Water-Energy-Food Nexus in Industrial Kitchens: Energy Efficiency and Management

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Abstract

The present thesis is being developed in the scope of the nexIK (Exploring the Human-Water-Energy Nexus in Industrial Kitchens project) research project. An overview of energy consumption in the food business sectors is provided, showing that IK (Industrial Kitchen) are considered the largest energy users in this sector. A generic framework proposes three main characteristics to classify the IK devices in terms of flexibility: time, power, and comfort. Moreover, this thesis also proposes a data-driven methodology to model the consumption of IK devices. Finally, two energy management methodologies are also developed and evaluated using data collected in three kitchens in real-world operational conditions. The first strategy is based on real-time decisions. The second is based on the forecast's consumption profiles, with decisions set one hour ahead. The second approach presented better results since there is knowledge of the device's consumption beforehand.
Keywords: Industrial Kitchens, Demand Response, Flexibility, Optimization, Energy Management Methodology

1. Introduction

IK are considered spaces with intensive consumption of electricity, gas, and water [13]. Despite their energy-intensive consumption, there is still a need for energy efficiency solutions since this sector has been neglected by the scientific community [4]. Furthermore, restaurants and catering services have the highest potential for energy savings, around 600 kWh per m^2 and year [7], compared with other non-residential building sectors.

The need to assess the impact of IK activity on the consumption of electricity and water leads to the nexIK [1]. This project will propose a new methodology to coordinate the interactions between Water, Energy, and Food in IK. The work in this thesis addresses the following objectives:

- 1: Study and define IK devices according to their flexibility potential;
- 2: Define a methodology for real-time control of appliance demand based on their flexibility potential;
- 3: Expand the real-time methodology to support control considering the possibility of having forecasts of future consumption, more precisely for hour-ahead demand profiles.

[1](https://nexIK.tecnico.ulisboa.pt)

2. State of the Art

Climate change concerns are changing the traditional primary energy sources [14]. One of the main changes is the electrification of end uses, such as heating systems and transports. This new paradigm implies a significant increase in electricity consumption. Therefore, making changes on the consumption side, through the device's flexibility, is fundamental.

2.1. Water-Energy-Food Nexus

The WEF (Water, Energy, and Food nexus) Nexus aims to study and understand the interactions between Water, Energy, and Food resources. Climate change and social changes, such as population and economic growth, are causing increased pressure on these resources, which have complex interactions [2]. The inter-dependencies between Water, Energy, and Food are highlighted in Fig. 1. Some of these interactions are present in IK. For example, water is a vital resource for food and energy production since it is necessary for cooking and electricity generation. Besides that, energy is also required for food processing.

2.2. Electricity Consumption Trends

Population growth has been followed by the continuing demand for new large and small appliances with new features [5]. As a result, electricity con-

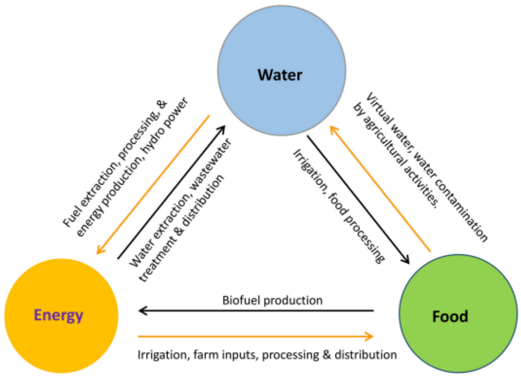

Figure 1: Interactions among the water, energy, and food (WEF) sectors [10].

sumption has been increasing at a high rate yearly in both the residential and service sectors [6]. One of the electrification scenarios developed [8] predicts that 94% of cooking end uses across residential and commercial buildings will be electrified by 2050.

2.3. Overview of Energy Consumption in IKs

A detailed study [4, 12] selected fourteen kitchens in England with typical appliances in general food sector business, such as Kitchens, restaurants, and bars, to analyze their energy consumption. This study concluded that kitchens are the largest energy consumers, corresponding to 63% of the energy consumption by physical area.

A typical IK has a total energy consumption of around 300.00 kWh daily [4]. On the other hand, a domestic kitchen has a total consumption of around 1250 kWh per year, corresponding to 3.42 kWh per day. Therefore, a IK consumes around 88 times more than a typical domestic kitchen, reinforcing the need to study opportunities for demand-side flexibility to improve energy management.

2.4. Intelligent Use of Energy in IK

Restaurants are a big source of waste and resource consumption [4]. Hence, the self-awareness of the urgency of behavior change to make more intelligent use of energy is extremely necessary. Intelligent energy use can be achieved in two ways: 1) more efficient consumption and 2) smarter consumption.

2.4.1 Energy Efficiency

The GreenBuilding Programme is a study that aims to improve energy efficiency in European non-residential buildings [7]. The high energy consumption creates opportunities for energy savings through efficiency measures and RES (Renewable Energy Sources). Restaurants and catering services have the highest potential for energy savings, corresponding to around 600 kWh per m^2 and year, through efficiency measures.

2.4.2 Smarter Consumption through Demand Response (DR) Programs

According to [1], five demand-side strategies lead to better coordination between the grid operators and consumers:

- **Efficiency:** Continuous reduction of power consumption;
- **Load shedding:** Reduction of power consumption during the peak consumption hours;
- **Load shifting:** Change in load schedule to reduce the energy consumption during the peak consumption periods;
- **Modulating:** Adjust power demand due to grid signals;
- **Generation:** Local electricity generation to decrease the energy demand from the grid during peak consumption periods.

The balance between supply and demand has been a huge challenge due to the constant increase in consumption and the increased penetration of volatile distributed RES [15]. An effective approach to attenuate the energy requests to the PG (Power Grid) consists of DR participation [3]. In high-level terms, DR aims to change energy consumption patterns by shifting a portion of electrical demand for a certain period that is more PG "friendly."

2.5. Appliances Flexibility Classification

According to [11], several definitions of flexibility have been proposed in recent years. It is necessary to adapt the definition to each case. Hence, a clear definition of flexibility is essential to properly classify IK appliances [1].

Each author categorizes the different residential loads according to their definitions of energy flexibility. The appliances are generally classified as time-flexible, power-flexible, or non-flexible. Flexibility in time is the capacity of the load to be shifted; flexibility in power corresponds to the potential for load decrease or increase, keeping the user comfortable. Most authors classify the washing and dryer machine, the dishwasher, freezer and refrigerator, and the HVAC (Heating, Ventilating and Air Conditioning) as time-flexible. Regarding lightning, it is common to consider flexibility in power. At last, different classifications for the cooking appliances are verified. Some authors considered them non-flexible, while others accepted the possibility of time flexibility. Some inconsistencies are observed in the literature regarding the classification of flexibility for each appliance. Besides that, a lack of explanations for the given classifications is noticed.

3. Flexibility Modeling of Industrial Kitchens Devices

This section will first begin by presenting a list of the IK devices considered in this work and their classification in terms of flexibility. Besides that, a strategy to transpose the physical models into data-driven models is proposed. Therefore, the device's modulation will be based on data regarding the device's cycles since the nexIK project has no measures of the internal temperature changes.

3.1. IK Devices Flexibility Classification

The nexIK project is the follow-up of a previous project called FIK (Future Industrial Kitchen). In the FIK project, three IK have been monitored in Funchal, Portugal. However, in the scope of this work, only the monitored devices of Kitchen 1 will be considered. Although some of the devices have the same purpose as domestic appliances, they differ in quantity, size, and intensity of use, being, obviously, higher in IK. They were grouped into five main categories according to their function: conserving and preparing food, cleaning efficiently, improving the service, and air conditioning.

The definition considered for the flexibility of IK sector in this work is the following: *flexibility refers to the capacity of electric devices to adjust their energy consumption to support the electric grid and keep the required comfort levels.* In this context, comfort level refers to the comfort required by the users, such as the temperature or lighting, but also to the functioning conditions of the devices, such as the internal temperature variation in the fridges. Based on the flexibility definition, the IK devices were classified as non-flexible, flexible in time, or flexible in power, as is shown in Table 1.

Although there is a need for different working temperature ranges, the cooling devices have similar physical principles of working, which include a compressor that can be turned *on/off* [16], and consequently postponing or preceding their operation during some periods is possible. Therefore, they are classified as time-flexible.

The orders in a IK must be prepared as they arrive. Therefore, shifting some food preparation devices, such as induction plates, convection ovens, and microwaves, will likely result in a loss of comfort during dinner at the restaurant. Nevertheless, it is important to notice that the time intervals of the analysis performed in the present work are very small (1 minute). This way, admitting some flexibility in time in the remaining food preparation devices is not unreasonable. Regarding the exhaust, it is possible to extract the air with more or less power. Hence, the exhaust will be considered a device with power flexibility.

The cleaning device, which corresponds to the dishwasher, has time flexibility since it is possible to change the time of its operation without losing comfort to the user. However, contrary to the cooling devices, from the instant the dishwasher is turned on, it is impossible to turn it off until the end of its operation.

Table 1: Proposal of classification of IK devices in terms of flexibility (NF: Non-Flexible; TF: Time-flexible; PF: Power-flexible).

		NF	**TF**	**PF**
Cooling Devices	Garde Manger		x	
	Refrigerator		x	
	Freezer		x	
	Blast Chiller		x	
	Ice Machine		x	
	Mise en Place		x	
Food Preparation	Induction Plate	x		
	Convection Oven	x		
	Microwave	x		
	Sous-Vide		x	
	Deep Fryer		x	
	Grill		x	
	Hot house		x	
	Hot plate stove		x	
	Salamander		x	
	Exhaust			x
Cleaning	Dishwasher		x	
Service	Infrared shelf		x	
	Heating Lamp		x	
	Stove of dishes		x	
HVAC	Air Conditioning		x	

The function of service devices is to keep the dishes warm until they are served. Once more, these devices need to keep the food to a specific temperature. Despite very narrow optimum temperature ranges, these devices also have some flexibility in time.

Finally, since the operation principle of air conditioning is similar to that of cooling devices, this device is also classified as flexible in time.

3.2. Data-Driven Device Models

Physical models impose the representation of each internal equipment existing inside the devices. In an IK, in most cases, the activation/deactivation of the devices depends on the temperature. Since the nexIK project has no measures of the internal temperature changes, the device's modulation will be based on data regarding the device's cycles provided by data-driven models.

3.2.1 Time Component Modeling

The decision of turning *on/off* the device depends on the temperature since the internal temperature must be within a specific range. Since this work does not have knowledge regarding the temperature changes, it was necessary to transpose the physical models into data-driven models. The author of [16] presents a fridge temperature modulation that is represented in Fig.2.

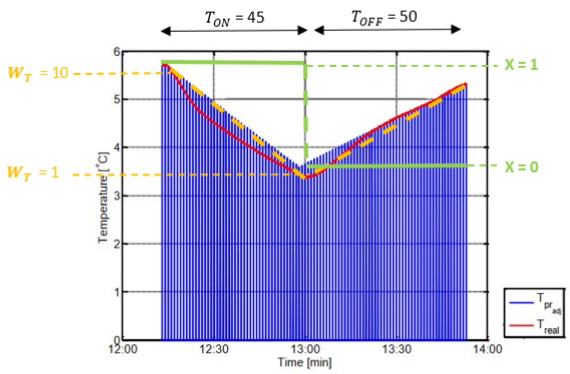

Figure 2: Interaction between the temperature change of a fridge's Physical Model adapted from [16], the device's status and weight factors.

The temperature varies approximately in [3.30;5.80]°C. Therefore, the fridge turns on when the temperature is the maximum and turns off when the temperature is the minimum. Instead of the temperature, the devices will be modulated through a scale of weight factors from 1 to 10, in which the maximum and minimal temperature limits correspond to a factor of 10 and 1, respectively. The variation of these weight factors depends on data regarding the device's cycles provided by data-driven models, namely the T_{ON} and T_{OFF}. T_{ON} corresponds to the time that a device is usually connected, whereas T_{OFF} corresponds to the time that it is disconnected. Therefore, if the device is turned on, the weighing factor will decrease by subtracting the ratio of $\frac{9}{T_{ON}}$ to the previous one, which is heightened in Fig.2 until 13:00. On the other hand, if the device is turned off, the weighing factor will increase by adding the ratio of $\frac{9}{T_{OFF}}$ to the previous one, as demonstrated from 13:00 to 13:50. Since these weight factors are used to modulate devices with time flexibility, they will be referred to as the time component of weight W_T.

3.2.2 Power Component Modeling

The weight factors used to model devices with power flexibility will be referred to as the power component of weight, W_P. The calculation of these weight factors, shown in Eq.1, depends on the maximum power (P_{max}) and the percentage of the minimum power relative to the maximum (Y_{min}).

$$W_P = W_P^{min} + \frac{(W_P^{max} - W_P^{min})(Y_{opt} - Y_{min})}{Y_{max} - Y_{min} + m} \quad (1)$$

The power component of weights must be within the range $[W_P^{min}; W_P^{max}]$, given as an input. These two parameters are not obtained from the data-driven model. They will be assumed, considering the user's actions and behaviors. The constant m avoids indeterminacy in the ratio.

4. Energy Management Methodology

This section will present the applicability of the energy management methods developed, considering only some of the devices mentioned in the previous section to facilitate the demonstration of the results. Two approaches to coordinate the devices will be considered: decisions made in real-time and based on device consumption forecasts.

4.0.1 Device's Priorities

According to the flexibility definition in Section 3.1, comfort levels must be considered during the optimization. Hence, for each event, turning *on/off* or decreasing the power consumption of some devices will have less impact on comfort than others. In other words, the device's priority for each event must be included in the methodology, which will be reflected in weight factors. Since both time and power flexibility are considered, the weight must have a time W_T and power W_P component for each IK device. Hence, the devices with a higher sum of time and power component of weight will have a higher priority. As mentioned before, the weight factors have a scale from 1 to 10. When the device is turned on, the weight factors will decrease. As it gets closer to factor 1, the optimization will try to turn it off, if necessary, due to a decrease in priority. On the other hand, when the device is turned off, the weight factors will increase. Therefore, devices close to reaching the factor 10 are the more suitable to turn on.

The loads' optimal management and flexibility can be used for different purposes, such as limiting the maximum power consumption, reducing energy invoices, coordinating with Renewable Energy Sources (RES) and Battery Energy Storage Systems (BESS), increasing self-consumption, and participation in demand response programs.

4.1. Flexibility Management in Real-Time

The real-time approach, with 1-minute intervals, aims to adapt the power consumption not to exceed the limit power P_{lim} [9], taking into account the comfort levels.

The workflow for the proposed control algorithm starts with the following: the input parameters were used to get the device's state, priority, and power. The system must be optimized if the total power consumption exceeds the P_{lim}. Therefore, the device's state, priority, and power update are needed.

4.1.1 Optimization

Two main objectives must be implemented: maximize comfort and minimize energy consumption. Hence, the optimization will decrease the power consumption of devices with power flexibility and/or cut devices with time flexibility and lower priority. In cases where there is no solution, the solver will relax the problem to continue the optimization. The optimization model will provide three outputs at a specific event t:

- The optimized status of each device, $X^{RT}_{opt_j}$;
- The percentage of power for each device, $Y^{RT}_{opt_j}$;
- The amount of power that exceeds the limit, P^{RT}_{rlx}.

4.1.2 Model Constraints

The optimization model must consider constraints regarding the device's status and power. All constraints presented are applied if the purpose is to maximize comfort. However, if the optimization intends to minimize energy consumption, constraints related to power change are not considered since the power is always the minimum.

Device's Status

Only devices with time flexibility can be turned off by optimization. Therefore, the status of devices with non-flexibility ($Type_j$=0) or devices with power flexibility ($Type_j$=1) can not be changed. Otherwise, devices with time flexibility can keep or turn the input status off, depending on the input status. The optimization will sometimes keep some devices turned off even if the weight exceeds factor 10 to fulfill the limit. To ensure that these devices respect their cycle, they will be assigned a weight of -1, which forces the connection through these constraints.

Device's Power

The sum of each device's power has to be lower or equal to the threshold P_{lim}. Since some devices can be turned off or their power may be reduced, the binary variable $X^{RT}_{opt_j}$ and the percentage of power $Y^{RT}_{opt_j}$ must be included. The optimal power percentage $Y^{RT}_{opt_j}$ has to be between the minimum and maximum power percentage, Y_{min_j} and Y_{max_j}, allowed by each device.

4.1.3 Objective Function

Two different objective functions have been implemented and tested: maximize the comfort levels and minimize the energy consumption. The comfort levels focus on the device's internal temperature variation in this context. Considering a fixed energy cost, minimizing energy consumption is equivalent to minimizing energy costs.

Maximize Comfort

The objective is to maximize the comfort levels, Eq.2, while keeping the total consumption below the P_{lim}. Since the optimization cuts the power consumption of devices with lower priorities, the temperature will tend toward an ideal value. In this case, the ideal temperature considered is the maximum due to the chosen scale of weight factors.

$$Maxf^{RT}_{(comf.)} = \sum_{j=1}^{Dev}[(W^{RT}_{T_j} + W^{RT}_{P_j})X^{RT}_{opt_j}] \qquad (2)$$

$$-kP^{RT}_{rlx}, \qquad \forall j \in [1, Dev]$$

Minimize Energy Consumption

The objective in Eq.3 is to minimize energy consumption, ultimately improving energy efficiency. The results are the same if a fixed energy price is considered. This way, minimizing the energy consumption will be equivalent to minimizing the energy cost.

$$Minf^{RT}_{(cons.)} = [\ \sum_{j=1}^{Dev}(P_{max_j} Y^{RT}_{opt_j} X^{RT}_j)\ ]\ \Delta T \qquad (3)$$

$$+kP^{RT}_{rlx}, \qquad \forall j \in [1, Dev]$$

Variable energy prices should also be considered. In this case, the power consumption should be lower during higher energy prices and higher during lower energy prices to minimize the final energy cost. However, it is impossible to ensure it since the Real-Time approach does not have information about future events. Because of this, the need arose to include the device's consumption forecasts.

4.2. Flexibility Management Based on Device Consumption Forecasts

The objective of the method based on the device's consumption forecasts is to set a schedule for the next hour based on the user's actions and behaviors given by consumption forecasts. Therefore, the optimization has more opportunities to manage the devices to stay within the power limit. In this method, the device's status is provided by the device's consumption forecasts.

4.2.1 Optimization

The optimization will manage the device's consumption according to the objective while the power limit is fulfilled. In cases where there is no solution, the solver will relax the problem for that instant. The optimization outputs are the following:

- The optimized status of each device for each time, $X^{FC}_{t,j}$;
- The priorities of each device for each time, $W^{FC}_{T_{t,j}}$;
- The percentage power of each device for each time, $Y^{FC}_{t,j}$;
- The amount of power that exceeds the limit for each time, $P^{FC}_{rlx_t}$;

4.2.2 Model Constraints

The approach based on the device's consumption forecasts considers constraints regarding the device's status, priorities, and power. Contrary to the Real-Time approach, the device's priorities are updated inside the optimization model. If the optimization purpose is to minimize energy consumption or costs, the constraints involving power variables are not considered since the power is the minimum.

Device's Status
Only devices with time flexibility can be turned *on/off*. Therefore, the model has to guarantee that devices with power flexibility and non-flexibility keep their state given as an input for optimization.

Device's Priorities
The device's priorities are calculated as demonstrated in the Real-Time approach but inside the optimization process.

Device's Power
For each event t, the total consumption can not exceed the power limit. Since the optimization can turn *on/off* or change the power, the variables $X^{FC}_{opt_{t,j}}$ and $Y^{FC}_{opt_{t,j}}$ are included. The optimal percentage of power, $Y^{FC}_{opt_{t,j}}$, can only vary between the limits: $[Y_{min_j}, Y_{max_j}]$.

4.2.3 Objective Function

The optimization based on the device's consumption forecasts has three primary objectives: maximize comfort, minimize energy consumption, and minimize energy costs. Two different ways of interpreting comfort levels are analyzed. The first one consists of setting the temperature to an ideal value established. The second one minimizes the differences between the usual and optimized operation cycles. Fixed and variable energy prices are considered to minimize energy costs.

Maximize Comfort - Set the temperature to an ideal value
The optimization must turn off devices with lower priorities and turn on devices with high priorities to fulfill the operation cycles. Therefore, the optimization will always turn on the device if the power and $W^{FC}_{T_{opt_{t,j}}}$ do not exceed the limit and the factor 10. Hence, being near factor 10 means that the optimization will indirectly set the temperature to the maximum range limit, which is the ideal temperature considering the objective function.

$$Max\ f^{FC}_{(temp.)} = \sum_{t=1}^{T} [\sum_{j=1}^{Dev} (W^{FC}_{T_{opt_{t,j}}} + W^{FC}_{P_{opt_{t,j}}} + kW_{rlx_{t,j}}) + kP^{FC}_{rlx_t}], \quad \forall t \in [1,T], \quad \forall j \in [1, Dev] \tag{4}$$

Maximize Comfort - Minimizing the differences between the usual and optimal cycles
Another way of interpreting comfort levels is as the minimum intrusion on the usual device's operation cycles. Changes will only be caused if the total consumption exceeds the power limit.

$$Min\ f^{FC}_{(differ.)} = \sum_{t=1}^{T} [\sum_{j=1}^{Dev} [[X^{FC}_{opt_{t,j}} - X^{FC}_{t,j}]^{\ 2} + [Y^{FC}_{opt_{t,j}} - Y^{FC}_{t,j}]^{\ 2} + kW_{rlx_{t,j}}] + kP^{FC}_{rlx_t}], \quad \forall t \in [1,T], \quad \forall j \in [1, Dev] \tag{5}$$

Minimize Energy Consumption
Another aim is to minimize energy consumption. Therefore, the power considered will be the minimum.

$$Min\ f^{FC}_{(cons.)} = \sum_{t=1}^{T} [(\sum_{j=1}^{Dev} (P_{max_j} X^{FC}_{opt_{t,j}} Y_{min_j} + kW_{rlx_{t,j}})) \Delta T + kP^{FC}_{rlx_t}], \quad \forall t \in [1,T], \quad \forall j \in [1, Dev] \tag{6}$$

Minimize Energy Costs
The last aim presented consists of minimizing energy costs. The results are precisely the same as the minimum energy consumption purpose if fixed energy prices are considered. Therefore, it will be considered RTP (Real Time Pricing) 15 minutes ahead.

In this case, it was verified a higher consumption during minor energy prices.

$$Min\ f^{FC}_{(cost)} = \sum_{t=1}^{T} [\ (\sum_{j=1}^{Dev}(P_{max_j} X^{FC}_{opt_{t,j}} Y_{min_j} \quad (7)$$

$$+kW_{rlx_{t,j}})\ )\ \Delta T\ c_t + kP^{FC}_{rlx_t}\ ],$$

$$\forall t \in [1, T], \quad \forall j \in [1, Dev]$$

5. Case Study

This chapter presents the results obtained with the methodologies, real-time and forecast consumption approach, with real values. This work will rely on the data collected in the FIK project, which consists of aggregated and individual appliance electricity consumption data collected from the three restaurant kitchens studied. However, only data regarding the Kitchen 1 will be studied. First, the base scenario will be presented. Therefore, for each objective, the optimization results of each methodology will be compared and discussed.

5.1. Base Scenario

This section presents the base scenario, which consists of the typical device cycles taken from data by data-driven models. In other words, it will be the input of the optimization methods. Therefore, it will work as a comparison model to discuss the results obtained from the Real-Time and based on forecasts consumption approaches. Since there was no data regarding devices with power flexibility for Kitchen 1, it will just be considered devices with time flexibility and one device with non-flexibility. The devices considered are the following: convection oven (CO), dishwasher (DW), glass washer (GW), infrared shelf (IS), salamander (S), dual fryer (DF), ice machine (IM), garde manger (GM), blast chiller (BC), and drinks refrigerator (DRF). The time interval from 13:00 to 14:00 on 14 February, which requires more devices connected since the orders must be prepared, is analyzed. The power limit considered is 12kW. Considering all the devices, the Stacked Power for this time interval is represented in Fig.5. There is a period from 13:30 to 13:45 where the total consumption exceeds the limit.

5.2. Results and Discussion

This section presents the optimization results, considering the base scenario of the previous section. The optimization results of each method will be discussed and compared. Therefore, the purposes analyzed are maximizing comfort, minimizing energy consumption, and minimizing energy costs.

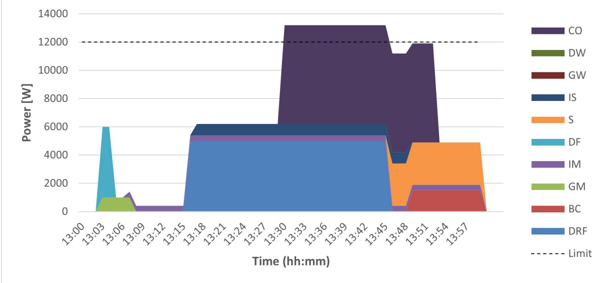

Figure 3: Reference Stacked Power.

5.2.1 Maximize Comfort

Two different approaches are considered to maximize comfort. The first one consists of setting the temperature to an ideal value established. The second one aims to minimize the differences between the usual and optimized operation cycles.

Set the temperature to an ideal value

In this case, both methods maximize the device's priorities, which means maximizing the weight factors. In other words, the optimization sets the temperature to the maximum limit since it is considered the ideal temperature due to the scale chosen for the weight factors variation. The Device's Stacked Power for Real-Time and Based on the forecast consumption approach are represented in Fig.6 and Fig.7.

Comparing the Fig.6 with the base scenario, a cut of consumption during the peak consumption is observed. Since the optimization is only requested when the total consumption exceeds the power limit, from 13:00 to 13:30, the total power consumption remains the same as the reference. However, there are some moments when the optimization can not limit the power consumption, namely in 13:45, 13:48, and 13:52. At that moment, the convection oven is turned on, and since it is a non-flexible device, the optimization can not turn it off or decrease the power. The remaining connected devices are in the extreme of the priorities range, which means they already have a weight factor equal to or higher than factor 10. Therefore, they can not be disconnected.

Besides turning off devices, the approach based on consumption forecasts can also turn them on since there is knowledge about future consumption. Therefore, the periods with peak consumption will be known with antecedents, and consequently, it is avoided to turn on devices during those intervals.

Minimize differences between the usual device's cycles with the optimal ones

Another form of interpreting the device's comfort is to follow the operation cycles as much as possible to

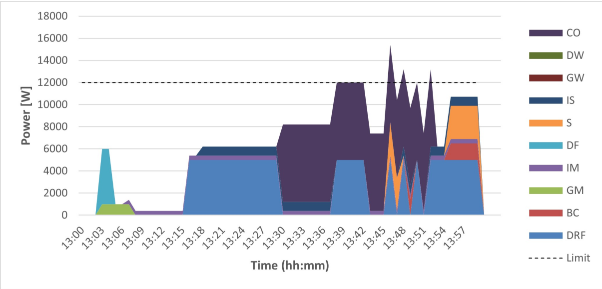

Figure 4: Device's Stacked Power, considering maximizing the comfort (setting the temperature to an ideal value) for Real-Time approach.

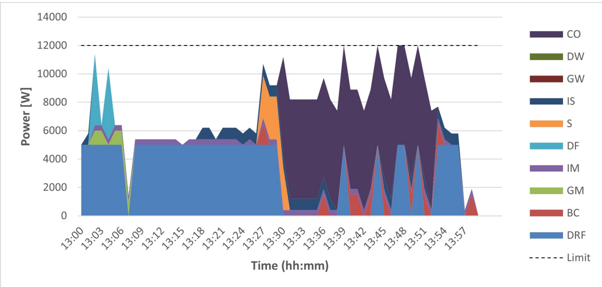

Figure 5: Device's Stacked Power, considering the purpose of maximizing the comfort (setting the temperature to an ideal value) for Based in forecasts consumption in hour-ahead approach.

avoid changing the usual behavior, as represented in Fig.8. Therefore, the optimization will test the minimization of the difference between the usual device status, X, and the optimized one X_{opt}. In this case, the total consumption also fulfills the power limit.

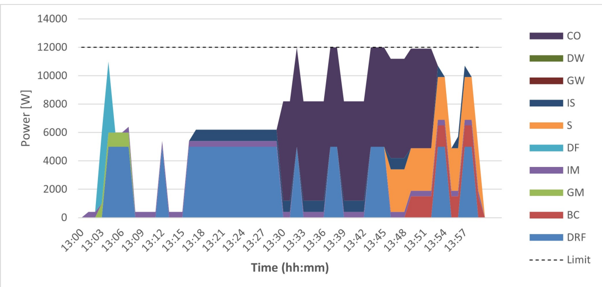

Figure 6: Device's Stacked Power, considering maximizing the comfort (minimize differences between the usual device's cycles with the optimal ones) for Based in forecasts consumption in hour-ahead approach.

5.2.2 Minimize Energy Consumption

To minimize energy consumption, the device's stacked power for real-time and forecast consumption is represented in Fig.9 and Fig.10, respectively. For the first approach, until the instant when the total consumption exceeds the limit, the evolution of power is the same as in the base scenario. However, while in the maximize comfort purpose, the optimization turned off devices with lower priorities (weights close to factor 1), in this case, the optimization disconnects the lower power devices. For both purposes, setting the power below the limit was impossible.

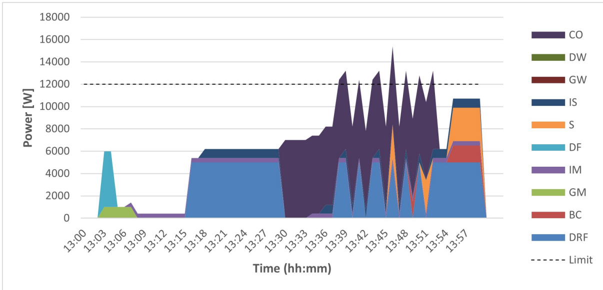

Figure 7: Device's Stacked Power, considering minimizing the energy consumption for Real-Time approach.

Regarding the forecast consumption method, the optimization solved the problem so that the total consumption of that hour was as low as possible. To avoid exceeding the power limit, the optimization once again preceded some devices' operation cycles.

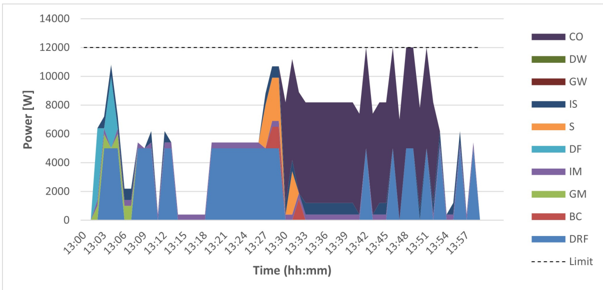

Figure 8: Device's Stacked Power, considering minimizing the energy consumption based on forecasts consumption in the hour-ahead approach.

5.2.3 Minimize Energy Cost

The last purpose analyzed consists of minimizing the energy cost. When energy prices are fixed, minimizing the energy cost will have the same results as minimizing the energy consumption. Hence, RTP will be considered to study the influence of energy prices in the forecast consumption approach. The Real-Time would minimize the energy price for each instant. However, the total cost for the whole interval is not guaranteed to be the lowest one. The energy prices considered were taken from Mercado Spot OMIE [2] for 31 October 2023. That day, the maximum energy price was 0,13€/kWh, and the minimum was 0,06€/kWh. Therefore, it will be considered an energy price of 0,06€/kWh during the first 30 minutes and an energy price of 0,13€/kWh for the last ones. The stacked power is represented in Fig.11.

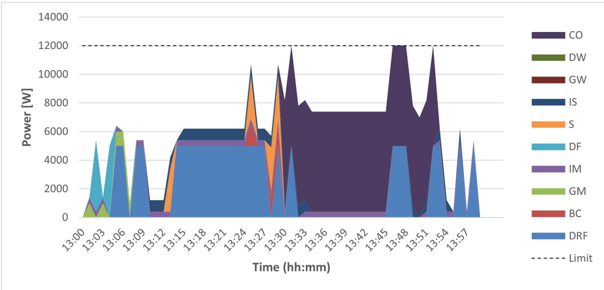

Figure 9: Device's Stacked Power, considering minimizing the energy cost based on forecasts consumption in the hour-ahead approach.

Comparing the results with the base scenario, a higher consumption during the first 30 minutes is noticed. For example, the salamander in the base scenario only consumes energy in the last 30 minutes, while in Fig.11, the consumption occurs in the first half hour.

5.2.4 Results Overview

After discussing the results, the total consumption and cost will be compared between all the time-real and forecast consumption approaches' aims. Table 2 presents the total consumption and cost for the base scenario, considering a fixed energy price of 0,13€/kWh and RTP. In this second case, an energy price of 0,06€/kWh during the first 30 minutes and an energy price of 0,13€/kWh for the last ones will be considered.

Table 2: Total Consumption and Cost for the Base Scenario, considering fixed prices (FP) and RTP.

	FP	**RTP**
Total Consumption [kWh]	7.19	7.19
Total Cost [€]	0.93	0.81

The energy prices are not considered when aiming to maximize comfort or minimize energy consumption. Therefore, the results are the same if fixed prices or RTP prices are considered. Regarding maximizing comfort in the real-time approach, the total consumption is lower than the reference. Since this method can only turn off devices, a decrease in consumption was expected. The forecast consumption method, considering the purpose of setting the temperature to an ideal value, has the highest energy consumption since it will constantly turn on the devices. When the comfort is intended to keep the operation cycles as long as possible, it was expected to have the most similar consumption compared to the reference. The total energy consumption, in both cases, is lower than the consumption of the base scenario. The total consumption of the forecasts consumption approach is lower than the real-time approach. Since the forecast consumption knows the device's behavior in the future, it can better coordinate devices so that the consumption is as low as possible.

When the aim is to minimize energy costs, the total cost differs according to the dynamic price chosen. Therefore, the total consumption and cost for the real-time approach are presented in Table 3, whereas the consumption forecasts approach is in Table 4. When fixed prices are considered, the results are the same to minimize energy consumption.

The total consumption for the real-time approach considering RTP prices is the same as with fixed prices. In fact, for each instant that optimization is needed, the cost is minimized, and since the first half hour has lower prices, the total cost is also lower.

Table 3: Total Consumption and Cost for the real-time approach to minimize energy costs with fixed prices (FP) and RTP.

	FP	**RTP**
Total Consumption [kWh]	6.65	6.65
Total Cost [€]	0.86	0.74

Regarding the forecast consumption approach, the total consumption for RTP is the same as the reference. However, since there is knowledge of the energy prices beforehand, there is higher consumption during lower prices and lower consumption during higher prices, resulting in a lower total energy cost.

Table 4: Total Consumption and Cost for forecasts consumption approach to minimize energy costs with fixed prices (FP) and RTP.

	FP	**RTP**
Total Consumption [kWh]	6.13	7.19
Total Cost [€]	0.80	0.62

6. Conclusion

Two energy management methodologies have been developed and evaluated using data collected in three kitchens in real-world operational conditions.

[2](https://www.omie.es/en/spot-hoy)

The first strategy is based on real-time decisions. The second is based on profile forecasts, and the decision is set one hour ahead based on the forecasts' consumption profiles.

It is not possible to affirm each of the optimization results presented is the best choice to implement. There are better approaches when the aim is concrete. If the user intends to set the temperature of IK devices to his "ideal" or keep the usual devices's cycles as much as possible, the optimization results considering this purpose is the optimal choice. If the user intends to decrease the energy invoice, minimizing the total energy cost purpose analyzed should be implemented.

Overall, the energy management methods developed achieve better results according to the purpose analyzed. However, comparing both methodologies, the consumption forecasts present a better solution since there is knowledge of future events.

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References

[1] Energy flexibility of residential buildings: A systematic review of characterization and quantification methods and applications — Elsevier Enhanced Reader.

[2] A review of the current state of research on the water, energy, and food nexus — Elsevier Enhanced Reader.

[3] M. Afzalan and F. Jazizadeh. Residential loads flexibility potential for demand response using energy consumption patterns and user segments. 254:113693.

[4] M. C. Almeida. *Analysis of Energy Consumption in the Food Service Sector*. MSc Thesis, IST, Universidade de Lisboa, Lisboa, Portugal, June 2019.

[5] M. Aouad, H. Hajj, K. Shaban, R. A. Jabr, and W. El-Hajj. A cnn-sequence-to-sequence network with attention for residential short-term load forecasting. *Electric Power Systems Research*, 211:108152, 2022.

[6] L. F. Cabeza, D. Urge-Vorsatz, M. A. McNeil, C. Barreneche, and S. Serrano. Investigating greenhouse challenge from growing trends of electricity consumption through home appliances in buildings. *Renewable and Sustainable Energy Reviews*, 36:188–193, 2014.

[7] D. D'Agostino, B. Cuniberti, and P. Bertoldi. Energy consumption and efficiency technology measures in European non-residential buildings. 153:72–86.

[8] J. Deason and M. Borgeson. Electrification of buildings: potential, challenges, and outlook. *Current Sustainable/Renewable Energy Reports*, 6:131–139, 2019.

[9] F. Fernandes, H. Morais, Z. Vale, and C. Ramos. Dynamic load management in a smart home to participate in demand response events. 82:592–606.

[10] R. G. Lawford. A Design for a Data and Information Service to Address the Knowledge Needs of the Water-Energy-Food (W-E-F) Nexus and Strategies to Facilitate Its Implementation. 7:56.

[11] K. M. Luc, A. Heller, and C. Rode. Energy demand flexibility in buildings and district heating systems – a literature review. 13(2):241–263.

[12] S. Mudie, E. A. Essah, A. Grandison, and R. Felgate. Electricity use in the commercial kitchen. 11(1):66–74.

[13] S. Mudie and M. Vadhati. Low energy catering strategy: Insights from a novel carbon-energy calculator. 123:212–219.

[14] S. Paul, T. Dey, P. Saha, S. Dey, and R. Sen. Review on the development scenario of renewable energy in different country. In *2021 Innovations in Energy Management and Renewable Resources(52042)*, pages 1–2.

[15] M. A. Usova and V. I. Velkin. Possibility to use renewable energy sources for increasing the reliability of the responsible energy consumers on the enterprise. In *2018 17th International Ural Conference on AC Electric Drives (ACED)*, pages 1–4.

[16] A. Zarogiannis. *Integration of Price Based Demand Response Programs in a House Management System*. MSc Thesis, Technical University of Denmark, Lyngby, Denmark, jul 2014.

[3] (https://www.fct.pt/)