next we compute the residual and Kalman gain. The residual of the measurement $\mathbf{z}$ is trivial to compute:

$$\mathbf{y} = \mathbf{z} - \boldsymbol{\mu}_z$$

To compute the Kalman gain we first compute the [cross covariance](https://en.wikipedia.org/wiki/Cross-covariance) of the state and the measurements, which is defined as:

$$\mathbf{P}_{xz} = \sum_{i=0}^{2n} w_i^c (\boldsymbol{\mathcal{Y}}_i - \bar{\mathbf{x}})(\boldsymbol{\mathcal{Z}}_i - \boldsymbol{\mu}_z)^\mathsf{T}$$

And then the Kalman gain is defined as

$$\mathbf{K} = \mathbf{P}_{xz}\mathbf{P}_z^{-1}$$

If you think of the inverse as a *kind of* matrix reciprocal, you can see that the Kalman gain is a simple ratio which computes:

$$\mathbf{K} \approx \frac{\mathbf{P}_{xz}}{\mathbf{P}_z} \approx \frac{\text{belief in state}}{\text{belief in measurement}}$$

Finally, we compute the new state estimate using the residual and Kalman gain:

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Ky}$$

and the new covariance is computed as:

$$\mathbf{P} = \bar{\mathbf{P}} - \mathbf{KP_z}\mathbf{K}^\mathsf{T}$$

This table compares the equations of the linear KF and UKF equations.

Kalman Filter	Unscented Kalman Filter
	$\boldsymbol{\mathcal{Y}} = f(\boldsymbol{\chi})$
$\bar{\mathbf{x}} = \mathbf{Fx}$	$\bar{\mathbf{x}} = \sum w^m \boldsymbol{\mathcal{Y}}$
$\bar{\mathbf{P}} = \mathbf{FPF}^\mathsf{T} + \mathbf{Q}$	$\bar{\mathbf{P}} = \sum w^c (\boldsymbol{\mathcal{Y}} - \bar{\mathbf{x}})(\boldsymbol{\mathcal{Y}} - \bar{\mathbf{x}})^\mathsf{T} + \mathbf{Q}$
	$\boldsymbol{\mathcal{Z}} = h(\boldsymbol{\mathcal{Y}})$
	$\boldsymbol{\mu}_z = \sum w^m \boldsymbol{\mathcal{Z}}$
$\mathbf{y} = \mathbf{z} - \mathbf{Hx}$	$\mathbf{y} = \mathbf{z} - \boldsymbol{\mu}_z$
$\mathbf{S} = \mathbf{H}\bar{\mathbf{P}}\mathbf{H}^\mathsf{T} + \mathbf{R}$	$\mathbf{P}_z = \sum w^c (\boldsymbol{\mathcal{Z}} - \boldsymbol{\mu}_z)(\boldsymbol{\mathcal{Z}} - \boldsymbol{\mu}_z)^\mathsf{T} + \mathbf{R}$
$\mathbf{K} = \bar{\mathbf{P}}\mathbf{H}^\mathsf{T}\mathbf{S}^{-1}$	$\mathbf{K} = \left[\sum w^c (\boldsymbol{\mathcal{Y}} - \bar{\mathbf{x}})(\boldsymbol{\mathcal{Z}} - \boldsymbol{\mu}_z)^\mathsf{T}\right] \mathbf{P}_z^{-1}$
$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Ky}$	$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Ky}$
$\mathbf{P} = (\mathbf{I} - \mathbf{KH})\bar{\mathbf{P}}$	$\mathbf{P} = \bar{\mathbf{P}} - \mathbf{KP_z}\mathbf{K}^\mathsf{T}$

Chapter 5

Case Studies: Single Cube and a Energy Plus validation

In this chapter, the *Data-Driven Model* with the Unscented Kalman Filter, RC network and parameters estimation procedure, accurately described in the previous chapter, is validate through the case studies. The objectives of this test are to evaluate the filter stability, potentialities and usability. Moreover, in literature there is no specific guide about how to properly set Unscented Kalman filter, the main contribution of this work, shown in this chapter, is to compensate such a lack of information, giving a validated implementation and a guideline to follow in implementing Unscented Kalman filter to estimate and monitor parameters to use in prediction model. The two case studies that have been addressed are:

- A **Single Cube**: essentially a room which exchanges heat with the external environment. This case is composed by two nodes network model, one internal and one external with infinite capacity that have been used to start validating the Unscented Kalman Filter performances. Since clear application developed are not available in literature, this step was necessary to deal with Unscendet Transform parametrization and noise matrix fix. Moreover, the general estimation strategies have been developed and tested.

- An **Energy Plus** validation has been performed to appreciate the quality of the result compared to a specialized energy simulation software. This first validation was necessary to make a real application possible, once real data twill be available on site.

This thesis is a small part of a big project of Politecnico di Torino and Fiat Chrysler Automobilies. Final objective is to apply these technologies in plant, starting from the case of **Mirafiori**

Plant. The author's contribution is the feasibility study, starting from scratch without available data, of gray-box and data-driven model, illustrating the limit found in literature and the proposed solutions, giving to the project an Unscendent Kalman Filter application that can be enforced to apply in a real industrial context.

The Chapter is organized as follows: first the Single Cube procedure and strategies will be illustrated in 5.1, together with the benefits coming from an iterative approach in estimation procedure; then, a Virtual Model created on Revit and by means of Design Builder, finally evaluated by Energy Plus Section will be presented in 5.2 and finally some remarks will be presented in 5.3. For what it concerns the implementation and information used to develop the studies in [25][4][26][23][21][13][19] have been evaluated and taken into account for the problem modelling, collecting their works and benefit into a solution.

5.1 Single Cube

The Single Cube case study has been adopted, because the proposed solution has been developed from scratch, then a first feasibility study was necessary to move on to a more complex validation. Even if its simplicity may result questionable from the reader's point of view, it allows to highlight the problematic behind the application of Unscented Kalman Filter for estimation and then prediction of the thermal dynamics.

In this case study, we consider a cube that exchanges heat flux with the external environment. In 5.1 the RC network topology of this case study is shown. The main applications implemented in this part are:

- Internal temperatures *Simulator*: starting from known RC values, external temperatures and inputs, it computes the internal temperatures which consist in its output. This data were necessary for the update step of UKF, they act as sensor's data ;

- *Estimator*: starting from external temperatures, RC topology and "sensor's data", it computes the RC and Input estimation process, giving their value as output;

- *Validation*: it uses the estimator's output and compare the result obtained with the simulated one.

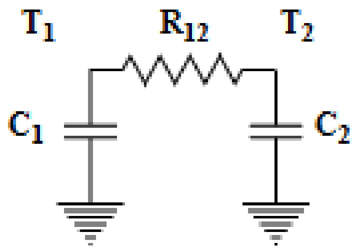


Figure 5.1: RC network topology of the single cube.

The internal temperatures of the simulation were necessary, firstly to have data that simulates the internal behaviour because the Estimator needs in the update step an information of sensed temperatures. So the reason why a Simulator has been implement is to have plausible internal data to pass at the Estimator. The Simulator has been also useful to understand the data behaviour given an RC value, external temperatures and inputs. The Simulator creates external and internal temperatures, this data were then passed throws the Estimator for the estimation process by means of UKF. Then the result had to match both the RC and input $(b(t)/C)$ of the simulation.

Three different kinds of external data temperatures have been used: flat, trend in ascendant and descendent steps(5.3). For what it concerns the integration steps of internal data generation, Odeint module of SciPy[1] library has been used, using as model equation 4.3. The function developed for data creation is shown in Listing 5.1 . Moreover, to simulate sensor's accuracy, for each internal temperature values in output for each time stamp has been added a random Gaussian distributed value from $(-8, +8)$ (sensor accuracy of $0.8°C$). The scheme of the simulator is reported in figure 5.2, with both the case without any input and with input, it is important to note, that the simulator generates always just internal temperatures.

```
def data_simulation(TeShape, RC, B, input=False, plot = False, noise = False):
    '''Definition of samples and respective size of Te and Tin'''
    size=7*24*60*60 #7days    24hours    60minutes    60seconds
    dt = 15*60      #15min    60seconds
    samples = int(size/dt)   #number of points in which we receive a sensor data
    Te=np.zeros(samples)   #initialization
    Tin=np.zeros(samples)  #initialization

    '''External Temperature definition'''
```

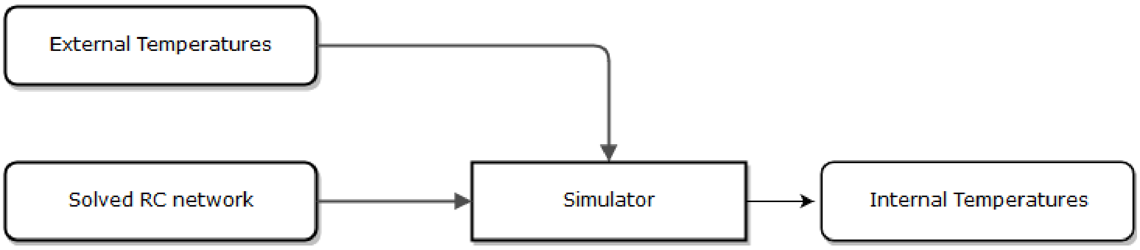
[1]The SciPy library is one of the core packages that make up the SciPy stack. It provides many user-friendly and efficient numerical routines such as routines for numerical integration and optimization.

```
    if(TeShape == 0):   #gradino
        Te[100:]=50
    elif(TeShape == 1): #discesa
        Te[:100]=50
        Te[100:]=0
    elif(TeShape == 2): #flat
        Te[:]=0

    def dTdt(Tin,t,Te,RC,i):
        if(input):
            if(t>15*60*28 and t<(15*60*35)):
                dTdt=((Te-Tin)/RC)+(B)
                return dTdt
            else:
                dTdt=(Te-Tin)/RC
                return dTdt
        else:
            dTdt=(Te-Tin)/RC
            return dTdt

    t=np.linspace(0,size,samples)
    Tin[0] = 50.

    for i in range(1,samples):
        tspan=[t[i-1],t[i]]
        T=odeint(dTdt,Tin[i-1],tspan,args=(Te[i],RC,input,))
        Tin[i]=T[1]

    if(noise):
        for i in range(0,Tin.size-1):
            Tin[i] = Tin[i]+np.random.normal(0,0.8,1)
```

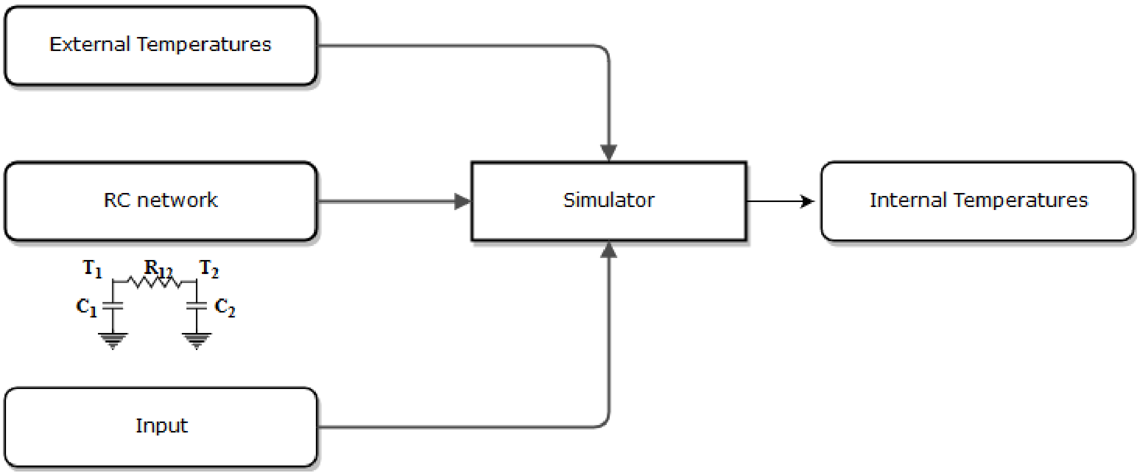
Listing 5.1: Data simulator function.

The output generated by the Simulator, the internal temperatures, were needed to reproduce sensor's data in a real case and pass them as temperatures information in the update step. By means of this information the UKF adjusts its parameter to bring them to be as close as possible to the next sensed information. Internal temperatures are one of the input for the estimation process. The Estimator scheme in 5.4 graphically shows the information in inputs and its relative output for both RC estimation and RC plus input estimation. For the estimation problem the Unscented Kalman filter had to be properly set. The first problems encountered were the inequity of the result depending by the given initial state, initial variance, process noise and measurement noise values in their matrix. For the measurement noise, the uncertainty values used to emulate sensor's accuracy has been used.

The different problematics were solved starting from initialization issue. A random initialization for RC parameters has been adopted, using values from 0 to 1000 which is the magnitude order of the value used in the simulator. This assumption reflects the uncertainty of an estimation process in real case estimation. In this way specific parametrization due to initial values has been



(a) *External Temperatures and RC values in given, Internal temperatures in output.*



(b) *External Temperatures,RC values and Input given, Internal temperatures in output.*

Figure 5.2: Simulator scheme: External Temperatures and RC values and input, if any, Internal temperatures in output.

cut. The temperature is initialized always to $0°C$. The variance matrix P, for the temperature is chosen depending on previous information and the delta time between two different time steps. In case no previous knowledge about the internal temperature is available at the starting point, a standard deviation of $20°C$ has been imposed, which means variance of $400°C^2$, that covers the most probable temperatures interval for a location like Turin, from minus $10°C$ to $30°C$. Instead, the RC variance is equal to the lowest value with the same magnitude of the parameter to be estimated, or bigger if this information is unknown. The variance matrix P is initialize just for the diagonal values, supposing no influences between the 2 parameters, then the covariances fields are zero at the beginning. Then the filter, will find relationships, were being, between different parameters and so covariance field may change in successive time instants.

The process noise matrix Q needs to be discussed apart. It is fixed as a diagonal matrix, because is not possible to know a priori the the parameters' relatives influences in term of noise. The one related to temperatures which strictly depends on time stamps interval or sensor's sampling frequency, since measurements are spaced every 15 minutes, $3.5°C$ change has been taken as feasible amount. For the process noise of the RC value, a too small value restrict estimator convergence, causing in many cases diverges. On the other hand a too big one makes the filter converge on wrong value, because the estimator does not trust the model compared to the sensor data, making unable the filter to track parameter influence. The strategy proposed by the author is to adopt an iterative step, with progressive small values. The intuition came from the necessity of the filter to be able to rapidly change RC value at the begging, since a random RC value is the starting point and it may be far from the real one. Then iteration after iteration the uncertainty became smaller and also the reliability of the model increases. Then in each iteration on available data the process noise matrix decreases its values, instead for the temperature until it reaches the technological accuracy limit. The process noise matrix numerically represents how much the adopted model is trusted, then by means of iterative approach the confidence in the model intensifies when its uncertainty decreases.

When inputs too have to be taken into account, the estimation process is split into two different phases:

- RC estimation, during low disturbance period, then mainly by night;
- Input estimation, once RV value has start to converge.

This procedure is necessary for the filter to address at each component of the thermal dynamic, its weight and value. Considering a real case application, the RC value will be estimated during low disturbance periods, which usually is during the night, where the solar radiation is minimum and inputs are off. Then during the morning solar radiation information will integrated and inputs estimated.In this case variance matrix Q again is used to tell to the filter in which parameter to trust and in which not. After the RC estimation converged, its process noise is set to be much smaller than the one related to the input. In this way the UKF forces to work on the most uncertain parameter. To better improve the filter output, the estimation procedure has been enforced with two constraints to avoid possible filter's divergences caused by negative values, both RC and then input have been set to be non zero value. Without the previous assumption, few divergences cases were encountered, lower than the 10%, but with those constraints divergences are zero. The above method allowed to achieve good result, as shown in the next section.

5.1.1 Results

In this section the achieved results are shown, starting from one case with only RC estimation and then one with RC plus an input. The simulation run considered are more than 120 considering the three cases of external temperatures. In all cases the average error is around 3% or lower in the final estimated value. Bigger error are registered just for the first iteration. The result obtained for an RC ($\frac{degree}{watt}\frac{Joule}{degree}$)value equal to 5600 ($\frac{1}{second}$) are show in table 5.1 starting from the second iteration, in which it is clear that a good result is achieved. Moreover, in figure 5.5 the simulated data (a), the verification result (b) and RC trend values during estimation are shown.

RC:5600 Te: trend in descendent				
iteration number	Initial value(i=0)	Estimated RC	Error in relative percentage	Process noise matrix Q
2	[1. 859.]	5534.83928782	1.16358415%	[(0.64, 0.0), (0.0, 0.84)]
3		5585.39552994	0.26079411%	[(0.64, 0.0), (0.0, 0.37)]
4		5585.23381055	0.26068195%	[(0.64, 0.0), (0.0, 0.21)]
2	[1. 158.]	5550.41080867	0.88552127%	[(0.64, 0.0), (0.0, 0.84)]
3		5585.32231755	0.26210147%	[(0.64, 0.0), (0.0, 0.37)]
4		5585.23423868	0.26367431%	[(0.64, 0.0), (0.0, 0.21)]
2	[1. 512.]	5542.99307866	1.01798074%	[(0.64, 0.0), (0.0, 0.84)]
3		5585.35925661	0.26144185%	[(0.64, 0.0), (0.0, 0.37)]
4		5585.23402265	0.26367817%	[(0.64, 0.0), (0.0, 0.21)]

Table 5.1: Data-driven model results.

The result obtained for an RC ($\frac{degree}{watt}\frac{Joule}{degree}$)value equal to 5500 ($\frac{1}{second}$) are show in table 5.2 for the estimation of the single RC. In table 5.3 the result with Input estimation too and monitoring are shown. In figure 5.6 the simulated data (a) and the related model prediction (b) using the value in output is shown.

RC:5500 ($\frac{1}{second}$) Te: trend in descendent B:0.0035 ($\frac{°C}{second}$)				
iteration number	Initial value(i=0)	Estimated RC	Error in relative percentage	Process noise matrix Q
1	[3.27e-02,3.33e+03]	3333.23287739	39.39576587%	[(12.25, 0.0), (0.0, 3.3856)]
2	[2.15e-01,5.22e+03]	5229.68728522	4.91477663%	[(0.64, 0.0), (0.0, 3.3856)]
3	[2.15e-01,5.16e+03]	5165.41936428	6.08328429%	[(0.64, 0.0), (0.0, 0.8464)]
4	[2.15e-01,5.16e+03]	5161.27375171	6.15865906%	[(0.64, 0.0), (0.0, 3761)]

Table 5.2: Data-driven model results.

The results shown in this section are not the best ones, neither the worst ones, these reflect the general and average trend of the conducted simulations. Starting from these results and approaches used to solve the first case study, the data-driven model has been used to work with Energy Plus

RC:5500 ($\frac{1}{second}$) Te: trend in descendent B:0.0035 ($\frac{°C}{second}$)				
iteration number	Initial value	Estimated B	Error in relative percentage	Process noise matrix Q
1	[2.95e-02,1.00e-04,5.22e+03]	9.99e-05	97.142%	[(12.25), (1.22e-05), (1e-06)]
2	[2.15e-01,6.72e-03,5.22e+03]	0.00672	92.252%	[(0.64), (1.22e-05), (1e-08)]
3	[2.18e-01,3.93e-03,5.22e+03]	0.00393	12.549%	[(12.25), (3.06e-06), (1e-08)]
4	[2.15e-01,6.83e-03,5.22e+03]	0.006835	95.307%	[(12.25), (1.36e-06), (1e-08)]
5	[2.18e-01,3.97e-03,5.23e+03]	0.00369	95.307%	[(12.25), (7.65e-07), (1e-08)]
6	[2.18e-01,3.69e-03,5.23e+03]	0.00264	95.307%	[(12.25), (4.90e-07), (1e-08)]

Table 5.3: Data-driven model results for input case. Only the diagonal values of Q matrix report, the other are zero.

data, to compare their results and have stronger validation of the model quality.

5.2 Energy Plus Validation

As it has already been mentioned at the begging of the chapter, this thesis is a first part of a bigger project made by Politecnico of Turin in collaboration with FCA. In this project also BIM approach has been evaluated by another student, Roldolfo Rotti, a part of his work is used for the following validation. A fisrt CAD model was necessary to then evalute it with Energy Plus, the mentioned model has been done using CAD modelling software such as Revit and Design Builder to provide the virtual model for this case study.

The developed gray-box model needed a validation, to verify the model functionalities with a benchmark and get results about its reliability. Even if the connected devices spread in the last decade, it is still hard to find well monitored environment regard HVAC consumption, this market still has not involved connected devices for commercial applications. In industrial plant, this technologies may be found, but the sensors may not cover enough the environment for unsurpervised monitoring. Considering the Mirafiori case study, old temperatures data-set were not available. So in order to test the solution quality, the output of the software EnergyPlus has been used as benchmark. EnergyPlus actually is the leading software for energy analysis and thermal load simulation program.

It is right to spend a few more words about what EnergyPlus is and why a data-driven solution should be developed, if there already exits a product that deals with thermal energy modelling. Based on the building's physical structures, its mechanical systems seen from user's perspective description of that building, EnergyPlus computes HVAC loads necessary to maintain thermal control setpoints and the energy consumption, and many other simulation details that are necessary. On the other hand it is important to note what EnergyPlus is not[17] :

- EnergyPlus is not a user interface: it needs other software;
- EnergyPlus is currently not a life cycle cost analysis tool;
- EnergyPlus does not check input, acceptability or range of various parameters.

In the first and second points are closed some of the difficulties encountered in this thesis. One first approach for this project aimed to interact directly on EnergyPlus input file (*edf*), tuning its building characteristics to respond correctly to sensor's data. But this direction loses in term of simplicity, because it is hard, this way, to model a wall without the details that characterize it, and good knowledge about Energy Plus way to work is mandatory to avoid inconsistency of the model, which is hard to control. Even not considering the complexity that this kind of approach brings with it, EnergyPlus detail in output requires more computational time making it is not suitable for online solution. Moreover, it needs a starting edf file, which can be formed by CAD software which then uses EnergyPlus, and there are many, such as Revit, DesignBuilder, Sketchup and also other tools to improve EnrgyPlus like OpenStudio for Sketchup. So depending on the used software, differences in edf file may be encountered, then it does not represent at all a scalable solution, including all the troubles that this path introduces because another estimator is necessary a part from a edf editor, which needs great information of the buildings.

The idea behind data-driven model reasons should be now clearer to the reader, so now, moving on to the validation, a parallelepiped Virtual Model which aims to represent body-shop area of Mirafiori Plant, has been passed through EnergyPlus with a weather file in *epw* format. Then, its output has been used for validation. In particular the output of the EnergyPlus simulation is used as sensor's track, from the Virtual Model the RC circuit information is passed (5.1) to the estimator to emulate the sensor's information. The Estimator takes external weather information, plus the network and the internal temperatures from EnergyPlus output, then by means of these information it computes firstly RC value, then solar radiation. Once the two parameters are extracted, those are used to predict trends and test how much these fit EnergyPlus simulations, which is used as benchmark. Figure 5.7 shows graphically the scheme of this case study, illustrating the inputs and ouputs of the main components: EnegyPlus and gray-box model.

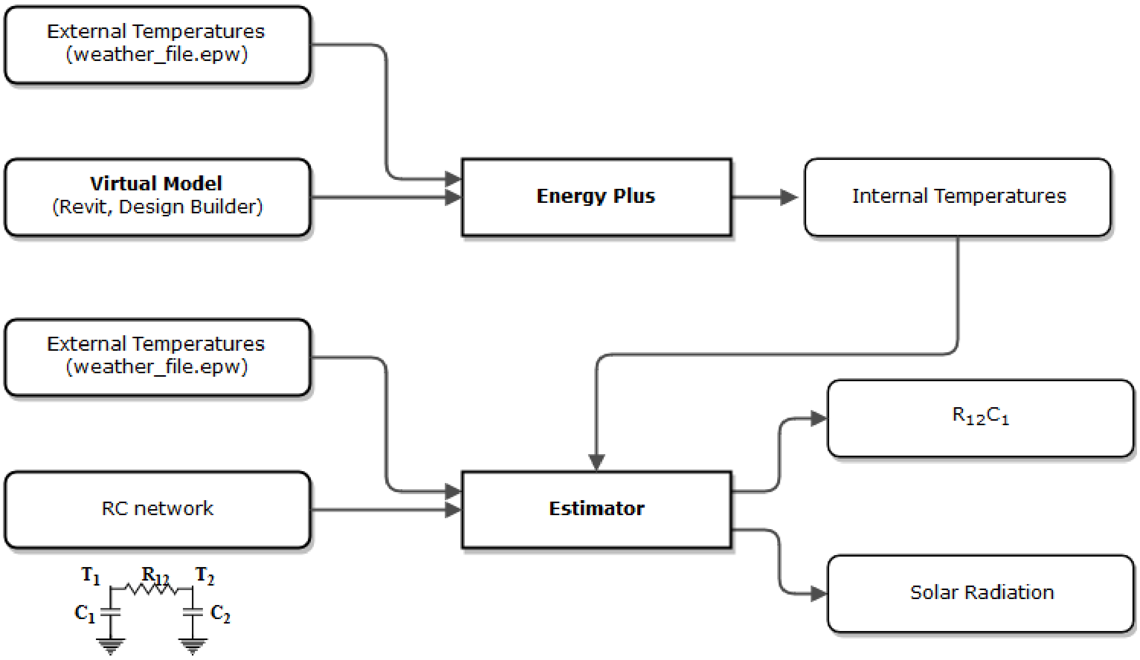


Figure 5.7: Global scheme of the Estimator for EnergyPlus validation case study.

The first six lines of the EnergyPlus output used is shown in table 5.4. The timing information plus the internal temperatures information make possible to switch from estimation problem of RC and estimation problem of solar radiation. The estimation of the solar radiation is a first estimation of an input, in this case an unknown input. In the next section about results, will be shown also a case in which the solar radiation component is passed to the filter without estimating it. About the initialization and parametrization adopted, there are not important differences compared to the one adopted for the single cube case.

5.2.1 Results

The results have been reached adopting the solution scheme in 5.7, mainly following three steps:

- RC estimation: during low disturbance periods, then during the night;
- Solar radiation estimation: once RC parameter converge, solar radiation component estimation starts;

EnergyPlus output.		
Date/Time	Environment:Site Outdoor Air Drybulb Temperature [C](TimeStep)	LOCALE1:LOCALE1:Zone Mean Air Temperature [C](TimeStep)
01/01 00:10:00	1.91	5.63
01/01 00:20:00	1.63	5.58
01/01 00:30:00	1.35	5.52
01/01 00:40:00	1.06	5.46
01/01 00:50:00	0.78	5.38
01/01 01:00:00	0.50	5.31

Table 5.4: EnergyPlus output.

- : Validation: using the two estimated parameter, trend for the next days have been performed and compared with the ones of EnergyPlus.

The estimation problem has been conducted for a week and then a week of prediction is compared. The first part of RC estimation has been performed 10 times using different Q matrix to test stability and usability of the filter. The estimation brings the same solution in all iterations, this is due to a good initialization. In particular in all cases it is associated a great uncertainty in model in both temperature and RC value at the first iteration, because the initialization values of the filter can't be trust. This way the filter adjusts in the first iteration the values, bringing good results with an error around 1.79% referring to the final estimated value, for each different Q matrix. The estimation of RC parameter represents the first part of the estimation process and it is conducted during no disturbance period. In table 5.5 it is presented the 6th over 10 run of RC estimation problem for the $8^(th)$ week of the available data. It is important to note that the week chosen for the estimation problem of RC changes the final RC value of the less than 2% and the final estimated value, if the iterative approach which reduces its value at each iteration, does not change depending on the Q intial value.

Once RC has converged, the solar radiation component starts being estimated during disturbance period. The solar radiation, despite RC value is not constant and it may change a lot during the day, depending by many factors, the most important one is the height of sun. For this reason, once the solar radiation is estimated on an average value, it is multiplied by a sinusoide wave, which is zero during no solar period and maximum at 12 am. This sinusoide is necessary to reproduce the solar radiation effect, which is not constant, stronger at midday and lower at dusk and dawn. The sinusoide form per hour in a day is shown in figure 5.8 (a) and in figure 5.8 (b) it has been

RC estimation result using EnegyPlus internal temperatures and weather file of Turin in 1986.			
iteration number	Initial value	Estimated RC	Process noise matrix Q
1	[1.273e+01 9.334e+04]	93338.87	[(12.25, 0.0), (0.0, 36)]
2	[1.275e+01 9.337e+04]	93367.39	[(0.64, 0.0), (0.0, 36.0)]
3	[1.275e+01 9.341e+04]	93395.78	[(0.64, 0.0), (0.0, 9.0)]
4	[1.275e+01 9.342e+04]	93424.05	[(0.64, 0.0), (0.0, 4.0)]
5	[1.275e+01 9.345e+04]	93452.20	[(0.64, 0.0), (0.0, 2.25)]
6	[1.275e+01 9.348e+04]	93480.24	[(0.64, 0.0), (0.0, 1.44)]
7	[1.275e+01 9.351e+04]	93508.17	[(0.64, 0.0), (0.0, 1.0)]
8	[1.275e+01 9.354e+04]	93535.98	[(0.64, 0.0), (0.0, 0.74)]
9	[1.275e+01 9.356e+04]	93563.67	[(0.64, 0.0), (0.0, 0.56)]

Table 5.5: RC estimation result using EnergyPlus data.

modeled, after the estimation, as an unknown input $u_2 = (b(t)/C)$. The estimation of the solar radiation can be thought as a first input estimation. The result obtained in this estimation process are shown in table5.6, the founded value is constant in all iteration, both in cases in which process uncertainty is bigger or lower than the one related to the input. Another important point to note is that meanwhile Input is estimated RC value is estimated too, even if it does not rapidly change because it already converged, its value is kept under monitoring and it case the resistance changes, the model will be able to adapt its value with the physical changes in which it is applied.

Input estimation result using EnegyPlus internal temperatures and weather file of Turin in 1986.				
iteration number	Initial value	Estimated B	Estimated RC	Process noise matrix Q
1	[1.61e+01,1.e-04,9.35e+04]	0.00010	93563.68	[(9.0), (1.0), (3.38)]
2	[1.61e+01,1.e-04,9.35e+04]	0.00011	93563.67	[(0.64), (0.001), (1.84)]
3	[1.61e+01,1.e-04,9.35e+04]	0.00010	93563.67	[(0.64), (0.001), (0.115)]
4	[1.61e+01,1.e-04,9.35e+04]	0.00011	93563.67	[(0.64), (0.001), (0.0025)]
5	[1.61e+01,1.e-04,9.35e+04]	0.00010	93563.66	[(0.64), (0.001), (2.81e-05)]
6	[1.61e+01,1.e-04,9.35e+04]	0.00010	93563.66	[(0.64), (0.001), (1.88e-07)]
7	[1.61e+01,1.e-04,9.35e+04]	0.00010	93563.65	[(0.64), (0.001), (8.45e-10)]

Table 5.6: Input estimation results and RC monitoring using EnergyPlus data. Only the diagonal values of Q matrix report, the other are zero

The estimated values (B=0.00010 multiplied by the sinusoide in figure (a), RC=93563.65) have been used for predict internal temperature over the week after the estimation process. In figure

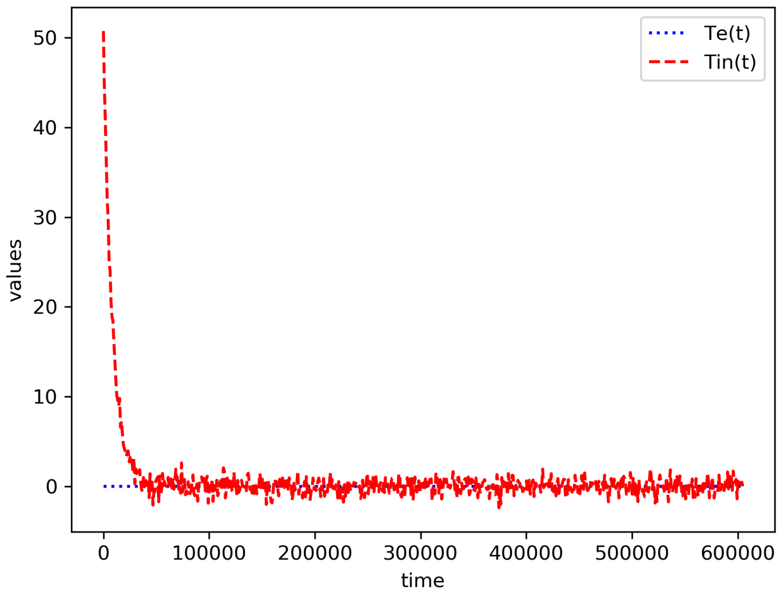
5.9 the curves obtained by the data-driven model developed and the one with energyPlus data are plot. The result are really close, with a maximum error of 2.2 $°C$ due to the difference between the predicted solar radiation and the real one. In fact looking at the inclination of the two curves, the RC component perfectly match the one of the Virtual Model. To better understand how strongly affect the result the solar component, in figure 5.10 the same prediciton without any solar radiation attribute is shown.

5.3 Remarks

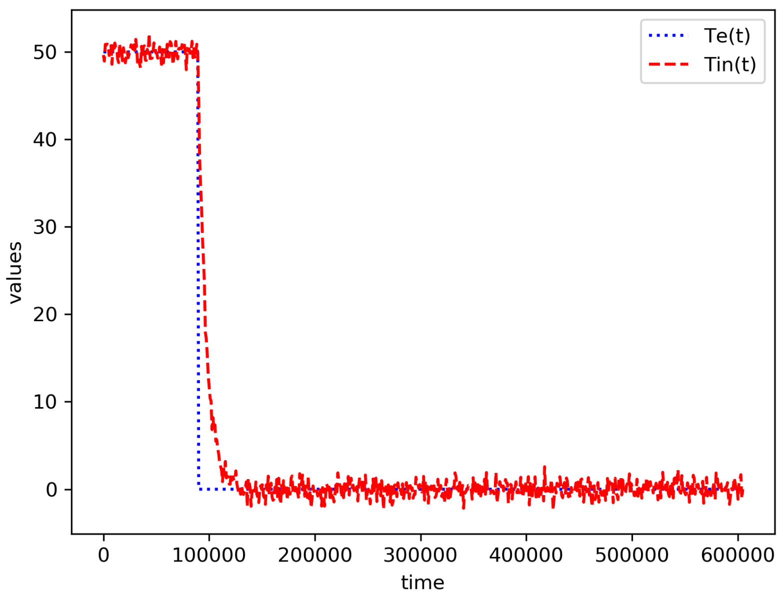
Once the results and the approach are made clear, the principal outcomes are discussed. In order to facilitate the results analysis, they have been grouped in three main areas: *stability*, *potentialities* and *usability* of the data-driven model.

- **Stability** The Energy Plus validation has proved that the data-driven model is absolutely stable. Even if a previously estimated value changes, the filter tracks its difference and adjust it, no stability problems show up. Therefore, in case of divergence, the filter can easily recover parameter convergences in the next iteration working with previous data, because its computational time allows it to fast run estimation processes.
- **Potentiality** The network potentialities are many. In fact, as discussed previously, the data-driven model is highly scalable since it can be easily expanded and shrunk according to the requests. In addition, it is strongly case independent, which means that it can be applied in any possible monitored area having a well spread sensor network. Anyway, still some effort in improving the RC network should be put. Currently, the RC network used is simple, however the Author is confident that it could already be augmented.
- **Usability**At the moment, the usability is the main weakness of the data.driven model. Even if the results achieved by the case studies are great, the mechanism should be augmented in order to track and monitor a real application in industrial plant. In fact, apart from simulation validation and Energy Plus validation, it is necessary to track this result with a real monitored room. Therefore, this validation step just requires a real monitored room, because the scalability of the developed solution allows to easily switch from simulated internal data, with real data.

All these considerations have been useful to address the main strengths and weaknesses of the gray-box model. In particular, for what it concerns the weak points, they are reflected in the proposed future developments, addressed in the next Chapter.

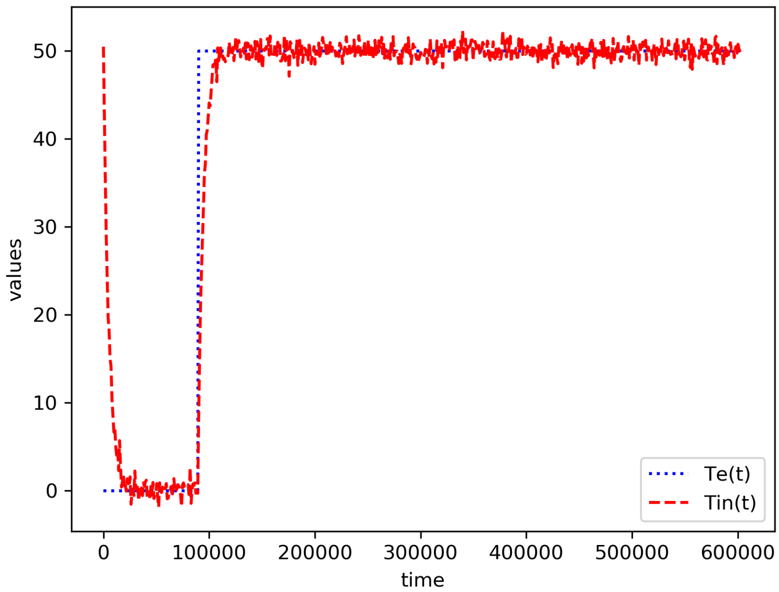


(a) *Flat external temperatures(blue) and relatives internal temperatures (red).*



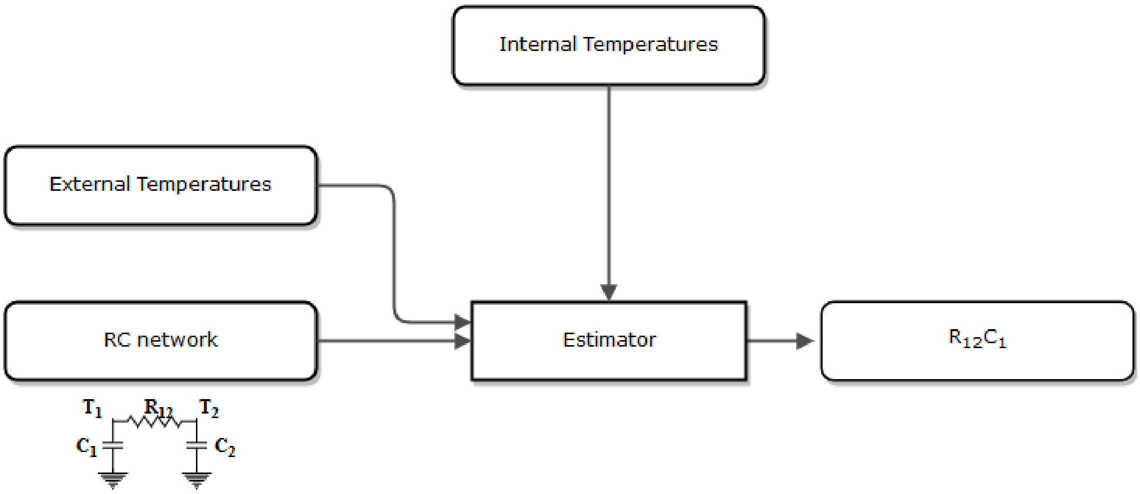
(b) *Eternal temperatures with trend in ascendant step and relatives internal temperatures (red).*

Figure 5.3: External data temperatures in blue and respective results of the internal temperature plus noise in red (continued on next page).

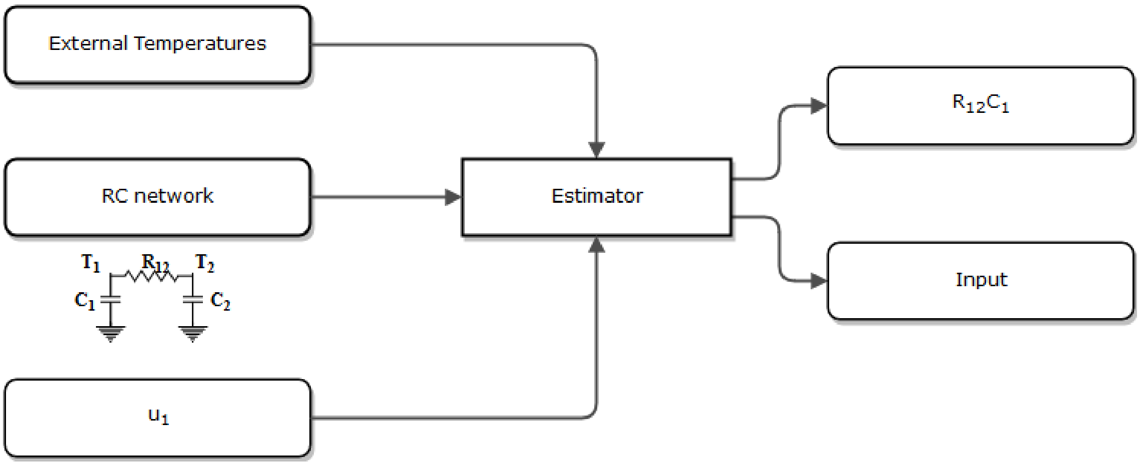


(c) *Eternal temperatures with trend in descendant step and relatives internal temperatures(red).*

Figure 5.3: External data temperatures in blue and respective results of the internal temperature plus noise in red (continued from previous page).

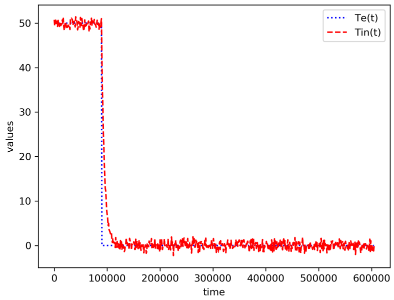


(a) *External Temperatures and RC network is given, RC value in output.*

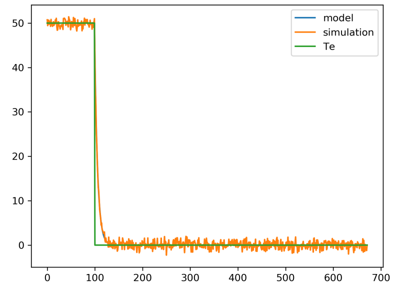


(b) *External Temperatures,RC network and Input given, RC and Input value in output.*

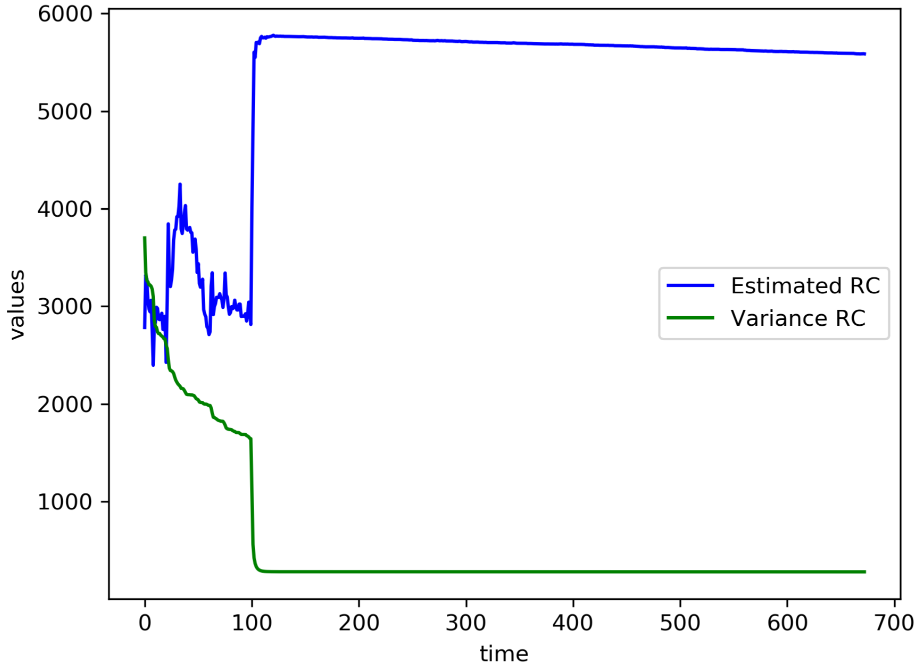
Figure 5.4: Estimator scheme: external temperature, RC network and input, if any, in input; solved RC parameters in output.



(a) *Simulator output, then sensor data for the Estimator*

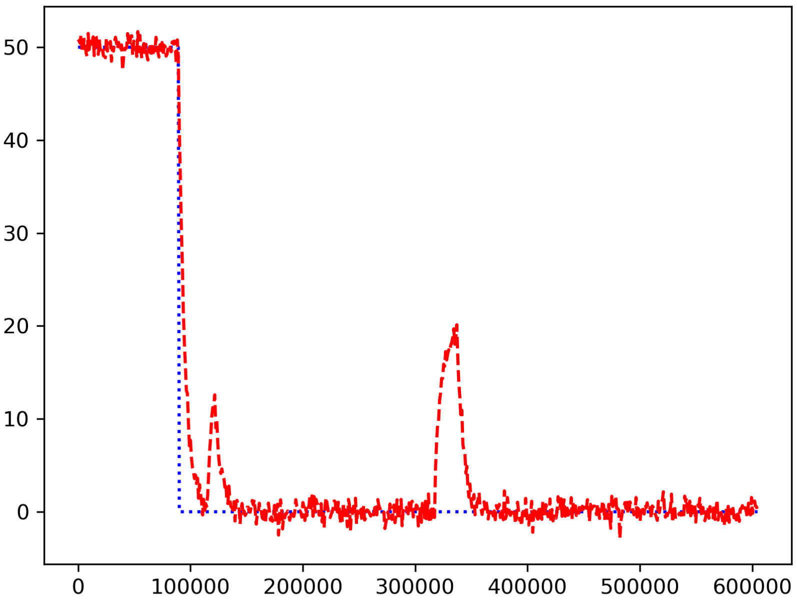


(b) *Comparison between simulator and prediction throws estimator result.*

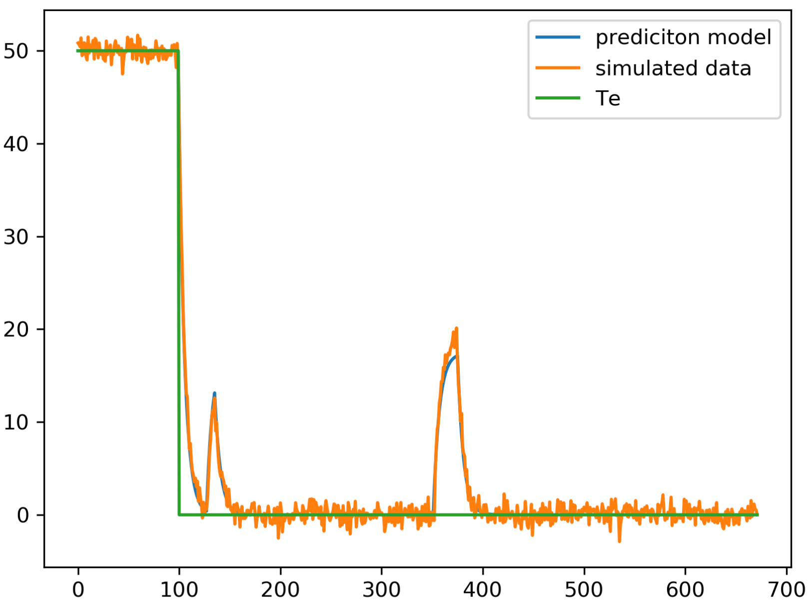


(c) *RC values during estimation process.*

Figure 5.5: External data temperatures in blue and respective results of the internal temperature plus noise in red (continued on next page).

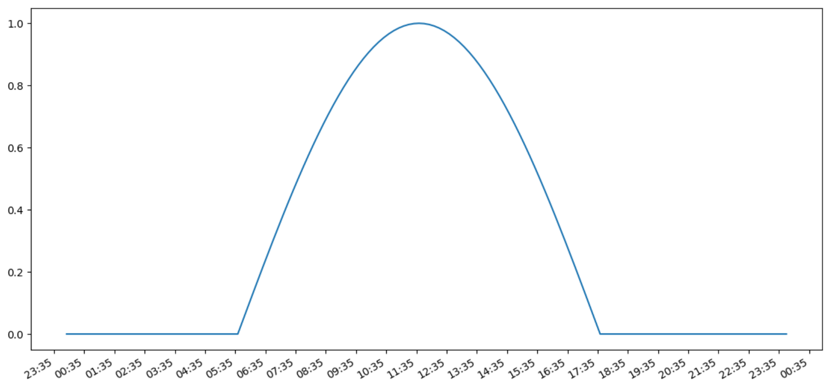


(a) *Simulator output, then sensor data for the Estimator*

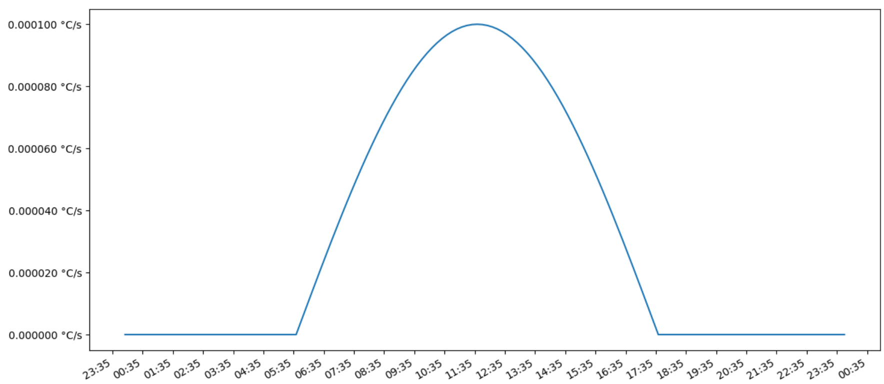


(b) *Comparison between simulator and prediction throws estimator result.*

Figure 5.6: Results for the single cube estimation with input.



(a) *Radiation sinusoide during a day.*



(b) *Solar radiation component* $b_s olar(t)/C$ *during a day.*

Figure 5.8: Solar radiation trend (a) and solar radiation estimated component (b) during 24 hours.

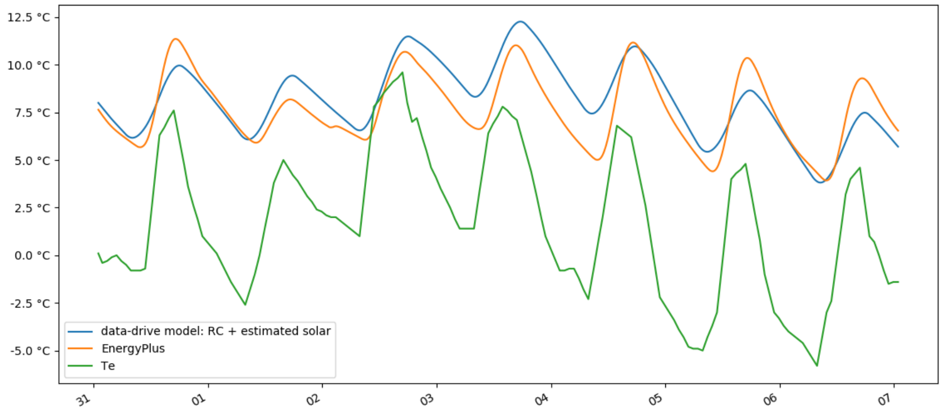


Figure 5.9: Data-driven prediction for 7 days and EnergyPlus data compared. In green the external temperature

without solar radiaiton.png

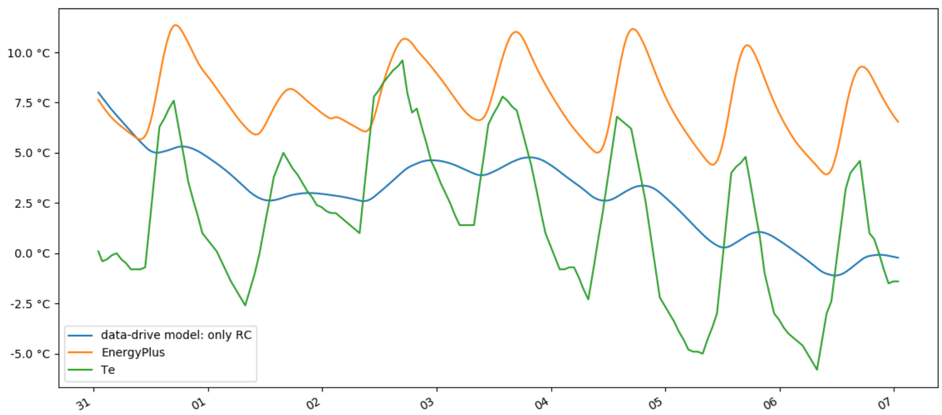


Figure 5.10: Data-driven prediction without considering the solar contribution for 7 days and EnergyPlus data compared. In green the external temperature

Chapter 6

Conclusions

This Master Thesis provides a theoretical background and an applicative project on *Energy Modelling* in buildings. The applicative part can be divided in two different sections: the first section focuses on a study of energy modelling and possibilities to use IoT technologies to build a solution for Industry, whereas the second part focuses on develop the gray-box and data-driven model providing an applicative experiments to test its performances and understand improvements necessary to build a real commercial solution to reduce losses and improve comfort.

This final Chapter presents the main results achieved by the Author work and the future developments that can be performed to improve them. The Chapter, accordingly to the main project developed, covers the *Energy Model* problem, then the *Data-driven Model* is addressed in Section 6.1. Finally, some conclusive comments on the Author personal experience are presented in Section 6.2.

6.1 Data-driven Model

The Data-Driven Model has been implemented in the this Thesis using an Energy Model descriptor and a relative Estimator. It aimed at arrive with not high computational power demand at a good enough energy exchange approximation between environments, which characterizes buildings temperatures trend. The short computational time is required to apply such a kind of solution on an online application, which is a limit of the current white-box solutions. The development of the data-driven model involved an Energy descriptor, accurately presented in 4 and an Estimator system to computes the parameters which describe the energy model. The latter involved the use of Unscented Kalman Filter in which particular attention and time has been spent on uncertainty values set up, in order to track and converge on values that may change during the time.

6.1.1 Results

The contribution succeeded in implementing the data-driven model. The goal of the project has been achieved, however it is currently a prototype, not ready to be used in commercialized product. Therefore, some interesting results are provided, together with some advises oriented to move the application from an experimental environment to a commercial one. In particular, the following results are of main interest:

- An accurate description ,absent in literature, about UKF settings for an on-line application has been described. Moreover, filter results have been augmented by means of an iterative approach, which reduces the amount of data necessary for the estimator to converge.
- The gray-box model is able to track the RC values in short time, having a good accuracy after maximum three iteration.
- The model is also able to track input disturbances like for the case of solar radiation.
- Once the parameter' values are found, the model keeps them under monitoring and it is able to change them in case they change during the time.

The results of the 2 case studies assert that the model's prediction are good enough and this data-driven model opens to build a real solution based on it. Thanks to these relevant results, the work represents a first brick for the project between FCA and Politecnino which will continue following the path designed in this Thesis. The Author wants to highlight that this model can be a base tool for a Model Prediction Controller (MPC) and from this strategies solutions can designed to reduce losses and improve comfort.

6.1.2 Future Developments

Even though the results achieved are impressive, some further effort can be spent to improve the application. The following suggestions are for those intentioned to enhance the performances of the project:

- First, the Author thinks that the accuracy of estimated values considering both RC and B can still be improved. Since the variable are modelled as Gaussian, the information of the variance matrix can be used to define a confident interval for that parameters. Then all the values in the internal can used to track a curve and then correlate each curve with the real one. The parameters belonging to the curve with higher correlation, referring to the real one, are the ones which better fit the model.

- Second, since in 5 is shown that even integrating diffuse solar radiation component a small error in prediction still remain, the model should consider also the cloud cover number and the orientation of the building.

- Finally, a basic MPC has to be designed and implemented to start with decision making part, based on the prediction given by the data-driven model. This way the data-driven model is tool to understand thermal behaviour of the cosidered building and MPC uses it to reduce losses and improve comfort.

6.2 Final Remarks

This Thesis work has been a really valuable experience for the Author. Francesco Canuto from FCA, has been always collaborative and he gave the Author and he steered me in the right the direction whenever he thought I needed it. Prof. Andrea Acquaviva gave me the possibility to learn many concepts about IoT applications and energy modelling. Besides, they gave a taste on how it is to work in a multinational company, developing solution from scratch, dealing with many departments to share information for a final global aim. Most of the targets that were set before starting the Thesis have been achieved, and the work done will be of great help for the next steps and future development of the project between FCA and Politecnico di Torino.

Moreover this collaboration gave the author the opportunity to learn how to use several technologies that were involved in this Thesis project. In particular, the following have been used for the first time:

- **Zolertia ReMote** sensor has been used as hardware environment and **Contiki OS** has been used as operative system with **C** programming language, during the studies about Internt of Things at the UPC of Barcelona.

- **SketchUp**, **Revit**, **DesignBuilder** software have been used in the very first part of the project to create a virtual model for **Energy Plus** and understand how it works.

- **Python** programming language has been used to develop and implement every solution. In particular the skills about **SciPy**, **NumPy** and **Pandas** libraries have been pushed on an higher level.

- **Unscented Kalman Filter** to estimate parameters in a dynamic model. In particular how to properly set its uncertanty to guarantee its convergence on right values.

These tools are now part of the Author competencies and this is all thanks to this Thesis experience.

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