POLITECNICO
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SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

# Modeling domestic non-linear loads for energy meter analysis

TESI DI LAUREA MAGISTRALE IN
ELECTRICAL ENGINEERING
INGEGNERIA ELETTRICA

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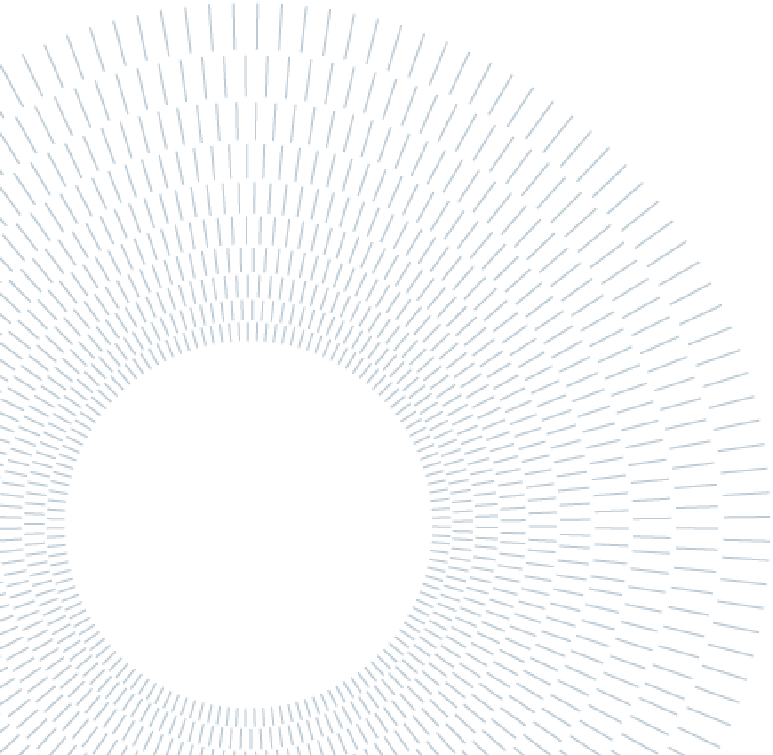
Academic Year: 2024-25



# Abstract

**Key-words:** *Smart Meter, Non-Linear Loads, Harmonics Measurement Accuracy, Power Quality, Load Simulation, MATLAB/Simulink, Sampling Frequency, Nyquist Theorem, Total Harmonic Distortion (THD), Power Factor.*

The growing integration of non-linear loads in residential residences threatens significantly with power quality and the integrity of energy measurement systems. Smart meters deliver advanced monitoring, but their accuracy is under threat from the harmonic distortions these loads inject into the electricity supply. The main aim of this thesis is to quantify the impact of this by creating an overall simulation framework in MATLAB/Simulink.

The core of the project was the simulation of several contemporary non-linear household devices, like PC chargers, induction cookers, and washing machines. A real functional smart meter was then built to mimic key operation parameters like a sampling frequency of 2 kHz and 15-minute data averaging interval, so that its indications can be compared with ideal theoretical results.

According to different studies listed here there are possible sources of error that can produce lower measurements in the smart meters. This low-basing is caused by two main reasons: the harmonic distortion of the current waveform and the meter's low sampling frequency, which is not sufficient to accurately record high-order harmonics in a case where the Nyquist theorem is never met.

The study we will look if there are design limitations in smart meters may cause significant measurement errors when presented with modern loads. This points to the imperative necessity of advanced measurement algorithms and high-end sampling standards to deliver accurate energy billing in today's electricity regime.

# Abstract in italiano

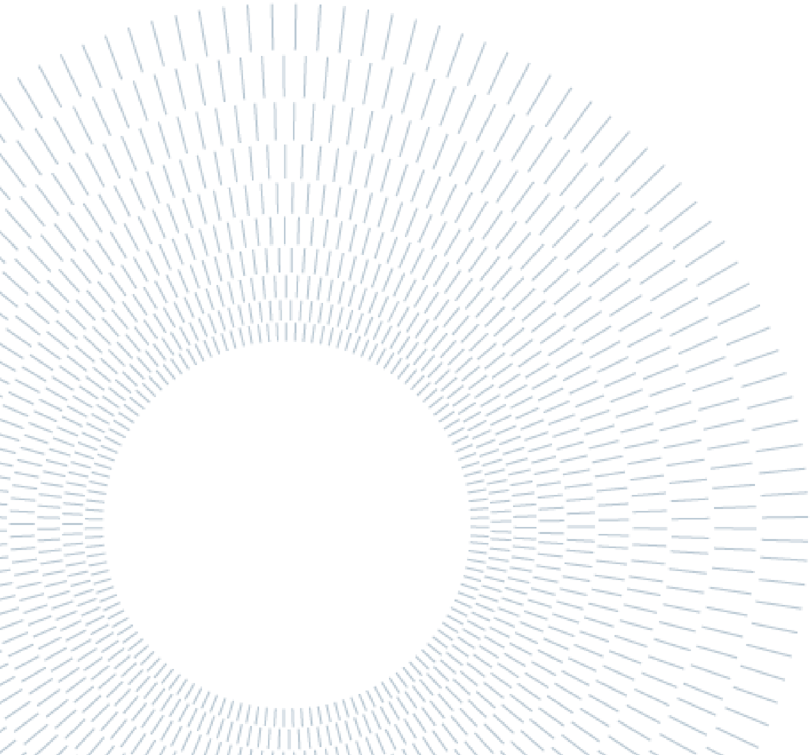
**Parole chiave:** Contatore Smart, Carichi Non Lineari, Precisione della Misurazione delle Armoniche, Qualità dell'Energia, Simulazione del Carico, MATLAB/Simulink, Frequenza di Campionamento, Teorema di Nyquist, Distorsione Armonica Totale (THD), Fattore di Potenza.

L'integrazione crescente di carichi non lineari nelle residenze private minaccia significativamente la qualità dell'energia e l'integrità dei sistemi di misurazione dell'energia. I contatori smart offrono un monitoraggio avanzato, ma la loro precisione è messa a rischio dalle distorsioni armoniche che questi carichi iniettano nella rete elettrica. L'obiettivo principale di questa tesi è quantificare l'impatto di ciò creando un framework di simulazione complessivo in MATLAB/Simulink.

Il fulcro del progetto è stata la simulazione di diversi dispositivi domestici non lineari contemporanei, come caricabatterie per PC, piani cottura a induzione e lavatrici. È stato quindi costruito un contatore smart funzionale reale per imitare parametri operativi chiave come una frequenza di campionamento di 2 kHz e un intervallo di media dei dati di 15 minuti, in modo che le sue indicazioni possano essere confrontate con risultati teorici ideali.

Secondo diversi studi citati, esistono possibili fonti di errore che possono produrre misurazioni inferiori nei contatori smart. Questa sottostima è causata principalmente da due ragioni: la distorsione armonica della forma d'onda della corrente e la bassa frequenza di campionamento del contatore, che non è sufficiente per registrare accuratamente le armoniche di ordine elevato, specialmente nei casi in cui il Teorema di Nyquist non viene mai rispettato.

Lo studio esaminerà se le limitazioni di progettazione nei contatori smart possano causare errori di misurazione significativi quando si confrontano con i carichi moderni. Questo sottolinea l'imperativa necessità di algoritmi di misurazione avanzati e standard di campionamento di fascia alta per garantire una fatturazione energetica accurata nell'attuale regime elettrico.



# Contents

# Introduction

The growing integration of non-linear loads in domestic households, such as new appliances and electronic devices, represents a significant risk to power quality and measurement system integrity. While high-level monitoring is offered by smart meters, their operation can be compromised by the harmonic distortions that are injected into the power system by these loads. In this thesis, the problem is addressed by developing a comprehensive simulation framework to examine this impact in a thorough yet controlled manner.

The core of the project was the modelling and simulation of a variety of contemporary home non-linear loads in MATLAB Simulink. Modern equipment with its widespread use of power electronics was selected, including computer chargers, induction cookers, electric ovens, washing machines, and dishwashers. For each of them, an electrical model was developed that replicates its internal configuration, including the power conversion stages (AC-DC, DC-DC, and DC-AC) that are the main cause of harmonic generation.

Then, individual load profiles of these appliances were simulated based on realistic daily usage patterns. These individual simulations allowed the electrical behavior of each load to be inspected independently. The models were then included in a collective simulation of the overall consumption of a household during a complete day, allowing the interaction among the loads and their combined effect on the quality of the delivered energy to be evaluated.

Finally, a functional smart meter model was designed and established in Simulink. The virtual meter was programmed to replicate the most significant functions of a real device, e.g., data acquisition at a specified sampling rate and processing voltage and current signals to achieve active power consumption. To test the model's validity in accuracy terms, the measurements obtained through the simulated meter were compared systematically with ideal theoretical values generated by the simulation environment itself. By means of such a comparison, the measurement error could be measured and the limits of the meter defined, notably its ability to record correctly quick, transient consumption peaks.

# 1 Smart Meters

This chapter will discuss smart meters, their history, their characteristics, and how they work. It will also address the sources of error that can affect the accuracy of these devices.

## 1.1. Introduction

Since electricity became available to the world, the need to measure its consumption also arose. Over the past 100 years, various types of traditional electric meters have been developed, each with different mechanisms designed to convert electrical energy consumption into a readable value for tracking industrial and household usage. The most common of traditional electricity meters are the Ferraris meter. These meters operate by using an aluminum rotating disk control by the interaction of the magnetic fields from two electromagnets (one for the voltage and one for the current) [12]. However, these meters had significant limitations. One of the main issues was the need to send inspectors to check them individually, forcing billing companies to allocate resources to hiring personnel solely for verifying recorded values [1]. Additionally, traditional meters lacked the ability to communicate with other electronic devices, preventing advanced monitoring and real-time data processing.

When these meters were invented, the idea behind it was to measure the electric energy consumed from the grid by the user. These meters were unidirectional, meaning they can only detect power flowing in one direction. Initially, the technology of traditional meters was based on the premise that consumers would only consume energy, not generate it [2]. These meters were unidirectional, meaning they could only measure power flowing from the grid to the household, which made it impossible for a company or household to generate and sell its own energy back to the distribution company.

Smart meters provide a direct solution to these limitations. A key advantage is their bidirectional capability, which allows them to accurately measure energy flowing both from the grid into the house and from the house back to the grid [11]. Furthermore, their ability to communicate with other devices on the network greatly facilitates the monitoring process for companies [2]. This technological shift is fundamental, as the digitization of the energy industry is a key element for a successful energy transition.

Metering of primary energy has been around for many years, with fuel, water, gas, and electricity being the most common for most people. However, in the last 20 years, there has been an increase in data analysis research in the field of electrical power consumption [3]. The reason behind this increase is related to the amount of data available due to the increase of smart meters in households. According to the U.S. Energy Information Administration (EIA), from 2007 to 2012, the installation of smart meters increased 17-fold [4].

These Smart meters can collect data every 15 minutes, compared to traditional meters, which were checked only once per month. This represents a 3,000-fold increase in the data collection [4].

Not only does this improve the precision of long-term analyses and consumption predictions, but it also provides greater insight into how and where energy is being used [3]. With this information, users can better understand and plan strategies to optimize their energy consumption, ultimately leading to energy savings.

## 1.2. Smart Meters in Italy

In Italy there has been an upgrade in the smart meters. Since 2020 the new Smart meters 2.0 by Unareti have started updating the past smart meters 1.0 and the plan is to complete the massive change until 2034 [20]. The advantage of these new meters is the ability to have a better estimation and control of energy consumption in the household.

## 1.3. Properties of Smart Meters

This chapter will discuss how smart meters measure the energy consumed and how they process this information to be connected to the Internet of Things (IoT).

### 1.3.1. Working principles

Smart meters measure electrical energy using advanced sensing technologies. They typically contain two measurement circuits: one for voltage and another for current [13]. To measure voltage, smart meters use generally a Voltage Transformer (VT) or voltage divider, while for current measurement, they use a Current Transformer (CT) or shunt resistor, depending on the design. The working principle of these instrument transformers is that they receive the high voltage or current at their primary winding and step it down to a lower, more manageable value at the secondary winding. This makes the signal easier to sample and convert into a digital format using an Analog-to-Digital Converter (ADC) and creating galvanic insulation between the source and the metering unit [14]. Galvanic insulation is when there is no direct connection between two circuits, this means power pass through them without current flowing directly. Once digitized, the measured values are used to calculate energy consumption, which is then stored in the meter's memory. At regular intervals of time, this data is transmitted to the supplier's database via communication protocols such as PLC (Power Line Communication), RF (Radio Frequency), or cellular networks [13].

### 1.3.2. Data Acquisition

For the proper billing of the smart meters the acquisition of the data of energy consumption must be as precise as possible. The main parameters for proper sampling that should be considered are Sampling Frequency ($fs$), Resolution (Bit Depth), Duration of Sampling. For starters, the sampling frequency according to the Nyquist-Shannon theorem must be at least twice the highest frequency in the signal ($f_s \geq f_{max}$) [23] In general, the smart meters sampling frecuency is normally over 1kHz. According to Pereira, L., Costa, D. & Ribeiro, M [19], in Portugal the most common sampling frequency used in smart meters for residential household is 2. kHz. For the resolution it is known that the bigger the number of bits, the better sampling will be due to the reduction of the quantization error. In addition, in this paper they mentioned that the DAQ (data acquisition) used in the meters is 16-bit [19]. Finally, it is very important that during the sampling process, all possible events are captured. In systems like the power grid, where fluctuations are frequent due to the connection and disconnection of household devices, selecting an appropriate sampling time is crucial.

## 1.4. Factors affecting Smart meters.

This section will discuss the factors that affect the accuracy of smart meters and the sources of error associated with them.

### 1.4.1. Power quality

To understand the root of the possible issues with smart meters, it is necessary to analyze the parameters that can affect their measurements. In an ideal scenario where none of the system loads generate distortion, power quality would not be a concern. However, due to the integration of electronic devices in households and the significant number of harmonics and distortions they introduce into the system, power quality has become a critical issue [16].

At the beginning of the electrical system, power quality was assessed mainly based on two factors: long interruptions and short interruptions, sometimes including voltage dips [16]. Voltage dip is a reduction of the voltage level from its nominal value [29]. Nowadays, these are not the only criteria used to evaluate power quality. The main concerns now are voltage and current quality. These terms are defined by the deviation between the ideal sinusoidal waveform with constant amplitude and the actual waveform, as well as the phase shift between the voltage and current waveforms (power factor).

In a normal AC system, power factor is determined solely by the Displacement Power Factor (DPF), which accounts for the phase shift between voltage and current waveforms. However, in nonlinear systems, this approach is insufficient. In these cases, the Distortion Power Factor (DHF) must also be considered, as it accounts for the Total Harmonic Distortion (THD) of the current.

The total power factor in a nonlinear system is given by:

$$\mathrm{Pf} = \mathrm{DPF} \times \mathrm{DHF}$$

Where, $\mathrm{DHF} = \frac{1}{\sqrt{1+\mathrm{THD}^2}}$.

This means that as THD increases, the overall power factor decreases, leading to a reduction in power quality and higher system losses [17].

Standard EN 50160 which discusses the maximum supplied voltage variation tolerance ($\pm 10\%$), frequency variation ($\pm 1\%$) and the maximum permissible system of THD for residential systems of 8% [18]. In this standard it is not discuss about current THD because as current is depending on the voltage, the focus of the power quality is centered in the voltage.

However, current distortion can be indirectly impacted by the presence of harmonic distortions in the voltage supply, especially in systems where nonlinear loads (like computers, LED lights, and electronic appliances) cause current harmonics. The harmonics in the current will depend on the voltage distortion and the characteristics of the load, which is why the voltage THD is a key consideration.

### 1.4.2. Harmonics

Harmonics are voltage or current waveforms in an electrical system that occur at integer multiples of the fundamental frequency (50 Hz or 60 Hz) and are caused by nonlinear loads. These harmonics can degrade power quality in the electrical grid, as demonstrated in a study by K. Nikum, R. Saxena, and A. Wagh [5].

There are several ways of how increase level of harmonics not only can reduce power quality but also harness the power grid. Harmonics, increase system losses due to Total Harmonic Distortion (THD). Since $I_{rms} = I_1\sqrt{1 + THD^2}$,the higher the THD, the greater the current will be. Given that power losses in cables are calculated as ($P = {I_{rms}}^2 * R$), an increase in THD leads to higher energy losses in the system [6].

Another issue with harmonics in transformers and induction machines [21], is their sensitivity to harmonic pollution, which affects eddy current and hysteresis losses, finally causing core heating and a reduction in efficiency. In transformers, overheating can damage the insulating material and potentially cause insulation failures. In the case of induction machines, distorted current can directly affect their torque. This torque pollution can generate vibrations in the machines, which, in turn, can reduce their lifespan [21].

Additionally, in power system distribution, capacitors and inductances can create resonant conditions. A resonant condition happens in an electrical system when the inductive reactance and the capacitive reactance cancel each other out at a particular frequency. This situation can lead to the amplification of harmonics, generating overvoltage and overcurrent that could accidentally get trip system protection [22].

The effect of harmonic pollution not only reduces the life expectancy of electronic devices but also impacts on their proper functioning. For example, smart meters rely on a precise voltage waveform to operate according to their specifications. If this waveform is distorted, their accuracy may be compromised, leading to billing errors [8].

### 1.4.3. Non-Linear loads

A nonlinear load is an electrical device or system that draws current in a non-sinusoidal manner, meaning the current waveform is distorted and does not follow the applied voltage waveform [7].

Examples of such devices include laptops, desktops, chargers, printers, TVs, and LED lights. All this equipment can cause distortion in the power grid in the form of harmonics [5].

There are three main sources of non-linear loads in the grid: ferromagnetic saturation, arc-type loads, and power electronics. Ferromagnetic saturation occurs when the iron core of transformers or reactors reaches magnetic saturation, causing a distortion in the current waveform. Arc-type loads are loads that due to high voltage changes generated electric arc and this arc generated distortion in the current. These arcs lead to highly irregular and random variations, introducing significant non-linearity in the system. The non-linearity in power electronics, which will be the focus of this paper, is mainly generated by AC-DC converters [9]. These converters use semiconductor devices to modify the alternating waveform of the source and convert it into a DC output. This is achieved by rapidly switching the semiconductors on and off, ultimately generating a DC current [10]. All these non-linear loads produce harmonics, which are injected into the power grid, potentially affecting its stability and power quality. This can be seen in the following image, retrieved from the paper by Mageed et al. [15], which illustrates how non-linear loads affect the properties of a sine wave. The image shows how these loads distort the sinusoidal waveform by introducing harmonic components, adding noise, and altering its shape, making it more erratic.

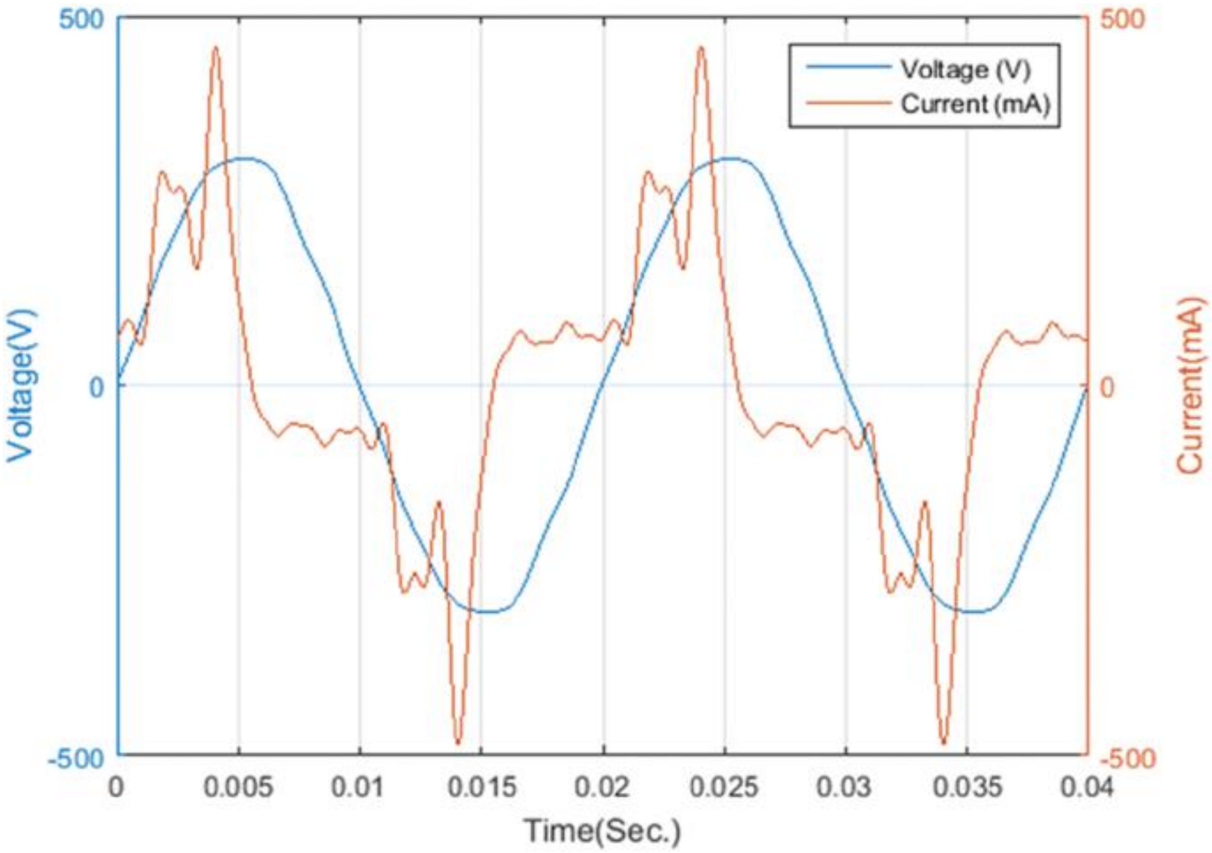


Figure 1.PC's Voltage and current waveforms versus time. [15]

The main benefit of smart meters compared to traditional metering devices is their capability to transmit consumption data to remote processing systems. However, for this to work, the data transmitted must be accurate. One of the challenges of smart meters is that, even though they are built to operate in real world conditions (accounting for some distortion), if the harmonic distortion of the waveform is too high its accuracy may vary. The massive integration of nonlinear loads into the power system can introduce significant waveform distortions, potentially impacting meter measurements. According to studies conducted by Chandel et al., the addition of just the third harmonic to a sinusoidal waveform can introduce a measurement error of up to 10% in the device [8].

### 1.4.4. Methodology for Accuracy Verification in Smart Meters

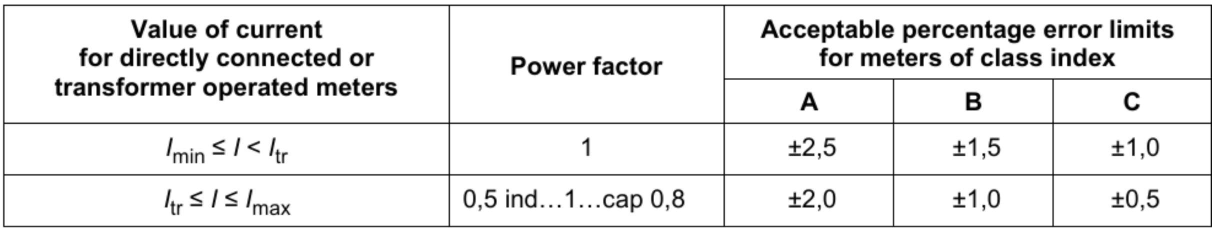
The testing of accuracy of smart meters is a very formalized process that is necessary to ensure justice in energy billing. This is not a test on a single reading but on confirmation that the deviation of the meter is within very strict tolerances under reproducible and controlled working conditions.

These standards in this field, principally the European series of standards EN 50470 [35] and international standards IEC 62053 [37] and IEC 62057 [36], specify methodology, accuracy classes, maximum permissible errors, and test equipment requirements. Specifically, the BS EN 50470-3:2022 standard defines the exact requirements for static active energy meters, while the BS EN IEC 62057-1:2023 standard defines the Meter Test Units (MTUs) specifications used in a laboratory setting to perform these verifications.

Energy meters are categorized by their "accuracy class". This is the maximum acceptable percentage error the meter can have in reference conditions. Static a.c. meters have three main classes for measurement of active energy defined by standard EN 50470-3:

- Class A: The least demanding class.
- Class B: Commonly used for residential meters.
- Class C: The most accurate class, generally reserved for industrial or high-precision applications.

And according to EN 50470-3:2022 the Acceptable percentage error limits at reference conditions for each class is:



| **Value of current for directly connected or transformer operated meters** | **Power factor** | **Acceptable percentage error limits for meters of class index** | | |
|---|---|---|---|---|
| | | **A** | **B** | **C** |
| $I_{min} \leq I < I_{tr}$ | 1 | ±2,5 | ±1,5 | ±1,0 |
| $I_{tr} \leq I \leq I_{max}$ | 0,5 ind…1…cap 0,8 | ±2,0 | ±1,0 | ±0,5 |

Figure 2. Acceptable percentage error limits at reference conditions

# 2 Load Profile for Non-linear and Linear loads

## 2.1. Parameter for load simulation

To design a precise load profile, it is necessary to carry out a detailed study of the characteristics of the user who uses those loads. In other words, it is not enough to model the device; one must also consider how, when and how often it is used, which varies from person to person and household to household. In household the parameters that establish how to create an accurate load profile are demographics (number, age, sex, race), economics (income, level of education) and lifestyle (time people spend indoors, amount of home cooking etc.) [24].

### 2.1.1. Type of loads

When discretizing the loads that are in the household, it is important to know if they are either linear loads or non-linear. As shown before, the non-linear loads in common households are electronic equipment.

In the past century, most equipment within the household did not use electronics and was less available to the common people due to its high prices. For these two reasons harmonic pollution was not a problem back then [25]. In recent decades, electronics have been widespread in every part of the household. For example, LEDs, computers, freezers, washing machines or any inverter driven appliance. Before, these items were either linear loads like the incandescent lightbulb or just where not common nor existed like computers. All this common house equipment has the particularly that they need DC current to work. They can achieve this by using power electronics first by using a rectifier to change the voltage from AC to DC and then a DC-DC converter to control the voltage regulation in which the machine is meant to work. The way this power electronics equipment can change the waveform of the power is by using switches that by opening and closing at very high frequency create harmonics that would later go to the source that is powering them [28].

### 2.1.2. Simulation of linear loads

Linear loads are all the loads that have a linear relationship between voltage and current. These loads have constant impedances and the current that goes through them is proportional to the voltage applied. This includes resistors, inductors, and capacitors. Even though they are not very common in today’s households, some examples of resistors are incandescent lamps and heaters. And for inductive loads, motors are the best examples. To simulate its energy consumption, it’s enough to get the equation of the circuit that is being fed by the voltage, and by computing its impedance, we can get the current profile that this load is consuming. In purely resistive loads, it is straightforward because all the energy that is consumed is active energy, it means it can produce work. Meanwhile, for inductive and capacitive loads, they consume reactive energy that cannot produce any work. When the load is either RL, RC, or RLC, it consumes a portion of active and reactive energy and must follow the following relationship: the apparent power is equal to: $S = \sqrt{P^2 + Q^2}$. In the case of smart meters, they are meant to only measure active energy, and this type of load does not affect the smart meters’ accuracy [26].

### 2.1.3. Simulation of non-linear loads

As seen before non-linear loads do not follow the same rules as linear loads. Its power consumption is not linear to the voltage applied and doesn’t have a constant impedance. This is because they posses' non-linear elements like, diodes, switch, BJT, Mosfets, etc. These elements have the particularly that depending on the conditions can change the topology of the circuit, for example diodes behave like an open circuit when their threshold voltage is not reach and as a short-circuit when the voltage across its terminal is bigger than its threshold. To simulate this type of loads needed to be used and algorithm that can change the topology of the circuit depending on the conditions of the circuit. For example, an induction stove that has an rectifier (AC-DC) and then an inverter (DC-AC) that increases the initial 50/60 Hz frequency to 20-100kHz. This change of frequency is achieved by the BJT and MOSEFT that turn on and off changing the properties of the waveform, adding distortion to the system. By doing this the induction in the coil of the pan heats up due to eddy currents [27].

If the consumption of the household is mainly linear and just a small amount of non-linear, the consumption measured by the smart meter would not be affected. But in case of many loads creating distortion and affecting the property of the waveform then we could have issues on the accuracy of the measurements [8].

As explained before, the relationship of power consumption that linear loads follow $S = \sqrt{P^2 + Q^2}$ does not apply to non-linear loads. The reason for this is the distortion generated by the switches and the other nonlinear elements that generated a distortion power delta $(\mathrm{D})$. In nonlinear loads the distortion power is the one generated by the harmonics caused by the high frequency switching $\mathrm{D} = V_1 * I_{harmonics}$. This power is different from the reactive power factor, it is produced by the phase shift of the voltage waveform with the current. So, for this type of loads to compute the total apparent power the formula to follow is the following $S = P^2 + Q^2 + D^2$ [28].

# 3 Simulation

This section describes the process carried out during the development of the project. It is divided into three main parts: first, the creation of various nonlinear loads; second, the simulation of their individual operation during a typical day; and third, the simulation of the electrical behavior of a complete household with all loads connected simultaneously.

For the load design, criteria such as consumption profiles, electrical topology, and absorbed power were considered. Modern versions of the equipment were selected, characterized by a greater use of electronic components and power electronics, which are responsible for increased harmonic generation and, consequently, a decrease in power quality.

The individual simulation of the loads was performed by applying a voltage supply to each one according to its load profile. The resulting current response was then analyzed in order to study the electrical behavior of each nonlinear load in isolation.

Finally, the complete operation of a household was simulated, with all the loads connected to a single voltage source. In this stage, each load followed its operating profile based on the time of day, thus allowing the evaluation of the interaction between them, the total harmonic distortion, and its impact on the quality of the energy supplied to the system.

Before describing how each device was implemented in Simulink, an explanation of its real-world operation will be provided, in order to justify the modeling and parameterization choices made.

## 3.1. Non-Linear Loads Simulation

**COMPUTER CHARGES (AC-DC and DC-DC):** The parameters of this charger are input voltage of 230V 50Hz, output voltage 20V DC, 12A and 2000W. For the simulation of the computer charger, it is needed to develop two step conversions. Since the output of the charger is DC, first is needed to converter the voltage coming from the grid from AC to DC with a single-phase rectifier. Second, regulate the power that arrives to the PC, this is done with a buck DC-DC converter.

Th first conversion step (AC-DC) consists of four diodes and a capacitor as shown in the figure below.

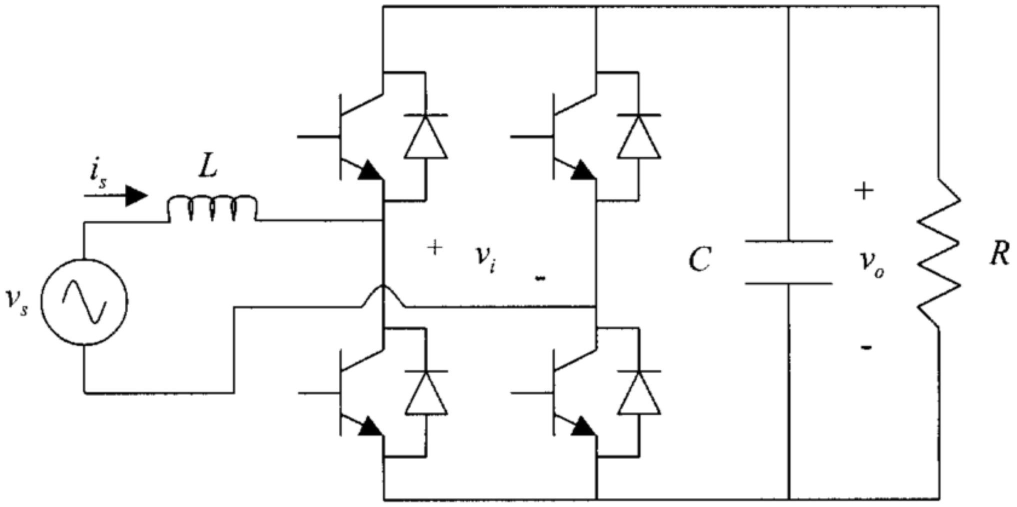


Figure 3. Single Phase AC-DC Rectifier

The function of the diodes is to change the sinusoidal waveform into an only positive waveform and the role of the capacitor is to reduce the ripple of the output voltage. If the input voltage of the rectifier is 230Vrms the output would be $Vpeak \approx Vout.\ Vout = 325V$[28].

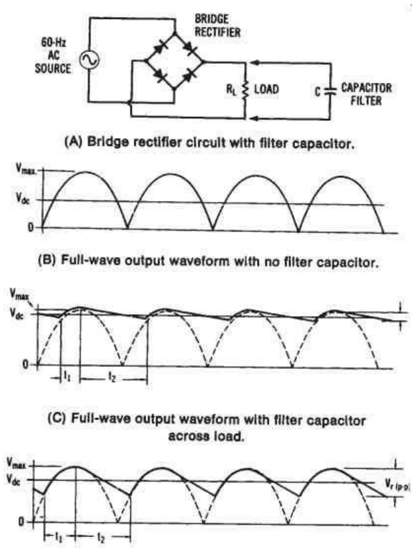


Figure 4 Rectifier Output Wave from [34]

After the voltages become DC, then to regulate the output that will supply the computer, a buck converter is needed. This converter contains a switch (BJT or Mosfet), a diode and a LC filter.

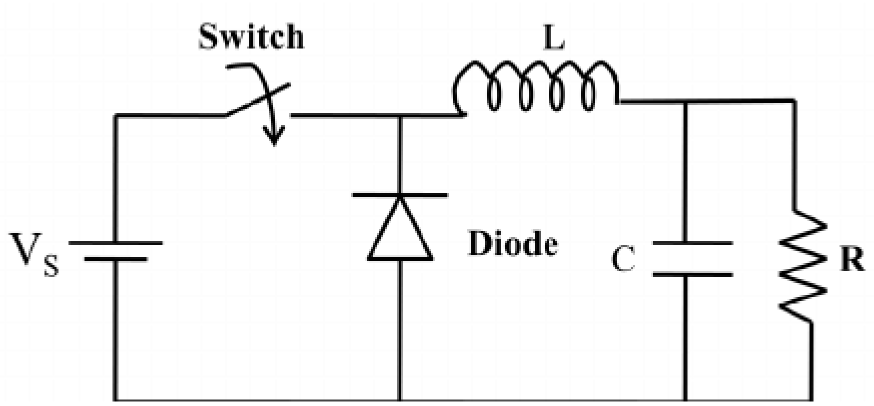


Figure 5 DC-DC Buck Converter [34]

The switch is controlled by a pulse that opens and closes depending on the duty cycle required. The duty cycle of this converter is computed by $D = \frac{Vout}{Vin}$ [28]. So, follow the example if we need 20V at the output and the input is 325V we need and D of 0.061. When the value of the duty cycle is obtained, we just need a pulse generator to power(close) the switch for 6% of the period of the pulse.

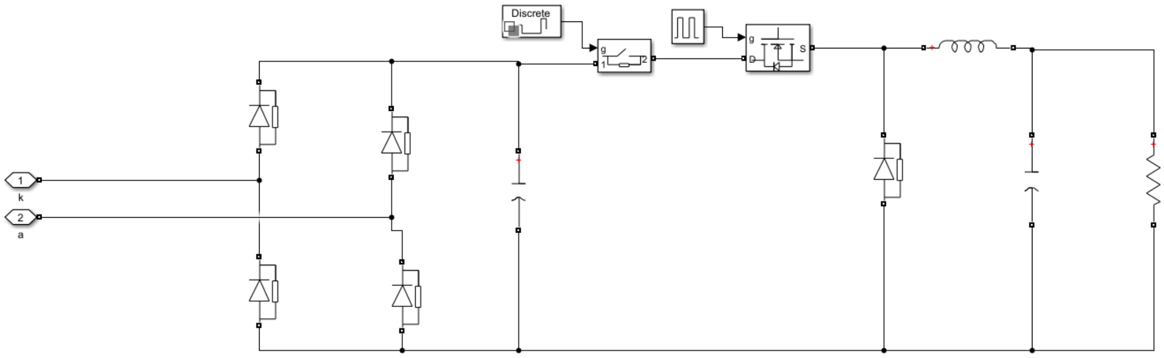


Figure 6 PC charger Simulink

For the low-profile simulation, it is assumed that the resident uses the device for 6 hours per day, distributed throughout the day in 2-hour blocks. The hour blocks when the PC will be on are 8:00am–10:0am, 14:00-16:00 and 18:00-20:00.

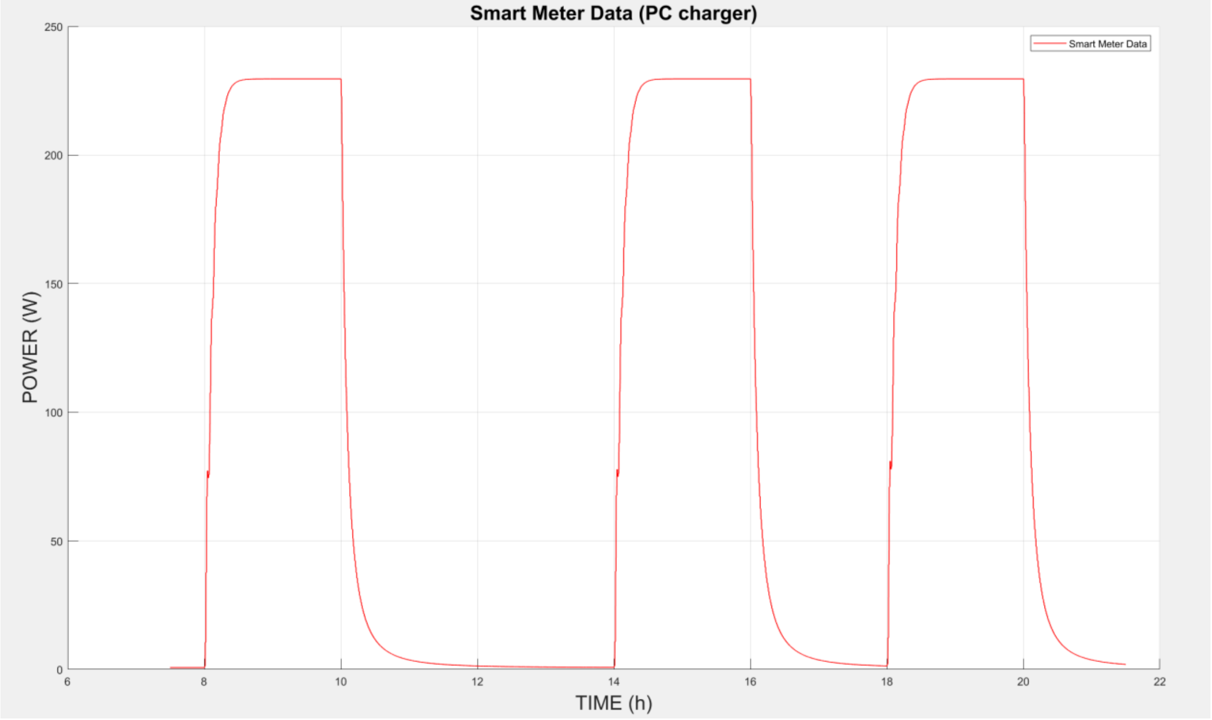


Figure 7 Load Profile of PC charger

**INDUCTION STOVE (AC-DC and DC-AC):**

For the induction stove as explained before, the initial conversion is the same as the computer charge. The difference is that the output should be AC with a high enough frequency that could generate high eddy current in the pan coil to heat up. The inverter topology is as follows:

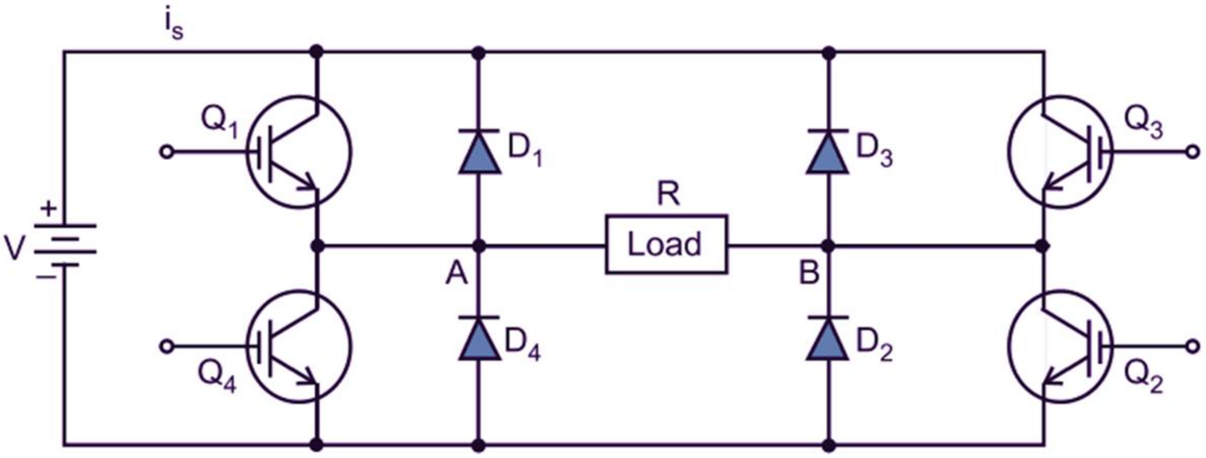


Figure 8 DC-AC Single Phase Inverter [33]

To achieve the desired output frequency, we need to control the trigger of the switch. This is done by SPWM (Sinusoidal Pulse Width Modulation) and by its carrier (triangular signal) and the desire output frequency. SPWM is a way of modulation in which to generate a sinusoidal AC waveform from a DC source using high-frequency switching [28]. It works by comparing a sine wave with a high-frequency triangular wave. If the desire output is a sine wave with a 10kHz frequency, then the fs=10kHz but the fc (carrier) must be multiple of this frequency so that the frequency modulation ration is an integer [28]. When this current frequency is active then the induction stove can work properly.

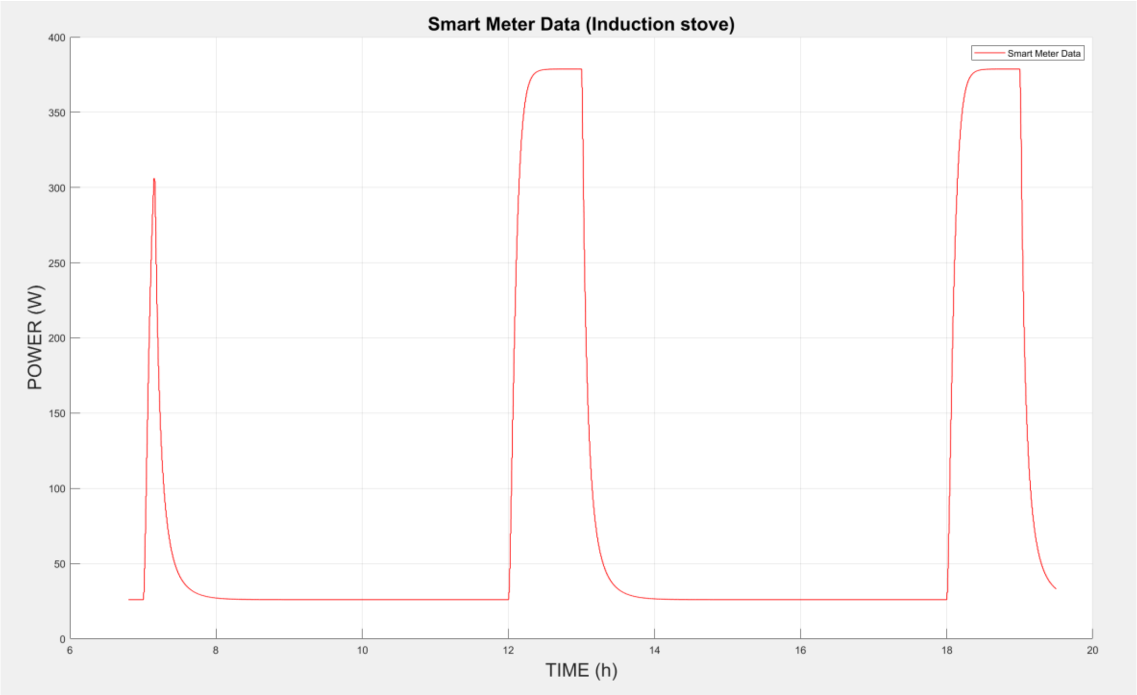


Figure 9 Load Profile of Induction Stove

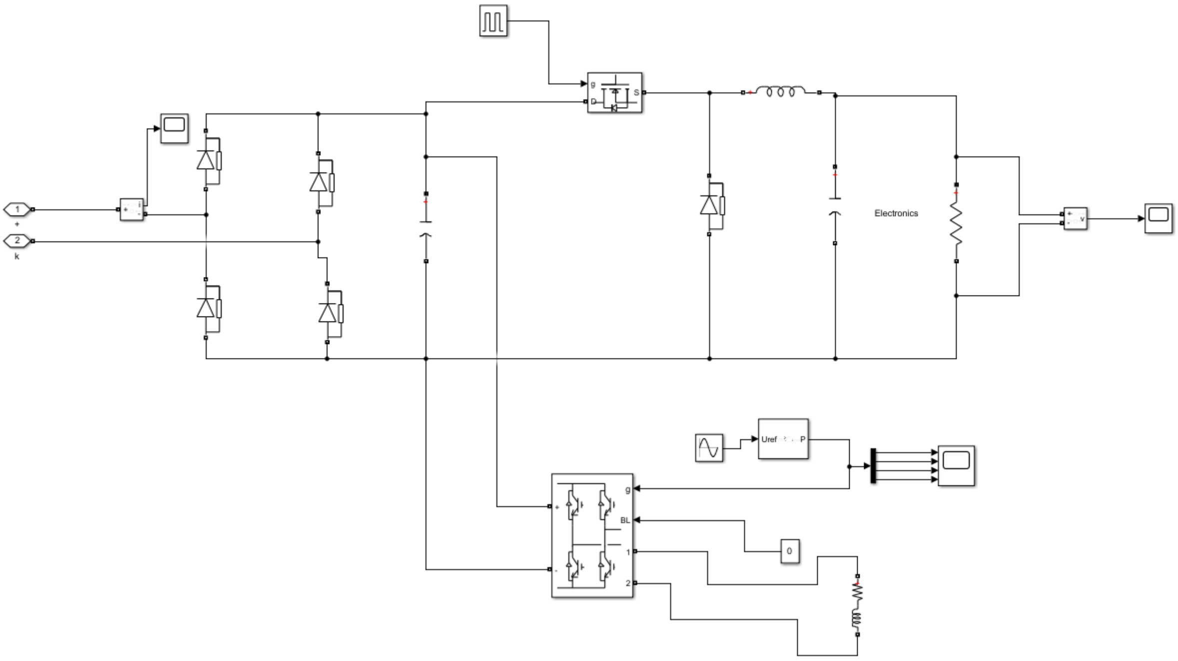


Figure 10 Induction Stove Simulink

**LED (light emitting diodes) (AC-DC and DC-DC):** the principal of LED is similar to the computer charger where there is a first conversion from the grid ac voltage to dc voltage and then either a buck or boost DC-DC converter to regulate the output of the voltage supplied to the LED and control the amount of light coming out of it. The difference is that the load is the light emitting diode.

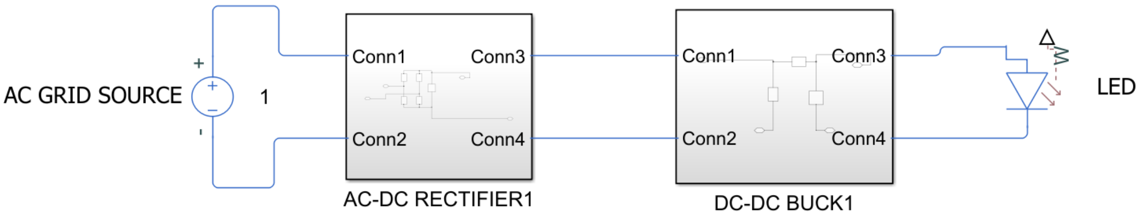


Figure 11 MATLAB LED Circuit Simulation

**ELECTRIC OVEN (AC-DC AND DC-DC+ DC-AC):** For modern electric ovens they have the same working principle as most non-linear loads. The oven has three main loads that are the electronics, the heating circuit and the fan circuit. With a first conversion step from AC to DC that creates the DC bus the is further use control de electronics. For the heating circuit it is usually implemented and AC-AC converter to regulate the out voltage that is supplied to the resistance that is used for heating up.

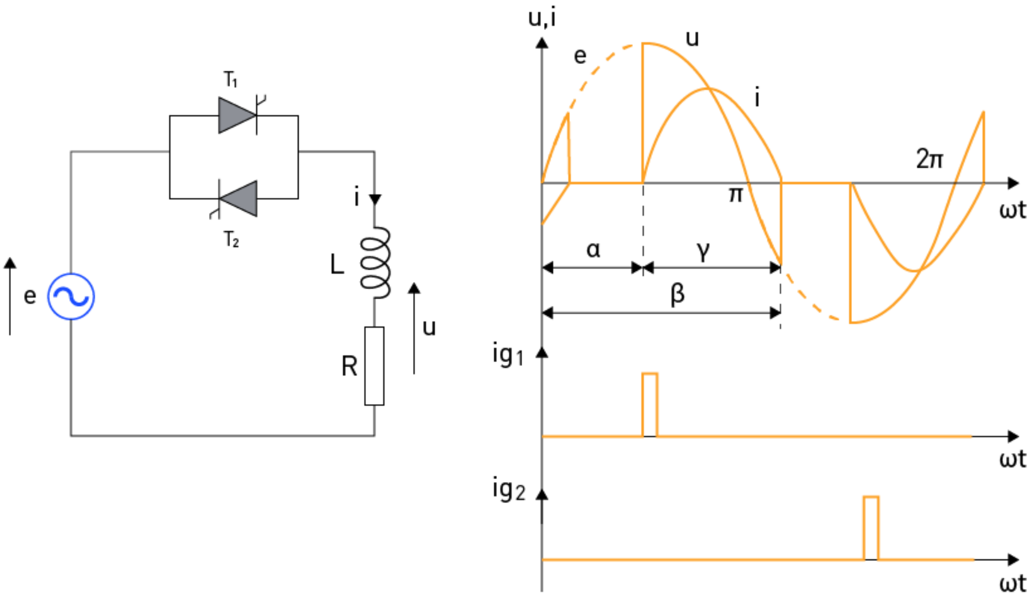


Figure 12 Single phase AC-AC Converter [32]

In the figure above it can be seen the topology of the AC-AC converter. The working principle consists of 2 thyristors in anti-parallel that are controlled by shooting angle $\alpha$ (alfa) and by setting this angle value from 0 to 180° it's posible to control the output of the signal. This can be seen in the following equation:

$$V_{\text{out, rms}} = V_s \cdot \sqrt{\frac{1}{\pi}\left[(\pi - \alpha) + \frac{\sin(2\alpha)}{2}\right]}$$

Equation1. RMS output voltage phase-controlled single-phase AC-AC converter.

For the fan circuit is just simulated as a motor that is connected to the AC bus of the oven. This load is not controlled by any converter or inverter it only has one speed and is controlled by an on-off switch that is turned on depending on the type of cooking the user wants.

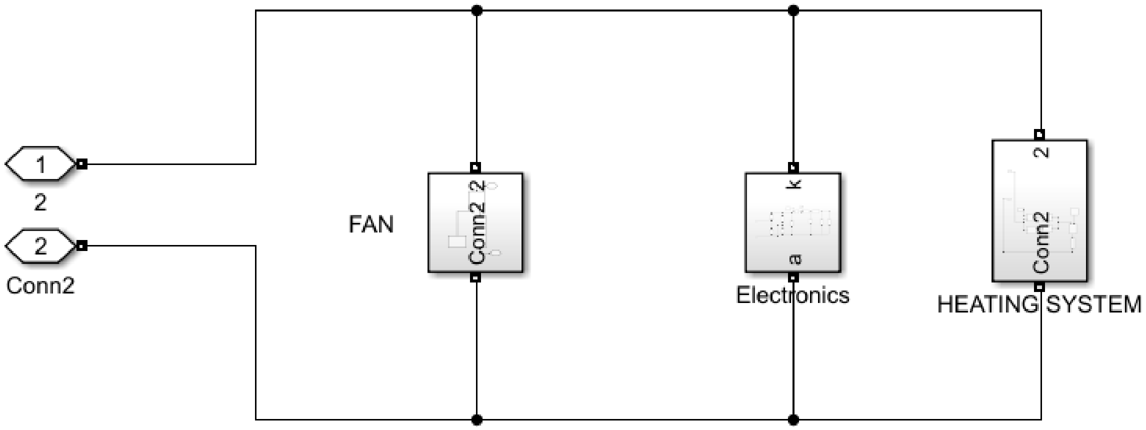


Figure 13 SIMULINK Oven Simulation

For the oven load profile of the oven, it was taken that the oven was used two times per day from 12:00 to 13:00 and from 18:00 to 19:00. In this 2-time interval it was established that the fan and the oven would be working for the same amount of time to simulate a certain cooking operation. The result of it is:

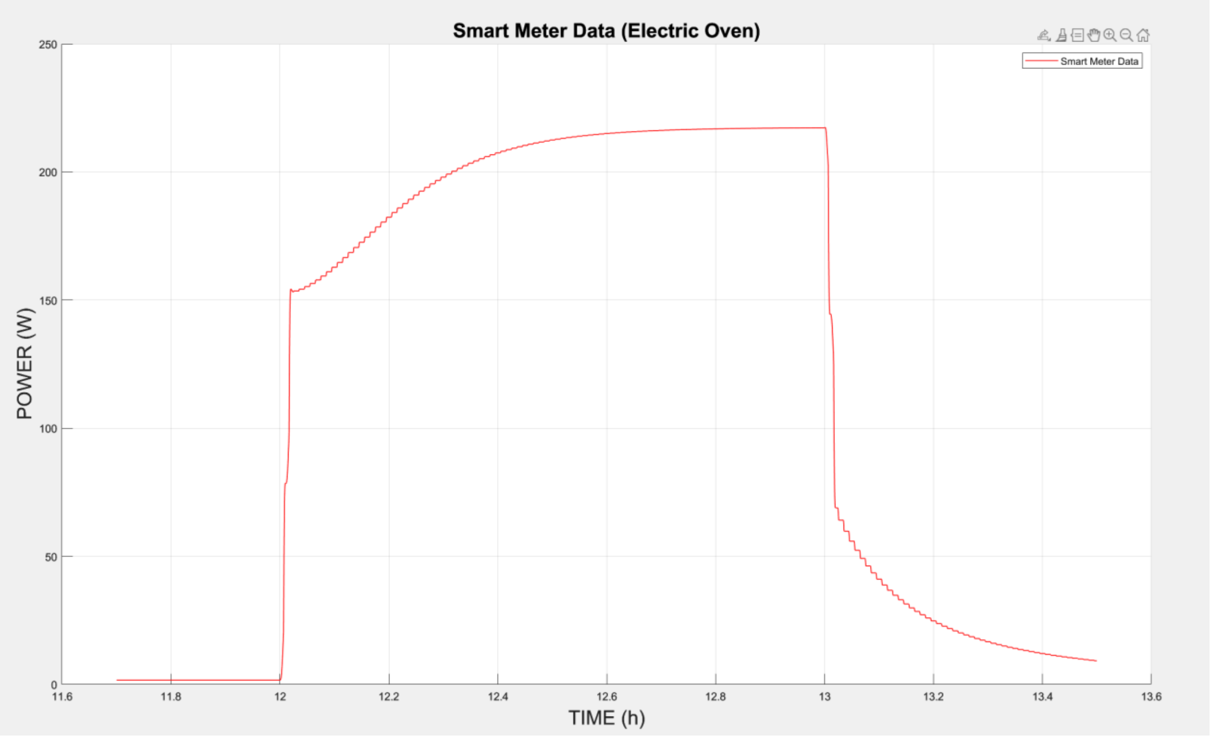


Figure 14 Load Profile of Induction Stove

**WASHING MACHINE (AC-DC AND DC-DC+ DC-AC):** For the washing machine the topology is similar as the other household appliances before. First the AC-DC conversion and then depending of the washing machine it can have normal single phase asynchronous motor or a BLDC (Brushless DC Motor) that in this case is controlled by a three-phase inverter. For this study it would be considered the BLDC due to its nonlinear controlled system. The washing machine has 4 main loads, one of them is electronics, the other is a motor that spins the machine, an electro valve that supplies and removes water from the machine and finally a water heater that is in charge of supplying heat to the water inside the washer. For the part electronics the topology is the same as the other non-linear loads with first its AC-DC conversion and then a DC-DC conversion that supplied the electronic board that controlled the other elements of the system.

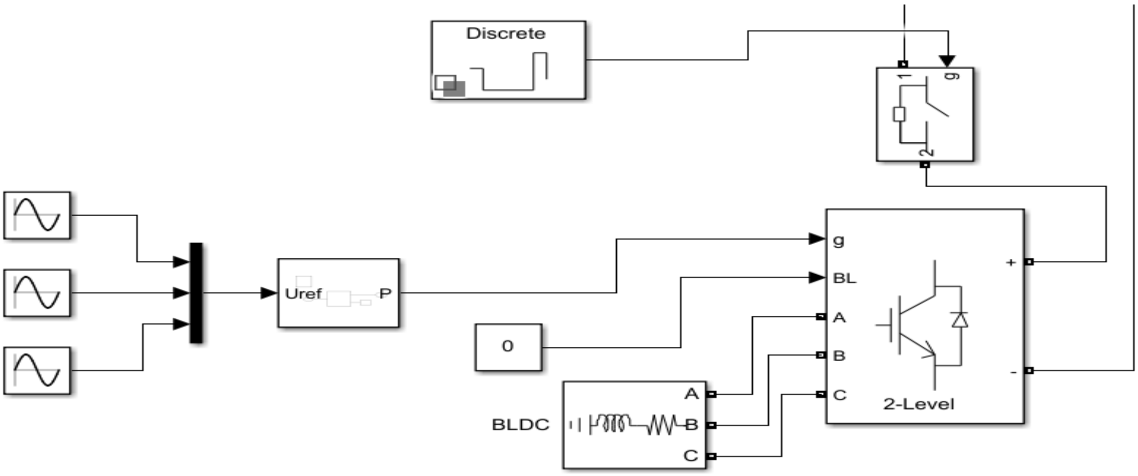


Figure 15 SIMULINK W.M BLDC circuit

For the BLDC, as seen in the figure above, first the DC bus supplied the three-phase inverter and this supplies the BLDC. For simulation purposes the BLDC is simplified as an RL load that absorbed constant apparent power. This technology of BLDC in washing machines is used in the newer machine to have more accurate control of the spin cycle of the machine.

As can be seen in figure 4 the inverter is supplied from the DC bus, which controls SPWM (sinusoidal pulse width modulation), and finally the output of the inverter supplies the RL load (simplify BLDC).

For an accurate load profile simulation of the washing machine, we follow the load profile done in the study of Issi, F., & Kaplan, O. (2018)[31].

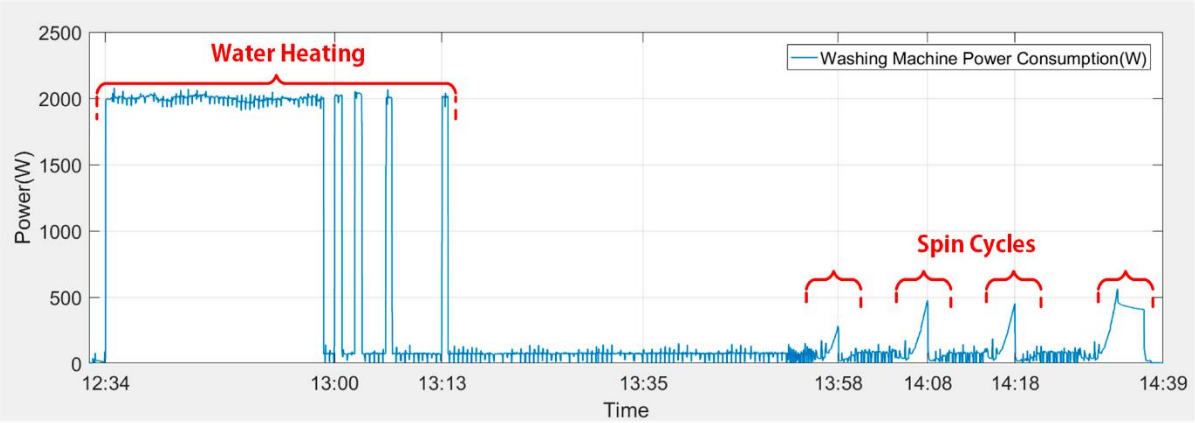


Figure 16 Washing machine Load profile [31]

The washing machine has three actions that determine its power consumption. First as it can be seen in the picture, the water is being heated, in this moment, is when the machine consumes the most amount of power. To simulate this on Simulink, we put an ideal switch in series with the water heating resistance and this switch was closed for the amount of time the water needed to be heated and open for the rest of the load profile. For the water pump and the spin cycle, the same logic is followed where an ideal switch with a specific time intervales that establishes when water needs to flow into the machine and the same for when it should rotate.

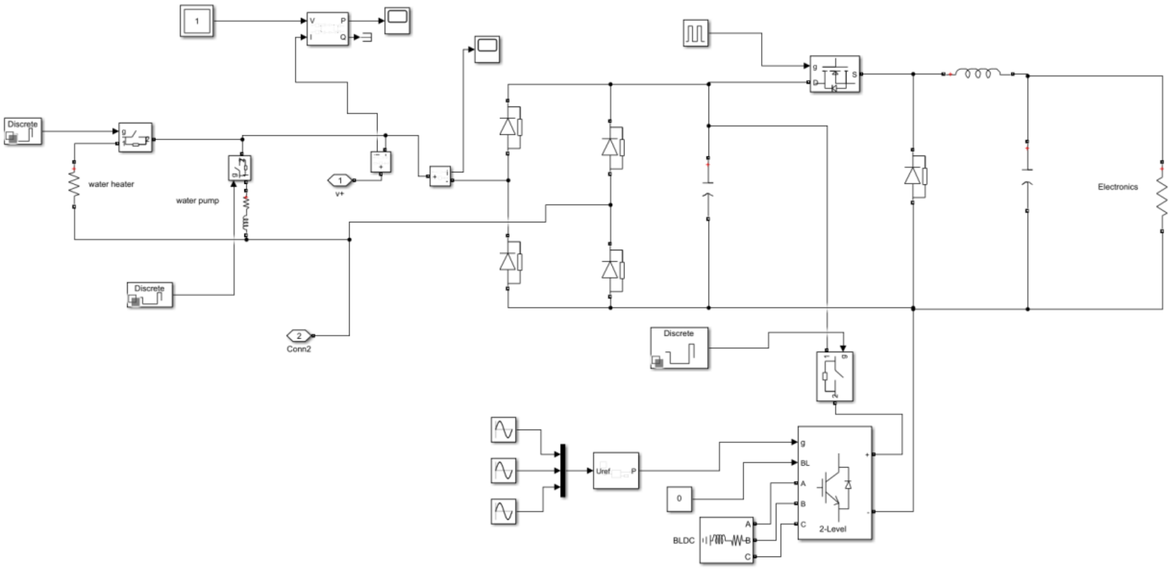


Figure 17 Washing Machine Simulink

For the washing machine's daily load profile, it is used once a day for a total duration of 2 hours. It is important to note as stated previously that not all internal components operate simultaneously during this period. This causes the load profile to vary over time, depending on which elements (motor, water pump, water heater, and electronic components) are active at any given moment. A timeline table will be presented below, indicating when each internal load is active and for how long.

Table 1 Washing machine loads working time.

| WASHING MACHINE | |
|---|---|
| LOADS | TIME ON |
| WATER PUMP | from 8:15am to 10amin 9 min intervals |
| WATER HEATER | 8:00am to 8:15 am |
| MOTOR (BLDC) | from 8:24 am to 10amin 9 min intervals |

With the resulting load profile:

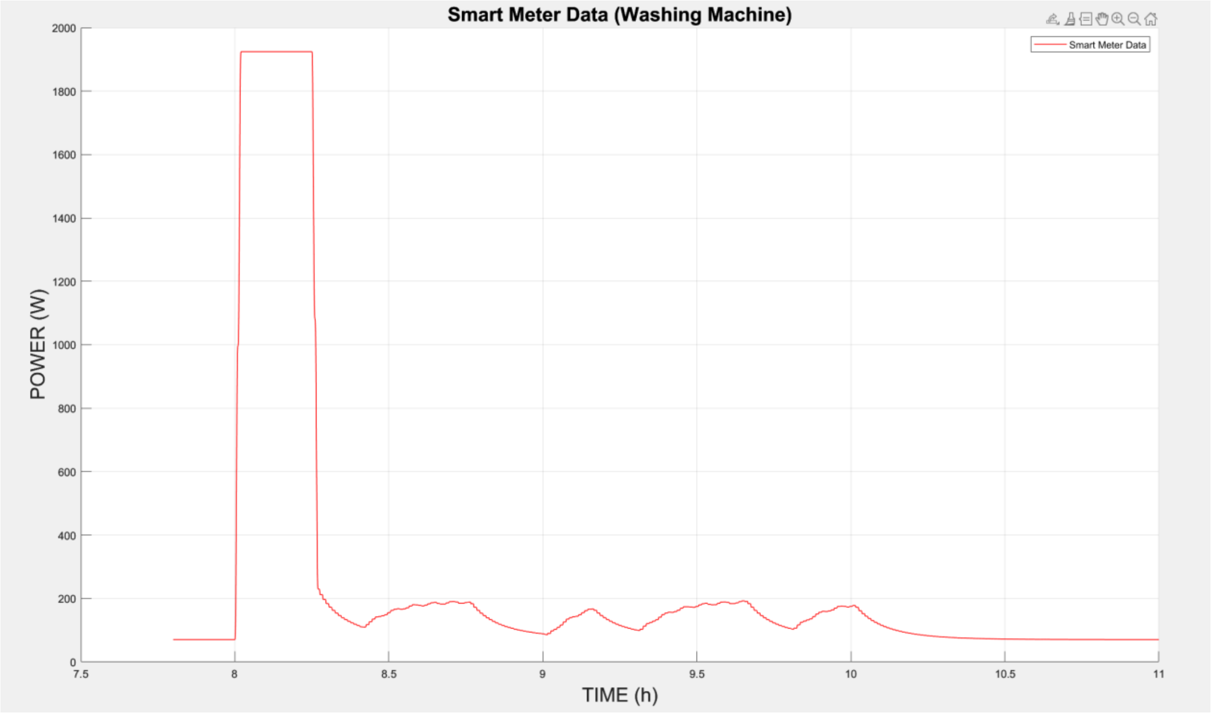


Figure 18 Washing Machine Load Profile Simulation

**DISHWASHER (AC-DC AND DC-DC):** The dishwasher, like the washing machine, shares almost the same components, but unlike the dishwasher, the washing machine does not have a powerful motor. Instead, the dishwasher has a slightly larger water pump which, when expelling the water, makes some propellers spin that move the water inside it. The rest of the electrical topology is the same; it has an AC-DC converter that creates a DC bus which later controls the electronic part of the equipment, and like all the previous equipment, it has a Buck converter. The topology can be seen in more detail in the following figure.

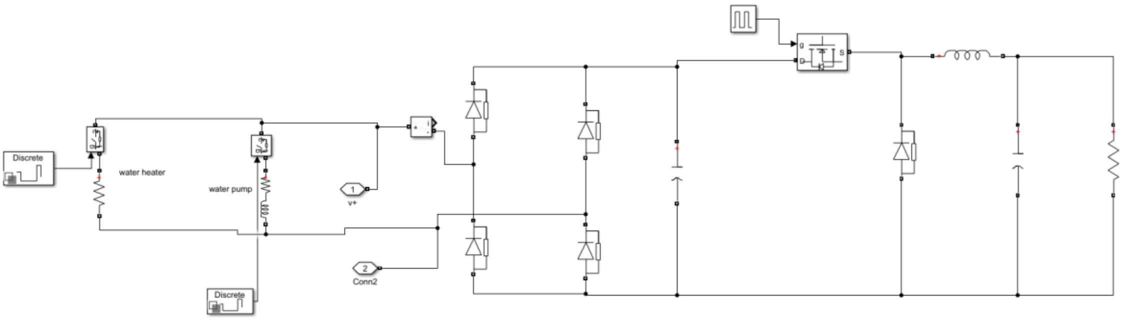


Figure 19 Dishwasher Simulink

For the dishwasher's load profile, it is assumed to be used daily for two hours in the evening (from 7:00 p.m. to 10:00 p.m.). For this appliance, water temperature is critically important due to hygiene reasons, which results in high energy consumption mainly because of the water heater. This can be appreciated in the following figure.

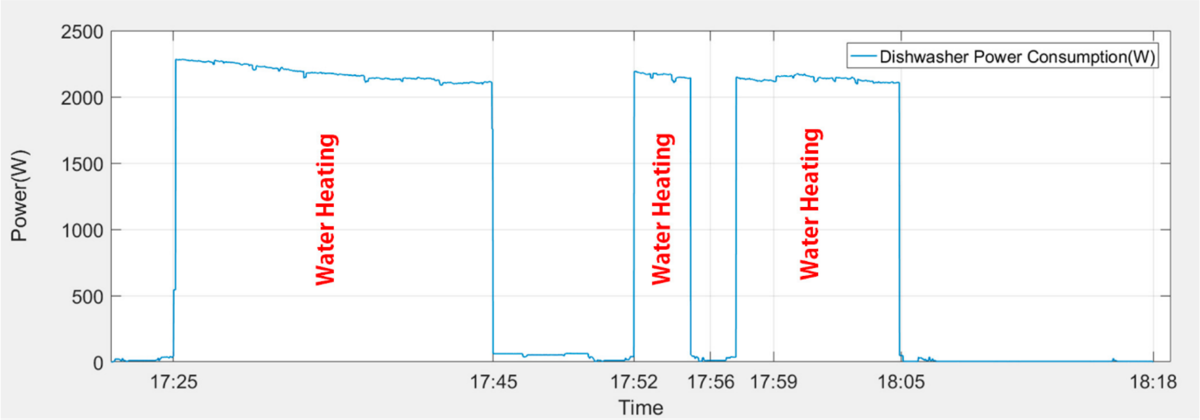


Figure 20 The power consumption of the dishwasher for the 55 °C economy program [31].

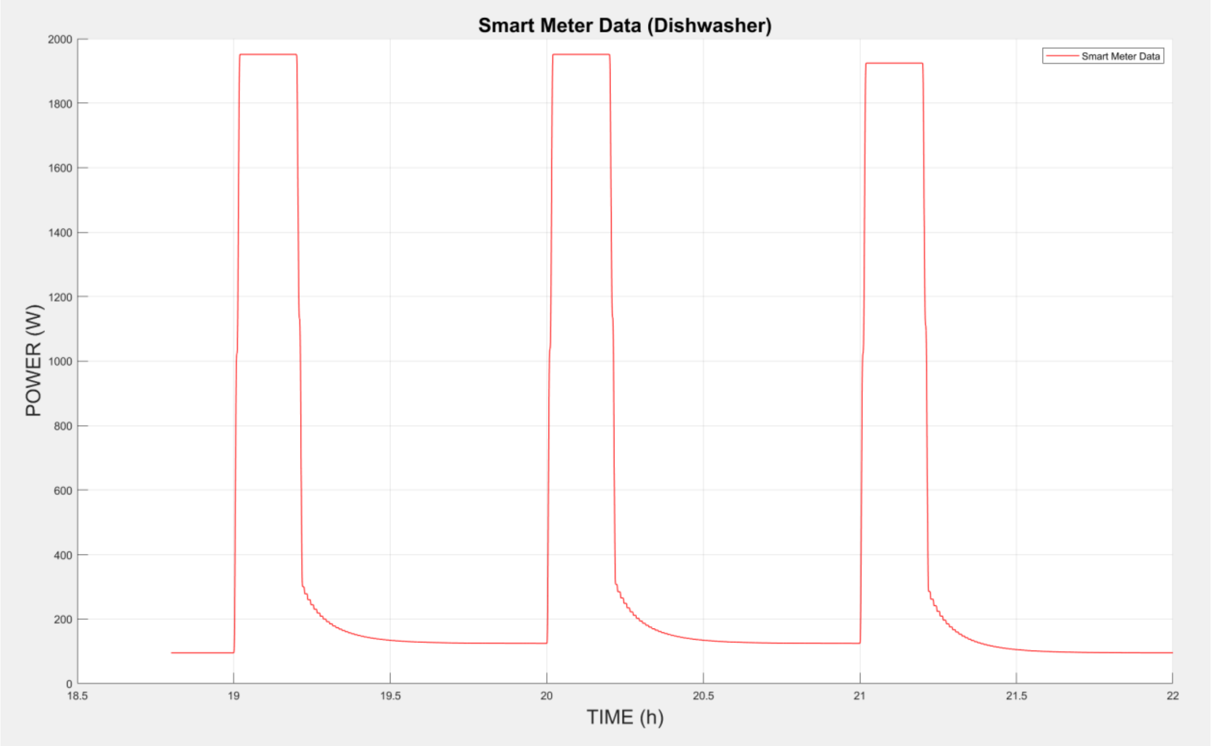


Figure 21 Dishwasher Load Profile Simulation

## 3.2. Smart Meter simulation

This section describes the method and results of the implementation of a smart meter (smart meter) in MATLAB's Simulink simulation environment. The main purpose is to develop an imitation tool that is able to provide precise measurements of the electrical parameters of already simulated non-linear household loads. This allows for an accurate calculation of the energy consumption in a simulated context and comparison of the outcomes generated with the optimal meters delivered by Simulink, thus validating our model (figure 20).

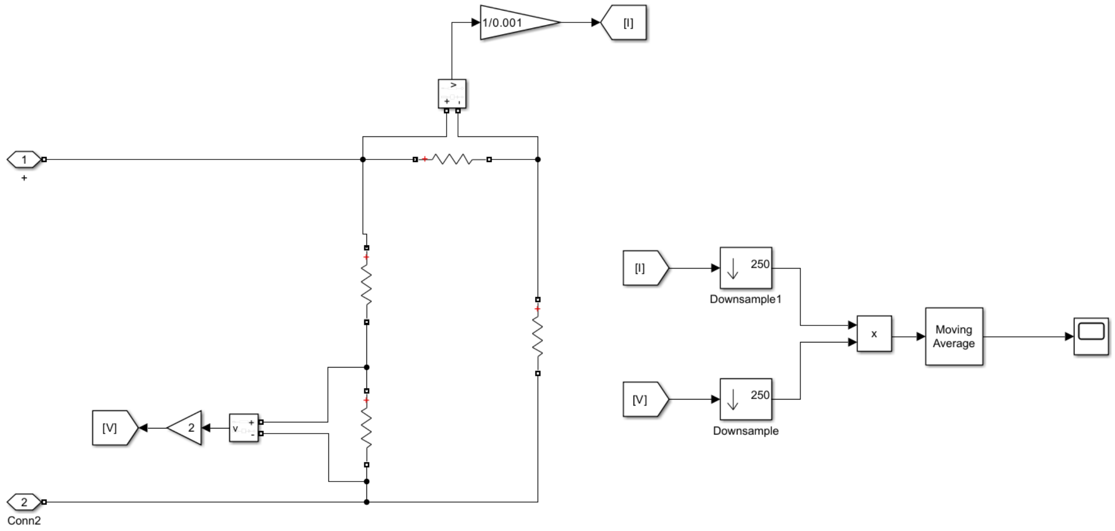


Figure 22 Smart Meter Simulink

### 3.2.1. Modelling of the smart meter using Simulink

The design of the smart meter in Simulink is based on a modular framework that replicates the most crucial functionalities of an actual device, including data acquisition, signal processing and communication. In order to simulate electrical equipment measurement, the smart meter is configured to measure the voltage (V) and current (I) signals at input of all the loads, as is shown in the following figure.

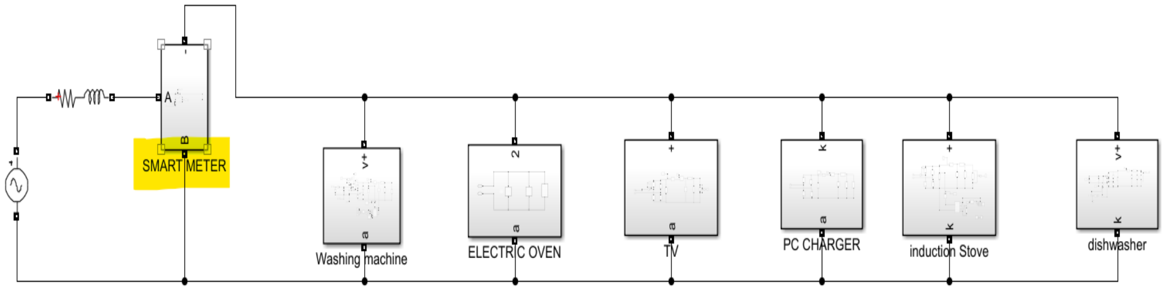


Figure 23 Complete Simulink Topology

### 3.2.2. Principal components of the smart meter

**Voltage and current sensors:** For simulating the physical sensors, the model utilizes some components. Current sensor is realized through a low value of shunt resistance, measuring the voltage across it to determine the flow of current. For voltage measurement, a voltage divider is utilized that scales the signal levels to be processed later. This can be seen in the following figure.

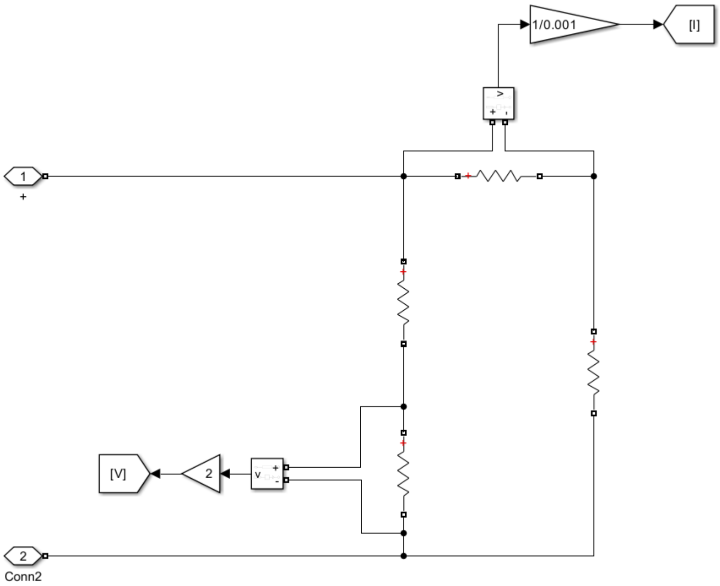


Figure 24 Voltage divider and Shunt Resistor

**Data acquisition module (DAQ):** this module simulates analog signal conversion to digital form. It was observed that although the simulation is executed at a time step of 2e-6 seconds (i.e., a frequency of 500 kHz), a real smart meter operates at lower sample rates, commonly up to 2 kHz. For emulating this in a realistic manner, the Simulink **Downsampling** feature was used (figure 22). To reduce the frequency of sampling from 500 kHz to the target frequency of 2 kHz, the system was designed to sample every 250 system steps since a sample was required every 500 microseconds (2 kHz) and the system provided one every 2 microseconds (500 kHz).

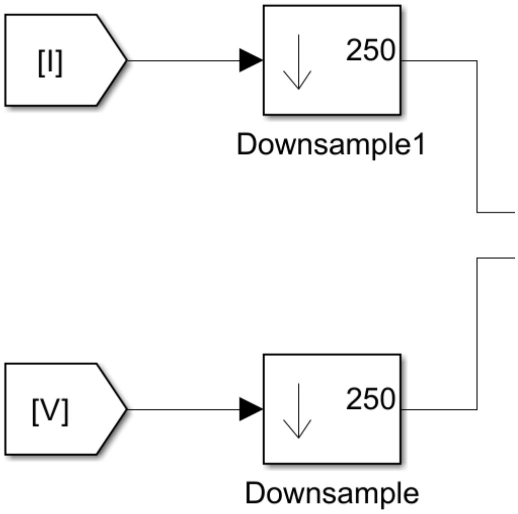


Figure 25 Downsample for Current and Voltage

**Digital Signal Processing (DSP):** Upon digitization, current and voltage signals are now being processed to derive active power (P). To achieve this, the first step involves multiplying instantaneous samples of voltage and current that are gathered from the DAQ module (figure 23). The result of this process is instantaneous power.

Next, for achieving a stable and significant value, the average of this instantaneous power over a specified time interval is calculated. Actual time of 15 minutes was utilized for analytical functions. Though total simulation of 24 seconds is equivalent to 24 hours, the actual 15 minutes correspond to 0.25 seconds (250 ms) in simulated time.

Because the sampling rate is 2 kHz (sampling every 0.5 ms), it implies that there are 500 points of data (250 ms / 0.5 ms) used to compute every average reading. Averaging is needed in order to get an accurate and realistic measurement of the active power consumption of the load.

An important piece of information about this moving average is that it varies depending on energy consumption. If the system detects an increase of more than 200W, the system no longer averages every 15 minutes (250ms in the 24 second propose model) but instead averages every 1 second. So, instead of averaging every 500 data points, it does so every two (considering the proposed model of 24 hours = 24 seconds).

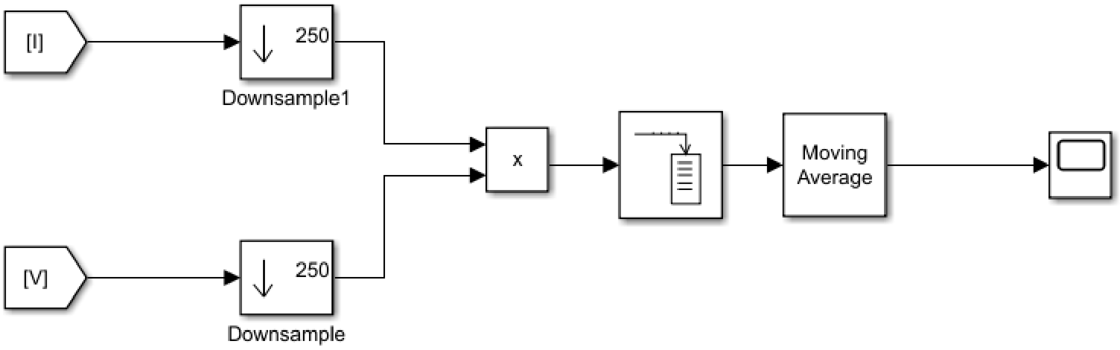


Figure 26 Smart Meter Power computation

**Visualization**

In visualization of the outcomes, a Scope block is utilized. This displays a power-time graph with which to visually examine the consumption of the load.

## 3.3. Results

This section presents the results obtained from the simulation process described in the methodology. The primary objective is to validate the performance and accuracy of the constructed smart meter through Simulink by comparing it with optimal theoretical readings from the same simulated system as a reference point.

The procedure for the comparison will be the following: First, we show the simulink power algorithm theoretical results to show the ideal reference. Second, we show the output obtained from the implemented smart meter. The table below shows the distribution of the different equipment's usage over time.

Finally, the section shall conclude with a detailed comparative analysis of both data sets, where the difference between the results will be assessed and determined if they are accordingly with the manufacture and normative compliance.

Table 2. Household appliance Timetable

| Appliance | Start Time | End Time |
|---|---|---|
| Induction Stove | 07:00 | 07:15 |

| | | |
|---|---|---|
| Washing Machine | 08:00 | 10:00 |
| Pc Charger | 08:00 | 10:00 |
| Electric Oven | 12:00 | 13:00 |
| Induction Stove | 12:00 | 13:00 |
| Pc Charger | 14:00 | 16:00 |
| Induction Stove | 18:00 | 19:00 |
| Pc Charger | 18:00 | 20:00 |
| Dishwasher | 19:00 | 21:00 |
| TV | 19:00 | 22:00 |

### 3.3.1. Theoretical results

The following data are the theoretical reference values, obtained from the ideal meters in Simulink. These numbers represent a perfect measurement, and we will use them as a benchmark to evaluate the performance of our meter.

The figure displays the load profile of all devices connected to the power source. Over the 24-hour simulation (equivalent to 24 seconds of simulation time), power peaks are observable. These peaks are attributed to the varying times at which different equipment is used throughout the day.

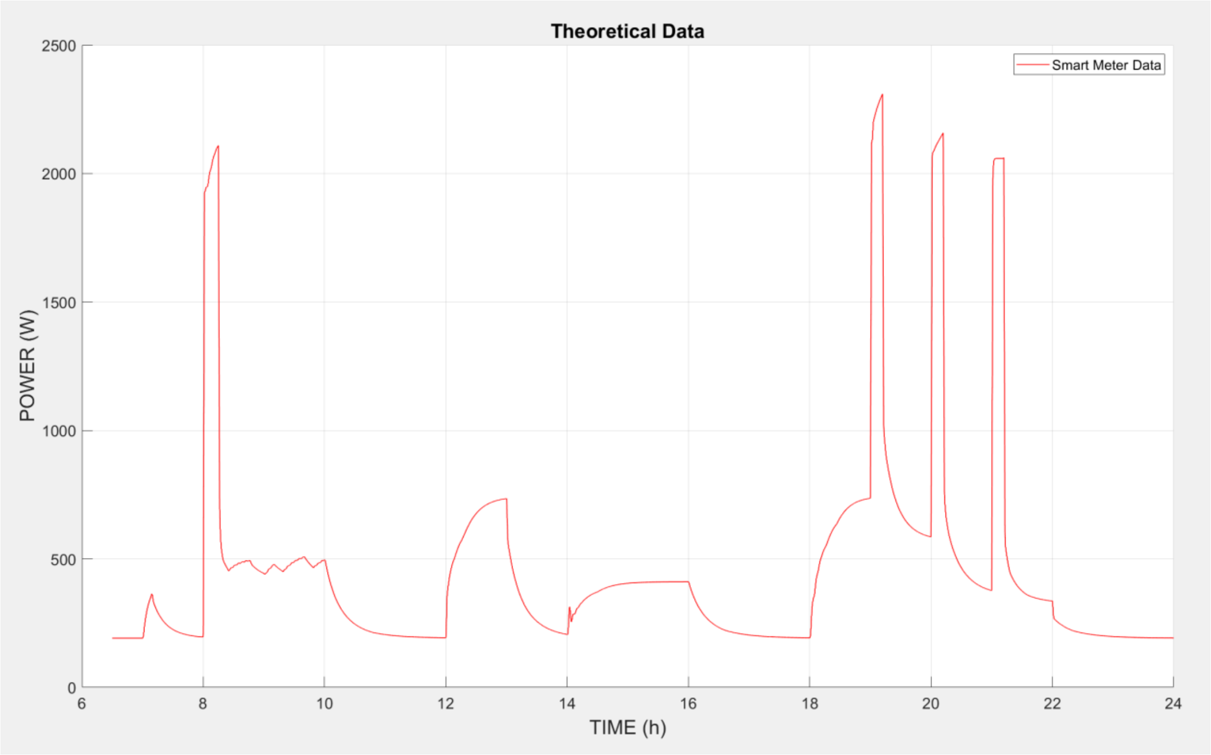


Figure 27 Load Profile Simulation full day Theoretical Data

The following three figures (25, 26 and 27) will display the same load profiles, but broken down into different time slots. This approach aims to improve visualization and make it easier to distinguish between the various loads during specific periods.

Figure 25 In the interval between 7:00 and 10:00 AM Table 2 identifies that in those hours the appliances are working: induction stove, washing machine, and PC.

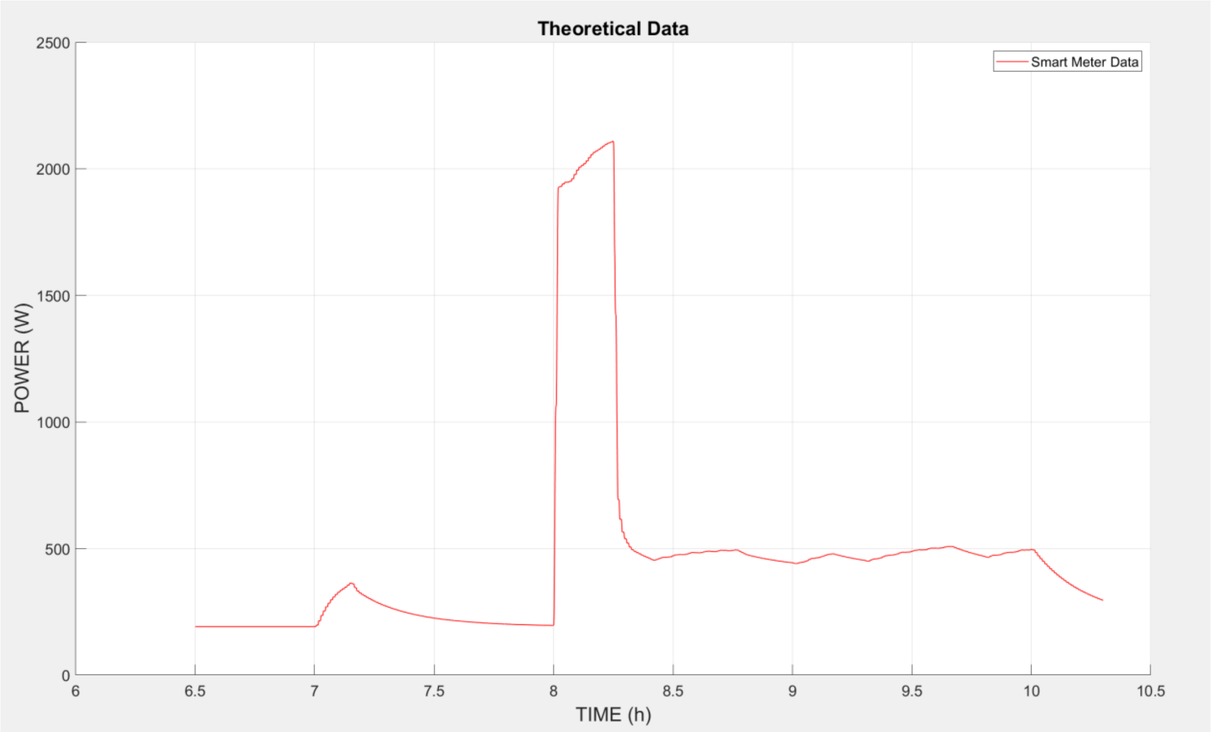


Figure 28 Load Profile Simulation 7:00 - 10:00

For the induction stove it can be seen how its power consumption takes place from 7:00 up to 7:15. Then, at 8:00 the beginning of the washing machine cycle is recorded. At that point in time, there is a consumption peak because of the heating element warming up the water. As soon as the water is warmed up, this peak drops, and one can discern the power profile relating to the motor and water pump.

Even though the PC is also running simultaneously, its related consumption cannot be identified clearly since it is too small compared with that of the washing machine.

For figure 26 (Load Profile Simulation 10:00 - 16:00)

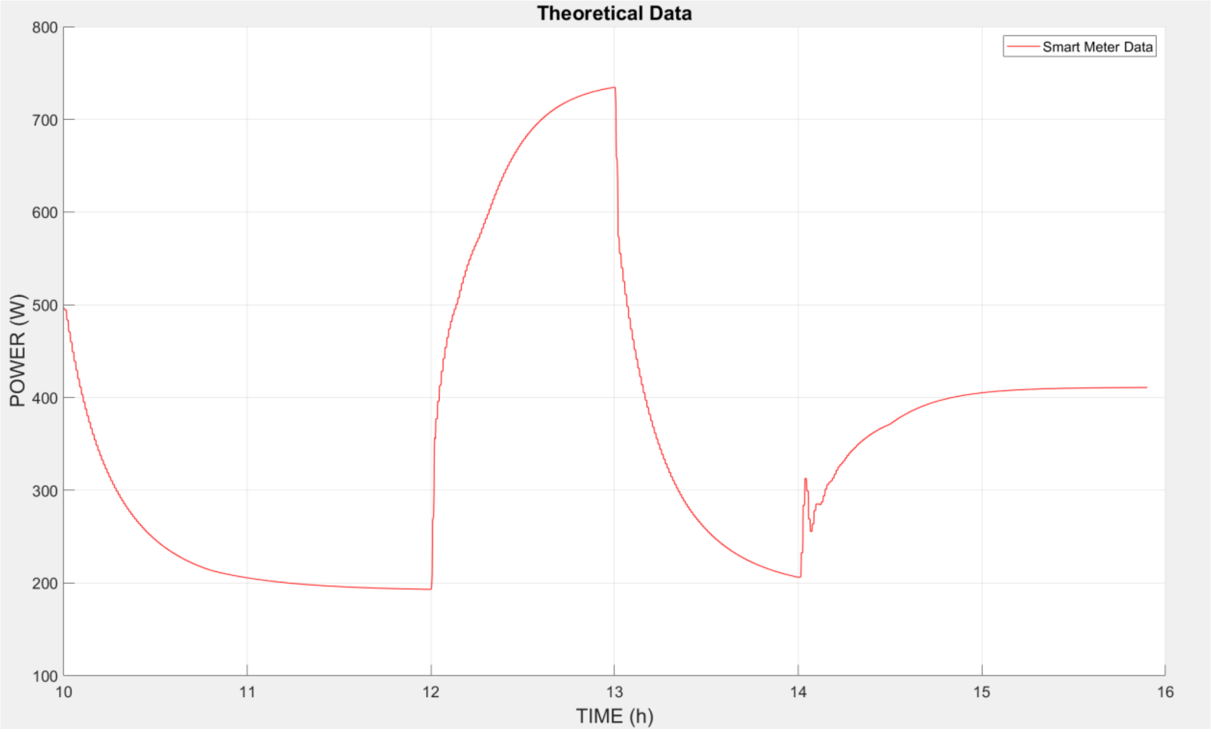


Figure 29 Load Profile Simulation 10:00 - 16:00

For figure 27 (Load Profile Simulation 18:00 - 23:00) following the table xx identifies that in those hours the appliances are working: induction stove, dishwasher, and PC.

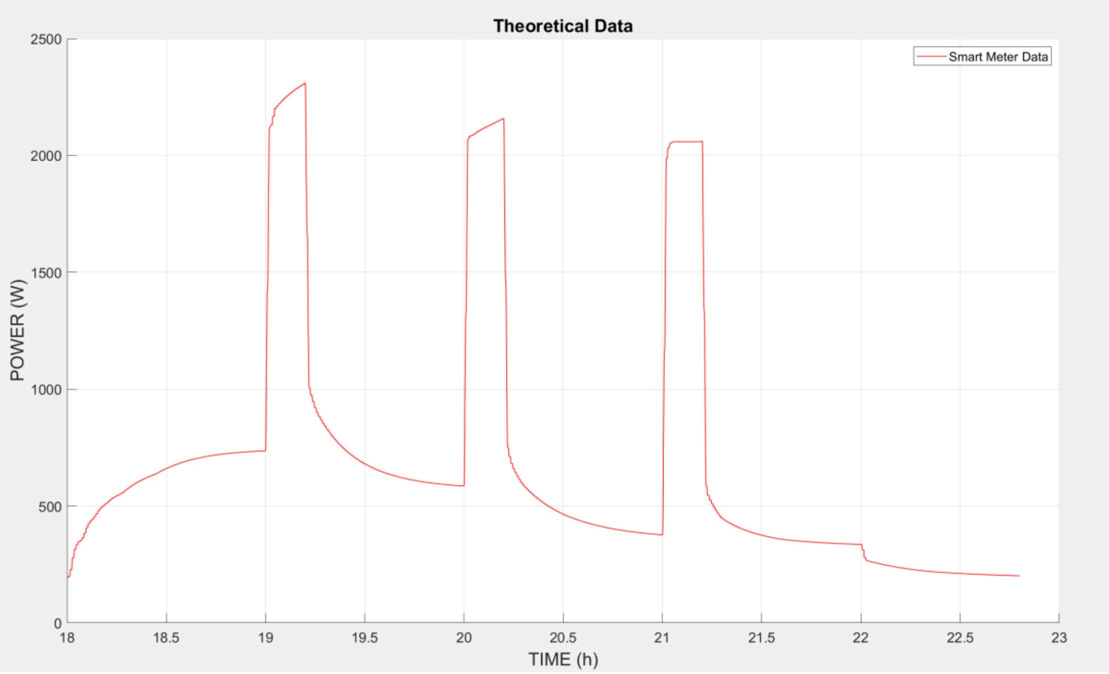


Figure 30 Load Profile Simulation 18:00 - 23:00

For the induction stove it can be seen how its power consumption takes place from 18:00 up to 19:00 and at the same time the PC charger starts consuming. The dishwasher starts its cycle at 19:00, and you can observe three distinct water heating cycles, which correspond to the peaks in energy consumption.

### 3.3.2. Smart Meter Results

The data obtained from the smart meter simulated in Simulink has some disadvantages compared to the theoretical data, which are as follows:

- Sampling Frequency: The smart meter captures the voltage and current waveforms at a discrete sampling frequency of 2 kHz. This contrasts with the continuous nature of ideal theoretical waveforms and sets a practical limit on the bandwidth of the measurement.
- Data Averaging: The raw data acquired by the meter is processed and averaged over a 15-minute interval. The resulting value is then logged as a single data point for that period.

These two differences can be sources of error in the measurement. The figure below shows the results obtained:

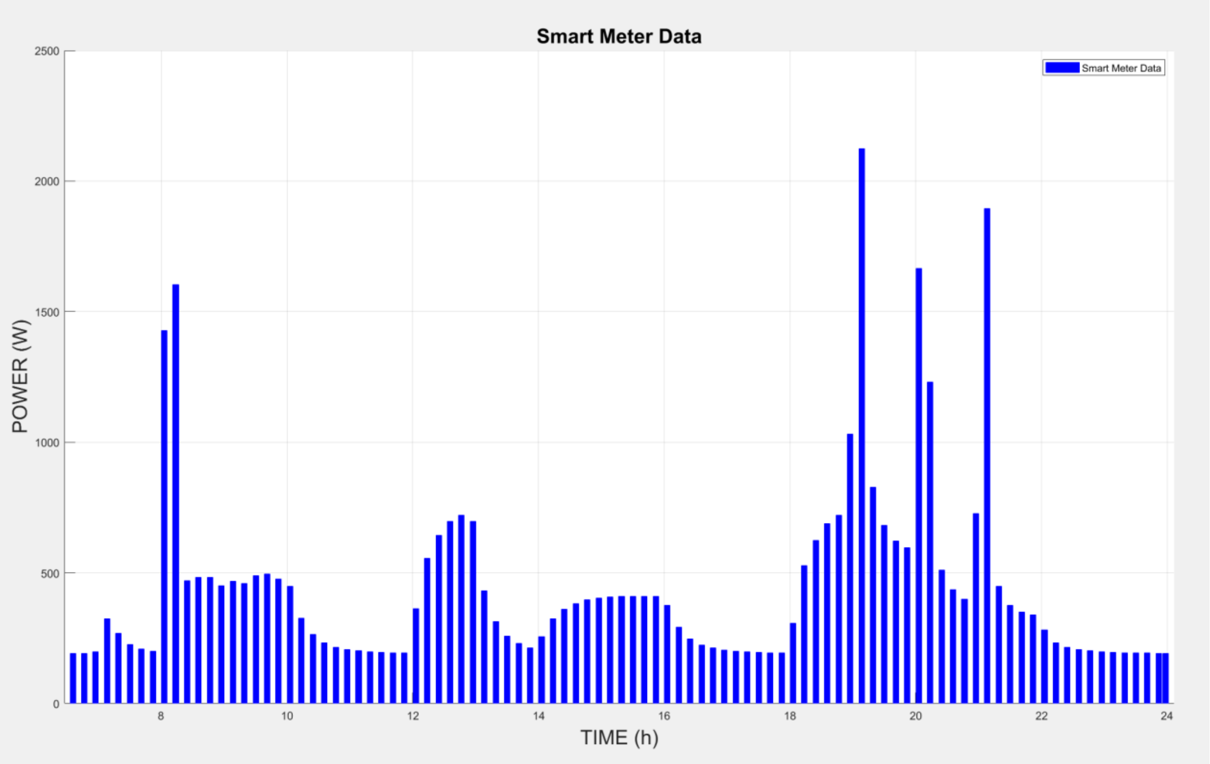


Figure 31. Load Profile Simulation full day Smart Meter Data.

## 3.4. Results Analysis

This section gives a detailed account of the outcome obtained from the smart meters developed in the Simulink and MATLAB. These readings, representing the 'real-world' or simulated energy consumption pattern under the given conditions, will be compared meticulously with theoretical values of energy consumption, which are determined analytically also in MATLAB. The primary goal of the comparison is to determine the error in the smart meter model through determining and measuring deviations. To achieve this, we will attempt to compute the percentage error in the total energy approximated by both methods, which would allow for the reliability of the suggested system to be determined and potential deviations from simulated versus expected behavior to be identified. In the figure below is the graph that shows the plot of both the theoretical values and the Smart meter values, where the differences in errors can be seen.

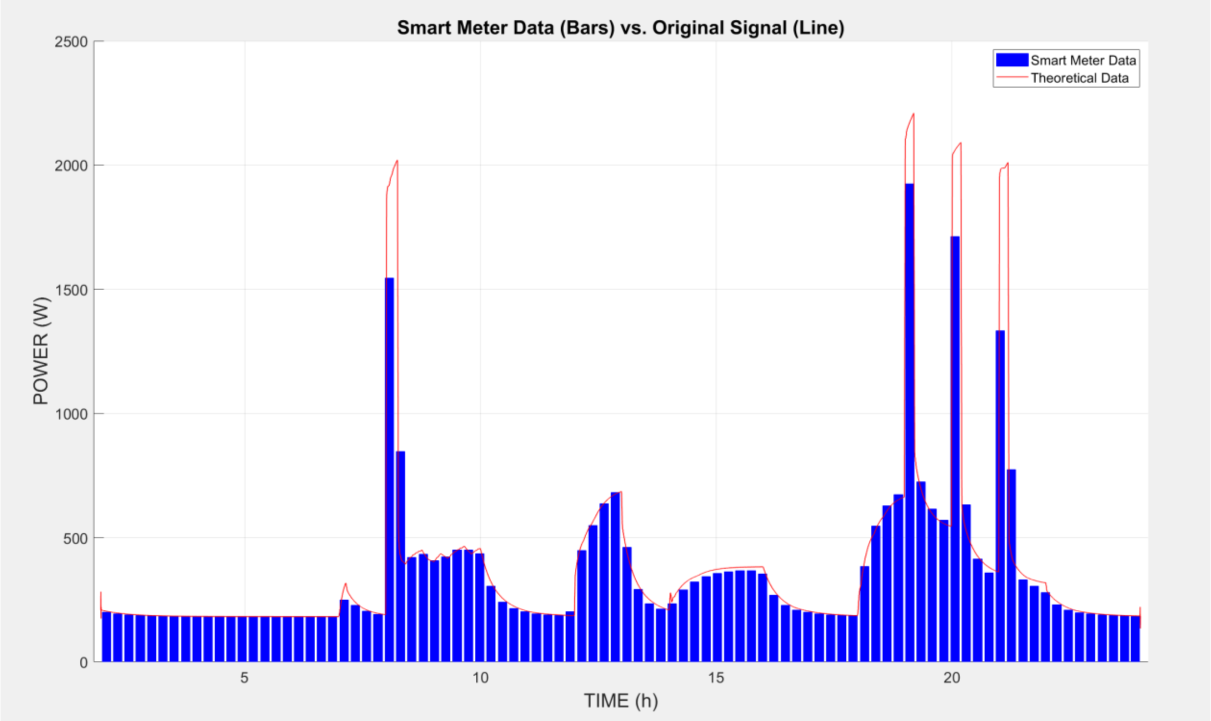


Figure 32. Smart Meter Data vs. Original Signal

The figure displays a comparative graph titled "Smart Meter Data (Bars) vs. Original Signal (Line)," representing POWER (W) consumption over TIME (h) during a 24-hour period. The Smart Meter Data is graphed in the form of discrete blue bars, while the original signal or theoretical measurements are graphed in the form of a continuous red line.

There is a general trend in which the Smart Meter (blue bars) generally follows the shape of the theoretical signal (red line) during the day, recording consumption patterns. Yet, when looking at the fast and intense power peaks (around 8, 12.5, 19, 20.5, and 21.5 hours), a significant limitation is apparent: the Smart Meter has difficulty keeping up with the complete speed and scale of these sudden rises.

Especially in these moments of sudden consumption peak, the blue bars of the Smart Meter don't reach the peak level of the theoretical red line. This indicates that the system lacks a sufficiently high sampling speed or response to follow the complete dynamics of these transient peaks. This suggests potential failure of the smart meter to properly record high-power events in short time intervals and thereby underestimating the actual consumption during such rapid changes.

### 3.4.1. Energy computation

In order to determine the total energy that was absorbed by all the loads, both by the Smart Meter and in the theoretical data, the area under the curve method of calculation was employed. This was done within MATLAB using the **trapz()** command, which applies the trapezoidal rule to numerically integrate a dataset and hence return an accurate estimation of energy from power data taken discretely with respect to time. Next, the measured error between the two methods was calculated according to standard EN 50470-1:2006+A1:2018, which states that:

$$\text{percentage error} = \frac{\text{energy registered by the meter} - \text{true energy}}{\text{true energy}} \times 100$$

Equation 2. Percentage error formula [35]

The result of this computation was the following:

Table 3. Energy Consumption Computation

| Energy Consumption (kWh) | |
|---|---|
| Theoretical | 8.24 |
| Smart meter | 8.08 |
| Difference | -0.16 |
| Error (%) | 1.99 |

As shown in Table 3, the measurements obtained from the smart meter were lower than the calculated reference measurements. This can be attributed to the reasons previously explained throughout this study; the distortion generated by harmonics from both the non-linear loads and the harmonics inherent in the electrical grid distorts the waveform that reaches the meter. This causes the meter to have problems when sampling the data, as these higher frequencies cannot be detected by the standard sampling frequencies of these meters (1-2 kHz). This is directly related to the Nyquist theorem, which states that the sampling frequency must be at least twice the frequency to be measured, a condition that may not be met for some harmonics. This distortion can be observed in the current profiles, as seen in the following image.

Figure 33 Current Profile.

Furthermore, it can be seen in Figure 32 that during high consumption peaks, the smart meter is not fast enough to capture the energy consumed in that time interval, causing it to measure less than expected. It should be clarified that the meter features an adaptive precision mechanism. If power increments exceed 200 watts, the device increases its sampling precision to ensure a correct measurement.

However, this introduces a potential source of error in scenarios like the one presented in the example. If a power increase is significant but remains just below the 200-watt threshold, the meter does not trigger the enhanced precision mode. Consequently, the probability of measurement error increases, as the system continues to operate with a lower precision than what would have been necessary to accurately record that substantial change in consumption.

# 4 Conclusion and future developments

This thesis aimed to investigate the impact of non-linear home loads on smart meter reliability, a problem that is becoming increasingly significant with the proliferation of power electronics in residential homes today. To address this problem, a full simulation platform was simulated in MATLAB/Simulink involving the simulation of several of non-linear devices in the details, simulation of their daily load profile and finally, developing a functional model of a smart meter to analyze its performance

The most important finding of this study is that the simulated meter consistently measures less energy than theoretical reference values. Underreporting occurs for two major reasons. First, harmonic distortion caused by non-linear loads contributes high-frequency components to the current waveform. Second, the meter design itself, e.g., its 2 kHz sampling rate, places an absolute constraint on the capacity of the meter to accurately measure these higher harmonics, an absolute requirement of Nyquist's theorem that is not necessarily fulfilled.

In addition, averaging data every 15 minutes, although a standard practice, masks transient peak consumption, contributing to lower recorded energy. It was also shown that the adaptive accuracy mechanism of the meter, designed to increase sampling at large power changes (>200W), could not solve alone this problem if the value does not exceed this threshold, leaving the meter with insufficient accuracy for actual demand. The visual comparison between theoretical and measured data confirmed that, during high consumption peaks, the meter is not able to capture the entire energy consumed.

It is important to note that even though electronics are a significant part of modern household items, the largest loads within a household are typically the water heaters in appliances like washing machines and dishwashers. These loads remain predominantly linear. However, if these high-power loads were also non-linear, they could generate errors even larger than those achieved in this study.

These results show the challenge of accurate energy measurement in modern electrical grids and the critical importance of meter design. Research confirms that, beyond the device itself, its interaction with the network and connected loads is a determining factor in its accuracy.

### Future Developments

This work opens several lines of research for the future. It recommends:

1. Experimental Validation: Compare simulation results with measurements in a controlled laboratory environment, using physical equipment and developed load models. This should be implemented to verify the validity of the Simulink model and can me used to have more precise reference data.

2. Development of Compensation Algorithms: Design and implement software algorithms within the simulated meter that can estimate and compensate for unmeasured energy due to harmonics, thus improving accuracy without changing the hardware.

3. Load Catalog Expansion: Incorporate models of other emerging non-linear devices, such as electric vehicle chargers, to assess their combined impact on the home network.

4. Different areas: this study should be performed in industrial environment where the loads are mainly non-linear for example data centers and see if in those areas we can have the same result as in residential areas.

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# A Appendix A

In this appendix the code is use to process the information derive from the Simulink environment.

## A.1. Smartmeter_VI

```
clc;
clear;
cut_down = 11675002*(2/24);
cut_up = 11675002*(22.80/24);
load('current_har_new.mat')
current = data.data(cut_down:end);
c1=current;

current = current(1:250:end);
load('voltage_har_new.mat')
voltaje = data.data(cut_down:end);
v1=voltaje;

voltaje = voltaje(1:250:end);
power = movmean((voltaje.*current),40);

y1=c1.*v1;
power_real=movmean(y1,10000);
x= data.Time;
x = x(cut_down:end);
x1=x;
x = x(1:250:end);

[dato, tiempo] = dynamic_averaging_filter(power,x);
%% plot
figure(1);
clf;
hold on;
grid on;
bar(tiempo, dato, 'FaceColor', 'b', 'EdgeColor', 'b');
plot(x1, power_real, 'r-', 'LineWidth', 0.8);
ax = gca;
ax.FontSize = 14;
title('Smart Meter Data (Bars) vs. Original Signal (Line)','FontSize', 18);
xlabel('TIME (h)', 'FontSize', 18);
ylabel('POWER (W)', 'FontSize', 18);
legend('Smart Meter Data', 'Theoretical Data');
hold off;
ENERGY_THE=trapz(x1, power_real)
ENERGT_SM=trapz(tiempo,dato)
energy_100 = 100*(ENERGY_THE-ENERGT_SM)/ENERGY_THE
```

```
function [y_averages, x_averages] = dynamic_averaging_filter(y, x)
THRESHOLD_DIFF = 200;
SCAN_LIMIT = 480;
y_averages = [];
x_averages = [];
current_idx = 1;
vector_len = length(y);
while current_idx <= vector_len
    found_large_diff = false;
    scan_end_idx = min(current_idx + SCAN_LIMIT - 1, vector_len);
    break_point_idx = -1;
    scan_idx_for_diff = current_idx;
    while scan_idx_for_diff < scan_end_idx
        dato1_y = y(scan_idx_for_diff);
        dato2_y = y(scan_idx_for_diff + 1);
        if abs(dato2_y - dato1_y) > THRESHOLD_DIFF
            found_large_diff = true;
            break_point_idx = scan_idx_for_diff + 1;
            break;
        end
        scan_idx_for_diff = scan_idx_for_diff + 1;
    end
    if found_large_diff
        if break_point_idx > current_idx
            segment_before_diff_y = y(current_idx : break_point_idx - 1);
            segment_before_diff_x = x(current_idx : break_point_idx - 1);
            promedio_anterior_y = mean(segment_before_diff_y);
            promedio_anterior_x = mean(segment_before_diff_x);
            y_averages = [y_averages, promedio_anterior_y];
            x_averages = [x_averages, promedio_anterior_x];
        end
        current_idx = break_point_idx;
        while current_idx <= (vector_len - 1)
            dato1_y = y(current_idx);
            dato2_y = y(current_idx + 1);
            dato1_x = x(current_idx);
            dato2_x = x(current_idx + 1);
            diff_between_pair_y = abs(dato2_y - dato1_y);
            if diff_between_pair_y < THRESHOLD_DIFF
                break;
            else
                promedio_par_y = mean([dato1_y, dato2_y]);
                promedio_par_x = mean([dato1_x, dato2_x]);
                y_averages = [y_averages, promedio_par_y];
                x_averages = [x_averages, promedio_par_x];
                current_idx = current_idx + 2;
            end
        end
    else
        segment_to_avg_full_chunk_y = y(current_idx : scan_end_idx);
        segment_to_avg_full_chunk_x = x(current_idx : scan_end_idx);
        if ~isempty(segment_to_avg_full_chunk_y)
            promedio_segmento_y = mean(segment_to_avg_full_chunk_y);
            promedio_segmento_x = mean(segment_to_avg_full_chunk_x);
            y_averages = [y_averages, promedio_segmento_y];
            x_averages = [x_averages, promedio_segmento_x];
```

```
        end
        current_idx = scan_end_idx + 1;
    end
end
if current_idx <= vector_len
    promedio_restante_y = mean(y(current_idx:end));
    promedio_restante_x = mean(x(current_idx:end));
    y_averages = [y_averages, promedio_restante_y];
    x_averages = [x_averages, promedio_averages];
end
e
```

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# Acknowledgments

I would like to express my deepest gratitude to my supervisor, Professor Marco Faifer, for his constant guidance, valuable advice, and continuous support throughout the development of this thesis. His expertise, patience, and constructive feedback have been fundamental at every stage of this work.

I also want to sincerely thank my co-advisor, Christian Laurano, for his technical support, availability, and insightful suggestions that greatly contributed to improving the quality of this research.

Their dedication and commitment have been crucial in helping me overcome the various challenges of this process. It has been a privilege to work under their supervision.

Additionally, I would like to thank all the people who have been with me on this long, 7-year journey. I want to thank those who were there from the beginning: my parents, my siblings, and the friends I made over the years, with whom, for life's reasons, our paths have diverged. They may not be with me today, and they may not be here on the day I finally complete my studies, but I want them to know that if for some reason they read this, believe me, I am thinking of each and every one of you. To all those with whom I worked on a project, studied for an exam, or who simply brightened my day, I want you to know that I will always carry you with me.

I would also like to thank all the new friends who welcomed me into my new home on the other side of the world, and who have made this final part of the adventure incredible and better than I could have ever imagined. Although the path has had its ups and downs, sometimes more downs than ups, it has been the path I chose. I will always be infinitely grateful for all the good and bad things that have happened to me, because I know this is the path I chose, and if I could choose it again, I would do it all over.

Finally, I just want to say that I have not included names in this second part of my acknowledgments because with names alone, I would run out of pages. However, I am convinced that anyone to whom these words are dedicated will know who they are.

¡Gracias totales!