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# PLANNING FOR ENERGY RESILIENCE: APPLICATION TO INDIVIDUAL BUILDINGS

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Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título

Planning for energy resilience: application to individual buildings

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# PLANNING FOR ENERGY RESILIENCE: APPLICATION TO INDIVIDUAL BUILDINGS

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## RESUMEN DEL PROYECTO

Muchos han teorizado buscando medir la resiliencia de un sistema eléctrico, pero pocos han intentado construir o planificar con esta componente. El objetivo de este proyecto es planificar el suministro de energía eléctrica a nivel local de un edificio ante eventos extremos, empleando un modelo de consumidor final con una triple componente en coste, resiliencia y descarbonización. Los resultados incluyen la inversión en equipos necesaria para alcanzar diferentes grados de resiliencia, esto es, diferentes tiempos de supervivencia en caso de que un evento extremo ocurra. Los resultados también incluyen cómo esta inversión afecta a la factura energética.

**Palabras clave**: suministro de energía eléctrica, consumidor final, eventos extremos, resiliencia, inversión, factura de energía

### 1. Introducción

Los desastres naturales o las consecuencias de la guerra están evidenciando la baja resiliencia que tienen los sistemas eléctricos. Planificar con resiliencia es esencial para minimizar el impacto de este tipo de eventos con poca probabilidad de suceder, pero que conducen a consecuencias fatales en términos económicos y humanos cuando suceden. El concepto de resiliencia ha surgido como una consideración fundamental a la hora de diseñar y operar infraestructuras de energía críticas. En 2016, Ernest Moniz (Secretario de Energía de los Estados Unidos) afirmó: "Construir las redes eléctricas con una componente resiliente ha adquirido mayor urgencia en los últimos años, como demuestran las pérdidas económicas y personales debidas a los cortes de electricidad causados por el clima severo".

Una característica clave de los sistemas resilientes es su capacidad para degradarse de manera controlada y sobrevivir, manteniendo una funcionalidad limitada pero crítica. Experiencias pasadas han demostrado que los recursos energéticos distribuidos son clave para mantener la supervivencia parcial.

### 2. Definición del proyecto

A la resiliencia energética a nivel local se le ha dado diversos enfoques. El uso de generación local (paneles solares o módulos fotovoltaicos, producción combinada de calor y electricidad) y tecnologías relacionadas con el almacenamiento de energía (baterías) parece ser el enfoque más efectivo. De esto es lo que trata precisamente este proyecto, de aportar resiliencia a los sistemas eléctricos invirtiendo en módulos de baterías (BESS) y, potencialmente, paneles solares.

Este proyecto tiene como objetivo establecer un precio realista para la resiliencia eléctrica de edificios individuales. Aumentar el tiempo de supervivencia de un sistema eléctrico tras un evento extremo, es decir, lograr un mayor grado de resiliencia, implicará valores monetarios más elevados.

El proyecto evaluará la resiliencia de un hogar individual. Se han empleado datos reales de consumo eléctrico en hogares. Estos datos provienen de hogares ubicados en el condado de Essex, Massachusetts, Estados Unidos. Este hecho es relevante porque el consumo de electricidad, la radiación solar, la temperatura, etc., pueden variar según la ubicación.

El plan o esquema de trabajo seguido se indica en la Figura 1:

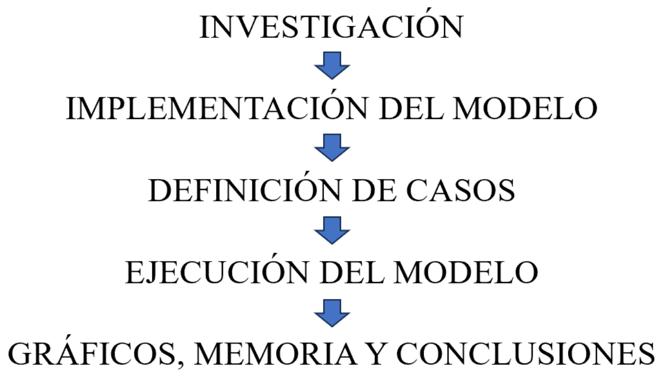


*Figura 1: esquema de trabajo*

## 3. Descripción del modelo

Debido a la mayor complejidad de los sistemas energéticos emergentes, donde los consumidores finales ya no son simples enlaces pasivos, sino participantes activos capaces de satisfacer sus propias necesidades energéticas, se requieren nuevas herramientas de modelado para analizarlos. Un ejemplo de ello es un modelo de optimización lineal mixta entera como el utilizado en el MIT Energy Initiative Utility of the Future Study. Este modelo opera a nivel local y optimiza los costes de inversión y operación de una variedad de recursos energéticos distribuidos (DER, por sus siglas en inglés):

- Calefacción, ventilación y aire acondicionado para calentar y enfriar el habitáculo
- Calentadores de agua responsables del agua caliente sanitaria
- Producción combinada de calor y electricidad a partir de gas natural
- Paneles solares capaces de producir electricidad
- Tecnologías de almacenamiento de energía. Baterías

Los únicos módulos de inversión activos en el modelo son los paneles solares y las baterías. El modelo solo invertirá en un elemento de la tecnología específica si resulta económicamente óptimo, o si sirve para cumplir con un nivel de supervivencia.

La optimización de los costes de operación está relacionada con señales económicas, como el precio minorista de la electricidad y el del gas natural. El objetivo final es satisfacer de manera eficiente las necesidades energéticas y térmicas del edificio, minimizando las compras de energía a la red.

El modelo puede optar por precalentar o preenfriar el edificio en función de las señales de precios, como las tarifas de combustible y electricidad. Esto permite pasar por períodos de altos precios de energía al tiempo que se garantiza el confort térmico.

El modelo ha sido desarrollado utilizando un lenguaje de programación llamado Julia. En particular, se ha utilizado un paquete de modelado específico para optimización matemática integrado en Julia llamado JuMP.

## 4. Resultados

Se comparan cuatro casos: dos tipos de tarifa, plana y con discriminación horaria; y dos tipos de instalación, con gas y sin gas para calefacción. En ningún caso el edificio tiene previamente instalado paneles solares o baterías. Además, se define la supervivencia como el número de horas seguidas que unas baterías pueden mantener el suministro de energía sin disminuir el confort, aunque no exista suministro desde la red principal.

En el primer caso de estudio, la instalación del edificio funciona de manera casi exclusiva por electricidad, no existe un consumo significativo de gas natural. El calentador de agua es el único dispositivo que consume una pequeña cantidad de gas natural. Un dispositivo de calefacción, ventilación y aire acondicionado se encarga de calentar y enfriar el edificio. Por tanto, esta instalación contribuye a descarbonizar el acondicionamiento de edificios a base de un mayor consumo eléctrico.

Las inversiones obtenidas con tarifa plana (azul oscuro) y tarifa con discriminación horaria (azul clarito) para distintos niveles de supervivencia se muestran en la Figura 2.

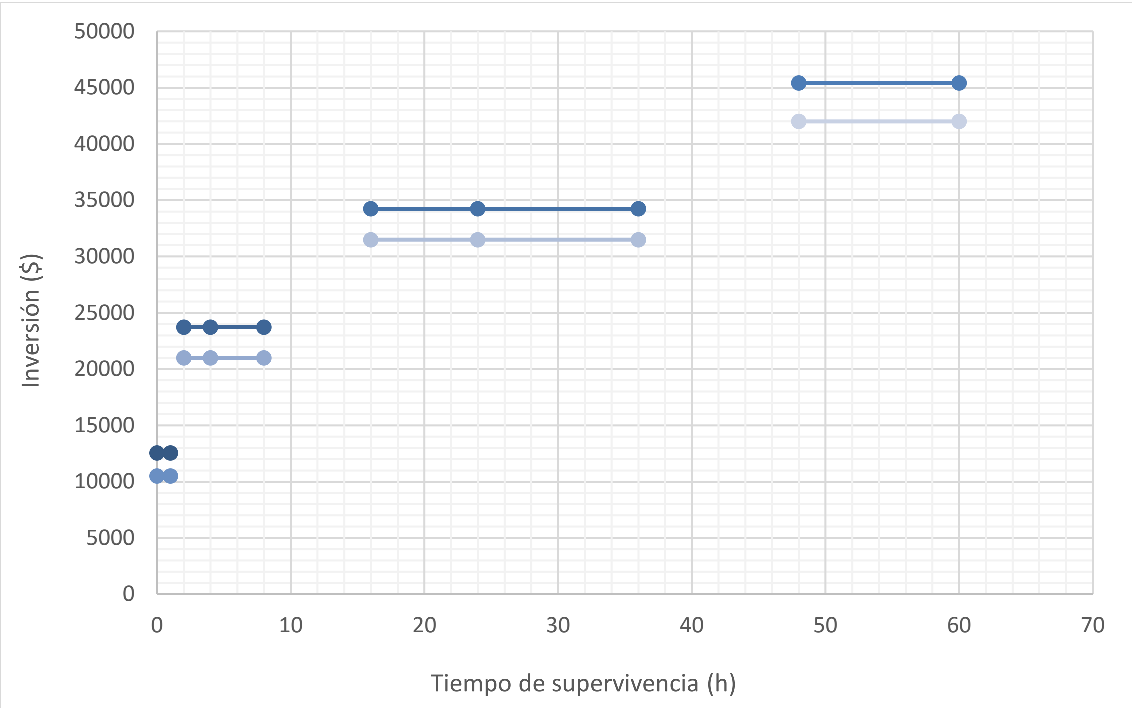


*Figura 2: comparación de inversiones (primer caso de estudio)*

Para la tarifa con discriminación horaria, el modelo solo invierte en baterías, mostrando que este tipo de tarifa puede desincentivar la inversión en paneles solares.

El segundo caso de estudio consiste en una instalación que requiere grandes cantidades de gas natural para satisfacer las exigencias del edificio debido a que la calefacción del edificio se realiza mediante un dispositivo de producción combinada de calor y electricidad. Un dispositivo de aire acondicionado alimentado eléctricamente se encarga de la refrigeración. El coste inicial de la instalación es 2.5 veces superior (18.268 $ vs

6.933 $). Sin embargo, este tipo de instalación es común en muchos hogares, y, por tanto, un coste hundido. En el caso de hogares en construcción, esta inversión inicial sí sería relevante.

La inversión en baterías (el modelo no invierte en paneles solares) con tarifa plana y tarifa con discriminación horaria es idéntica. Se muestra en la Figura 3.

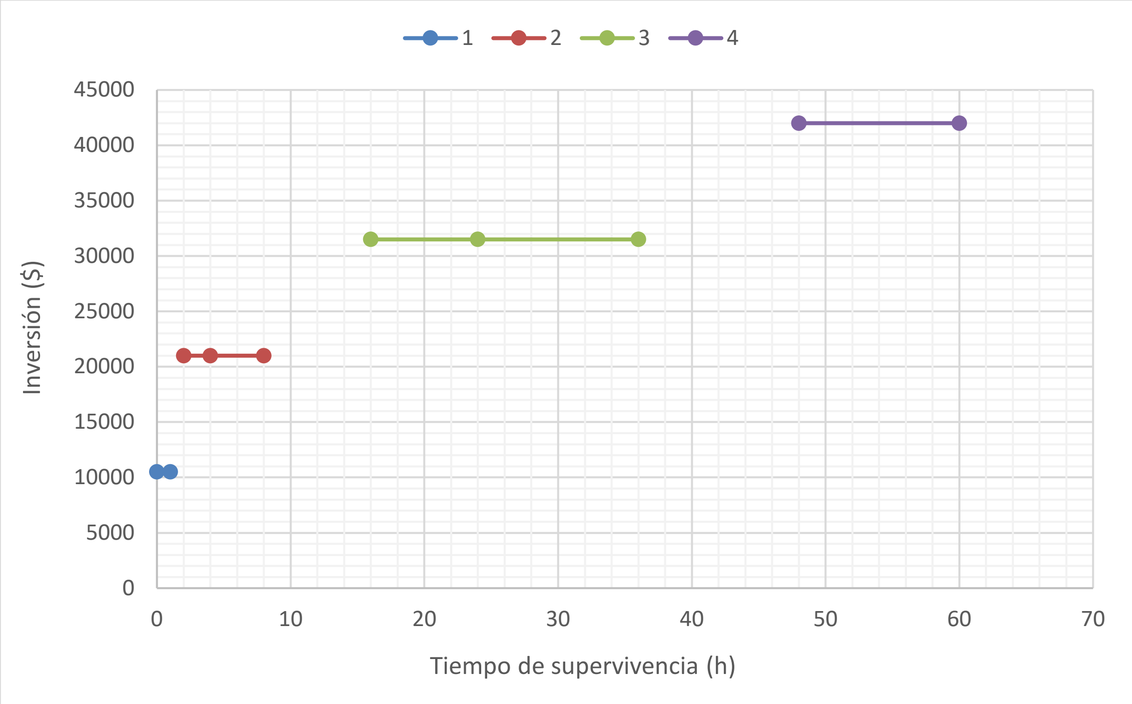


*Figura 3: inversión en módulos de baterías (segundo caso de estudio)*

Los diferentes colores del gráfico (azul, naranja, gris y amarillo) representan el número de módulos de baterías en los que el modelo ha decidido invertir.

## 5. Conclusiones

La resiliencia eléctrica se consigue gracias a la inversión en módulos de baterías. Para el primer caso de estudio y tarifa plana, existe inversión en módulos fotovoltaicos y baterías, siendo la inversión en baterías más significativa pues su coste inicial de capital es 15 veces mayor. La demanda de electricidad es constante y abastecida por la generación eléctrica de los paneles solares y la electricidad que se absorbe de la red. A medida que el tiempo de supervivencia aumenta, la electricidad que se compra de la red se reduce debido a que la instalación cada vez consta de más dispositivos capaces de producir energía (paneles solares) y almacenarla (baterías).

Cuando se trata de una tarifa con discriminación horaria, o bien se trata del segundo caso de estudio, tanto para tarifa plana como con discriminación horaria, el modelo en ningún caso invierte en paneles solares, únicamente lo hace en baterías. El motivo es respectivamente el siguiente; la batería se carga durante las horas valle y se descarga durante las horas pico; el bajo consumo de electricidad de la red debido a que la calefacción del edificio se hace a base de gas natural.

De esta manera, se muestra que la electrificación y descarbonización de los edificios puede colaborar en su resiliencia.

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## ABSTRACT

Many have theorized about resilience metrics when it comes to energy systems, but very few have attempted to plan with a resilience component. The objective of this project is to plan local energy supply of an individual building for extreme events, based on an existing end-consumer model with a triple component of cost, resilience, and decarbonization. Results include the investment needed in equipment to achieve different grades of resilience, this is, different survival times when an extreme event occurs. Results also include how this investment affects annual energy bill.

**Keywords**: local energy supply, extreme events, resilience, investment, energy bill

### 1. Introduction

Natural disasters, or consequences of hybrid or conventional warfare are evidencing the low resilience of energy systems. Planning with resilience is essential for minimizing the impact of these high-impact and low-probability events, which lead to fatal consequences in economic and human terms. The concept of resilience has thus appeared as a crucial consideration when designing and operating critical power infrastructures. In 2016, Ernest Moniz (US Energy Secretary) stated: "Building in grid resilience has gained greater urgency in recent years, as demonstrated by the economic and personal losses from electricity outages due to severe weather."

One key feature of resilient systems is the ability to degrade gracefully, to survive, whereby limited but critical functionality of systems remains. Past experiences have shown distributed energy resources as key to maintain partial survivability.

### 2. Definition of the project

Local energy resilience has had various approaches. Using local generation (PV, CHP) and technologies related to energy storage (BESS) seems to be the most interesting approach. This is what this project is all about: achieving resilience by investing in battery modules (BESS) and, potentially, in PV panels.

This project aims to set an actual price for energy resilience of individual buildings, giving energy resilience at a local level a monetary value (an economic value). Increasing survival time of a local energy system after an extreme event, that is, achieving some higher level of resilience, will involve higher monetary values.

The project will appraise the resilience of a single household. Real household electricity consumption data has been used to fuel the multi-criteria model. Data come from individual households located in Essex County, Massachusetts, U.S. This is relevant because the electricity consumption, solar irradiance, temperature… may vary between locations.

The work plan followed is indicated in Figure 1:

RESEARCH

IMPLEMENTATION OF THE MODEL

CASE DEFINITION

EXECUTION OF THE MODEL

GRAPHICS, REPORT AND CONCLUSIONS

*Figure 2: work plan*

## 3. Model description

Due to the higher complexity of emerging energy systems, where end-consumers are no longer passive links but active participants capable of meeting their on-site energy needs, new modelling tools are required to analyse them. A mixed-integer linear optimization model as used in the MIT Energy Initiative Utility of the Future Study is one example. It operates at building level and optimizes the investment and operation costs of a range of available on-site DERs:

- Heat and Ventilation Air Conditioning (HVAC) systems for supplying cooling and/or heating energy requirements.
- Water Heaters (WH) for providing sanitary hot water.
- Combined Heat and Power (CHP) systems driven by natural gas for supplying heat and electricity.
- Photovoltaic (PV) panels for producing and providing electricity.
- Energy Storage (ES) systems for storing electricity. Batteries.

Unique investment modules that are going to be active in the model are PV and BESS (electricity storage). The model only invests in one element of the specific technology if economically optimal, or if needed to comply with a level of survival time.

Optimizing operation costs has to do with economic signals such as retail price of electricity purchases and retail price of natural gas. The final objective is to efficiently meet on-site energy and thermal (cooling and heating) needs, minimizing energy purchases from the grid.

The model calculates the energy requirements for cooling and heating certain building. This calculation has to do with various factors including outdoor temperature, building characteristics, equipment installed in the building and thermostat set points.

To retain heat, the model characterizes the thermal properties of a building. The model can choose to pre-heat or pre-cool the building based on price signals like fuel and electricity rates. This allows to go through periods of high energy prices while still ensuring thermal comfort.

The model has been developed using a programming language called Julia. In particular, a domain-specific modeling package for mathematical optimization embedded in Julia has been used. It is called JuMP.

## 4. Results

There is a comparison of four cases: two types of tariffs, flat and time of use; and two types of installation, with and without gas for heating. In no case will the building have already had installed PV panels or battery modules for every simulation made. Furthermore, survivability is defined as the number of continuous hours that batteries can maintain the supply without diminishing the comfort, even when there is no supply from the main grid.

The first case study consists of a building which functions almost exclusive by electricity, meaning that no significant amount of natural gas is required. The water heater is the unique device that consumes a very short amount of gas for supplying the building with sanitary hot water. An HVAC unit is responsible for providing the cooling and/or heating desired. Thus, this building´s electrical installation contributes to decarbonize the conditioning of buildings but has a higher electricity consumption.

Investment with flat-rate tariff (dark blue) and time of use tariff (light blue) for different survival times are shown in Figure 2.

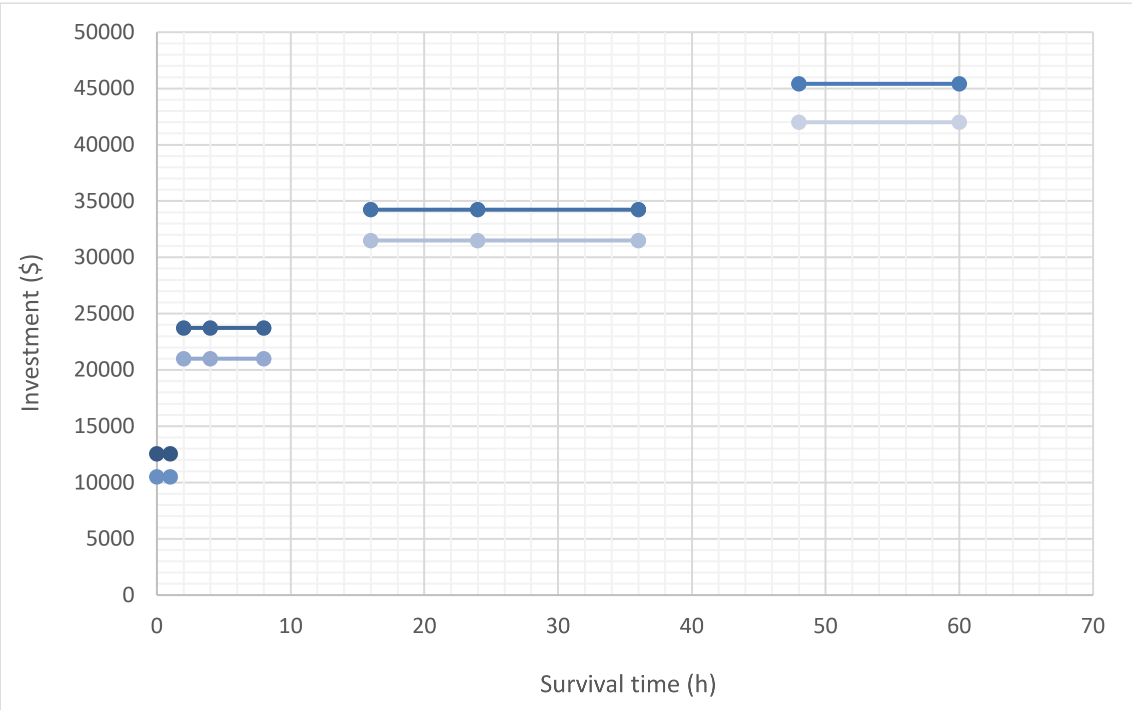


*Figure 2: comparison of investment (first case study)*

In case of time of use tariff, the model only invests in battery modules, revealing that this type of tariff may deter investment in PV capacity.

The second case study consists of a building which requires significant amount of natural gas to meet the demands. Heating of the building will be task of the CHP unit, consuming high volumes of gas. There is also a short consumption of gas by the water heater unit that supplies the building with sanitary hot water. An AC unit is responsible for providing the cooling desired, requiring electricity to function. The initial cost of the installation is approximately 250% more expensive (18.268 $ vs 6.933 $). However, this initial situation is common in many houses and, hence, a sunk cost. So, the initial investment would be relevant for new houses.

Investment in battery modules (the model does not invest in PV modules) with flat-rate and time of use tariff are exactly the same and shown in Figure 3.

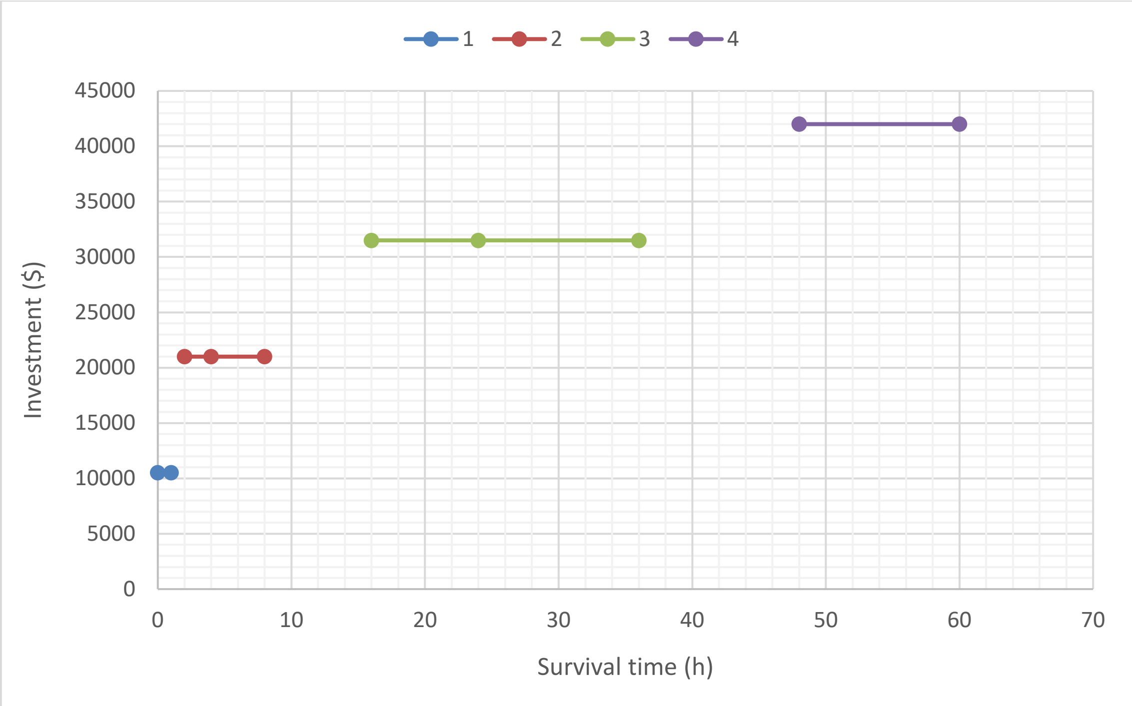


*Figure 3: investment in battery modules (second case study)*

The different colours in the graph (blue, orange, grey and yellow) represent the number of battery modules in which the model has decided to invest in.

## 5. Conclusions

Resilience is achieved by investing in battery modules. For the first case study and flat-rate tariff, there is investment in battery and PV modules, being the first one more significant since its capital costs per module are 15 times greater. Constant power demand supplied by PV power generation and power purchases from the grid. As survival time increases, electricity purchases from the grid are reduced due to the installation having more device/s capable of producing electricity (PV modules) and device/s prepared to store it (battery modules).

For the first case study and time-of-use tariff and both data tariff of second case study, the model does not invest in PV modules for any survival time, only in battery modules for the following reasons; battery charges during off-peak hours and discharges during on-peak hours; the lower consumption of electricity from the grid since heating is supplied by the CHP unit.

In short, it is shown that the electrification and decarbonization of buildings can contribute to improve their resilience level.

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# CHAPTER 1. INTRODUCTION

For many years, critical power infrastructures have been designed and operated under two principles: adequacy and security. The goal of these principles is to ensure that the infrastructure can handle known and credible threats and provide power supply, meeting a certain level of quality, to end users with minimal interruptions. This approach has resulted in a complex infrastructure in which we can rely deeply on. However, recent events have highlighted the need for a broader perspective that goes beyond traditional reliability-oriented principles. Several major catastrophes in the past decade, such as the Fukushima nuclear disaster and Hurricane Sandy, have demonstrated the limitations of the current approach and the importance of building resilient power infrastructures that can adapt and recover from unexpected disruptions. The concept of resilience has thus appeared as a crucial consideration when designing and operating critical power infrastructures.

But what exactly is resilience? In 1973, C.S. Holling was the first to define the concept as "the persistence of systems and their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables."

In Presidential Policy Direction 21 (PPD-21), resilience is defined as the ability to prepare for and adapt to changing conditions and quickly recover from all types of hazards, including natural disasters, industrial accidents, pandemics, cyber incidents, sabotage, acts of terrorism, or destructive criminal activity. This definition highlights the importance of being able to anticipate extraordinary events with high-impact and low-probability of occurring and respond and recover quickly to minimize their impact.

Various organizations within the power engineering communities, including the US Power Systems Engineering Research Center or the UK Energy Research Centre, have made several efforts to define resilience and establish its differences with reliability. Resilience not only includes reliability but also consists on additional elements like resistance, redundancy, response, and recovery, as stated by Cabinet Office. These attributes of resilience make it a more comprehensive and dynamic concept.

Related to dynamism, the term "resilience" in power infrastructures denotes the capability to absorb lessons and adjust its structure and operation to prevent or reduce the impact of high-impact, low-probability events.

It is essential to continually evaluate and enhance existing measures when improving the resilience of a power system. This involves using past experiences to assess the effectiveness of resilience strategies and making updates to planning and decision-making. Looking at past experiences can help identify weaknesses in a power system and thus create strategies to improve the power system's ability to respond to changing conditions during similar events that might happen in the future. This process is ongoing and represented by the resilience enhancement circle shown in Figure 1:

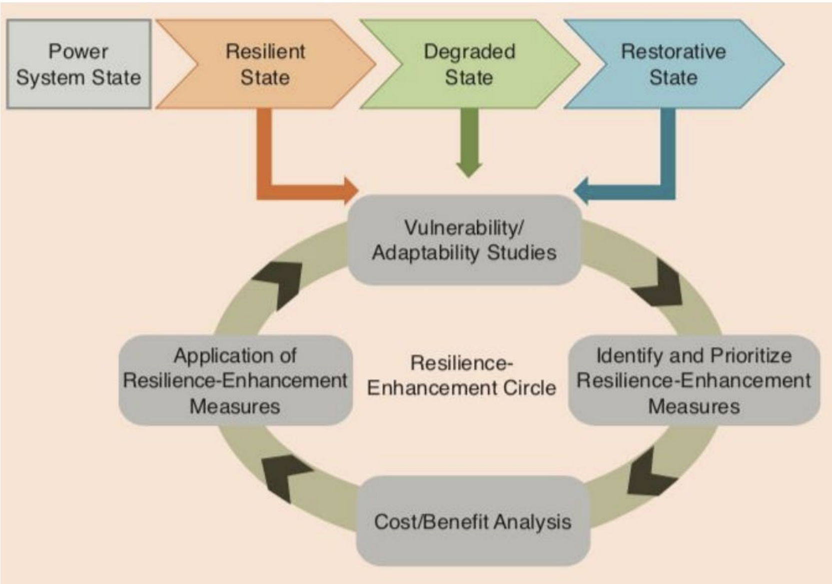


*Figure 1: resilience enhancement circle (Mathaios Panteli and Pierluigi Mancarella, IEEE power & energy magazine, 2015)*

To improve resilience, different measures are identified and ranked based on their importance and contribution to it. These measures can be related to how the system operates (smart operational measures) or how it is strengthened (reinforcement measures). Usually, smart operational measures are more cost-effective than reinforcement measures in enhancing resilience.

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# CHAPTER 2. STATE OF THE ART

The duration and frequency of power outages determines the reliability of a distribution system while the ability not to cut off supply of critical loads when an extreme event occurs determines the resilience.

However, a highly reliable distribution system is not necessarily resilient. How can electrical engineers create a network that is resilient and reliable? One solution is to build a stronger and more robust network with greater redundancy. This approach consists on hardening or reinforcement measures, which involves reinforcing the infrastructure to reduce the system's vulnerability to extreme events. However, this approach can be expensive and may not always be cost-effective.

Investing in smart operational measures could be a more cost-effective solution. Smart operational measures are those which can enhance a power system's observability, controllability, and flexibility, especially during extreme events. They are crucial for developing resilience, as they equip the system with monitoring and control tools to respond quickly and effectively to unfolding disasters. “The goal of operational measures is to make the system bend, rather than break in the face of a disaster.” (Mathaios Panteli and Pierluigi Mancarella, 2015). Some smart operational measures include distributed and renewable energy systems, decentralized control, and microgrids.

Following an extreme event, when evaluating the ability of the system to maintain service to critical loads with the available generation, transmission, and distribution facilities, modeling and simulation tools are needed. During and after an extreme event, the availability of distribution components may be compromised. These tools help evaluate this sort of phenomenon. These tools offer valuable insights for improving the redundancy and connectivity of distribution systems during system planning. During system operation, they can aid in identifying necessary emergency measures to restore critical loads and services.

The future of distribution systems' resilience lay in the enhancement by distribution automation and the enhancement by microgrids and distributed and renewable energy systems (Chen-Ching Liu, 2015).

When a distribution system is highly automated, service can be restored during extreme operating conditions by using remote-controlled devices to reconfigure the system. This creates multiple electrical islands that can serve the load. An example is the automatic grid recovery system demonstrated in Spain as part of GRID4EU, in which the grid is reconfigured to restore the maximum possible portion of the market.

The implementation of microgrids along with distributed renewable energy resources (DRESs) increase the redundancy of energy resources. This redundancy is followed by a higher capacity to supply critical loads. However, integrating DRESs may impact the real-time responsiveness of the system and increase the risk of potential problems. During a disaster, if microgrids are not powered by local renewable sources with adequate energy storage, their resilience may be subject to the functionality of their lifelines.

Numerous smart grid solutions have been developed. The Roppongi Hills Microgrid and Sendai Microgrid are great examples. Both of them functioned as secure islands (microgrids can disconnect from the grid and operate autonomously) during the earthquake and tsunami occurred on 2011 in Japan, proving that localized energy sources with strong lifelines are essential to maintain service under critical scenarios.

Microgrids are also a resource for the grid for the system responding and recovering faster. By coordinating its local generation capability and operational flexibility, the capacity of the grid for local restoration increases, recovering faster.There have been several recent approaches focused on local resilience of electric systems. The National Renewable Energy Laboratory (NREL) has long been assisting communities rebuild and recover their power system before and after disasters. Through this work, NREL has gained firsthand knowledge on communities' investments for resilient, affordable, and fair solutions. "With the right tools and investments, communities anywhere can be better equipped for the next storm." (Connor O'Neil and Moriah Petty, 2022).

A good example is Galena, where spring flooding was usual and so, its population had been planning renewable energy investments for years. Thanks to the Federal Energy Management Agency´s funding and NREL's assistance, Galena identified clean and resilient solutions such as renewable energy projects or measures of energy efficiency.

Develop resilience metrics is nowadays a need for achieving resilience in distribution grids. "Quantitative, risk-based metrics are needed to assess and measure the progress of the ability to plan, operate, and recover from extreme events." (Dan T. Ton and W-T. Paul Wang, 2015). Measuring resilience is a complex task since it is a dynamic and multidimensional concept. While several resilience metrics are available, they are often focused on a single dimension of resilience. The ability of the system to withstand an initial shock is one commonly evaluated dimension.

iGreen is a research initiative in Europe that aims to find the most effective approaches for integrating distributed and renewable energy resources by studying numerous projects. One of the benefits of the iGreen study is the provision of Key Performance Indicators (KPIs), which can be used to objectively compare and assess various proposals, ultimately serving as a metric for resilience.

# CHAPTER 3. PROBLEM AND JUSTIFICATION

Distribution system outages are common and often caused by events like weather, maintenance, or equipment failures. Usually, only a small group of customers are affected, and customers' service is typically restored within minutes. The repair and restoration processes are straightforward.

Nonetheless, there are rare occurrences of extreme events that can lead to fatal consequences. This is the case of Hurricane Sandy in 2012, also known as "Super-storm Sandy," that devastated seven countries. The hurricane led to the loss of at least 286 lives and an estimated $68 billion in damages. The storm affected 24 states in the US, destroyed thousands of homes, and left 8 million people without electricity.

Extreme events not only include natural catastrophes, but also acts of terrorism, disruptive failures, cyber-attacks, or public health crises.

Between 1980 and 2014, the United States experienced 178 climate disasters, each causing damages or costs of at least US$1 billion, with a total cost exceeding US$1 trillion. Severe weather is responsible for around 87% of outages that impact 50,000 or more customers since 2002 in this country. During these catastrophic outages, multiple components are often damaged, making repairs and restoration complex.

But these events are not US exclusive. Japan has also been affected by earthquakes and tsunamis. On March 11, 2011, the Great East Japan Earthquake occurred, leading to a re-evaluation of the public safety, energy supply and resilience of the country. The Fukushima Power Plant was severely affected due to the tsunami breaching the fence and damaging crucial components. This resulted in radiation leaks into the sea and atmosphere, and, consequently, the area was evacuated. Furthermore, the earthquake caused power outages for 4.66 million homes located in the ToPo (Tohoku Electric Power Company) and 4.05 million in the TEPCo (Tokyo Electric Power Company).

These events are just a few examples of how power infrastructure can be highly impacted by low probability, weather-driven events. In light of these events, it is essential to differentiate between blackouts and disasters.

When unplanned contingencies disable a significant portion of a power grid, a power interruption temporary occurs. This is known as a blackout. A reliable and well-designed power system should be able to minimize power outages and ensure quick recovery from any blackout.

A disaster, however, is a fast and severe changing situation that may not have been experienced before, and it often causes a blackout. Considerable parts of the grid can be disabled for a long time, subject to how severe it is. "A power infrastructure that can maintain high levels of performance under any condition should be reliable to the most common blackouts but also resilient to much less frequent disasters." (Mathaios Panteli and Pierluigi Mancarella, 2015).

Research and development (R&D) of distribution grids has traditionally prioritized flexibility, reliability, efficiency and affordability when delivering electricity. Severe climate events have not been a major focus. To address this gap, the US Department of Energy (DOE) has increased its R&D in improving the grid's resilience to events related to extreme weather. In 2016, Ernest Moniz (US Energy Secretary) stated: "Building in grid resilience has gained greater urgency in recent years, as demonstrated by the economic and personal losses from electricity outages due to severe weather."

The aim is to reduce the impact of natural disasters and climate change on our quality of life, national security, and economic activity. Given our significant dependence on electricity for essential services on day-to-day basis, this objective is crucial.

Some successful examples of locally resilient power infrastructures have been previously mentioned (The Roppongi Hills Microgrid, The Sendai Microgrid or Galena). Other examples are The Brooklyn Microgrid, The Vermont Green Line or The South Australian Virtual Power Plant. These approaches to building in resilience should be considered as a role model for other remote, smaller-scale communities. This is what the work presented here will focus on: planning for energy resilience at local level.

# CHAPTER 4. DEFINITION OF THE PROJECT

## 4.1. OBJECTIVES

The increasing worries about susceptibility to energy supply disruptions have led to a significant need or demand for resilient urban energy infrastructure provision. One of the objectives outlined in Japan's Strategic Energy Plan is to strengthen the domestic energy supply networks' resilience.

Local energy resilience has had various approaches. Using local generation along with demand-side response and technologies related to energy storage seems to be the most interesting approach. When extreme events happen, backup systems are necessary to maintain electricity supply. Integrating all these resources would notably increase the security of the energy supply to local communities, avoiding disruptions. A good example is a portable backup device called “Smart pole” which integrates a wind turbine of 1 kW, a PV array of 260 W, and a small battery bank of 400 Ah. The purpose of this device is to ensure uninterrupted electricity supply (100% continuity) at public facilities, with a particular focus on disaster response centers.

Even with a backup system, electricity supply is usually restricted during blackouts or disasters. Since it's unclear how long the outage will last, it's important to prioritize the most critical loads with the limited available electricity. Making backup generation more flexible can help achieve a more secure and cost-effective balance between demand and supply, enhancing the local supply's resilience.

Many have theorized about resilience metrics, but very few have attempted to plan with a resilience component. Resilience is not about something that the system has -a property of the system-, but does -the way the system performs-. (Hollnagel, 2015). The main objective of the work presented here is to develop a multi-criteria model to plan local energy supply for extreme events. Cost, resilience and decarbonization are the criteria taken into account. Our starting point will consist on an existing end-consumer model.

This project aims to set an actual price for energy resilience of individual buildings, giving energy resilience at a local level a monetary value (economic value). When a blackout or disaster occurs, the limited electricity supply must prioritize the most critical loads. One key feature of resilient systems is the ability to degrade gracefully, to survive, whereby limited but critical functionality of systems remains. Increasing survival time of a local energy system after an extreme event, that is, achieving some higher level of resilience, will involve higher monetary values. This will be reflected in the final outcome of the project: some 2d computer graphics displaying the cost of achieving resilience subject to the survival time desired.

The project will appraise the resilience of a single household.

## 4.2. *ALIGNMENT WITH THE SUSTAINABLE DEVELOPMENT GOALS*

The Sustainable Development Goals provide a roadmap for creating a more equitable and sustainable world, tackling pressing issues such as poverty, inequality, climate change, environmental deterioration, and peace and justice on a global scale. In particular, this project aims to fulfil with the following sustainable development goals:

- Goal 7: Affordable and Clean Energy.

Energy plays a pivotal role in addressing a wide range of significant challenges and opportunities and so, ensuring access to clean and affordable energy is really important. This project contributes to this goal since microgrids and distributed renewable energy resources allow high level of renewable generation penetration in electricity supply. Furthermore, one of the criteria of the model is decarbonization. When Galena hired NREL to identify resilient and clean solutions for its local power supply, Galena brought the cost down by 8 cents/kilowatt-hour, making electricity cleaner, more efficient and more affordable.

- Goal 11: Sustainable Cities and communities

For the creation of multiple electrical islands that can serve the load during extreme events, resilient planning of local energy infrastructures is necessary. These electrical islands make cities and communities less susceptible to energy supply disruptions and so, more sustainable since the system has the ability to survive on his own. There are several examples of communities with resilient energy supply around the world. A great example is Freiburg, Germany. This city has become a model for sustainable urban living, with a combination of solar, wind, and hydro power sources, coupled with energy-efficient building design and public transportation systems.

## 4.3. *WORK METHODOLOGY*

Real household electricity consumption data will be used to fuel the multi-criteria model. The collection of these data has been carried out before the implementation phase of the project. These data are essential for the correct planning for energy resilience of the local energy supply facing extreme events. In particular, data come from individual households located in North America. This is relevant because the electricity consumption may vary between countries. For instance, US households will tend to have higher consumption than European homes. The constructed surface area of US households is bigger and so, the consumption derived in heating and air conditioning. The electricity is also cheaper in this country since it is considered a rich country regarding natural resources such as fossil fuels. Consequently, there is not population awareness of electricity consumption.

## *4.4. RESOURCES*

The model has been developed using a programming language called Julia. This is considered a general-purpose, dynamic, high-level and high-performance programming language. Its characteristics are ideal for numerical analysis and computational science. Many, CEO of Shopify included, considered Julia to be the next-generation programming language for Machine Learning and Data Science. In particular, a domain-specific modeling language for mathematical optimization embedded in Julia will be used. It is called JuMP. It is useful for addressing linear, nonlinear, and mixed-integer programming problems. Microsoft Excel has been used for the treatment of the data.

# CHAPTER 5. MODEL DEFINITION

## 5.1. OBJECTIVES AND SPECIFICATION

The traditional structure of energy systems has been based on big power plants connected to consumers through high- to low-voltage lines. Factors like climate change, affordable renewables, and advancements in Information and Communication Technologies (ICT) are driving a new power system setup. In this new setup, end-consumers are no longer passive links but active participants. This shift allows for the establishment of distributed energy resources (DERs), energy communities, integrated energy stations and microgrids. These advancements enable consumers to meet their on-site energy needs.

Due to the higher complexity of these emerging energy systems, new modelling tools are required to analyse them at different timeframes, spatial scales and applications. A mixed-integer linear optimization model as used in the MIT Energy Initiative Utility of the Future Study is one example Perez Arriaga et al. (2016). It operates at building level and optimizes the investment and operation costs of a range of available on-site DERs. With this aim, the model has the capability to sell excess energy generated on-site back to the main grid. However, we are not considering the scenario of selling electricity to the grid by establishing a maximum grid power sellback of 0 kW and a grid power price sellback of 0 $/kWh. Optimizing operation costs has to do with economic signals such as retail price of electricity purchases and retail price of natural gas. The final objective is to efficiently meet on-site energy and thermal (cooling and heating) needs, minimizing energy purchases from the grid.

The available DERs are:

- Heat and Ventilation Air Conditioning (HVAC) systems for supplying cooling and/or heating energy requirements.

- Water Heaters (WH) for providing sanitary hot water and some capacity of storage for later use if desired.

- Combined Heat and Power (CHP) systems driven by natural gas for supplying heat and electricity.

- Photovoltaic (PV) panels for producing and providing electricity.

- Energy Storage (ES) systems for storing electricity. Batteries.

The model calculates the energy requirements for cooling and heating certain building. This calculation has to do with various factors including outdoor temperature, building characteristics, equipment installed in the building and thermostat set points.

In order to retain heat, the model characterizes the thermal properties of a building. The model can choose to pre-heat or pre-cool the building based on price signals like fuel and electricity rates. This allows to go through periods of high energy prices while still ensuring thermal comfort. Concepts like heat capacity (C)—ratio of heat absorbed by a material to the temperature change—, and building thermal resistance (R)—the ability of a material to resist heat flow—, are crucial for the modelling process, along with the specific thermal model selected for the building in question. In this case, a thermal model presented by Martín-Martínez et al. (2016) is going to be adopted. This model represents a residential thermal model, and it is depicted in Figure 2.

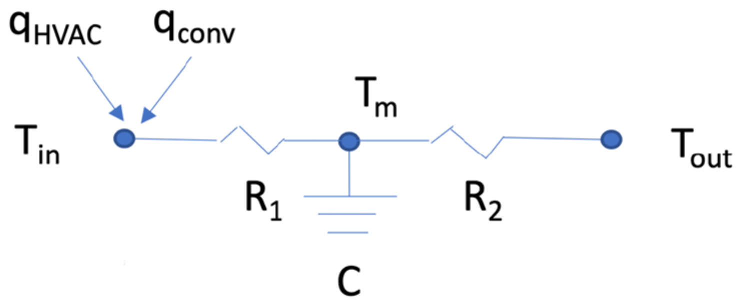



*Figure 2: residential thermal model*

All heat is inputted at $T_{in}$ and considered to be convective. Heat sources from the interior and HVAC are included. However, internal heat gains from occupancy, equipment (electricity load) and lighting are not going to be considered. $T_m$ is the controlled temperature and in steady state. The bigger value takes building thermal resistance (R), the higher resistance to heat flow has the building.

The model could also have the capability to consider environmental limitations, specifically regarding CO2 emissions, just by adding an additional constraint in the modelling.

## *5.2. DATUM*

Model is prepared to work with one-zone buildings. The building in study is located in Essex County, Massachusetts, U.S. as indicated in Figure 3.

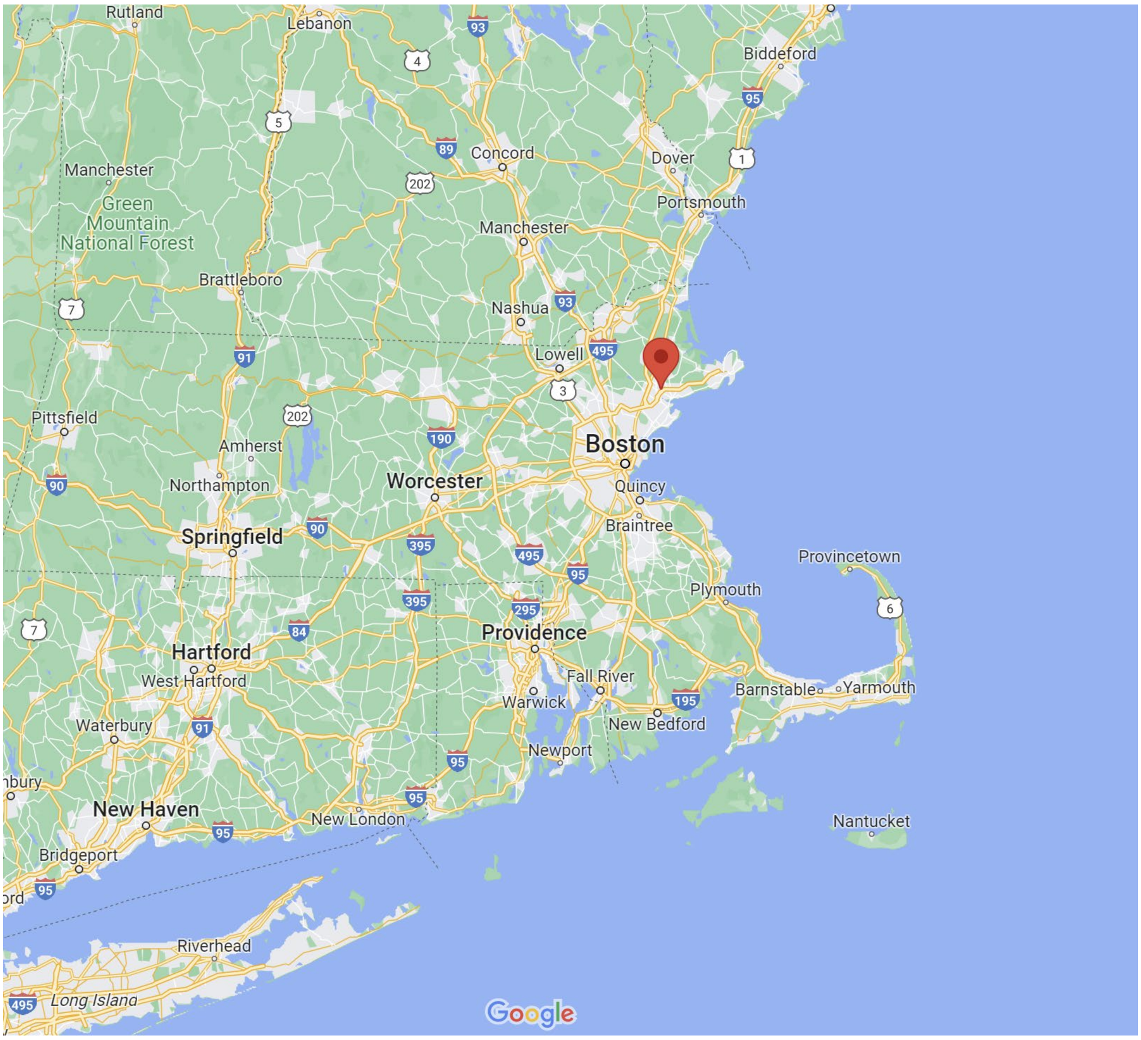



*Figure 3: location of the building in study*

Latitude and longitude geographic coordinates in decimal degrees (DD) are 42.58° and -70.92° and Altitude above sea level is 32 m. Massachusetts is in the Eastern Time Zone (ET).

The building´s footprint surface is 100 $m^2$. The number of CHP, HVAC and water heaters units that could be potentially installed is one in all cases. Regarding battery modules, it is possible for the building to have installed a maximum of four battery modules.

It is decisive for the investment module in PV to have access to the properties of the building´s roof shown in Table 1.

| | | |
|---|---|---|
| **PV available (roof) surface** | [$m^2$] | 26 |
| **PV tilt (roof) angle** | [°] | 35 |
| **PV azimuth (roof) angle** | [°] | 180 |

*Table 1: PV roof properties*

Regarding thermal properties, building thermal resistance (*R*) is inversely proportional to factor *UA*—where *U* represents the conductance of the material, how efficiently heat is transferred through a structure—and *A* is the surface area of the material. A low value of *U* is synonym of a well-insulated structure. This relation is shown in Equation 1.

$$R = \frac{1}{UA}$$

*Equation 1: building thermal resistance (R)*

In order to calculate the thermal resistance (*R*) of the slab of the building in question, the parameters contained in Table 2 have been used.

| | | |
|---|---|---|
| **Slab heat transfer coefficient** | [$W/m^2$-°C] | 5.00 |
| **Building footprint surface** | [m2] | 100 |

*Table 2: parameters for calculation of building thermal resistance (R)*

Slab heat transfer coefficient is equivalent to the conductance of the slab and building footprint to the surface area of the slab. Concrete typical values of slab heat transfer coefficient are between 4 and 20 W/m2-°C.

Heat capacity (*C*) of a material is given by Equation 2.

$$C = A \times Thickness \times \rho \times c$$

*Equation 2: heat capacity (C)*

$A$ represents the surface area of the material, $\rho$ the density of the material and $c$ the specific heat of the material. For calculating the heat capacity ($C$) of the slab of the building, parameters in Table 3 have been used.

| | | |
|---|---|---|
| **Building footprint surface** | [m$^2$] | 100 |
| **Slab thickness** | [m] | 0.02 |
| **Density of slab material** | [kg/m3] | 2305 |
| **Specific heat of slab material** | [J/kg-°C] | 920 |

*Table 3: parameters for calculation of heat capacity (C)*

Once again, building footprint is equivalent to the surface area of the slab.

The wall, roof and windows present in the building have different conductance, according to the different materials they are made of. It is important to know how much space these items take to calculate their associated $UA$. These data are collected in Table 4.

| **Lateral or roof building section** | **Surface** | **Material U-value or conductance** |
|---|---|---|
| | [m$^2$] | [W/m$^2$-°C] |
| Wall | 173 | 1.50 |
| Roof | 52 | 4.60 |
| Windows | 26 | 0.81 |

*Table 4: building characteristics*

The thermal resistance ($R$) of the building, excluding the slab, is given by Equation 3.

$$R = \frac{1}{UA_{wall} + UA_{roof} + UA_{windows}}$$

*Equation 3: calculation of thermal resistance (R) of the building, excluding the slab*

The model needs information about the initial and final boundary condition; initial and final state-of-charge of the batteries; initial and final tank level in the water heater; and initial indoor and outdoor temperature.

Time dependent data is introduced in the model by defining the simulation time horizon. It has been simulated a total time of 1 year in periods of 15 minutes. For every date in time format mm/dd/yyyy hh:mm, the model requires the following time varying and non-controllable information:

- Grid power cost purchase in $/kWh
- Grid power price sellback in $/kWh
- Gaseous fuel price in $/MMBtu
- Lighting electric load in kW
- Equipment electric load in kW
- Variation in outdoor temperature in relation to initial outdoor temperature [°C]
- Hot water demand in kWh
- Direct normal irradiance in $kW/m^2$
- Diffuse horizontal irradiance in $kW/m^2$

Price signals are thus entered as time series data, providing sufficient detail to represent different data tariffs. Two different data tariffs are going to be studied: flat-rate and multitiered rate.

Grid power cost purchase has to be necessary higher than grid power price sellback in order for the model to perform correctly. Otherwise, network purchases could be resold to the network leading to an infeasible and lucrative scenario. Since price sellback has been fixed to 0 $/kWh, the model never shows this behaviour.

Weather time series data for solar irradiance is inputted for determining the potential amount of electricity that could be generated by photovoltaic systems in a certain location, and estimating the solar heat gains through glazed areas.

Outdoor temperature data is used to determine the requirements for space conditioning.

Sun position enable the model to calculate solar heat gains.

The total glazing and lateral surface of the building exposed to the West, East, North and South is respectively shown in Table 5.

| | | |
|---|---|---|
| West-facing lateral area | [m$^2$] | 61.7 |
| East-facing lateral area | [m$^2$] | 61.7 |
| North-facing lateral area | [m$^2$] | 61.7 |
| South-facing lateral area | [m$^2$] | 61.7 |

*Table 5: total glazing and lateral area of the building subject to its orientation*

Regarding heat gain from solar irradiation, it has been estimated a particular irradiation on the different glazing surfaces of the building depending on its orientation and material. Table 6 illustrates this aspect.

| | | |
|---|---|---|
| West-facing solar heat gain factor | [%] | 30% |
| East-facing solar heat gain factor | [%] | 30% |
| North-facing solar heat gain factor | [%] | 30% |
| South-facing solar heat gain factor | [%] | 30% |

*Table 6: solar heat gain factors of the glazing surfaces subject to its orientation*

Due to the location and orientation in relation to solar position of the building in study, all heat gain factors have turned out to be the same.

It has been considered that there are no heat gains from solar irradiation coming from the roof (i.e., it is isolated), as indicated in Table 7:

| | | |
|---|---|---|
| Roof solar heat gain factor | [%] | 0% |

*Table 7: solar heat gain factor of the roof*

## 5.3. *MATHEMATICAL FORMULATION*

Prefix "p" has been used for model parameters and a prefix "v" for decision variables.

Considering the decision variables shown in Table 8, the objective function of the model consists of a total cost minimization (Equation 4):

| | |
|---|---|
| $vQcost_t$ | Cost of purchasing electricity [$] |
| $vQearn_t$ | Income from selling electricity [$] |
| $vGOcost_t$ | Cost of purchased fuel: natural gas or diesel [$] |
| $vNSEcost_t$ | Cost of non-served electricity [$] |
| $vNSTcost_t$ | Cost of non-served temperature [$] |
| $vNSHWcost_t$ | Cost of non-served hot water [$] |
| $vBESSinv$ | Annualized investment cost of electricity storage [$] |
| $vPVinv$ | Annualized investment cost of PV [$] |

*Table 8: decision variables for objective function*

Since retail price at which electricity is sold has been established to 0 $/kWh and maximum grid power sellback to 0 kW, variable $vQearn_t$ always takes the value of zero.

Unique investment modules that are going to be active are PV and BESS (electricity storage). The model only invests in one element of the specific technology if economically optimal. For every simulation that is going to be made, the building has already had installed the proper equipment for providing heating, cooling, and sanitary hot water. That is, a combination between HVAC, CHP and water heaters depending on the studied case. In no case will the building have already had installed PV panels or battery modules.

$$Min\ Cost = \sum_{t}^{P} (vNSEcost_t + vNSTcost_t + vNSHWcost_t + vQcost_t - vQearn_t + vGOcost_t) + (vPVinv + vBESSinv)$$

*Equation 4: objective function*

The objective function, hence, is composed of operating cost functions ($vNSEcost_t$ , $vNSTcost_t, vNSHWcost_t, vQcost_t, vQearn_t, vGOcost_t$) and annualized cost functions ( $vPVinv, vBESSinv$).

Going into greater detail, operating cost functions follow the expressions indicated in Set of equations 1:

$$vNSEcost_t = pNSEcost * vQNSE_t \; \forall t \in P$$

$$vNSTcost_t = pNSTcost_t * (vTup_t + vTlo_t) \; \forall t \in P$$

$$vNSHWcost_t = pNSHWcost * vNSHW_t \; \forall t \in P$$

$$vQcost_t = pQcostBuy_t * vQbuy_t \; \forall t \in P$$

$$vQearn_t = pQcostSell_t * vQsell_t \; \forall t \in P$$

$$vGOcost_t = pGcost_t * \left(vCHP_{G_t} \qquad + vWH_{G_t} + vTH_{G_t}\right)$$

$$+pOcost_t * \left(vCHP_{O_t} + \qquad + vWH_{O_t} + vTH_{O_t}\right) \forall t \in P$$

*Set of equations 1 expressions for operating cost functions*

With the following parameters:

| | |
|---|---|
| $pNSEcost$ | Cost of non-served electricity [$/kWh] |
| $pNSTcost_t$ | Cost of non-served temperature [$/°C-h] |
| $pNSHWcost$ | Cost of non-served hot water [$/kWh] |
| $pQcostBuy_t$ | Price of electricity purchase [$/kWh] |
| $pQcostSell_t$ | Price of electricity sellback [$/kWh] |
| $pGcost$ | Price of gas [$/kWh] |
| $pOcost_t$ | Price of diesel [$/kWh] |

The price at which electricity from the grid is being purchased depend on the data tariff selected. In case of flat-rate tariff, power from the grid has a fixed cost of 0,22 $/kWh. In a multitiered rate tariff, price depends on the time in which the electricity is being purchased:

- From 10 am to 14 pm, price of electricity is 0,33 $/kWh.
- From 18 pm to 22 pm, price of electricity is as well 0,33 $/kWh.
- Rest of the time, price of electricity is 0,11 $/kWh.

In both tariffs, maximum purchase of electricity from the grid has been limited to 100 kW.

Cost of non-served electricity has been established to 10 $/kWh, cost of non-served temperature (discomfort temperature cost) to 10 $/°C-h and cost of non-served hot water (discomfort hot water cost) to 10 $/kWh.

Price of gas (gaseous fuel) has been given an average value of 0,05 $/MMBtu. Only Combined Heat and Power (CHP) systems have a significant consume of natural gas.

The model does not use the price of diesel (liquid fuel) since neither the equipment installed on the building or the investment modules require diesel for operating.

And the following decision variables:

| | |
|---|---|
| $vQNSE_t$ | Non-served electricity [kWh] |
| $vTup_t$ | Excursion up temperature [°C] |
| $vTlo_t$ | Excursion low temperature [°C] |
| $vNSHW_t$ | Non-served hot water [kWh] |
| $vQbuy_t$ | Purchase electricity [kWh] |
| $vQsell_t$ | Sell electricity [kWh] |
| $vCHP_{G_t}$ | Gas purchased by CHP units [MMBtu] |

| | |
|---|---|
| $vCHP_{O_t}$ | Diesel purchased by CHP units [MMBtu] |
| $vWH_{G_t}$ | Gas purchased by Water Heaters [MMBtu] |
| $vWH_{O_t}$ | Diesel purchased by Water Heaters [MMBtu] |
| $vTH_{G_t}$ | Gas purchased by Supplemental Firing [MMBtu] |
| $vTH_{O_t}$ | Diesel purchased by Supplemental Firing [MMBtu] |

Water heaters are going to be fuelled with natural gas, but its consumption is not going to be relevant in comparison to the natural gas consumption of CHP units.

Finally, annualized cost functions follow the expressions indicated in Set of equations 2.

$$vPVinv = \sum_{v}^{PVs} \frac{pPVinv_v * pIR}{\left(1 - (1 + pIR)^{-pPVlife_v * \frac{8760}{pH}}\right)}$$

$$vBESSinv = \sum_{s}^{BESSs} \frac{pBESSinv_s * pIR}{\left(1 - (1 + pIR)^{-pBESSlife_s * \frac{8760}{pH}}\right)}$$

*Set of equations 2 expressions for annualized cost functions*

With the following parameters:

| | |
|---|---|
| $pIR'$ | Annual interest rate |
| $pH$ | Fraction of hour of simulated period (if 60 min, $pH$=1) |
| $pIR$ | Real interest for time scope $\left(pIR = pIR' * \frac{pH}{8760}\right)$ |
| $pPVinv_v$ | PV capital cost [$] |
| $pPVlife_v$ | PV lifetime [years] |
| $pBESSinv_s$ | BESS capital cost [$] |
| $pBESSlife_s$ | BESS lifetime [years] |

Annual interest rate has been given a value of 6 %.

The data related to capital cost and lifetime of the different equipment, as well as other interesting data such as nominal capacity and heat rate for CHP units, can be found in Table 9.

| **Type** | **Nominal capacity** | **Heat rate** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|
| | [kW] | [MMBtu/kWh] | [$] | [years] |
| NaturalGasFuelBoiler_90%AFUE | 5.93 | 1.11 | 8,267.60 | 20 |

*Table 9: CHP unit*

| **Type** | **Module capacity** | **DC/AC efficiency** | **System losses** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|---|
| | [kWp] | [%] | [%] | [$] | [years] |
| Tesla_Cash | 0.34 | 95% | 4.5% | 683.00 | 15 |

*Table 9: PV unit*

| **Type** | **Storage capacity** | **Charge rate** | **Charge efficiency** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|---|
| | [kWh] | [kWh/h] | [%] | [$] | [years] |
| TeslaPowerwall_Cash | 13.50 | 3.80 | 90% | 10,500.00 | 10 |

*Table 9: BESS unit*

| **Type** | **Heating power** | **Cooling power** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|
| | [kW] | [kW] | [$] | [years] |
| AC_SEER15 | 6.82 | 6.82 | 6,000.00 | 15 |

*Table 9: HVAC unit for cooling only*

| **Type** | **Nominal capacity** | **Heat rate** | **Storage capacity** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|---|
| | [kW] | [MMBtu/kWh] | [kWh] | [$] | [years] |
| NaturalGasPremium | 24.00 | 1.49 | 12.00 | 4,000.00 | 12 |

*Table 9: WH unit*

The anterior set of equipment corresponds to the case where the HVAC unit is responsible for the cooling of the building and the CHP unit consuming natural gas for the heating.

A prior case of study in this project will consist in cooling and heating the building with a unique device: a different HVAC unit. In this case of study, a CHP unit does not exist. Electricity consumption will be higher. HVAC unit presents the following characteristics:

| **Type** | **Heating power** | **Cooling power** | **Capital cost** | **Lifetime** |
|---|---|---|---|---|
| | [kW] | [kW] | [$] | [years] |
| ElectricityASHP_SEER22_11HSPF | 6.82 | 6.82 | 2,932.58 | 15 |

*Table 9: HVAC unit for heating and cooling*

Regarding system electricity balance, the model includes the constrains shown in Set of equations 3.

$$vQgen_t + vQbuy_t + vNSE\_Q_t = vQdem_t + vQsell_t$$
$$vQbuy_t \leq vQmx$$
$$vQbuy_t \leq pQmxBuy$$
$$vQsell_t \leq pQmxSell$$
$$vNSE\_Q_t \leq pQlight_t + pQequip_t$$

*Set of equations 3 modelling of system electricity balance*

Decision variables:

| | |
|---|---|
| $vQgen_t$ | Electricity generated [kWh] |
| $vQbuy_t$ | Electricity purchased from the grid [kWh] |
| $vQsell_t$ | Electricity sold to the grid [kWh] |
| $vNSE\_Q_t$ | Non-served energy [kWh] |
| $vQdem_t$ | Electricity demand [kWh] |
| $vQmx$ | Peak power demand [kW] |

Parameters:

| | |
|---|---|
| $pQmxBuy$ | Maximum purchase of electricity [kW] |
| $pQmxSell$ | Maximum sale of electricity [kW] |
| $pQlight_t$ | Lighting electric load [kW] |
| $pQequip_t$ | Equipment electric load [kW] |

As mentioned before, maximum grid power purchase is 100 kW and maximum sale of electricity 0 kW.

In order to meet the electrical demand, on-site electricity load has been modelled as indicated in Equation 5.

$$vQdem_t = (pQlight_t + pQequip_t) + \sum_s^S vBESSup_{t,s}$$
$$+ \sum_h^H (vHVAC\_HT_{t,h} + vHVAC\_AC_{t,h}) + \sum_w^W vWH\_Q_{t,w} \, \forall t \in P$$

*Equation 5: modelling of on-site electricity load*

With decision variables:

| | |
|---|---|
| $vQdem_t$ | Electricity demand in period *t* [kWh] |
| $vBESSup_{t,s}$ | Battery *s* charging [kWh] |
| $vHVAC\_HT_{t,h}$ | Electricity provided to heating equipment *h* [kWh] |
| $vHVAC\_AC_{t,h}$ | Electricity provided to AC equipment *h* [kWh] |
| $vWH\_Q_{t,w}$ | Electricity consumed by electric water heater *w* [kWh] |

And parameters:

| | |
|---|---|
| $pQlight_t$ | Lighting electric load [kW] |
| $pQequip_t$ | Equipment electric load [kW] |

Modelling of on-site electric generation is presented in Equation 6.

$$vQgen_t = \sum_{c}^{C} vCHP\_Q_{t,c} + \sum_{v}^{V} vPV\_Q_{t,v} + \sum_{s}^{S} vBESSdn_{t,s}$$

*Equation 6: modelling of on-site electric generation*

Decision variables:

| | |
|---|---|
| $vQgen_t$ | Electricity on-site generation [kWh] |
| $vCHP\_Q_{t,c}$ | CHP electricity production [kWh] |
| $vPV\_Q_{t,v}$ | PV electricity production [kWh] |
| $vBESSdn_{t,s}$ | Battery discharge [kWh] |

Thermal energy balance has been modelled as indicated in Set of equations 4.

$$\left(\frac{R1+R2_t}{R1R2_t}\right)\left(vT_{in,t}-vT_{in,t-1}\right)+\frac{\Delta t}{R1R2_tC}\,vT_{in,t-1}=$$

$$\left(vQ\_HTAC_t+pQ\_IHG_t\right)-\left(1-\frac{\Delta t}{R1\cdot C}\right)\left(vQ\_HTAC_{t-1}+pQ\_IHG_{t-1}\right)+$$

$$\frac{1}{R2_t}\left(pT_{out,t}-pT_{out,t-1}+\frac{\Delta t}{R1\cdot C}pT_{out,t-1}\right)+\left(\frac{R1+R2_t}{R1\cdot R2_t}\right)\frac{\Delta t}{C}pQ\_R_{t-1}$$

$$vQ\_HTAC_{t=1}+pQ\_IHG_{t=1}=\frac{\Delta t}{R1\cdot R2_{t=1}C}\left(vT_{in,t=1}-pT_{out,t=1}\right)$$

*Set of equations 4: modelling of thermal balance*

Decision variables:

| | |
|---|---|
| $vT_{in,t}$ | Indoor temperature at time t [°C] |
| $vQ\_HTAC_t$ | Thermal energy produced by heating/cooling equipment at time t (thermal gain) [kWh] |

Parameters:

| | |
|---|---|
| $pQ\_IHG_t$ | Convective heat [kWh] |
| $pQ\_R_t$ | Radiative heat [kWh] |
| $R1$ | Thermal resistance R1 [C°/kW] |
| $R2_t$ | Thermal resistance R2 [C°/kW]. Temporal variation dependence on conductivity due to ventilation (outside temperature, occupation) |
| $C$ | Heat capacitance [kWh/C°] |
| $pT_{out,t}$ | Outdoor temperature at time t [°C] |
| $\boldsymbol{\Delta t}$ | Time step |

Since resilience is achieved by investing in battery modules, the modelling of the state of charge of the batteries becomes relevant. Furthermore, energy balance depends on the state of charge in the previous period and any charging or discharging of the battery. Set of equations 5 contains the constraints imposed:

$$vBESSsoc_{t,s} - vBESSsoc_{t-1,s} = vBESSup_{t,s} * pBESSeffu_s - \frac{vBESSdn_{t,s}}{pBESSeffd_s}$$

$$vBESSsoc_{t=0,s} = pBESSsoc0$$

$$vBESSsoc_{t=P,s} = pBESSsocf$$

$$vBESSdn_{t,s} \leq pBESSdn_s$$

$$vBESSup_{t,s} \leq pBESSup_s$$

$$vBESSsoc_{t,s} \leq \ pBESSmx_s$$

*Set of equations 5: modelling of state of charge of batteries*

Decision variables:

| | |
|---|---|
| $vBESSsoc_{t,s}$ | Energy stored in battery [kWh] |
| $vBESSdn_{t,s}$ | Battery electricity discharge [kWh] |
| $vBESSup_{t,s}$ | Battery electricity charge [kWh] |

Parameters:

| | |
|---|---|
| $pBESSeffu$ | Battery charging efficiency [%] |
| $pBESSeffd_s$ | Battery discharging efficiency [%] |
| $pBESSup_s$ | Battery charging rate [kWh/h] |
| $pBESSdn_s$ | Battery discharging rate [kWh/h] |
| $pBESSsoc0$ | Battery initial state of charge SOC [%] |
| $pBESSsocf$ | Battery final SOC [%] |
| $pBESSmx_s$ | Battery maximum capacity [kWh] |

Initial and final state of charge is 100 % in both cases. Although of small quantity, this last constraint guarantees that no energy is gifted to or lost in the battery.

# CHAPTER 6. RESULT ANALYSIS

## 6.1. *FIRST CASE STUDY*

Following the multi-criteria—cost, resilience, decarbonization—feature of the model, the first case study consists of a building which functions almost exclusive by electricity, meaning that no significant amount of natural gas is required. The water heater is the unique device that consumes a very short amount of gas for supplying the building with sanitary hot water. An HVAC unit is responsible for providing the cooling and/or heating desired. Specific HVAC and water heater units selected are indicated in the section of datum. Thus, this building´s electrical installation contributes to decarbonize the conditioning of buildings.

The first data tariff considered has been a flat-rate tariff. Power from the grid has a fixed cost of 0,22 $/kWh, regardless the time of consumption. For a better understanding of what is going on, the first simulation has been executed in relaxed variables. Result is shown in Figure 4.

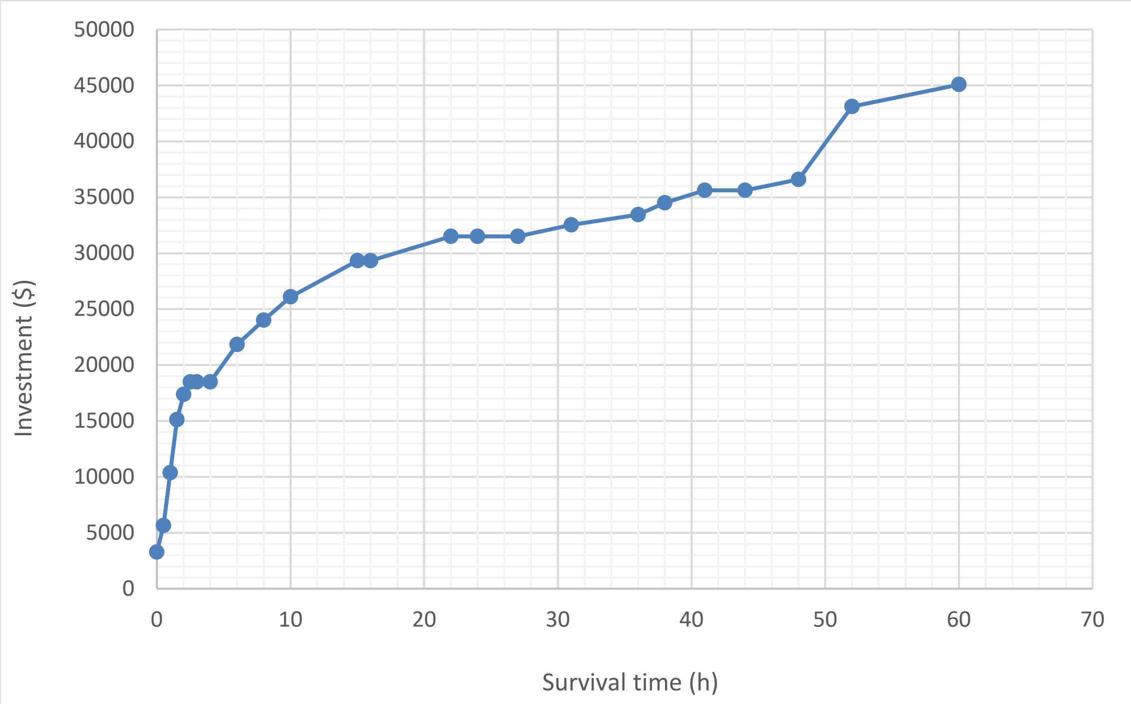



*Figure 4: investment in battery and PV modules for relaxed variables*

The figure represents the investment in battery and PV modules in relation to desired survival time. Investment does not include the HVAC and water heater units. Those are already part of the building´s equipment. Since variables has been relaxed, the model allows the investment in fractions of battery and PV modules, which results in an unrealistic scenario since the number of modules installed has to be a whole number. This is the reason because the investment graph takes the form of straight lines with slope. However, a useful preliminary image for selecting the survival time employed in the following simulations is obtained. The survival times in hours that have been considered more relevant for the upcoming simulations are 0, 1, 2, 4, 8, 16, 24, 36, 48, 60. The 50% of those survival times selected are comprehended between 0 and 10 h because; the investment graph presents a higher variation (less loss of precision in future simulations); and natural disasters usually cause power outages of that length.

It is interesting to break down the total investment cost into investment in battery modules and investment in PV modules since capital cost of a unit/module of battery is 15 times greater than capital cost of a unit/module of PV. Figures 5 and 6 illustrates this fact.

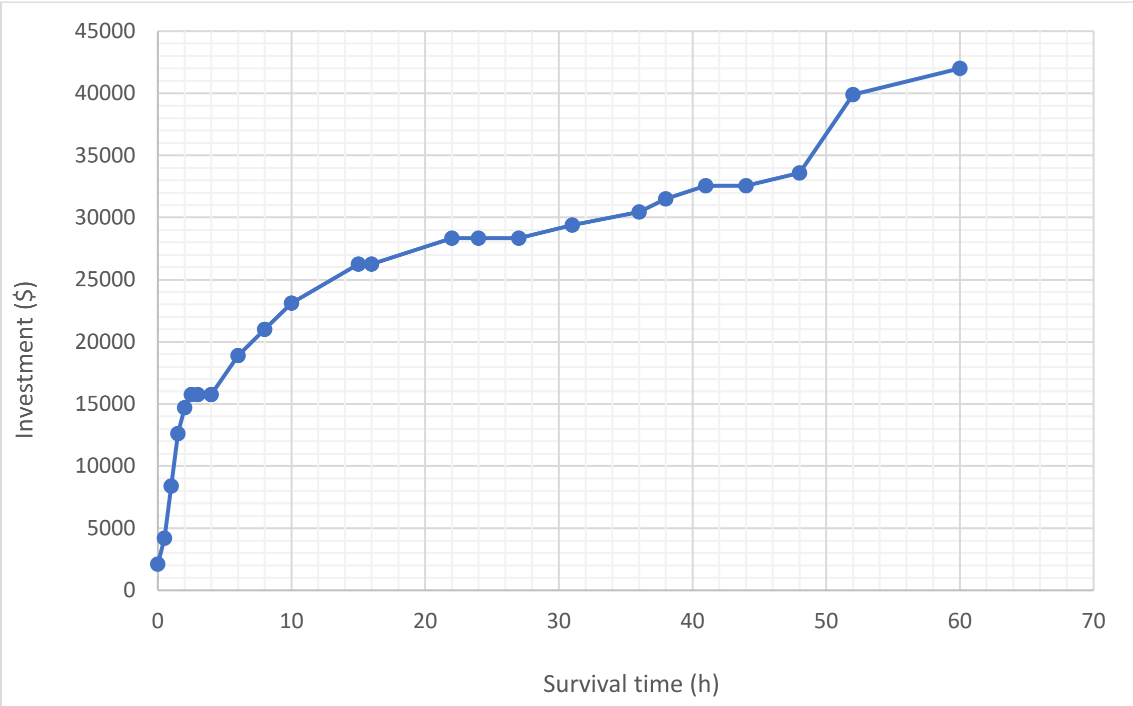



*Figure 4: investment in battery modules for relaxed variables*

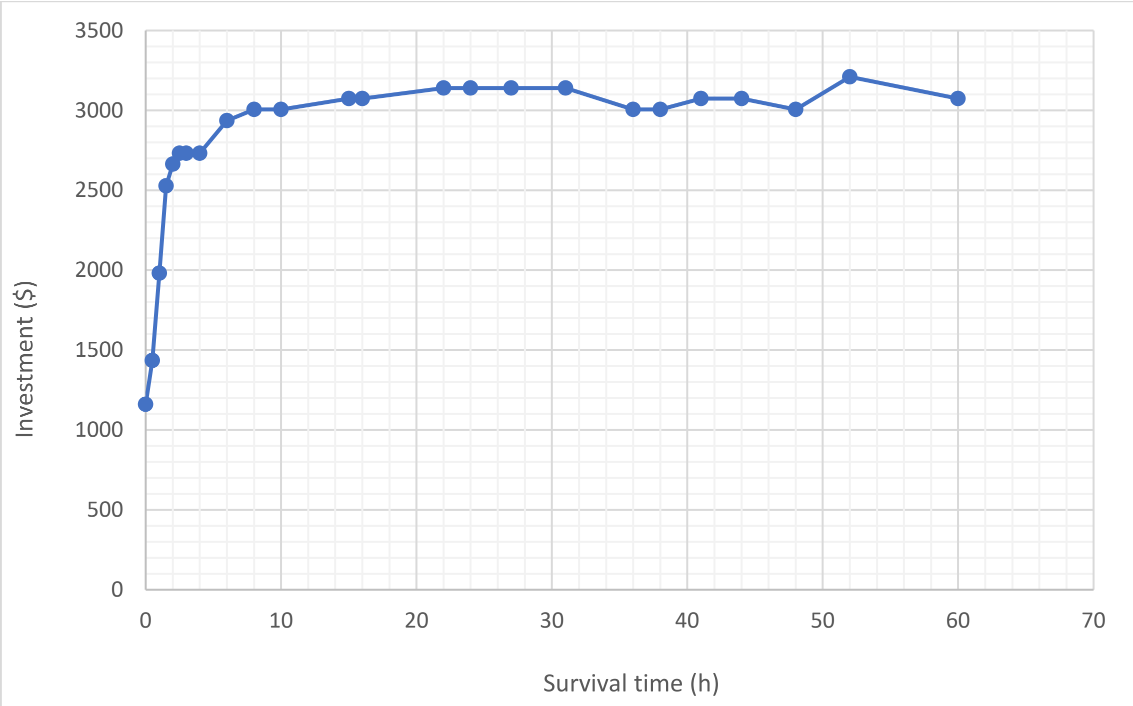



*Figure 5: investment in PV modules for relaxed variables*

As expected, investment in battery modules is much more significant and gives shape to the total investment graph. The higher time the electrical installation of the building needs to survive on his own, this is, the higher level of resilience obtained, the higher number of batteries modules are needed. At the end of the day, the batteries are the element that provides resilience to the system. The investment cost in batteries rises with the survival time. However, this is not the case of PV modules which remain approximately stable since a survival time of 8 hours.

As the equipment of the building grows with the investment in both battery and PV modules, which is synonym of higher survival times, electricity purchases from the grid are reduced. This is because the installation will have device/s capable of producing electricity (PV module) and device/s prepared to store it (battery module). Less purchases of electricity end up in a lower annual energy bill. This fact is shown in Figures 7 and 8.

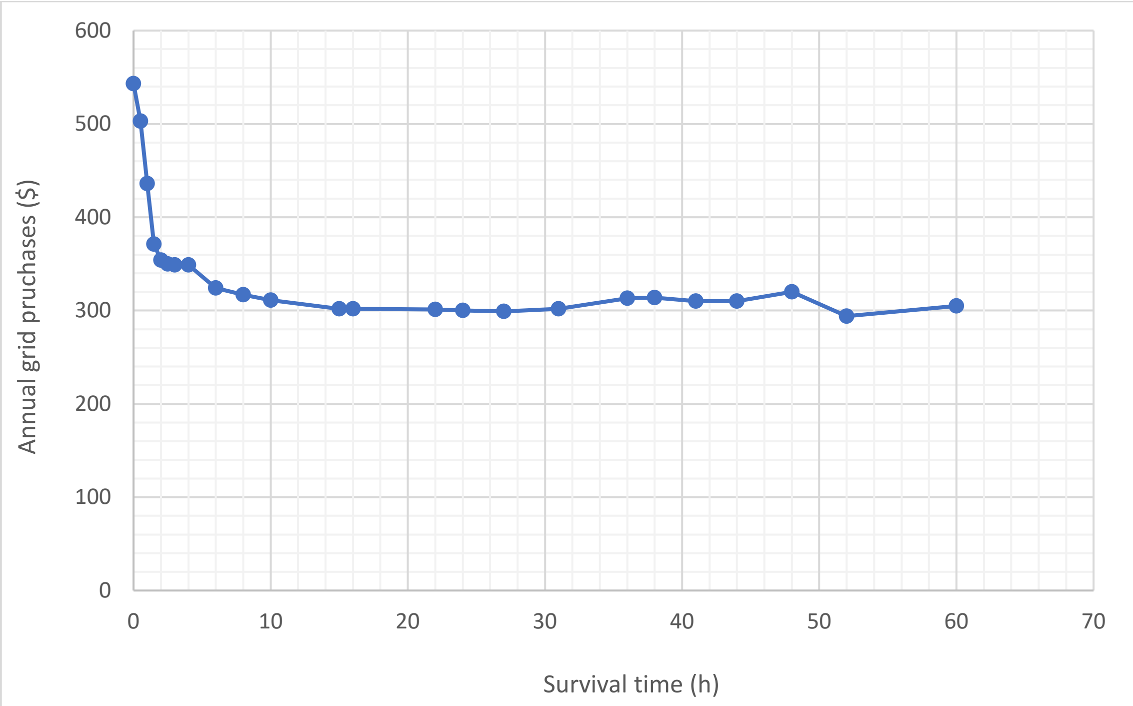



*Figure 6: annual grid purchases from the grid*

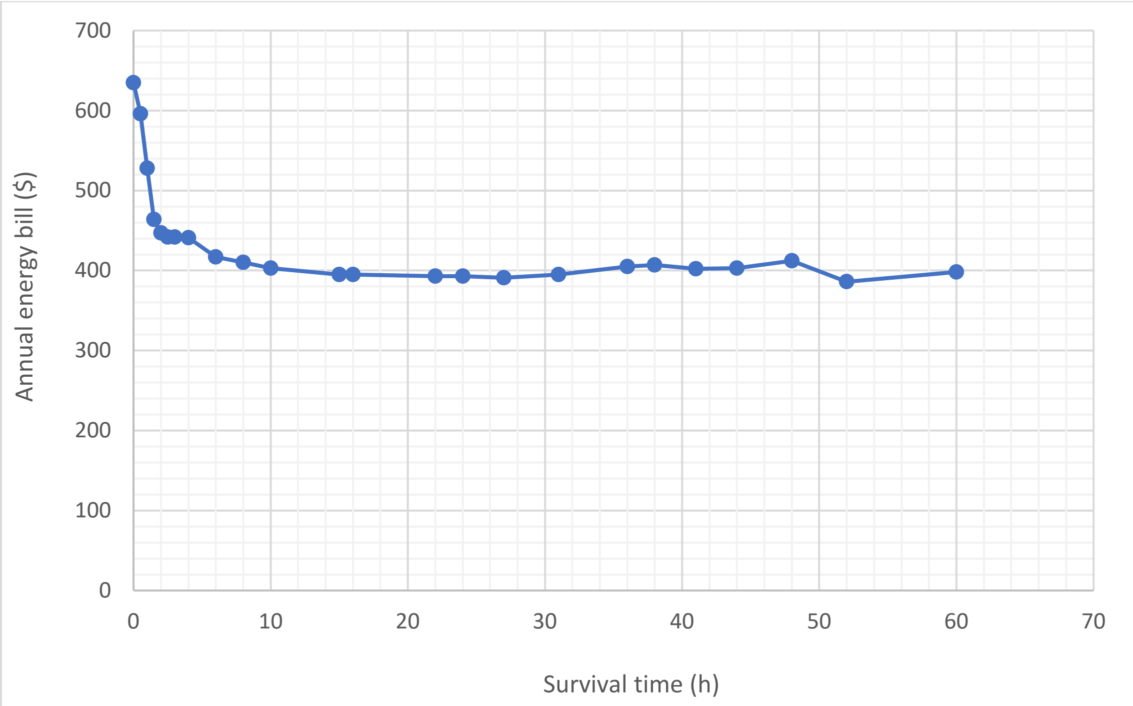



*Figure 7: annual energy bill*

For all survival times, natural gas fuel purchases of all year have a value of 92 $ and annual C02 emissions are 96.24 kg.

If the model is now solved in integer variables instead of relaxed variables and relevant survival times previously mentioned are considered, total investment cost depending on the survival time varies. Result is show in Figure 9.

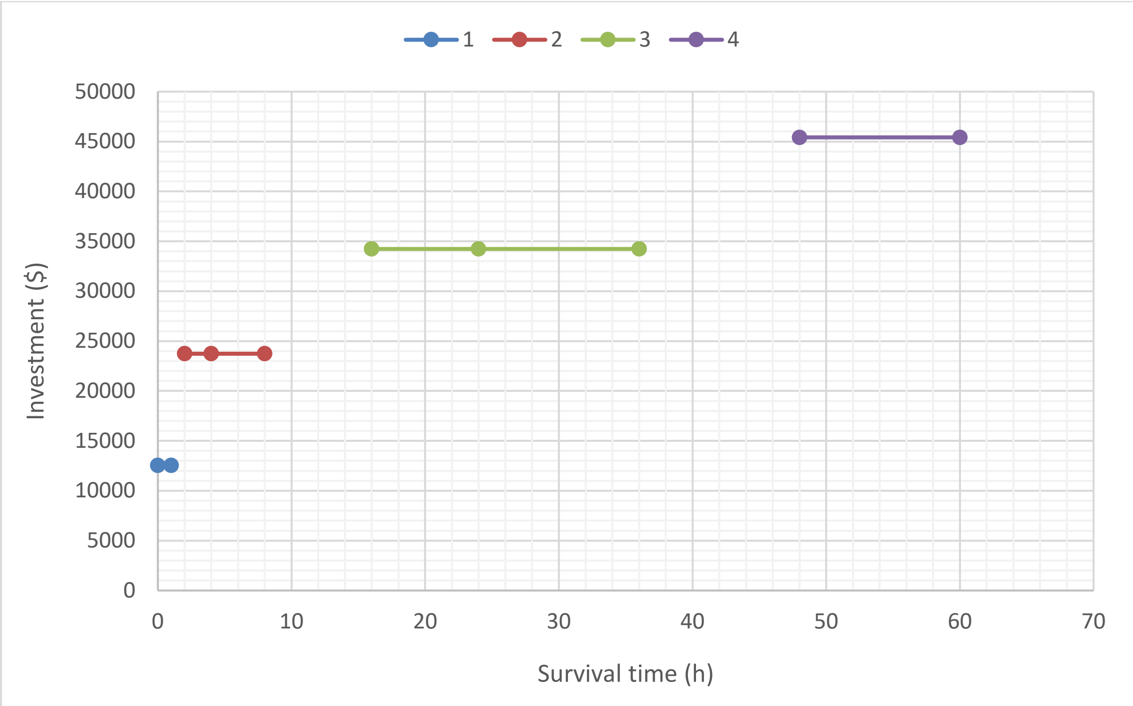



*Figure 8: investment in battery and PV modules for integer variables*

Now, the model does not allow the investment in fractions of battery and PV modules. The investment in both battery and PV modules has to be a multiple of the unitary capital cost of a module; 10,500 $ for a battery module and 683 $ for a PV module. The different colours in the graph (blue, orange, grey and yellow) represent the number of battery modules in which the model has decided to invest in. The investment graph is now a step chart for this reason.

Breaking down the total investment into investment in battery modules and investment in PV modules, Figures 10 and 11 emerge.

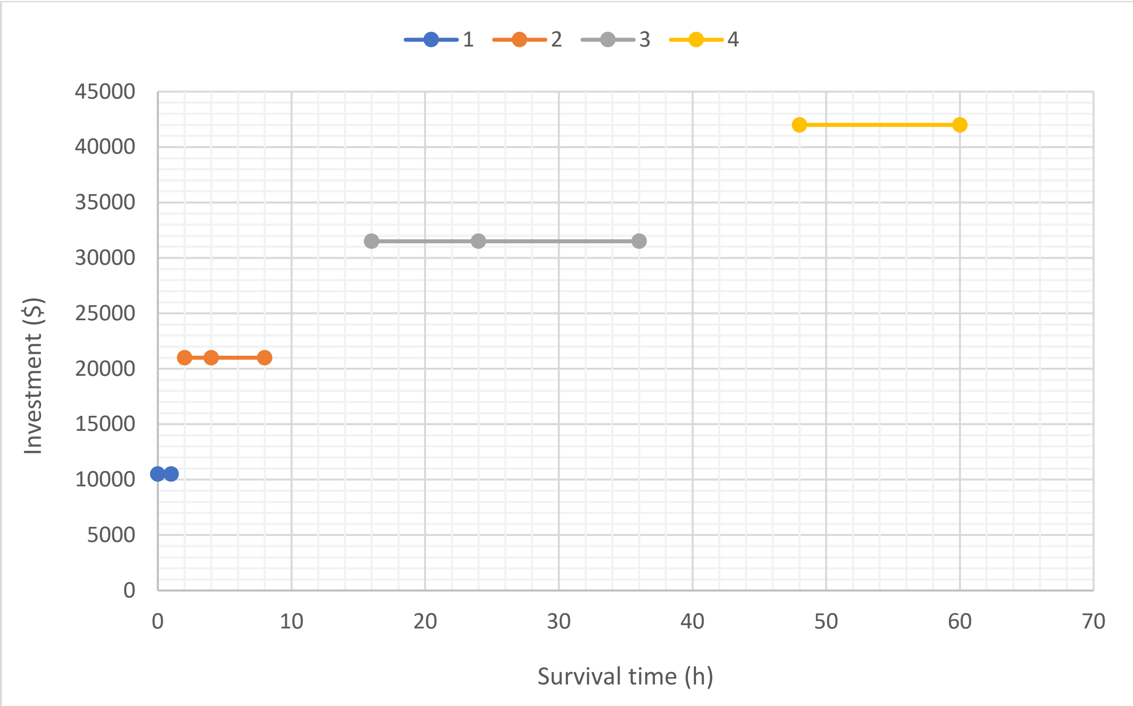



*Figure 9: investment in battery modules for integer variables*

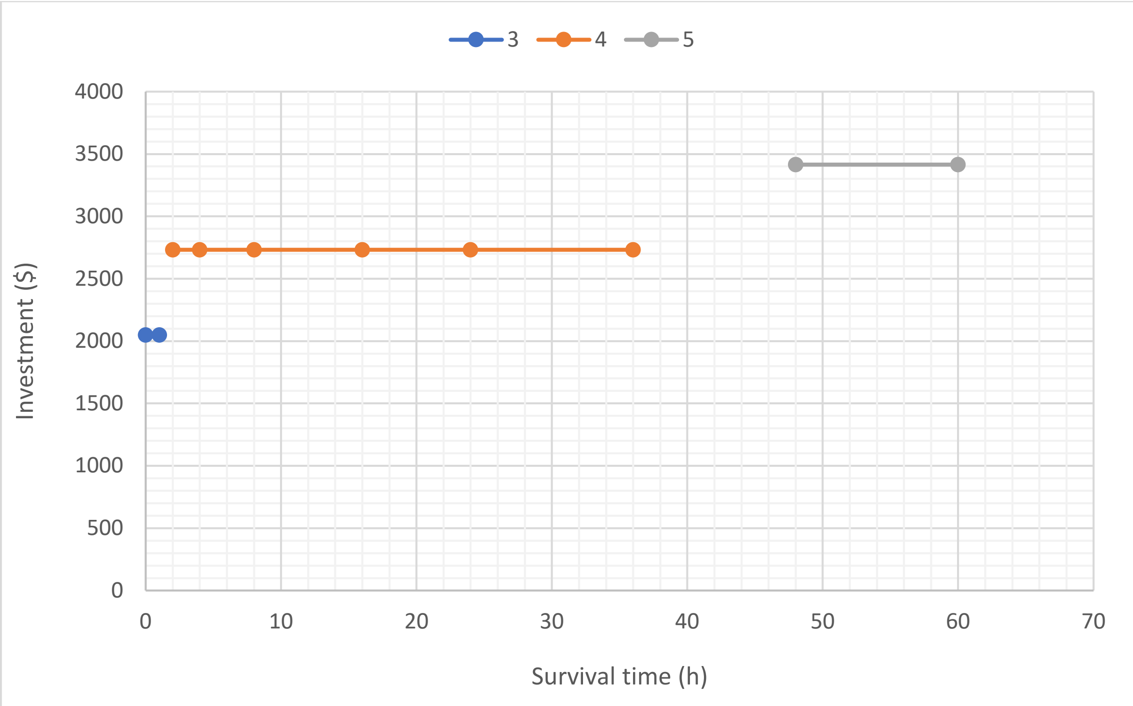



*Figure 10: investment in PV modules for integer variables*

In Figure 10, the colours in the graph represent the number of PV modules.

Once again, investment in battery modules is much more significant and gives shape to the total investment graph. In contrast with the case in which the model is solved in relaxed variables, both the investment cost in battery and PV modules rise with the survival time. It is interesting to observe that when the model decides to invest in 2 or 3 battery modules, the investment in PV remains at 4 modules.

Operating with integer variables, annual grid purchases from the grid and annual energy bill result in Figures 12 and 13.

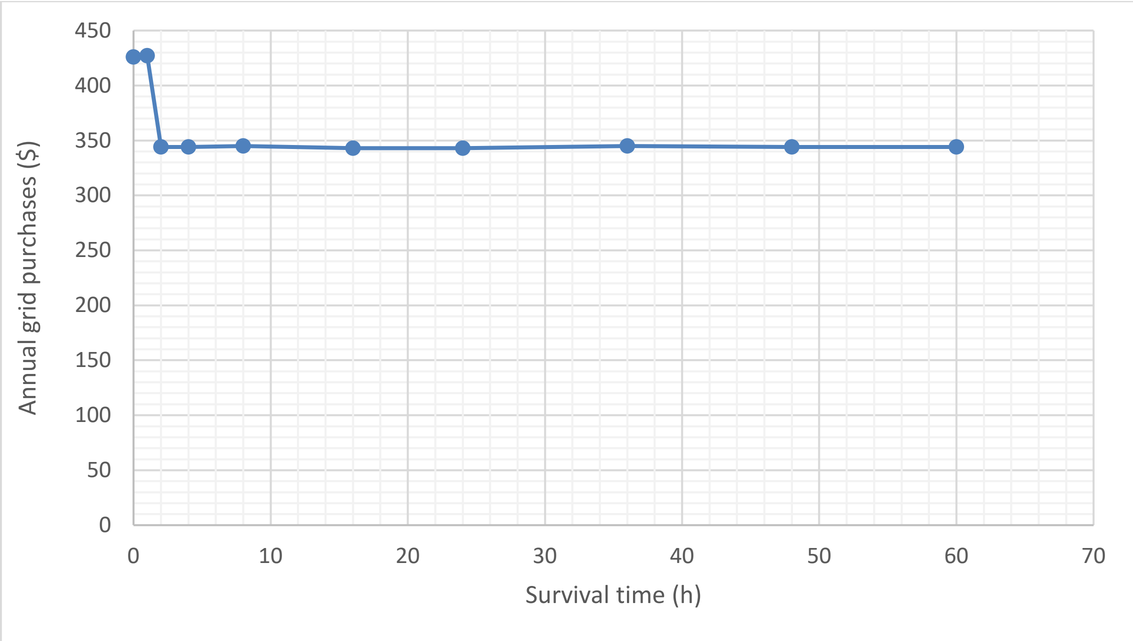



*Figure 11: annual grid purchases from the grid*

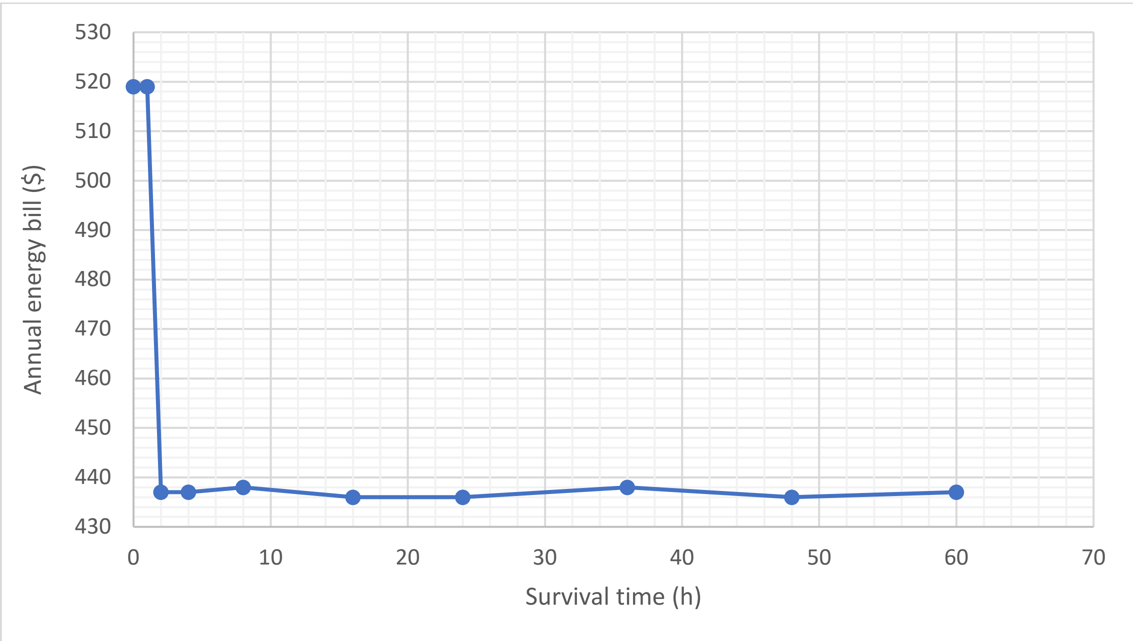



*Figure 12: annual energy bill*

For all survival times, natural gas fuel purchases of all year have a value of 92 $ and annual C02 emissions are 96.24 kg. With relaxed variables, the results were the same.

Representing together the components of the annual energy bill: annual grid purchases and natural gas fuel purchases, a better understating of the weight of the different components emerges in Figure 14:

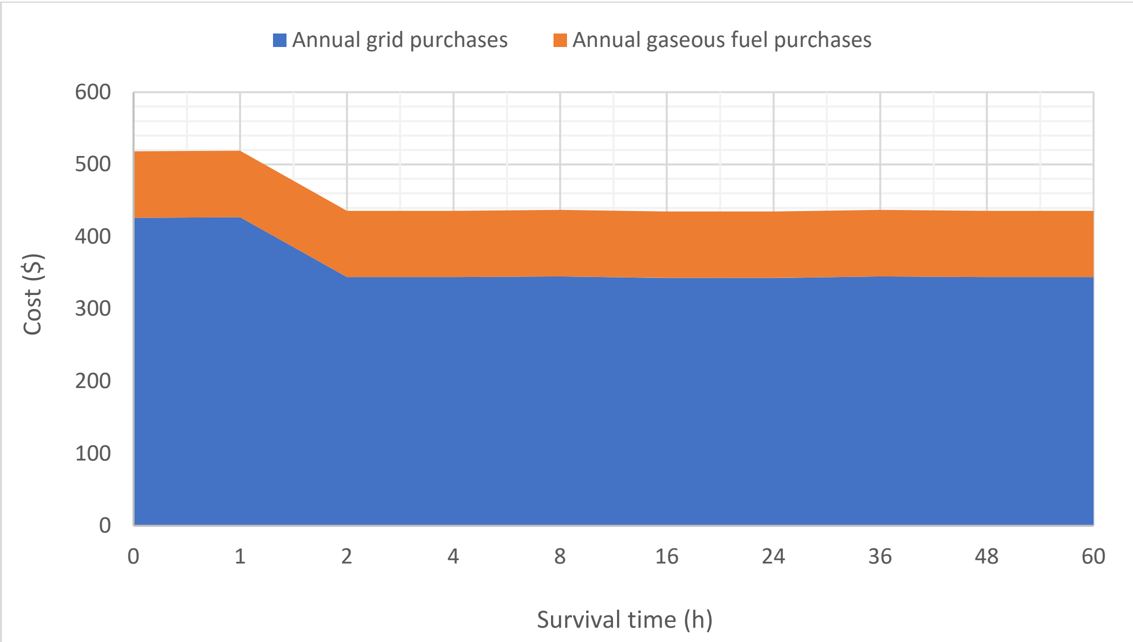
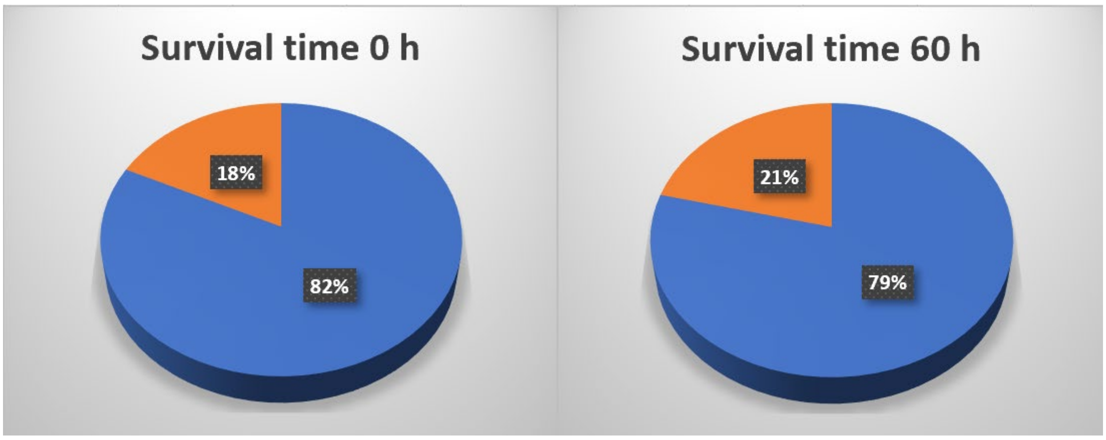



*Figure 13: annual energy bill by components*

Creating a pie chart for survival time 0 h and 60 h in order to appreciate the percentages, where blue represent annual grid purchases and orange gaseous fuel purchases:



A representation of power generation from solar PV and power purchased from the grid, both in kW, can be helpful to understand the generation of electricity, approximately equal to the demand of electricity (12660.79 kW). Figure 15 illustrates the stability that exists:

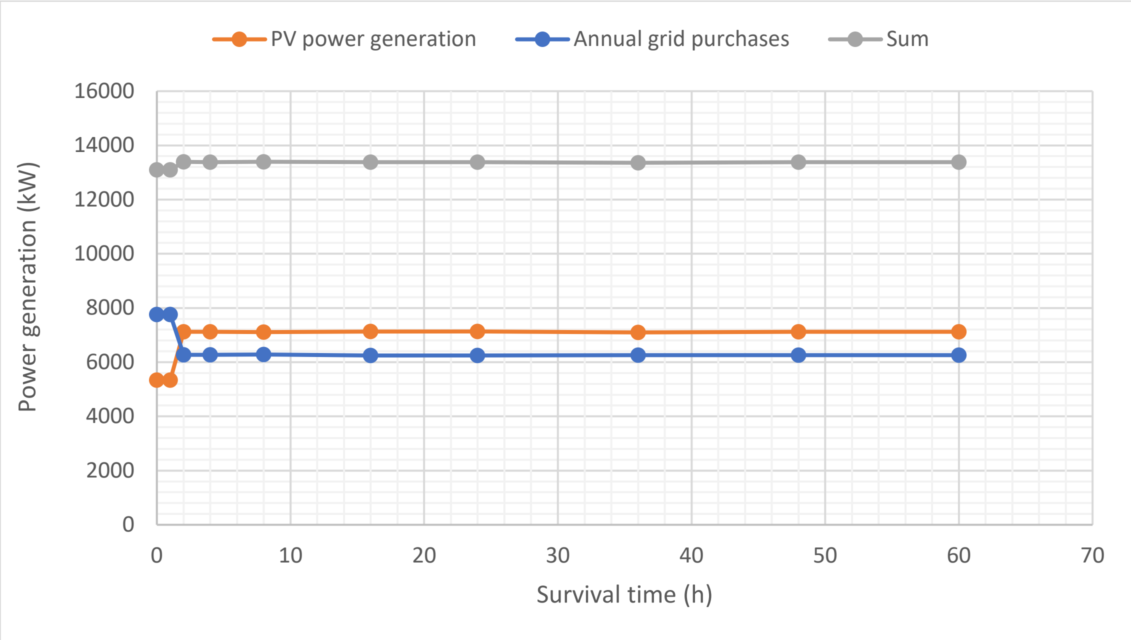



*Figure 14: power generation by source*

The second data tariff considered for this first case study (HVAC providing cooling and heating, no significant natural gas consumption) has been a multitiered tariff. Now, electricity price is not fixed, it depends on the time in which electricity is being purchased/consumed:

- From 10 am to 14 pm, price of electricity is 0,33 $/kWh.
- From 18 pm to 22 pm, price of electricity is as well 0,33 $/kWh.
- Rest of the time, price of electricity is 0,11 $/kWh.

Solving the model in integer variables (no relaxation of the model), the result obtained is shown in Figure 16.

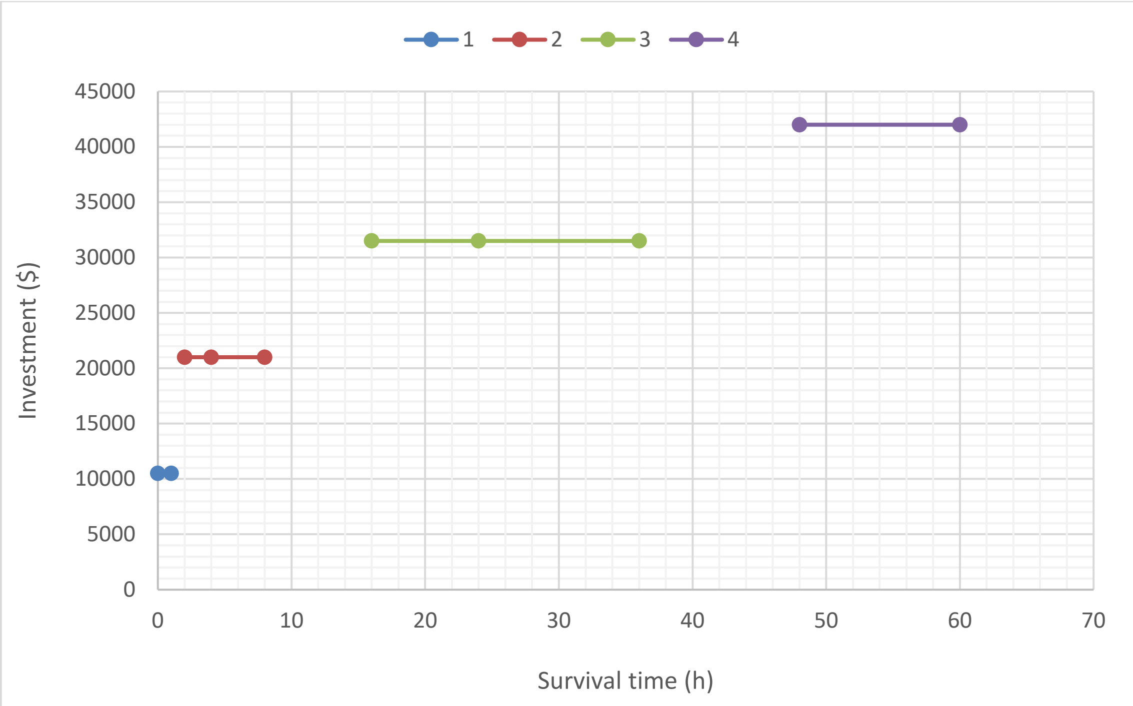



*Figure 15: investment in battery and PV modules with time of use tariff*

Once again, the different colours in the graph (blue, orange, grey and yellow) represent the number of battery modules in which the model has decided to invest in. The result obtained is the same than the one obtained with flat-rate tariff unless the model does not invest in PV modules for any survival time, only in battery modules. Thus, this graph is exactly the same than the one in Figure 10 (investment in battery modules for integer variables).

Figures 17 and 18 depict annual grid purchases from the grid and annual energy bill.

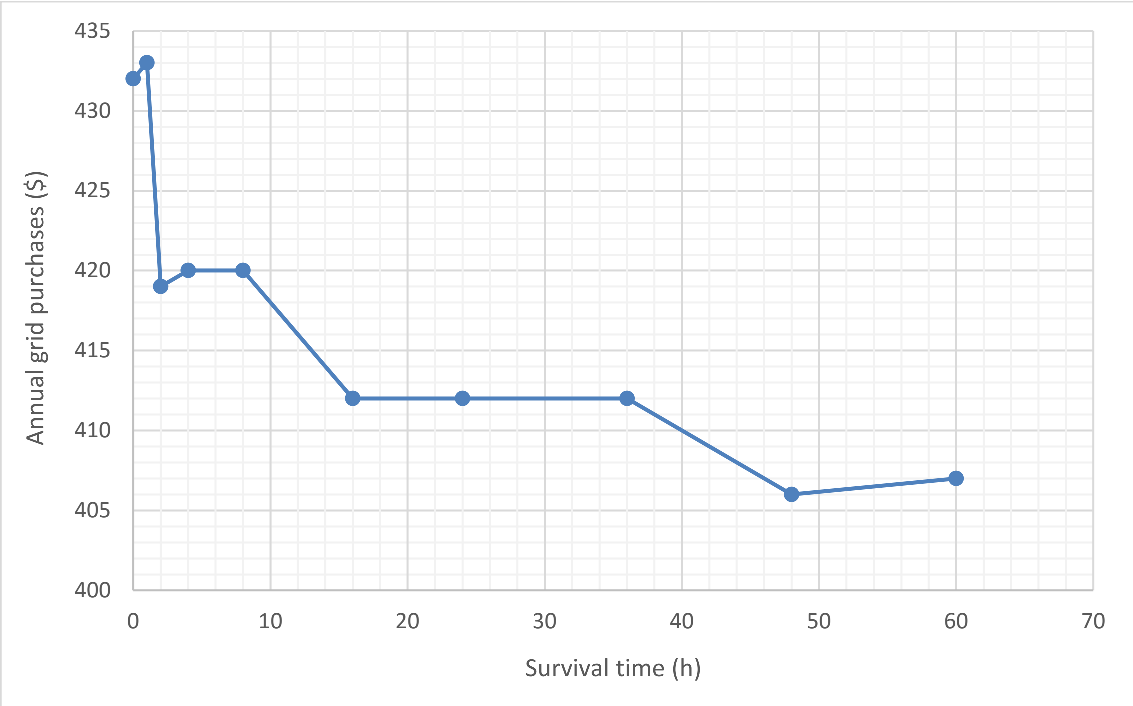



*Figure 16: annual grid purchases from the grid*

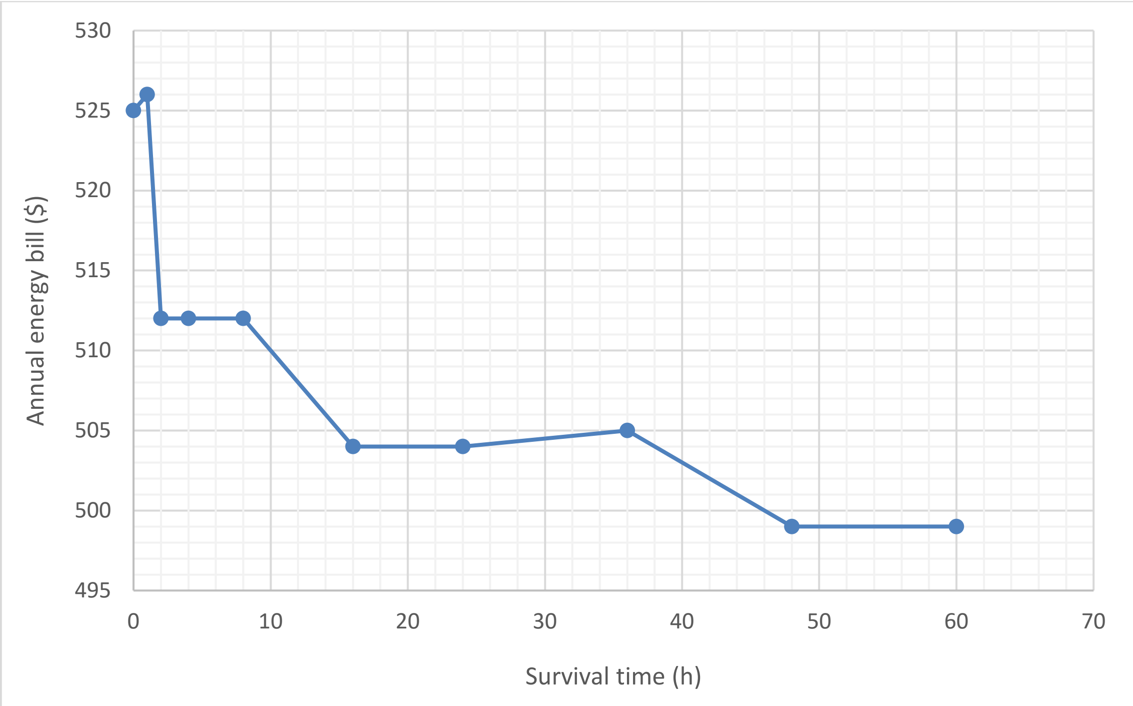



*Figure 17: annual energy bill*

Once again, for all survival times, natural gas fuel purchases of all year have a value of 92 $ and annual C02 emissions are 96.24 kg.

Comparison graphs between flat-rate and time of use tariff are show in Figures 19 and 20.

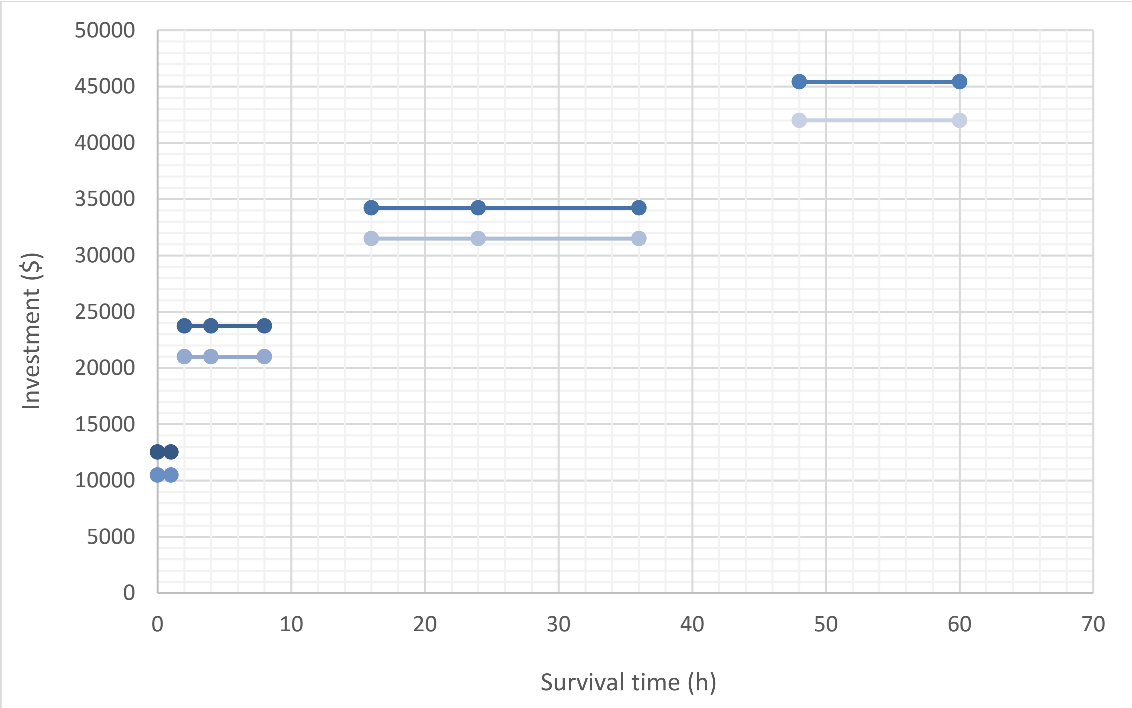



*Figure 18: comparison of investment*

Where dark blue represents investment in the case of flat-rate tariff (battery and PV modules) and light blue in case of time of use tariff (only battery modules).

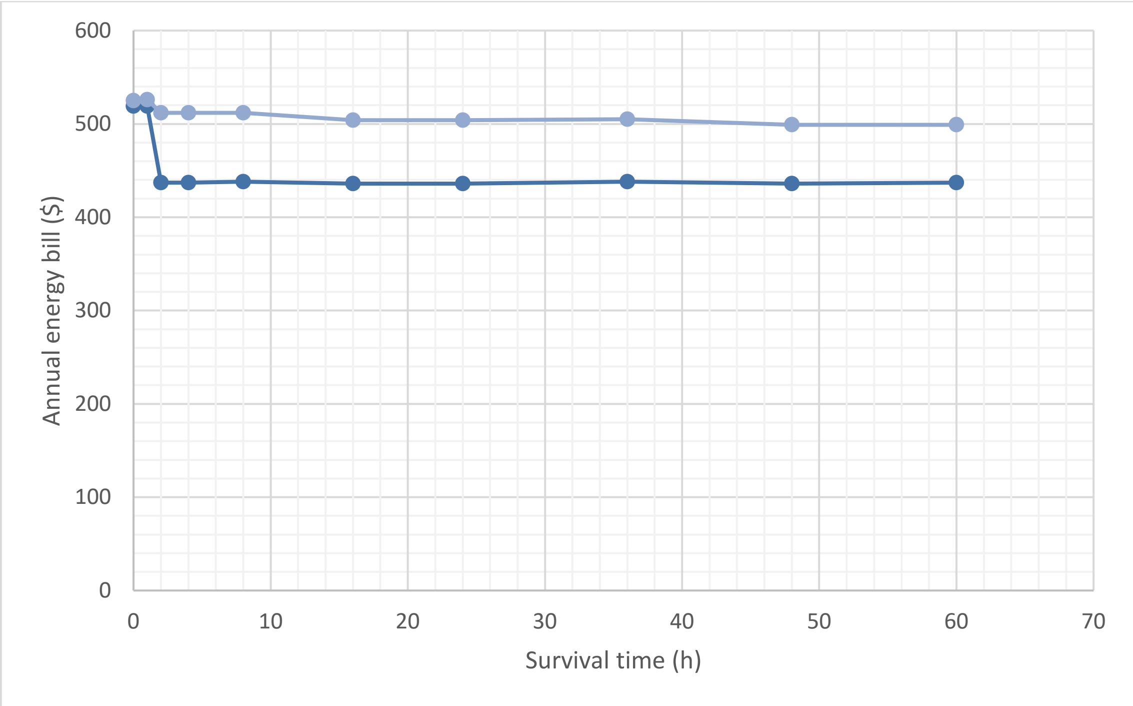



*Figure 19: comparison of annual energy bill*

For a time of use tariff, the initial investment in equipment is lower but the annual energy bills to be paid are higher. As a matter of fact, the model does not invest in PV because the battery charges during off-peak hours and discharges during on-peak hours. The energy bill is higher, but the absence of PV investment makes the total energy expenditure lower.

## 6.2. SECOND CASE STUDY

The second case study consists of a building which requires significant amount of natural gas to meet the demands. Heating of the building will be task of the CHP unit, consuming high volumes of gas. There is also a short consumption of gas by the water heater unit that supplies the building with sanitary hot water. An AC unit is responsible for providing the cooling desired, requiring electricity to function. Specific AC, water heater and CHP units selected are indicated in the section of datum.

Although this building´s electrical installation does not contribute to decarbonize the conditioning of buildings, it is expected that energy bill will lower. This is due to the fact that CHP units are a technology that produces thermal energy at high efficiencies using fuel (natural gas). Electric heating of the previous case of study is not that efficient. It is important to note that in this case study the initial cost of the installation is higher since the building had installed three devices instead of two and capital cost of the CHP unit is very significative. This set of devices for meeting the loads is approximately 250 % more expensive (18.268 $ vs 6.933 $). However, this initial situation is common in many houses and, hence, a sunk cost. So, the initial investment would be relevant for new houses.

In this second case study, the first data tariff considered has been a flat-rate tariff too. Once again, power from the grid has a fixed cost of 0,22 $/kWh, regardless the time of consumption. Result is shown in Figure 21.

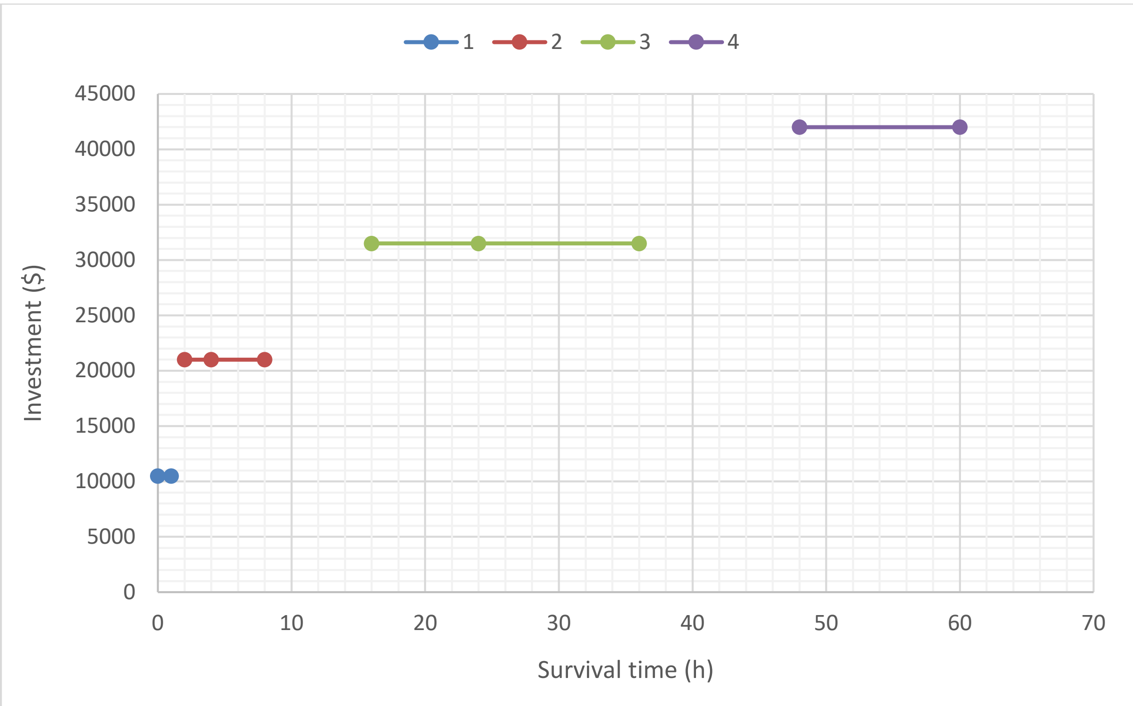



*Figure 20: investment in battery modules with flat-rate tariff*

The different colours in the graph (blue, orange, grey and yellow) represent the number of battery modules in which the model has decided to invest in. It is interesting to mention that no investment in PV modules has been made for any survival time. The model does not consider it economically optimal. The batteries are the element that provides resilience to the system, not the PV units. As expected, the investment cost in batteries rises with the survival time. The fact that the model is not investing in PV modules, which can produce electricity, is due to the lower consumption of electricity from the grid since heating is supplied by the CHP unit and, furthermore, the CHP unit is generating electricity.

General electricity demand or consumption is constant for every survival time and equals to 12660.49 kW. This power is purchased from the grid, but most significantly produced by the CHP unit, as shown in Figure 22.

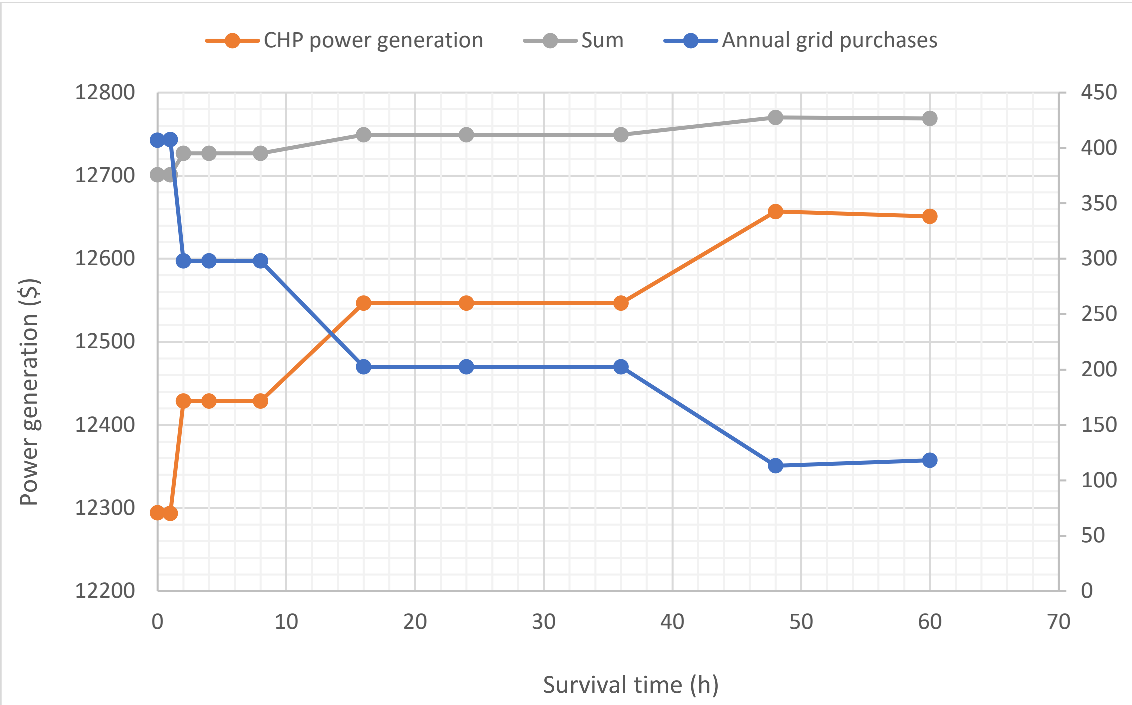



*Figure 22: power generation by source*

Annual grid purchases (blue in the graph) have the secondary axis of the right. Sum of CHP power generation and annual grid purchases is approximately equal to general power demand since generation and demand must match in order for the system to remain stable.

Regarding annual grid purchases from the grid and annual energy bill, Figures 23 and 24 emerge:

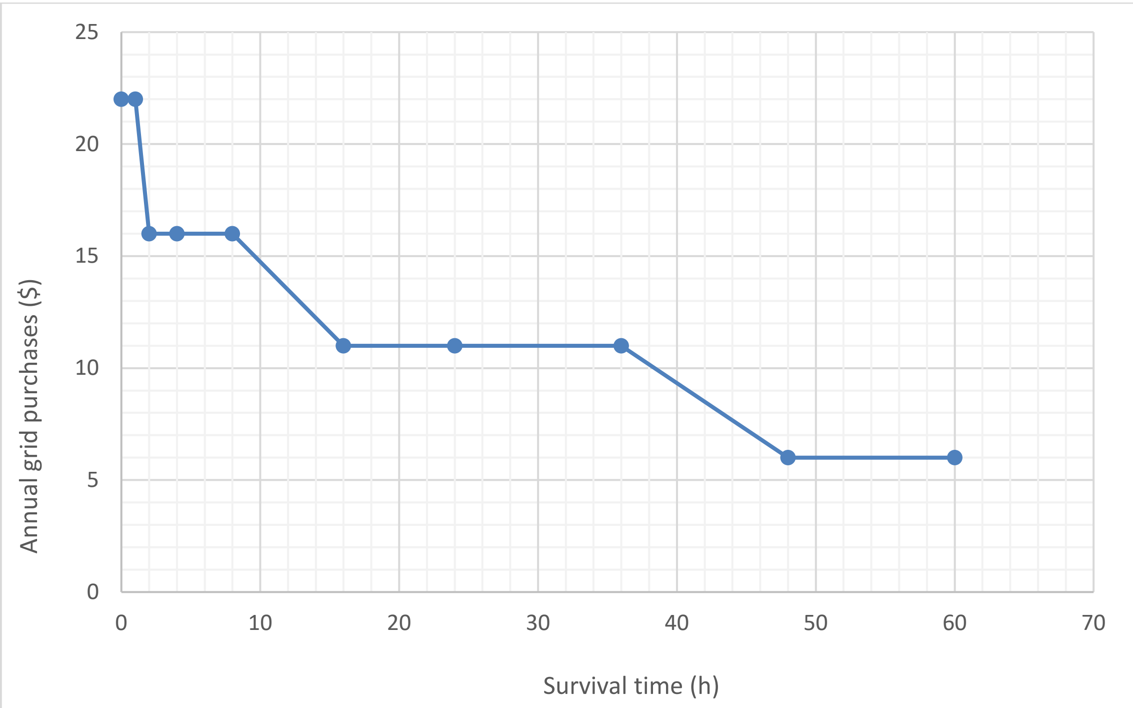



*Figure 23: annual grid purchases from the grid*

The shape of this graph is identical to power purchased from the grid in kW from Figure 22, since grid purchases is equals to power purchased multiplied by price of electricity purchase ($pQcostBuy_t$ [$/kWh]).

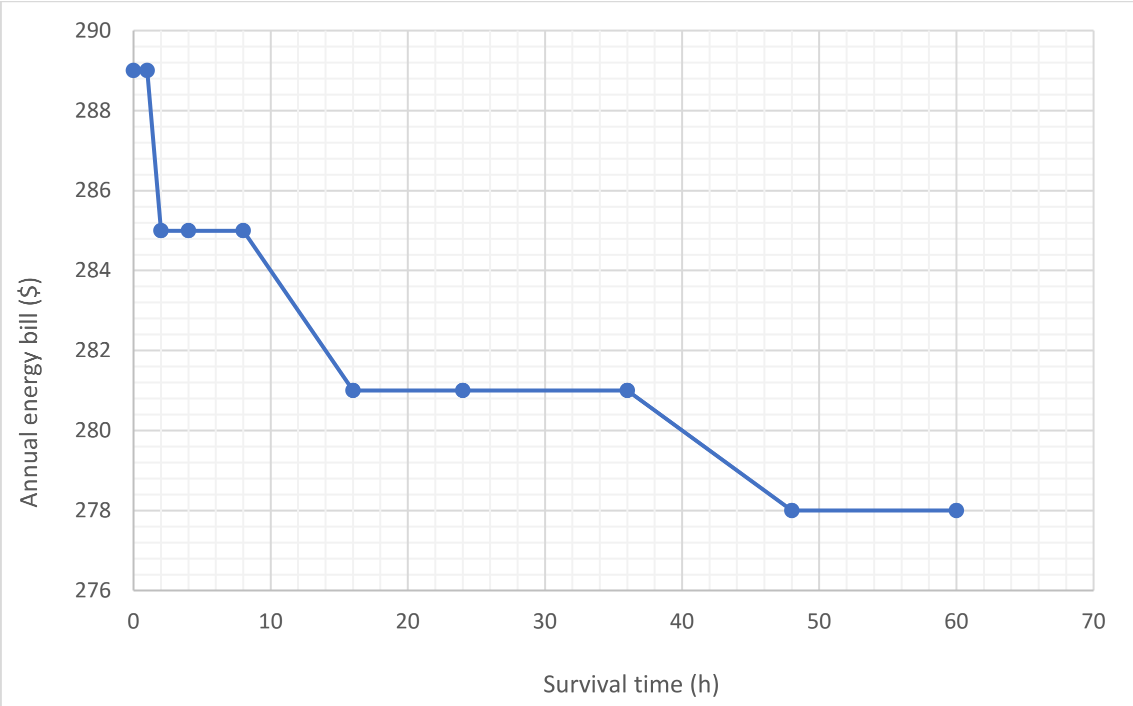



*Figure 24: annual energy bill*

Although the installation does not have device/s capable of producing electricity (PV modules), electricity purchases from the grid are reduced drastically. This is due to the fact that there is no electrical consumption for heating. Once again, less purchases of electricity end up in a lower annual energy bill.

Gaseous fuel purchases are responsible for the gap between the purchases of electricity and the energy bill. These purchases are depicted in Figure 25.

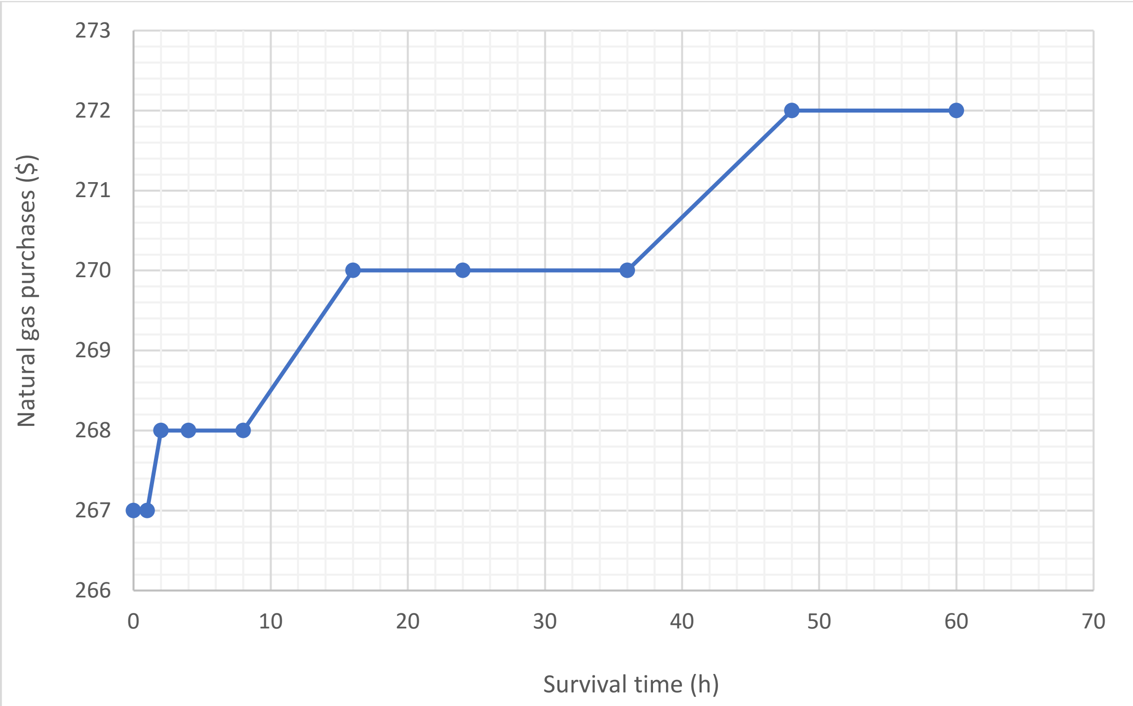



*Figure 25: annual natural gas purchases*

In the previous case study, annual natural gas fuel purchases were fixed to 92 $ for all survival times. Now, they vary with survival time and so, CO2 emissions will vary. Natural gas purchases vary from 267 to 272 $ and CO2 emissions vary accordingly from 277,34 to 282,68 kg.

Gaseous fuel or natural gas consumption vs survival time will have the same shape than the function shown in Figure 25 since gaseous fuel purchases are equal to gaseous fuel consumption multiplied by price of gas ($pGcost$ [$\$/kWh$]).

The second data tariff considered for this second case study (HVAC providing cooling and CHP providing heating with significant natural gas consumption) has been a multitiered tariff. Now, electricity price is not fixed, it depends on the time in which electricity is being purchased/consumed:

- From 10 am to 14 pm, price of electricity is 0,33 $/kWh.

- From 18 pm to 22 pm, price of electricity is as well 0,33 $/kWh.
- Rest of the time, price of electricity is 0,11 $/kWh.

The result obtained is shown in Figure 26.

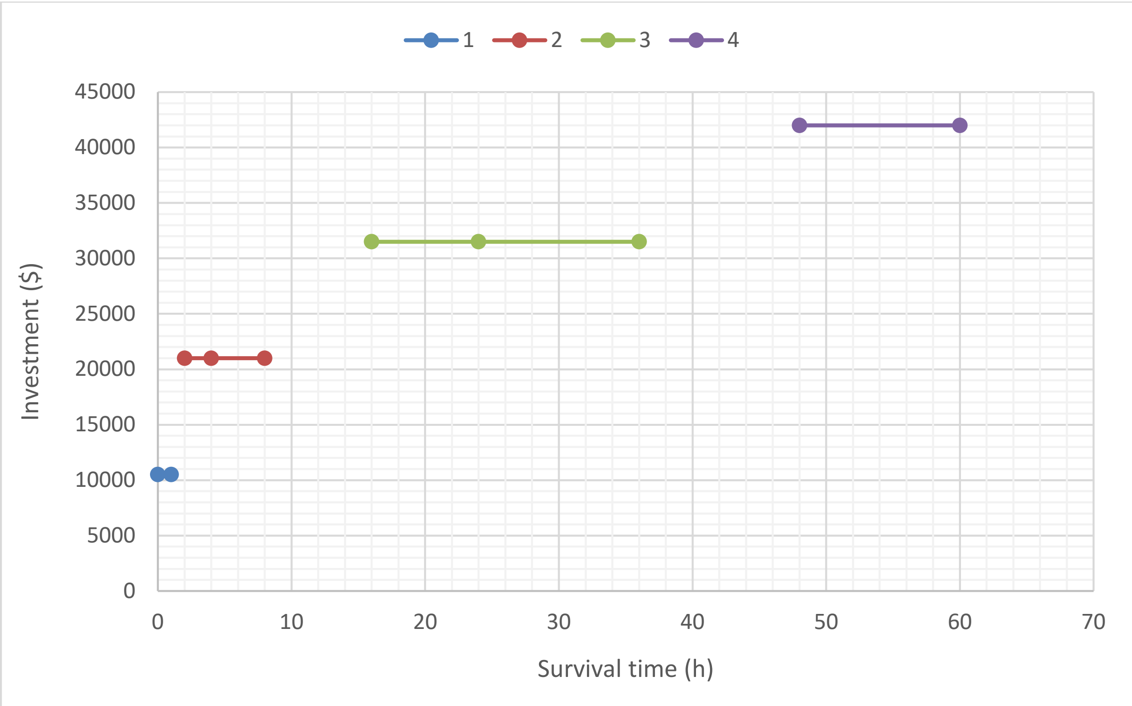



*Figure 26: investment in battery modules with time of use tariff*

The different colours in the graph (blue, orange, grey and yellow) represent the number of battery modules in which the model has decided to invest in. The investment obtained is exactly the same than the one obtained with flat-rate tariff. Once again, the model does not invest in PV modules for any survival time, only in battery modules.

Figures 27 and 28 depict annual grid purchases from the grid and annual energy bill, respectively.

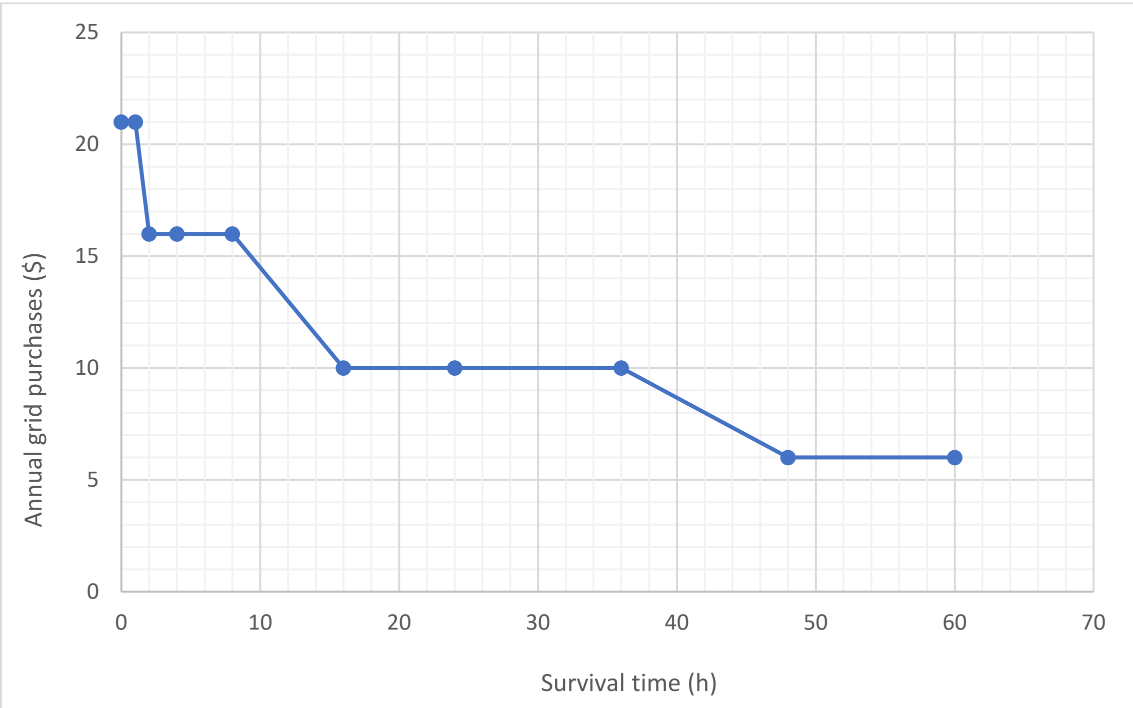



*Figure 27: annual grid purchases from the grid*

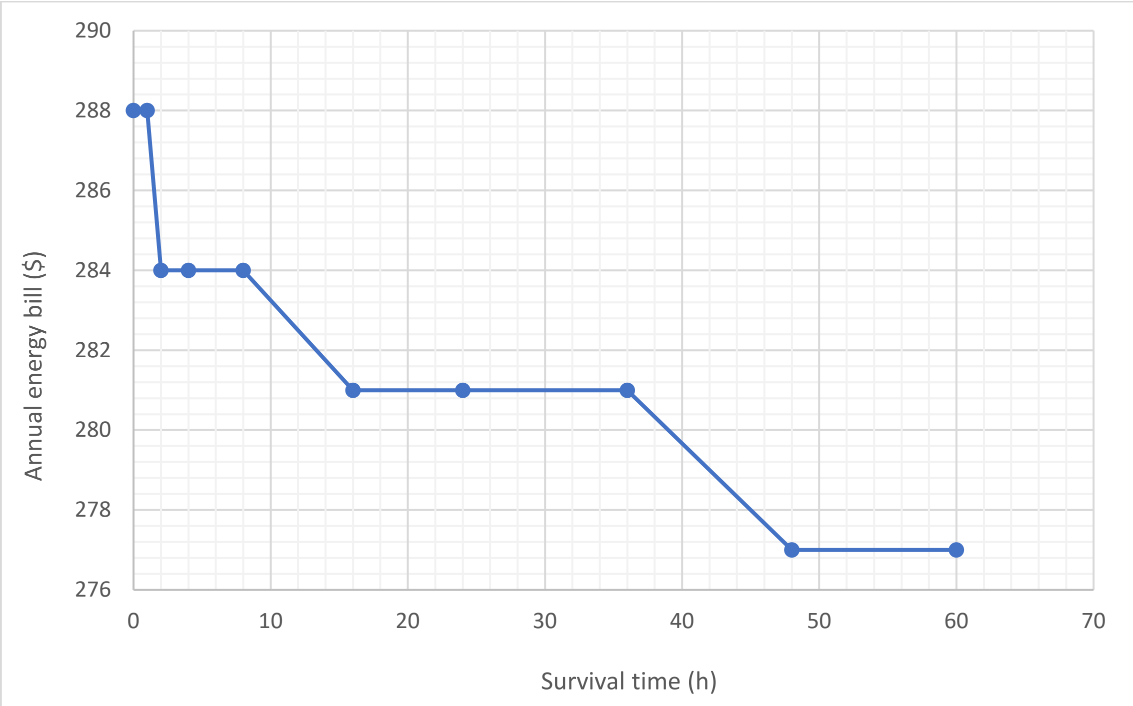



*Figure 28: annual energy bill*

Costs obtained from this second data tariff are almost identical to the ones obtained from flat-rate data tariff. Slight difference in the energy bill for the initial survival times (289 $ for flat-rate tariff vs 288 $ for time of use tariff, 285 $ vs 284 $) coming from slight differences in the grid purchases from the grid (22 $ vs 21 $, 11 $ vs 10 $). Thus, grid consumption of electricity is almost identical to the one obtained with flat-rate tariff and since general consumption of electricity is constant for all survival times (12660.79 kW), CHP power generation must be almost identical to the one obtained with flat-rate tariff (Figure 22). Once again, gaseous fuel purchases are responsible for the gap between the purchases of electricity and the energy bill. These fuel purchases are depicted in Figure 29.

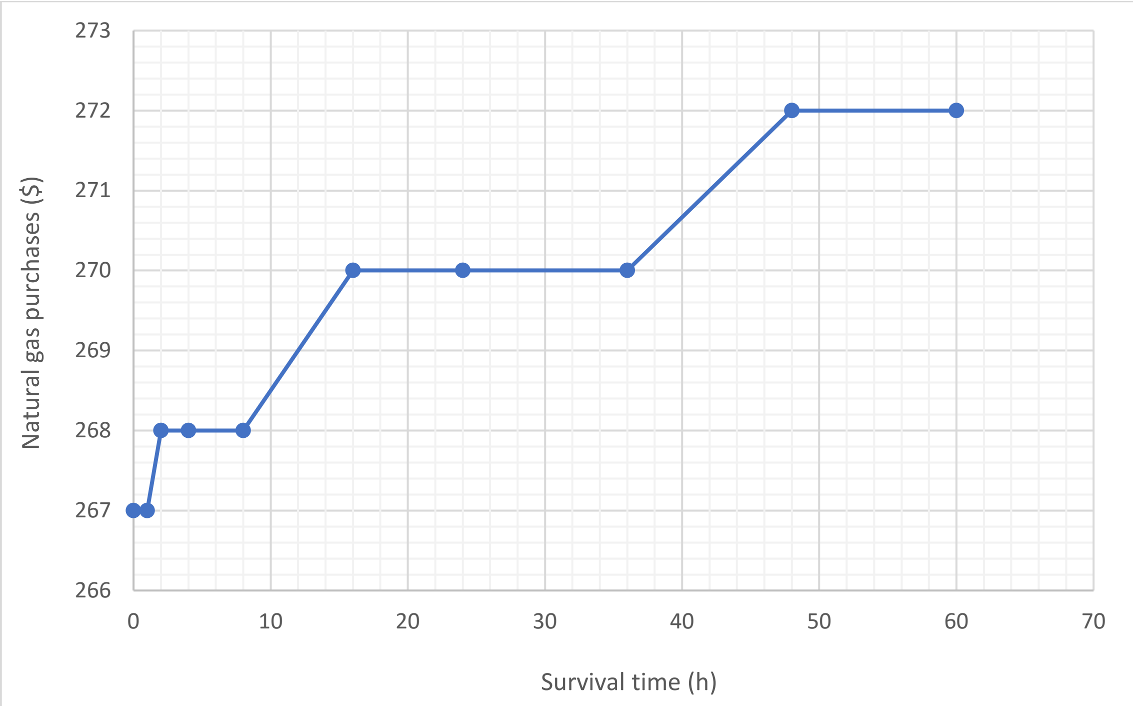



*Figure 29: annual natural gas purchases*

Natural gas purchases from flat-rate tariff and time of use tariff are identical. The model purchases the fuel necessary in order to meet the heating requirements, independently of the data tariff, which only establish the price of electricity. In this second case of study, electricity is not responsible for the heating of the building.

Natural gas fuel purchases vary with survival time and so, $CO_2$ emissions will vary. Natural gas purchases vary from 267 to 272 $ and $CO_2$ emissions vary accordingly from 277,34 to 282,68 kg.

# CHAPTER 7. CONCLUSIONS

## 7.1. *FIRST CASE STUDY*

There is a small and constant consumption of gaseous fuel due to the water heater supplying sanitary hot water, which leads to constant natural gas fuel purchases and CO2 emissions. However, there is a big consumption of electricity due to the HVAC providing heating and cooling to the building.

Resilience is achieved by investing in battery modules. The higher time the electrical installation of the building needs to survive on his own, this is, the higher level of resilience obtained, the higher number of batteries modules are needed.

When the data tariff contracted is a flat-rate tariff, the model invests in battery and PV modules, being the first one more significative since its capital costs per module are 15 times higher. A constant power demand is supplied by PV power generation and power purchases from the grid. As survival time increases, electricity purchases from the grid are reduced due to the installation having more device/s capable of producing electricity (PV modules) and device/s prepared to store it (battery modules). Less purchases of electricity end up in a lower annual energy bill. This drop is very pronounced till survival time of 2 h, in which purchases of electricity have dropped 20 %. From then, purchases of electricity barely decrease with higher survival times. For survival time of 0 h, grid purchases suppose 82 % of the energy bill. The remaining 18 % is relative to gaseous fuel purchases. For survival time of 60 h, grid purchases suppose 79 % of the energy bill. The remaining 21 % is relative to gaseous fuel purchases.

For a time of use tariff, there is not investment in PV modules for any survival time, there is only investment in battery modules. Thus, the initial investment in equipment is lower. The model does not invest in PV because the battery charges during off-peak hours and discharges during on-peak hours. A constant power demand is uniquely supplied by power purchases from the grid, which leads to higher energy bills. The energy bills are higher, but the absence of PV investment makes the total energy expenditure lower.

## *7.2. SECOND CASE STUDY*

In the second case study, the consumption of gaseous fuel is big and variable due to the CHP consuming high volumes of gas for supplying heating to the building and due to the water heater supplying sanitary hot water. Variable consumption of gas leads to variable gas fuel purchases and CO2 emissions. Consumption of electricity is small. The AC device is responsible of this consumption when providing cooling to the building.

Resilience is achieved by investing in battery modules. The higher time the electrical installation of the building needs to survive on his own, this is, the higher level of resilience obtained, the higher number of batteries modules are needed.

The energy bill is reduced in comparison to the first case study because purchases from the grid are lower. Purchases from the grid are lower because the CHP unit is a technology that produces thermal energy at high efficiencies using fuel (natural gas). Electric heating of the previous case study is not that efficient and consumes a lot of energy.

The initial cost of the installation is 2.5 times higher than the one in the preceding case study since capital cost of the CHP unit is very significative. However, this initial situation is common in many houses and, hence, a sunk cost. So, the initial investment would be relevant for new houses.

For both flat-rate tariff and time of use tariff, the model does not invest in PV modules for any survival time, there is only investment in battery modules. The fact that the model is not investing in PV modules, which can produce electricity, is due to the lower consumption of electricity from the grid since heating is supplied by the CHP unit and, furthermore, the CHP unit is generating electricity. A constant power demand is mainly supplied by CHP power generation. There are also power purchases from the grid. Gaseous fuel purchases are significant and responsible for the gap between the purchases of electricity and the energy bill. The model purchases the fuel necessary to meet the heating requirements, independently of the data tariff, which only establish the price of electricity.

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