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Master’s degree in management engineering

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Summary

1. Introduction to the energy transition

The synergy between energy production and consumption is a critical topic in the global context since it implies a delicate balance that needs to be taken care of.

Today most of the energy produced comes from fossil fuels, but during recent decades, the need to reduce the reliance on fossil fuels while promoting a shift towards renewable energy sources has become an increasingly urgent and relevant matter.

This shift, aimed at gradually phasing out fossil fuels, is commonly referred to as "energy transition". The goal of this transition is to replace fossil energy with green sources, which have a significantly lower environmental impact, therefore it is contributing to a substantial reduction in CO2 emissions and it addresses the related environmental concerns.

As the global energy landscape rapidly shifts toward low-carbon solutions, there is an urgent need to build energy systems that are clean, safe, efficient and low-carbon. Renewable energy technologies have garnered significant attention due to their environmentally friendly and sustainable nature.

To address the fossil fuel problem, the integration of different energy resources within an Integrated Energy System (IES) has been the focus of many studies and the scientific community for quite some time - Cambini, Congiu and Soroush (2020b); Cambini, Congiu, Jamasb, Llorca and Soroush (2020a).

Integrated Energy Systems (IES) are advanced frameworks that combine multiple energy sources, technologies and storage systems to efficiently produce, store and distribute energy across various sectors, such as electricity, heating, cooling and transportation. They aim to optimize energy use by integrating renewable sources like solar and wind with traditional energy infrastructure, enhancing system flexibility and sustainability.

IES leverage technologies such as batteries, hydrogen storage and smart grids to balance supply and demand in real-time while reducing waste and emissions. By coupling different energy forms (e.g., electricity and heat), they enable efficient energy cascades and maximize resource utilization. These systems are vital for achieving decarbonization goals, improving energy resilience and supporting the transition to low-carbon economies.

IES are a great and effective way to achieve sustainable energy development and create a low-carbon society.

However, the inherently intermittent and variable nature of renewable energy output presents challenges for traditional energy systems, making large-scale integration and consumption difficult to achieve (Yixing Zhou et at, 2023).

IES are a powerful tool, yet they need to be studied and well implemented.
Further research is needed to optimize the configuration and operation of their various components. To delve into the significant seasonal variations in user energy demands and renewable energy availability, it's important to consider an integrated energy system which incorporates a seasonal thermal energy storage system.

Another aspect to address is load prediction of renewable energies which is not always very reliable, apart from the uncertainty of green energies, climate change has to be taken into consideration.
Climate change can impact Integrated Energy Systems by altering energy demand patterns, such as increased cooling needs due to hotter summers. It can also affect the availability of renewable energy sources, like wind and solar, due to changing weather conditions. Extreme weather events, like storms or heatwaves, may disrupt infrastructure and destroy the energy supply chains.
Moreover, rising temperatures could reduce the efficiency of energy production, especially in thermal plants. In the long run, these shifts may require IES to adapt, incorporating more resilient and flexible technologies.

Incentives for Integrated Energy Systems play a crucial role in promoting their adoption and accelerating the transition to more sustainable and green energy solutions. Governments and international organizations often provide financial and regulatory support to encourage the development and implementation of IES technologies.
In some cases, performance-based incentives are offered to reward systems that achieve high energy efficiency or significant reductions in carbon emissions. Policies like feed-in tariffs or net metering also create favorable economic conditions for integrating renewable energy sources into IES.
Additionally, research and development funding is frequently allocated to advanced technologies like hydrogen production, smart grids and energy storage, which are critical components of IES. These incentives not only reduce the financial barriers but also stimulate innovation, making IES more accessible to both large-scale projects and smaller community-based systems.

However, it is important to note that, at the moment, it is unrealistic to expect that electricity, heating, and cooling demands can be fully met through renewable sources alone.
Dependence on fossil fuels remains high and will likely persist in the medium term. That said, advances in technology may open up new possibilities for decarbonization. Certain sectors, such as those related to thermal energy production, remain particularly challenging to decarbonize. Currently, natural gas and coal are still the dominant sources for meeting thermal demand. In Europe, for instance,

approximately 40% of primary energy consumption is devoted to heating buildings, underlining the sector's significant role in overall energy use (Simone Pio Tenuta, Antonio Valente, 2024).

The design of such a system requires a detailed analysis of the energy consumption patterns, considering factors such as seasonal temperature variations, the availability of renewable energy sources and the economic feasibility of various technologies. Renewable sources like solar and wind energy hold potential, though their availability is dependent on weather conditions and time of day. To ensure a reliable energy supply, especially for thermal and cooling needs when renewable generation is low, energy storage systems such as batteries or thermal storage will likely be necessary.

A significant challenge is balancing the supply and demand for electricity, heating and cooling. This requires not only selecting the right combination of energy sources and technologies but also effectively integrating energy management systems. These systems must monitor real-time energy demand and adjust energy production and dispatch accordingly, factoring in weather forecasts, temperature variations and fluctuations in renewable energy availability. Cost optimization is also crucial, as the project aims to provide a sustainable and economically viable energy solution for any kind of actors involved in the IES network.

To ensure the system’s efficiency and cost-effectiveness, the sizing of each component must be carefully calculated. Overestimating the capacity of certain technologies could lead to unnecessary costs, while underestimating them might result in insufficient energy supply. An in-depth understanding of the energy consumption patterns over the course of the year is essential for determining the optimal capacity of each production unit, whether it's a combined heat and power (CHP) system, a solar installation or energy storage.

Furthermore, the system must be designed keeping in mind future scalability. As renewable energy technologies evolve and local energy demands grow, the Integrated Energy System should remain flexible and adaptable to these changes. It will also be necessary to account for potential shifts in local grid infrastructure and broader energy market conditions to ensure the system stays aligned with changing energy policies and regulations.

The ultimate goal of this study is to demonstrate how an integrated energy system can reduce reliance on fossil fuels while providing a reliable and cost-effective solution to meet the energy needs.

While the energy transition is a complex, long-term process, more studies should provide valuable insights into practical applications of renewable energy technologies and advanced energy management systems. By optimizing the integration of renewable energy sources, energy storage and efficient energy use, this system could serve as a model for similar energy solutions in different IES around the world. Four different types of energy demand loads will be considered: electricity load, thermal load (heating or cooling) and hydrogen load for charging fuel cell electric cars at charging stations.

2. *Definition of Integrated Energy System*

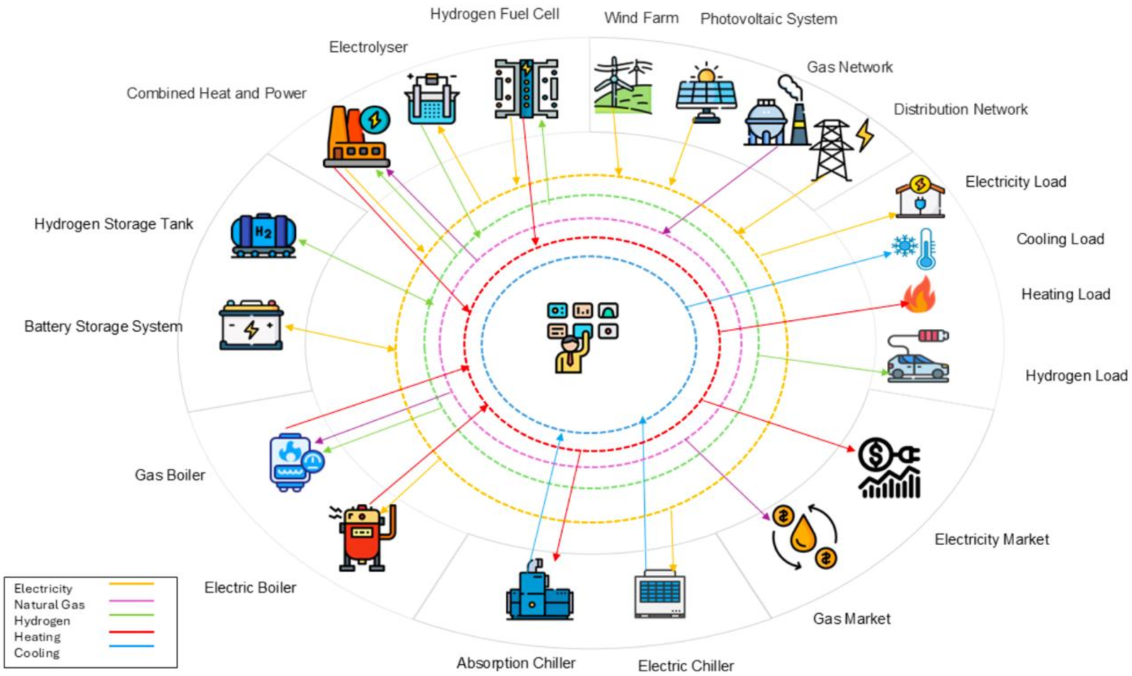


Figure 1: Structure of IES

The IES represents a modern interconnected framework designed to manage the generation, storage, and distribution of energy across multiple sectors, linking electricity, gas, heating and cooling networks. This system emphasizes efficiency, flexibility and sustainability by integrating a diverse set of energy technologies. The structure relies on synergy among various components to optimize resource utilization and minimize energy waste, enabling a shift toward low-carbon energy solutions.

The figure above represents a very close image of the IES that will be studied in the following research. As shown in the image above, four different types of energy demand loads are considered: electricity load, thermal load (heating or cooling) and hydrogen load for charging fuel cell electric cars at charging stations.

At the heart of the IES lies a network of energy sources that provide electricity, heat, and gas. Renewable electricity is primarily generated by photovoltaic (solar) systems, which serve as the backbone of clean energy production. These renewable sources feed electricity into the system, meeting immediate demands or being stored for later use. The electricity can be directed to various end uses, such as powering buildings, industries and electric vehicles or converted into other energy carriers for greater flexibility.

One of the key components enabling this flexibility is the electrolyzer. An electrolyzer is a device that splits water into hydrogen and oxygen using electricity through a process called electrolysis. The electrolyzer uses surplus electricity from renewable sources to produce hydrogen through the process of electrolysis. Hydrogen serves as a versatile energy carrier and can be stored in dedicated hydrogen storage tanks. From there, it can be reintroduced into the system to power hydrogen fuel cells, supply hydrogen loads or even be blended into the natural gas network. This integration of hydrogen not only enhances the system's storage capacity but also allows renewable energy to support a wider range of applications beyond electricity.

Energy storage plays a critical role in balancing supply and demand within the IES. In addition to hydrogen storage, battery systems store excess electricity for use during periods of high demand or when renewable generation is low. These batteries provide rapid response energy to stabilize the grid and ensure reliable power delivery. By linking battery storage and hydrogen storage, the system achieves a robust level of energy resilience, making it adaptable to fluctuating energy needs and weather conditions.

The IES also incorporates technologies for energy conversion and thermal management. Combined Heat and Power (CHP) systems are a central element, capable of simultaneously producing electricity and useful heat from natural gas and/or hydrogen. This dual-output capability maximizes fuel efficiency and provides a reliable source of thermal energy for heating needs. To complement this, gas boilers and electric boilers serve as additional means of producing heat with gas boilers utilizing natural gas or hydrogen and electric boilers relying on electricity. Traditional power plants waste a significant amount of heat during electricity generation. CHP systems capture this otherwise wasted heat and utilize it for various purposes such as heating, cooling or industrial processes. This leads to significant energy savings. By blending hydrogen with natural gas, the CHP plant burns fuel more cleanly, resulting in lower emissions of methane and other pollutants. Increasing the proportion of hydrogen in the fuel mix further decreases the carbon footprint of the CHP plant, contributing to a more sustainable energy system.

Cooling requirements are addressed through the integration of electric chillers and absorption chillers. Electric chillers operate using electricity, while absorption chillers leverage heat from other processes, such as the output of CHP systems. This dual approach ensures that both heating and cooling demands are met efficiently, leveraging waste heat whenever possible.

This device includes a particularly noteworthy design feature: it can operate using a fuel mixture of hydrogen and natural gas, though the hydrogen content is limited by specific operational constraints. Another key component, shown in the central section of Figure 1, is an electrolyzer designed for hydrogen production. To meet cooling demands, the system incorporates both an absorption chiller and an electric chiller, which are reverse-cycle machines that require careful design.

The IES structure extends its reach through robust distribution networks. The electricity distribution network delivers power generated by renewable sources, CHP systems and storage units to end users. Similarly, the gas network ensures the supply of natural gas and hydrogen to various components, such as boilers and CHP systems. These networks enable energy to flow seamlessly between production, conversion and consumption points, maintaining balance and efficiency throughout the system.

On the demand side, the IES is designed to accommodate a wide range of energy loads. Electricity loads include residential, commercial and industrial consumers, as well as emerging sectors like electric vehicle charging. Heating and cooling loads represent the thermal demands of buildings and industrial processes, while hydrogen loads encompass applications in transportation and industry. Each of these loads is dynamically managed to align with available resources and market conditions.

To further enhance efficiency and cost-effectiveness, the IES integrates with energy markets. The electricity and gas markets provide platforms for trading energy, allowing surplus energy to be sold or deficits to be covered through market transactions. This market participation ensures that the system remains economically viable while adapting to fluctuations in supply and demand.

The central control system of IES coordinates all components to optimize energy flows. It monitors real-time data from renewable sources, storage systems, distribution networks and end users to make informed decisions. For instance, it can prioritize the use of renewable energy when available, direct surplus electricity to storage or schedule energy-intensive processes during periods of low market prices. By intelligently managing these interactions, the control system ensures that the IES operates efficiently, reliably and sustainably.

In this paper we present an integrated framework, where the energy operator owns different energy production (including power-to-X and hydrogen-to-power) conversion and storage technologies to supply the different demand loads over a long planning horizon. The stakeholder decides on the capacity configuration and energy production of energy devices to design a reliable and cost-efficient energy system. — Zhou**,** Min, Wang, Xie and Fan (2023); Cambini et al. (2020b); Yang, He, Sun, Li, Li, Liu and Jiang (2024); Beraldi and Khodaparasti (2023a); Cambini et al. (2020a); Beraldi and Khodaparasti (2023b). — More specifically with a view to minimizing costs, the ambition is to size the size of each device and also to achieve optimal dispatch of the powers over the course of twelve typical days, each representative of one month of the year. So, it is necessary to design an IES (integrated energy systems) in which there are different energy sources, different technologies and devices aimed at best meeting the demand arising from the utilities.

Ultimately, the Integrated Energy System represents a transformative approach to energy management. By combining renewable generation, advanced storage technologies and interconnected networks, the IES creates a flexible and resilient energy network. It not only reduces dependence on fossil fuels but also provides a pathway to a sustainable, low-carbon future, meeting the diverse energy needs of modern society with efficiency.

3. *Literature Review*

Integrated Energy Systems have emerged as a valuable solution for improving energy efficiency and integrating renewable energy sources. Various studies have addressed different aspects of IES, including system optimization, seasonal thermal energy storage and wind power uncertainty.

However, significant research gaps remain concerning particularly in system scalability and policy incentives and real-world implementation challenges.

Optimization models for IES have been extensively explored, particularly through mixed-integer linear programming approaches (Zhou et al., 2023). While these models efficiently optimize system configurations and operational scheduling, they often assume fixed economic and environmental conditions. The work of Zhou et al. (2023) emphasizes the role of seasonal thermal energy storage in reducing operational costs and carbon emissions, demonstrating a 9.1% reduction in costs and a 12.6% decrease in CO_2 emissions.

However, a critical research gap remains in evaluating the long-term economic viability of such storage systems under fluctuating energy prices and evolving policies framework. More studies should incorporate dynamic pricing models and uncertainty quantification to improve the robustness of IES planning.

A major challenge in IES development is the integration of variable renewable energy sources (RES) with efficient storage mechanisms. Zhou et al. (2023) demonstrate that coupling seasonal thermal storage with heat pumps and solar collectors improves energy efficiency. However, their model primarily considers theoretical efficiency gains rather than real-world operational constraints, such as maintenance costs, degradation rates, and spatial limitations for seasonal thermal energy storages. There is a need for experimental studies and pilot projects that validate the practical performance of these systems under real operating conditions.

Several studies have proposed optimization frameworks to enhance the efficiency of IES. Zhou et al. (2023) investigated the role of seasonal thermal energy storage in reducing operational costs and carbon emissions. Similarly, Ran et al. (2024) developed a bi-level optimization model that considers uncertainty and climate change impacts, optimizing both system configuration and operation. However, while these models provide valuable insights into system efficiency, they do not explicitly incorporate the dynamic costs of renewable energy sources and policy incentives that influence investment decisions.

Fan et al. (2023) introduced a robust optimization model addressing wind power uncertainty in IES. This work is crucial for ensuring system reliability, yet it focuses primarily on technical feasibility rather than economic feasibility, leaving a gap in understanding how financial incentives shape renewable integration strategies.

Integrated Energy Systems have been widely studied as a means to improve energy efficiency, integrate renewable sources, and optimize energy distribution. Recent research has explored optimization methods and operational strategies, yet a critical gap remains in integrating renewable energy costs and government incentives into the decision-making framework.
Although much of the existing literature focuses on variability and uncertainty of the renewable energies or on the optimization of energies combination.
Not many researches value the economic and policy aspect of adopting IES. Despite incentives are a crucial element to promote and implement cleaner energy production, there is still no comprehensive framework that fully integrates incentives and costs into IES studies.
The main goal of this review is to focus on the role of incentive policies in promoting IES deployment. This study wants to highlight the effectiveness of bi-level optimization models for designing cost-efficient energy systems that balance investment and operational costs while minimizing carbon emissions. This paper aims to investigate policies aspects and integrate considerations related to the cost aspects of renewable energies.

4. *Mathematical model and constraints presentation*

The capacities for all devices except Electrolyzer (EL), Hydrogen Fuel Cell (HFC), and Hydrogen Storage Tank (HST) are fixed. The constraints in the Upper Level (UL) are set to force the activation of EL and HFC and HST and UL minimizes the total incentive cost paid to the IES plus the CO_2 cost. The Lower Level minimizes the cost of energy purchase, investment (only the part not supported by the policy maker), and the maintenance costs.

At this point, we proceed with the description of the mathematical model structure.

In what follows, the constraints of the problem are presented.

Photovoltaic System

The photovoltaic (PV) system consists of solar panels that convert the sunlight into electric power.

One of the biggest limitations of this technology is its low energy density, which means it requires large areas to generate relatively small amounts of power. In this study, the photovoltaic module efficiency is set to 15%, which is typical for an average monocrystalline module.

It is reminded that out of the total available solar radiation, approximately 1 kW/m^2, only 20% can generate the photoelectric effect, and consequently the photovoltaic effect, through which electrical energy is produced.

The low energy density is one of the major limitations of this technology, as it requires large surface areas to generate relatively modest power levels.

Regarding the efficiency of the solar collector, in this case, it is assumed to be 45%.

$$P_{PV}^{d\,t} = \eta_{PV} I^{d\,t} A_{PV}^{Cap} \tag{1}$$

$$P_{PV}^{d\,t} \leq P_{PV}^{Cap} \tag{2}$$

where

$P_{PV}^{d\,t}(kW)$ is the electric power output of the PV system on day d at time instant t.

η_{PV} and $I^{d\,t}(kW/m^2)$ are, respectively, the PV panel efficiency which is set to 45% and the solar radiation intensity on day d at the instant t.

$A_{PV}^{Cap}(m^2)$ is a decisional variable. It is the area that can be dedicated to the photovoltaic panels and is bounded by the parameter $A_{Available}$ which is the maximum available area.

P_{PV}^{Cap} denotes the maximum electric output of the system that is an input parameter.

The trend of the solar radiation intensity on day *d* at the instant *t* is represented in the graph below:

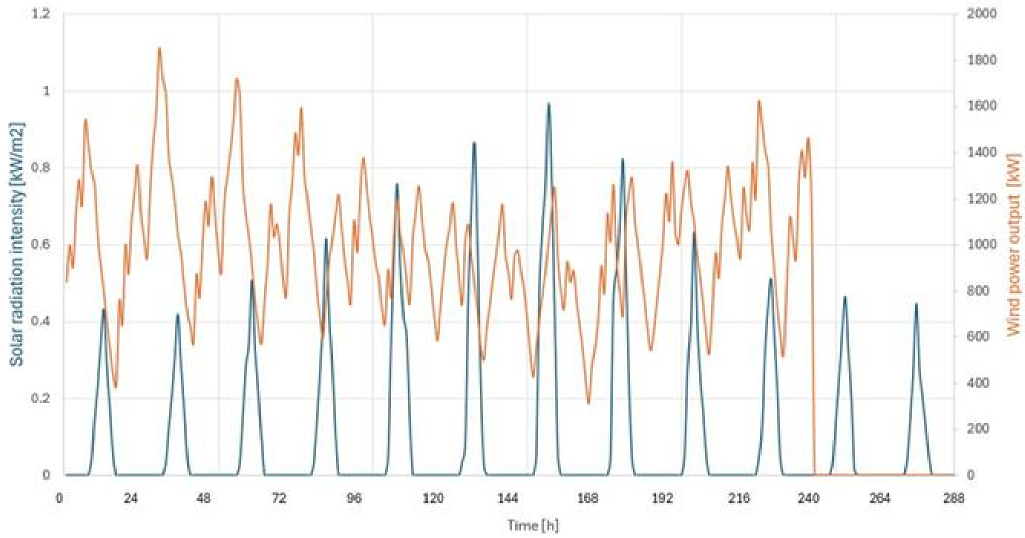


Figure 4.1.1: Solar Radiation Intensity on typical days of the month

Combined Heat and Power Plant

The Combined Heat and Power (CHPP) converts the fuel into electric power, in the system CHPP produces electricity and heating.

Additionally, the waste heat generated from combustion is utilized to produce thermal power, which is used for various purposes, including heating and thermal load supply.

It is important to emphasize that electrical power and thermal power are fundamentally different. Electricity is pure energy, meaning it can be directly converted into useful work. In contrast, thermal power must be converted (also using the Carnot factor) to produce work.

Moreover, there is a significant difference in terms of transportability. Electricity can be transmitted over long distances, with only some losses. On the other hand, thermal energy cannot be efficiently transported over long distances, making on-site utilization preferable. This issue can be partially mitigated through district heating, which enables the distribution of thermal energy over large urban areas.

CHPP is therefore a key technology in the modern energy landscape. Even though it relies on natural gas, it can lead to significant savings in primary energy consumption.

Thanks to the H2-NG technology, the fuel consumption in the CHPP can be a mix of hydrogen and natural gas. This has a significant impact on the methane consumption and the carbon footprint since they decrease.

The amount of hydrogen in the blended gas should be within a specific range and in most cases below 20% of the total volume.

The following equation describes the relation between fuel consumption and electric power output in the CHPP.

$$G_{H_2,CHP}^{d\,t} + G_{CHP}^{d\,t} = \zeta_1 P_{CHP}^{d\,t} + \zeta_2 U_{CHP}^{d\,t} \tag{3}$$

$$G_{H2,CHP}^{d\,t} \leq \kappa_{H_2}(G_{H2,CHP}^{d\,t} + G_{CHP}^{d\,t}) \tag{4}$$

where

$G_{H_2,CHP}^{d\,t}(kW)$ and $G_{CHP}^{d\,t}(kW)$ represent, respectively, the hydrogen and the natural gas fuel consumption in the CHPP on day d at time instant t. In this study they are 2.6 and 60.

$P_{CHP}^{d\,t}(kW)$ denotes the electric power output related to the Combined Heat Power during a time interval *t*.

$U_{CHP}^{d\,t}$ represents the state of the CHPP which is either on or off, so this parameter is ither zero or one.

ζ_1 and ζ_2 are two dimensionless parameters and represent the conversion of fuel to electric power in the CHPP.

κ_{H_2} is a parameter that denotes the hydrogen blending ratio that is set to 20%.

$$P_{CHP}^{d\,t} \leq MU_{CHP}^{d\,t} \tag{5}$$

$$P_{CHP}^{d\,t} \leq P_{CHP}^{Cap} \tag{6}$$

Constraint (5) describes the relation between the CHPP state and the electric power output while constraint (6) displays the maximum electrical output in the CHPP.

where

$P_{CHP}^{Cap}(kW)$ displays the maximum electric power output during the period of time *t* in the CHPP.

M is a sufficiently large constraint ($M \leq P_{CHP}^{Cap}$).

$MU_{CHP}^{d\,t}$ is the maximum usable power of the CHP system during the same time interval t, therefore it denotes the upper limit of the power the system can produce in the span of time considered.

Constraint (5) describes the relation between the CHPP state and the electric power output.

Furthermore, waste heat combustion can be exploited to produce thermal power to cover the thermal load.

$$H_{CHP}^{d\,t} = \frac{P_{CHP}^{d\,t}(1 - \eta_{CHP} - \eta_{Loss})}{\eta_{CHP}} \tag{7}$$

where

$H_{CHP}^{d\,t}(kW)$ represents the thermal output of the CHPP on a day *d* at the time *t.*

η_{CHP} and η_{Loss} describe, respectively, the power generation efficiency and heat dissipation loss coefficient. They are respectively equal to 0.32 and 0.28.

Electrolyzer

The electrolyzer unit is a key component of the power-to-gas process, responsible for converting electrical energy into hydrogen without generating C02. Its operation is modeled as follows:

$$H_{Prod}^{d\,t} = \frac{\eta_{EL} P_{EL}^{d\,t}}{LHV_{H_2}} \tag{8}$$

where

η_{EL} is the efficiency and it's 76%.

$P_{EL}^{d\,t}$ and $H_{Prod}^{d\,t}(kW)$ are respectively the power input and hydrogen output of the electrolyzer on a day *d* at a time *t,* the lower heating value (LHV) is set to 36.4 kW/kg.

It is highlighted that the power for a unit time interval corresponds to energy. An electrolyzer has been introduced to produce hydrogen, which partially supplies the gas boiler. This decision was made to reduce methane consumption and, consequently, to minimize environmental impact. For this reason, it is necessary to consider the following constraint in which:

$$G_{H_2,Tot}^{d\,t} = LHV_{H_2}\, H_{Prod}^{d\,t} \tag{9}$$

where

$G_{H_2,Tot}^{d\,t}$ represents the available hydrogen fuel in the system.

Constraint (9) allows the transition from hydrogen production to consumption through the LHV, as the consumption of natural gas has been expressed in kW.

The following constraint highlights the relation between the amount hydrogen production during a period of time *t* and consumption.

$$P_{EL}^{d\,t} \leq P_{EL}^{Cap} \tag{10}$$

Nominal capacity is a project parameter and it's equal to 400 kWh.

Gas Boiler

The natural gas, blended with hydrogen produced by the electrolyzer, is used as fuel for the GB to produce heat. This process is modeled as:

$$H_{GB}^{d\,t} = \eta_{GB}(G_{GB}^{d\,t} + G_{H_2,GB}^{d\,t}) \tag{11}$$

$$H_{GB}^{d\,t} \leq H_{GB}^{cap} \tag{12}$$

where

$H_{GB}^{d\,t}$ is the thermal power generated by GB on a day *d* at time instant *t*.

$G_{GB}^{d\,t}$ and $G_{H_2,GB}^{d\,t}(kW)$ are variables that represent the natural gas and hydrogen consumption in the GB.

H_{GB}^{cap} displays the installation capacity of the GB that is an input parameter.

Constraint (11) calculates the heat output of the gas boiler as a function of its efficiency , the gas energy input and the hydrogen energy input, while constraint (12) ensures that the heat output does not exceed the boiler's maximum capacity.

The following constraint shows that the volume of hydrogen blended with natural gas should be below a maximum value of κ_{H_2}.

$$G_{H_2,GB}^{d\,t} \leq \kappa_{H_2}(G_{GB}^{d\,t} + G_{H_2,GB}^{d\,t}) \tag{13}$$

Electric Boiler

The Electric Boiler (EB) is another thermal device taking the electric power as the input and produces the heating power.

$$H_{EB}^{d\,t} = \eta_{EB}P_{EB}^{d\,t} \tag{14}$$

$$P_{EL}^{d\,t} \leq P_{EL}^{Cap} \tag{15}$$

where

$H_{EB}^{d\,t}$ represents the thermal output of the EB.

η_{EB} indicates the electric boiler efficiency.

$P_{EB}^{d\,t}(kW)$ shows the electrical power input of the EB.

$P_{EL}^{Cap}(kW)$ is the maximum power capacity of the EB.

Electric Chiller

To meet the cooling demand, the IES employs an electric chiller (EC) that operates on a reverse cycle mechanism designed to provide cooling, primarily during the summer season, though not exclusively. The operation of the EC is described as:

$$Q_{EC}^{d\,t} = \eta_{EC} P_{EC}^{d\,t} \tag{16}$$

$$P_{EC}^{d\,t} \leq P_{EC}^{Cap} \tag{17}$$

where

$Q_{EC}^{d\,t}$ denotes the cooling output in the EC.

$P_{EC}^{d\,t}(kW)$ represents the electric power input in the EC.

P_{EC}^{Cap} displays the maximum capacity in the EC.

Absorption Chiller

The Absorption Chiller (AC) utilizes waste heat to generate cooling power. Its operation is governed by the following constraints:

$$Q_{AC}^{d\,t} = \eta_{AC} H_{AC}^{d\,t} \tag{18}$$

$$H_{AC}^{d\,t} \leq H_{AC}^{cap} \tag{19}$$

where

$Q_{AC}^{d\,t}$ is the cooling power output in the AC.

$H_{AC}^{d\,t}$ (kW) is the heating input in the AC.

η_{AC} is the efficiency parameter.

H_{AC}^{cap} is the parameter that denotes the capacity installation of AC.

Hydrogen Fuel Cell

Hydrogen can be injected into the Hydrogen Fuel Cell (HFC) to produce electric and thermal power. The HFC operations are described by the following constraints:

$$P_{HFC}^{d\,t} \leq \eta_{HFC}^{e} G_{H_2,HFC}^{d\,t} \tag{20}$$

$$H_{HFC}^{d\,t} \leq \eta_{HFC}^{h} G_{H_2,HFC}^{d\,t} \tag{21}$$

$$G_{H_2,HFC}^{d\,t} \leq G_{HFC}^{cap} \tag{22}$$

where

$P_{HFC}^{d\,t}(kW)$ is the power (thermal) output of HFC.

$G_{H_2,HFC}^{d\,t}\ (kW)$ is the hydrogen input of HFC.

η_{HFC}^{e} and η_{HFC}^{h} are parameters that represent the electricity and thermal generation efficiency of the HCP.

$G_{H_2,HFC}^{d\,t}$ represent the installed capacity in the HFC.

G_{HFC}^{cap} is the capacity installed in the HFC.

Hydrogen Storage Tank

The Hydrogen Storage Tank (HST) stores hydrogen produced from surplus energy, such as renewable sources, for later use by the GB, the CHP and the HFC or to satisfy the hydrogen load of the fuel cell electric vehicles.

$$S_{HST}^{d\,t} \leq S_{HST}^{cap} \tag{23}$$

$$P_{HST,ch}^{d\,t} \leq S_{HST}^{cap} - S_{HST}^{d\,t} \tag{24}$$

$$P_{HST,dis}^{d\,t} \leq S_{HST}^{d\,t} \tag{25}$$

$$S_{HST}^{1\,1} = S_{HST}^{DT} \tag{26}$$

$$S_{HST}^{d\,t} = S_{HST}^{d\,t-1} + P_{HST,ch}^{d\,t} - P_{HST,dis}^{d\,t} \tag{27}$$

where

$S_{HST}^{d\,t}$ is the state of change.

S_{HST}^{cap} represent the installed capacity of the HST.

$P_{HST,ch}^{d\,t}$ and $P_{HST,dis}^{d\,t}$ are variables that represent, respectively the charge and discharge in the HFC.

Battery Storage System

The Battery Storage System (BSS) is a device that stores electricity when total power generation exceeds the total load or when electricity prices drop significantly, making it economically advantageous to purchase and store additional power for later use. The battery provides electric energy during periods of high demand, compensating for peaks that cannot be met by the intermittent power generation of renewable energy sources. The introduction of the following constraints is needed:

$$S_{BT}^{d\,t} = S_{BT}^{d\,t-1}(1-\delta_{BT}) + (\eta_{BT}^{ch} P_{BT,ch}^{d\,t} - \frac{P_{BT,dis}^{d\,t}}{\eta_{BT}^{dis}}) \tag{28}$$

$$S_{BT}^{d\,t} \le S_{BT}^{cap} \tag{29}$$

$$P_{BT,ch}^{d\,t} \le S_{BT}^{cap} - S_{BT}^{d\,t} \tag{30}$$

$$P_{BT,dis}^{d\,t} \le S_{BT}^{cap} \tag{31}$$

where

$S_{BT}^{d\,t}$, $P_{BT,ch}^{d\,t}$, $P_{BT,dis}^{d\,t}$ and $S_{BT}^{cap}(kW)$ are non-negative variables that measure, respectively, the state of the battery, the power charging and discharging of the BSS on day d at time instant t and the capacity of BSS that is an input parameter.

δ_{BT} is a parameter that expresses the energy loss rate.

η_{BT}^{ch} and η_{BT}^{dis} are two parameters that display the amount of charging and discharging efficiency.

Constraint (28) shows the relation between the state of charge within every two consecutive time instants with the amount of charging and discharging power.

Meanwhile constraint (29) denotes the relation between the state of the charge and the installed capacity.

Constraint (30) and (31) express the logical bounds on the power charge and discharge. Since the technology in BSS does not allow simultaneous power charge and discharge the binary variable $\chi_{BT}^{d\,t}$ is introduced. The following constraints are introduced.

$$P_{BT,ch}^{d\,t} \le \mathrm{M}\chi_{BT}^{d\,t} \tag{32}$$

$$P_{BT,dis}^{d\,t} \le M(1-\chi_{BT}^{d\,t}) \tag{33}$$

The four following equations express the *power balance constraints* between the load and the unload of the four types of demand considered by the problem which are electric, cooling, heating and hydrogen.

$$P_{Buy}^{d\,t} + P_{PV}^{d\,t} + P_{WT}^{d\,t} + P_{CHP}^{d\,t} + P_{HFC}^{d\,t} + P_{BP,dis}^{d\,t} = P_{Load}^{d\,t} + P_{EB}^{d\,t} + P_{EC}^{d\,t} + P_{EL}^{d\,t} + P_{BT,ch}^{d\,t} \tag{34}$$

$$H_{CHP}^{d\,t} + H_{EB}^{d\,t} + H_{GB}^{d\,t} + H_{HFC}^{d\,t} = H_{Load}^{d\,t} + H_{AC}^{d\,t} \tag{35}$$

$$Q_{AC}^{d\,t} + Q_{EC}^{d\,t} = Q_{Load}^{d\,t} \tag{36}$$

$$H_{2\,Load}^{d\,t} + G_{H_2,GB}^{d\,t} + P_{BT,dis}^{d\,t} \leq G_{H_2,CHP}^{d\,t} + P_{HST,ch}^{d\,t} = G_{H_2,Tot}^{d\,t} + P_{HST,dis}^{d\,t} + H_{2\,Buy}^{d\,t} \tag{37}$$

where

$P_{Load}^{d\,t}$, $H_{Load}^{d\,t}$, $Q_{Load}^{d\,t}$ and $H_{2\,Load}^{d\,t}$ represent respectively electric, heating, cooling and hydrogen demand loads.

Constraint (34) expresses the balance in terms of electrical power.

On the left side of the equation, there are the "generators" of electrical energy, meaning the devices that supply electrical power. These include the photovoltaic field, CHP, hydrogen fuel cells and the power discharged from the battery.

On the right side of the equation, there are the loads, which represent all devices and systems that consume electrical power. These include the electrical load, power sold to the grid, power stored in the battery system and the power required to operate the electric boiler, electric chiller and electrolyzer.

Constraint (35) instead expresses the thermal power balance. Similarly to constraint (34), the thermal load and the input of the absorption chiller are found on the right side of the equation.

On the left side, there is the thermal power produced by the CHP, electric boiler and gas boiler. It is specified that the thermal power from the solar thermal system is not included, as it is directly stored.

Constraint (36) is conceptually identical to the previous ones and it expresses the cooling power balance.

Moreover, constraint (37) ensures that the total hydrogen consumption (loads, gas boiler and discharged battery) does not exceed the total production (CHPP and storage charging).

Additionally, the total hydrogen production is given by the sum of local production, discharged storage and purchased hydrogen.

This relationship is essential to ensure energy balance and optimize the system's operation.

The following set of constraints show the relation between the activation of the hydrogen-base technologies and the capacity installation:

$$P_{EL}^{cap} \leq Mx_{EL} \tag{38}$$
$$G_{HFC}^{cap} \leq Mx_{HFC} \tag{39}$$
$$S_{HFC}^{cap} \leq Mx_{HST} \tag{40}$$
$$P_{EL}^{cap} \geq \epsilon x_{EL} \tag{41}$$
$$S_{HFC}^{cap} \geq \epsilon x_{HFC} \tag{42}$$
$$S_{HFC}^{cap} \geq \epsilon x_{HST} \tag{43}$$
$$x_{EL}, x_{HFC}, x_{HST} \in \{0, 1\} \tag{44}$$

where
ϵ denotes the very small values.
M is the large values.

4.1 Implementation of the mathematical model

The following section will provide a detailed illustration and description of the mathematical model underlying the IES. Specifically, it is a linear model and, more precisely, a Mixed-Integer Programming (MIP) problem, which involves both continuous and integer variables. It is important to highlight that the purpose of this study is to size the devices and evaluate power dispatching at the lowest possible cost.

The mixed-integer programming model for the IES is detailed to determine the optimal scheduling of various technologies and the optimal capacity sizing for the electrolyzer, hydrogen fuel cell, and hydrogen storage tank. The objective is to minimize the total annual cost, which includes investment costs (excluding the portion covered by policymakers), operating and maintenance costs, and energy procurement costs.

To address long-term decisions regarding capacity sizing and installation, as well as operational scheduling, the IES stakeholders adopt a planning horizon of one year. This timeline is divided into days and hours to accurately capture variations in renewable energy resources, demand loads, and energy prices. Two sets are presented:

$\mathcal{D}$ ($\mathcal{D} = \{1, \cdots, d, \cdots, D\}$)

$\mathcal{T}$ ($\mathcal{T} = \{1, \cdots, t, \cdots, T\}$)

The first one represents the set of twelve nominal days, while the second one represents the period time used to break down each day.

In an optimization model, it is important to define the objective function. It is presented below:

$$\min: Z^{LL} = C_{Inv} + C_{EPS} + C_{OM} \tag{45}$$

where

C_{Inv} represents the investment costs for each device.

C_{EPS} represents the energy exchange cost.

C_{OM} represents maintenance cost during a year.

The formula for the investment cost takes into account the annual depreciation as a function of the device lifecycle (46).

$$C_{Inv} = \sum_{d=1}^{D}\sum_{t=1}^{K}\sum_{k=1}^{T}\left(1 - r_{Inc,k}\right)\Gamma_k^{cap}\,\frac{i(i+1)^{Y_k}}{(i+1)^{Y_k}-1} \tag{46}$$

$$C_{EPS} = \sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{k=1}^{K} N_d\,[\lambda_{\mathrm{Buy}}^{\mathrm{d\,t}}P_{\mathrm{Buy}}^{\mathrm{d\,t}} + \beta_{Gas}\left(G_{CHP}^{d\,t} + G_{GB}^{d\,t}\right) + \phi_{H_2}^{d\,t}H_{2Buy}^{d\,t}] \tag{47}$$

$$C_{OM} = \sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{k=1}^{K}\epsilon_k\Gamma_k^{cap} \tag{48}$$

where

γ and Y_k denote the installation costs per unit of capacity and the life cycle of device *k*.

K represents the total number of energy devices in the IES.

N_d denotes the number of days of type *d* over the year.

i represents the interest rate which is equal to 6%.

Γ_k^{cap} represents the capacity installation of device *k*.

β_{Gas} is the gas purchase price from the gas network.

$\lambda_{\mathrm{Buy}}^{\mathrm{d\,t}}$ denotes the electricity purchase price from the grid network.

$\phi_{H_2}^{d\,t}$ represents the hydrogen purchase cost.

$G_{CHP}^{d\,t}$ and $G_{GB}^{d\,t}$ are variables that represent the amount of natural gas network to supply the methane fuel for the CHPP and the GB respectively.
ϵ_k is a parameter that denotes the unit maintenance cost of device k.

	CHP	EB	PV	GB	EL	AC	EC
Installation Costs ($/kW)	1059	76	1319	113	750	118	169
Lifetime (year)	20	20	20	20	15	20	15

Tab 4.1 – IES economic parameters

In terms of the energy exchange cost it's present the electricity purchase price which is multiplied by the energy power bought from the network. For thermal energy, only the primary fuel consumption in the CHPP and the gas boiler is considered. It is specified that both consumption and power exchanged with the grid are variables, while the remaining items are parameters, which are shown below:

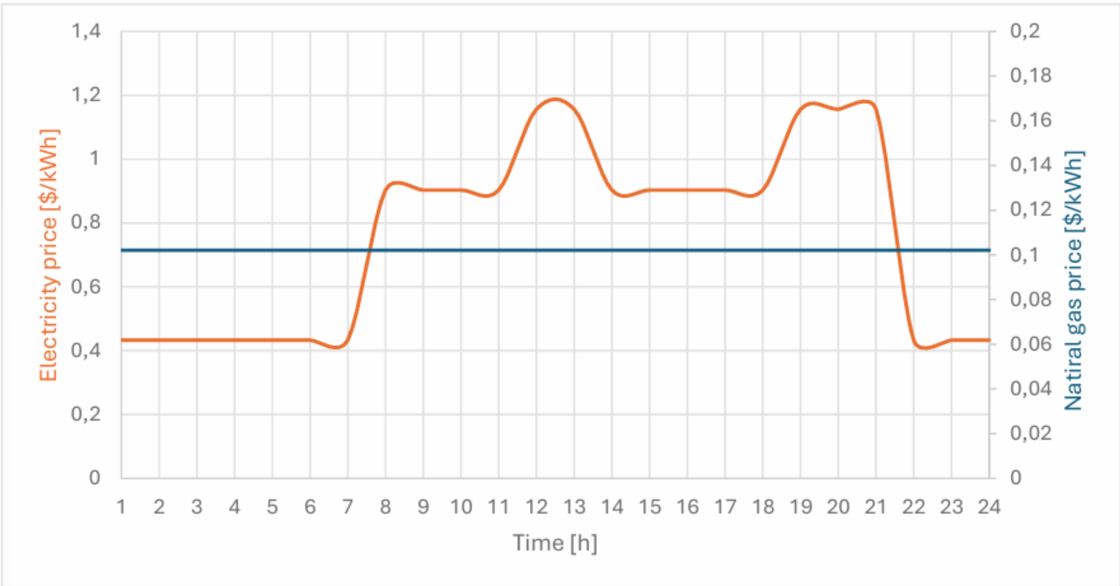


Figure 4.1.1 – Price of electric energy and gas

P_k^{MAX} represents the optimal installed capacity for each device, which is known only in the case of the photovoltaic system, and the electrolyzer. In the first case, the power of the field is determined using the maximum irradiation. For the electrolyzer, the nominal capacity is known. The remaining installed capacities are variables and are subject to sizing in the study.
Capacities for all devices except Electrolyzer (EL), Hydrogen Fuel Cell (HFC), and Hydrogen Storage Tank (HST) are fixed. We set constraints in the Upper Level (UL) to force the activation of EL and HFC and HST and UL minimizes the total incentive cost paid to the IES plus the Co2 cost.

The Lower Level minimizes the cost of energy purchase, investment (only the part not supported by the policy maker), and the maintenance costs.

The LL model is expressed from formula (1) to formula (48) and the lower level subproblem is modeled by the objective function expressed in the formula (45).

The policy maker authorities are considered the UL decision makers who aim to minimize the incentive cost for EL, HFC and HST and the environmental costs of CO2.

min:

$$Z^{UL} = \sum_{d=1}^{D} N_d \left(\sum_{t=1}^{T} r_{EL} P_{EL}^{cap} \frac{i(i+1)^{Y^{EL}}}{(i+1)} + r_{HFC} Get_{HFC}^{cap} \frac{i(i+1)^{Y_{HFC}}}{i(i+1)^{Y_{HFC}-1}} + r_{HST} S_{HST}^{cap} \frac{i(i+1)^{Y_{HST}}}{(i+1)^{Y_{HST}-1}} \right) + \sum_{d=1}^{D} Ndr \sum_{t=1}^{T} \sum_{k=1}^{K} \phi^e \left(P_{Buy}^{d\,t} + P_{CHP}^{cap} \right) + \phi^g \left(P_{CHP}^{d\,t} + P_{GB}^{d\,t} \right) \tag{49}$$

$$x_{EL} + x_{HFC} + x_{HST} = 3 \tag{50}$$

$$r_{EL} + r_{HFC} + r_{HST} \leq r_{MAX} \tag{51}$$

$$r_k = 0.1 \sum_{j=1}^{J} j z_k^j \quad k = \text{EL, HFC, HST} \tag{52}$$

$$\sum_{j=1}^{J} z_k^j = 1 \qquad k = \text{EL, HFC, HST} \tag{53}$$

$$z_k^j \in \{0, 1\}, \qquad \text{k} = \text{EL, HFC, HST} \tag{54}$$

where

ϕ^e and ϕ^g and *r* are parameters that show respectively the market carbon tax price, emission price of energy and gas flows. There is no compensation for the electric power produced by the HFC since it is carbon-free.

r_{MAX} represent the maximum upper bound of the total incentives.

z_k^j is a binary variable that discretizes the incentive rate r_k where $\text{j} \in \{0, 1, 2, \dots, \text{j}, \dots, \text{J}\}$.

The Upper level subproblem is modeled by the objective function (49) and the set of constraints (50)-(54).

In the paper we considered 3 different incentives for 3 different technologies but in the implementation, we consider all of them equal so basically 1 constraint.

These models represent a bi-level optimization process that involves two hierarchical levels of decision-making. This type of problem is common in energy system modeling, where one decision-maker (the "Leader") makes strategic decisions, and another (the "Follower") makes operational decisions.

It is specified that all cost items, and consequently the objective function, are non-negative variables.

5. AIMMS Software

AIMMS (which stands for Advanced Interactive Multidimensional Modeling System) is an advanced software platform designed for mathematical modeling and optimization of complex planning and decision-making problems. It has two main product offerings that provide modelling and optimization capabilities across a variety of industries. The AIMMS Prescriptive Analytics Platform allows advanced users to develop optimization-based applications and deploy them to business users. AIMMS SC Navigator, launched in 2017, is built on the AIMMS Prescriptive Analytics Platform and provides configurable Apps for supply chain teams. SC Navigator provides supply chain analytics to non-advanced users.

Along with a growing interest in embedded advanced analytics for supply chain management, AIMMS developed the AIMMS SC Navigator Platform to allow for supply chain analytics.

The AIMMS Prescriptive Analytics Platform consists of an algebraic modelling language, an integrated development environment for both editing models and creating a graphical user interface around these models, and a graphical end-user environment. AIMMS is linked to multiple solvers through the AIMMS Open Solver Interface. Supported solvers include CPLEX, MOSEK, FICO Xpress, CBC, Conopt, MINOS, IPOPT, SNOPT, KNITRO and CP Optimizer.

AIMMS features a mixture of declarative and imperative programming styles. Formulation of optimization models takes place through declarative language elements such as sets and indices, as well as scalar and multidimensional parameters, variables and constraints, which are common to all algebraic modelling languages, and allow for a concise description of most problems in the domain of mathematical optimization. Units of measurement are natively supported in the language, and compile- and runtime unit analysis may be employed to detect modelling errors.

Procedures and control flow statements are available in AIMMS for the exchange of data with external data sources such as spreadsheets, databases, XML and text files data pre- and post-processing tasks around optimization models user interface event handling the construction of hybrid algorithms for problem types for which no direct efficient solvers are available.

To support the re-use of common modelling components, AIMMS allows modelers to organize their model in user model libraries.

AIMMS supports a wide range of mathematical optimization problem types, such as linear programming, quadratic programming, nonlinear programming, mixed-integer programming, mixed-integer nonlinear programming, global optimization, complementarity problems (MPECs), stochastic programming, robust optimization and constraint programming.

Uncertainty can be taken into account in deterministic linear and mixed integer optimization models in AIMMS through the specification of additional attributes, such that stochastic or robust optimization techniques can be applied alongside the existing deterministic solution techniques.

Custom hybrid and decomposition algorithms can be constructed using the GMP system library which makes available at the modelling level many of the basic building blocks used internally by the higher-level solution methods present in AIMMS, matrix modification methods, as well as specialized steps for customizing solution algorithms for specific problem types.

Optimization solutions created with AIMMS can be used either as a standalone desktop application or can be embedded as a software component in other applications.

Primarily used in business, industrial, and operations research applications, AIMMS enables the construction of mathematical models that describe complex systems and facilitates the solution of problems through optimization techniques.

The main application of AIMMS is optimization, which involves finding the best solution based on specific criteria such as cost minimization or efficiency maximization, in contexts that involve multiple constraints and objectives. The software stands out for its ability to handle complex models without requiring advanced programming skills, thanks to an intuitive graphical interface and advanced modeling tools that simplify the process of creating, testing, and solving optimization models.

AIMMS Prescriptive Analytics Platform is used in a wide range of industries including retail, consumer products, healthcare, oil and chemicals, steel production and agribusiness.

5.1 The model on AIMMS software

In this chapter we are going to delve into the transformation of the mathematical model present is transferred and inserted inside AIMMS program. Objective functions, constraints, parameters, sets and variables are considered.

5.1.1 Sets

Declarations in AIMMS establish the structure and relationships of the model before any computations or optimizations take place. They are the foundation of a well-defined mathematical model. Declarations allow the definition of the model structure before execution, ensure clarity and modularity in the optimization process, moreover, improve computational efficiency by clearly specifying relationships.

A set is a collection of elements, typically representing entities such as products, time periods, or decision variables.

The set declaration defines collections of elements that can be used as indices in parameters and variables.

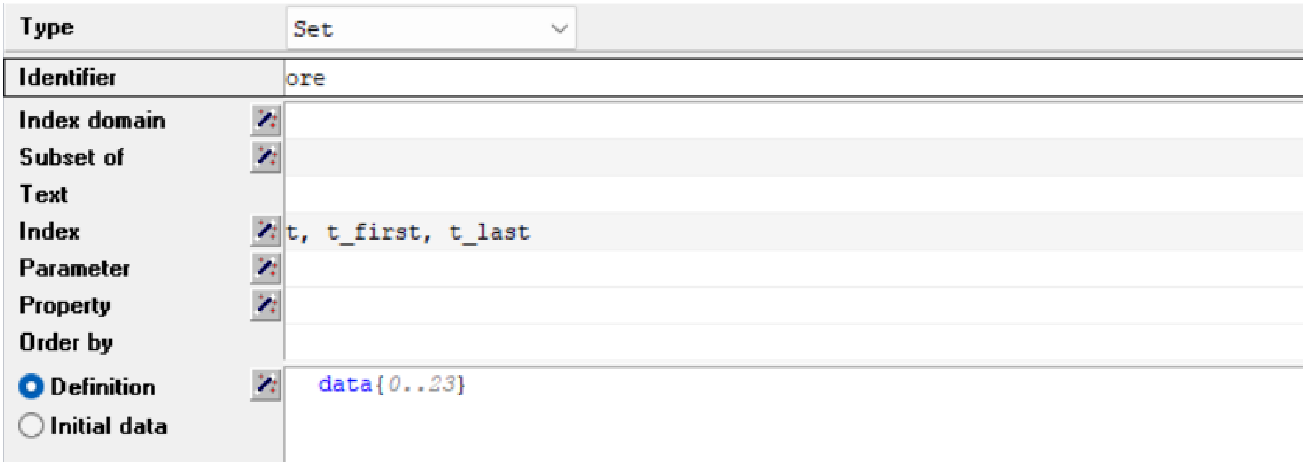


Figure 5.1.1.1: Hours Set

The set hours can assume values from 0 up to 23 in order to consider the energy, heating and cooling production and consumption over the entire typical day *d*.
Meanwhile the following set defines the total amount of months take into account in a year (0-11).

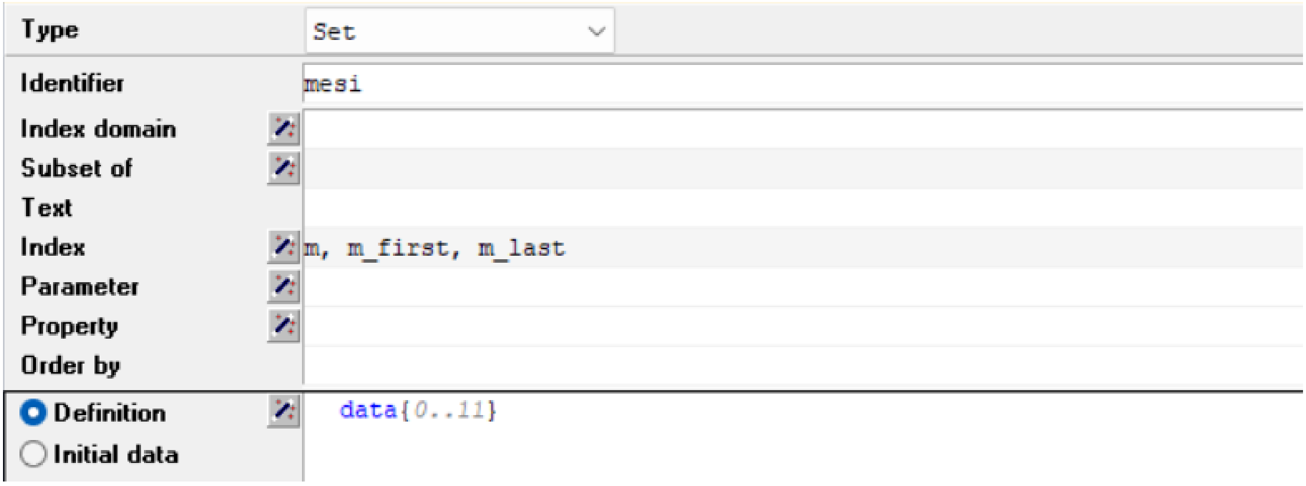


Figure 5.1.1.2: Hours Set

Lastly, the following set considers all the 12 technologies taken into account in the bi-level problem.

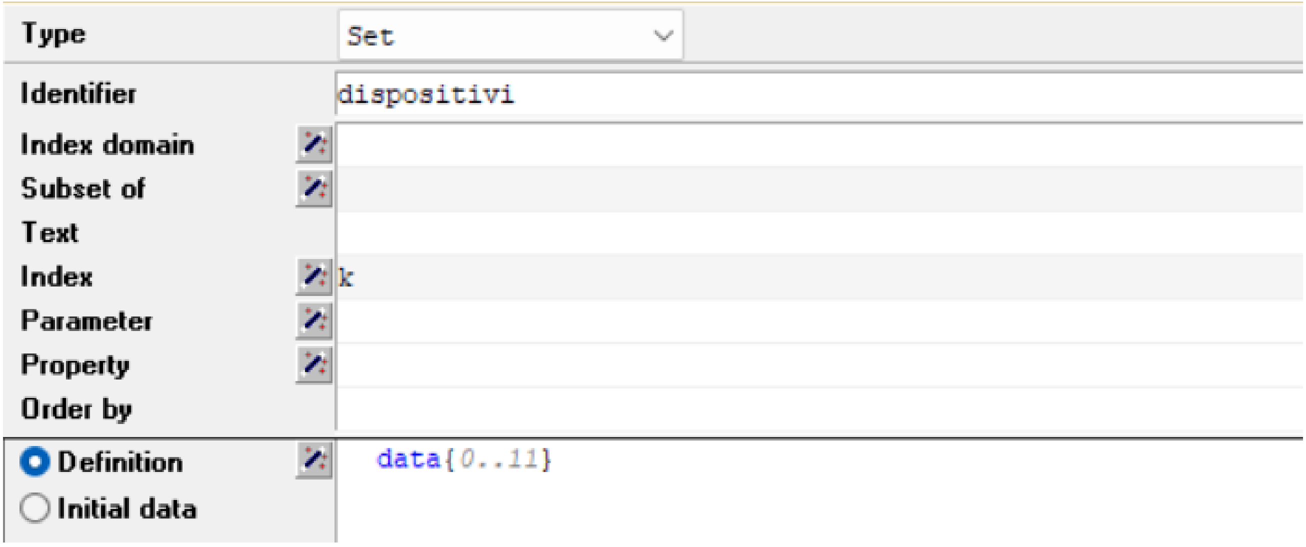
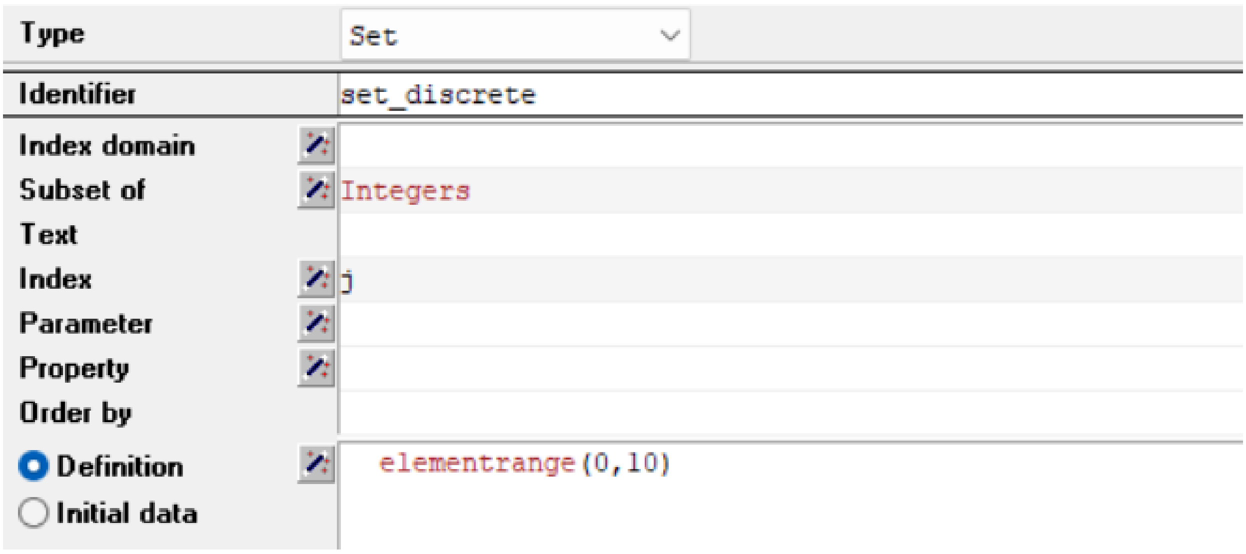


Figure 5.1.1.3: Technologies Set



5.1.2 Variables

In AIMMS, variables represent decision points in an optimization model. They are the values that AIMMS determines to achieve the best solution while satisfying constraints.
Variables can be continuous (any real number), integer (whole numbers), or binary (0 or 1).
Variables are used in objective functions and constraints, guiding the optimization process toward an optimal solution.

5.1.3 Parameters

Parameters are used to store data since they hold constant or predefined values used in a mathematical model, such as costs, demand, supply, efficiency rates.
In AIMMS, parameters are constant or data-driven values that store numerical information used in mathematical models. They can be scalars (single values) or indexed (linked to sets).
Parameters are essential for defining costs, capacities, demand, and other fixed or data-dependent values in optimization models. They allow the model to adapt dynamically based on input data.
Parameters can be static like fixed values or dynamic such as computed during execution using expressions or external data sources.

5.1.4. Constraints

In AIMMS, constraints are mathematical expressions that limit the values decision variables can take in an optimization model. They define feasibility conditions based on available resources, demand, or operational limits.

Constraints are typically written as inequalities or equalities involving variables and parameters.
Constraints help enforce business rules, physical limits, or regulatory requirements, ensuring that the solution remains practical and optimal.

5.1.5. Objective function

In AIMMS, the objective function is a mathematical expression that defines the goal of an optimization model. It is the function that AIMMS maximizes (e.g., profit) or minimizes (e.g., cost).

The objective function depends on decision variables and often includes parameters representing costs, revenues, or efficiencies.
The objective function guides the solver to find the best possible decision values while satisfying constraints.
In this case, we consider two objective functions depending on whether we are considering the upper or the lower level.

5.1.6 Mathematical Program

A mathematical model in AIMMS is a formal representation of a problem that describes relationships between variables using mathematical expressions like equations, inequalities, and objective functions. The model includes decision variables, constraints and an objective to be optimized. AIMMS allows you to define these components using its intuitive modeling language, making it easier to translate real-world problems into a structured format. The mathematical model can represent various types of problems, from linear programming to nonlinear and mixed-integer programming. Once the model is created, AIMMS uses solvers to find the best solution based on the defined objective. The model serves as the foundation for analysis and decision-making in optimization tasks.

5.1.7 Dataset

In AIMMS, data refers to the numerical or categorical values assigned to parameters, sets, and variables in a model. Data provides the necessary inputs for calculations, constraints, and optimization. Data can be static (manually defined in the model) or dynamic (imported from external sources like Excel or databases).
Data is crucial in AIMMS models as it feeds the optimization process, ensuring realistic and accurate results.

5.1.8 Procedure

In AIMMS, a procedure is a block of code that performs a specific task or function when called. Procedures can include a series of statements such as assignments, loops, and conditional operations. They allow for the modularization of code, making it reusable and easier to maintain. A procedure can accept parameters, which are input values passed to it when called, and it can return results. Procedures are typically used to implement complex logic or calculations that need to be performed multiple times within a model. They are useful for improving the readability and organization of the model by avoiding code duplication.

Additionally, AIMMS supports both built-in and user-defined procedures.

This section presents partially the code for the procedures used to solve the model.

The following figures represent the procedure of the bi-level model taken into consideration.

Some parts of the codes will be presented in the following snapshots.

```
Body

Elapsed_HPR(iterpar):=HPR_Model.SolutionTime;  Elapsed_LL(iterpar):=LL_Model.SolutionTime;

UB(iterpar):=  0.1* [sum (j,j*zpar_incen(j))*cap_EL*CC_EL*((i*(1+i)^LF_EL))/(((1+i)^LF_EL)-1)
+sum (j,j*zpar_incen(j))*cap_HFC*CC_HFC*((i*(1+i)^LF_HFC))/(((1+i)^LF_HFC)-1)
+sum (j,j*zpar_incen(j))*cap_HST*CC_HST*((i*(1+i)^LF_HST))/(((1+i)^LF_HST)-1) ]
+
[r*(sum(m,N(m)*sum(t,costoeq_metano*(F_CHP(m,t)+F_GB(m,t))+
costoeq_el*(Cap_CHP+P_buy(m,t))+ costEq_H2_buy*H2_buy(m,t)
)))
];

LB(iterpar):=HPR_Model.Objective  - MM * sum(iter, D(iter));
record_objs(iterpar,'Leader'):=UB(iterpar);
record_objs(iterpar,'Follower'):=LL_Model.Objective;

display HPR_Model.Objective, UB,LB,record_objs;

if(UB(iterpar) < Incumbent) then
display "update";
Incumbent:=UB(iterpar); best_iter:=iterpar;
Best_cap_EL:=cap_EL;  Best_cap_HFC:=cap_HFC;  Best_cap_HST:=cap_HST;
Best_Inc_EL:=vec_INC(iterpar);
display Incumbent;
endif;

!check_sol;
z_incen(j).nonvar:=0;
break when loopcount > Max_Iter or sp_ElapsedTime>108000 [s]
 or abs(UB(iterpar)-LB(iterpar) )<epsilon ;
endrepeat;

display diff, zpar_iter;
```

Figure 5.1.8.1

```
Body
+sum (j,j*zpar_incen(j))*cap_HST*CC_HST*((i*(1+i)^LF_HST))/(((1+i)^LF_HST)-1) ]
+
[r*(sum(m,N(m)*sum(t,costoeq_metano*(F_CHP(m,t)+F_GB(m,t))+
costoeq_el*(Cap_CHP+P_buy(m,t))+ costEq_H2_buy*H2_buy(m,t)
)))
];

LB(iterpar):=HPR_Model.Objective  - MM * sum(iter, D(iter));
record_objs(iterpar,'Leader'):=UB(iterpar);
record_objs(iterpar,'Follower'):=LL_Model.Objective;

display HPR_Model.Objective, UB,LB,record_objs;

if(UB(iterpar) < Incumbent) then
display "update";
Incumbent:=UB(iterpar); best_iter:=iterpar;
Best_cap_EL:=cap_EL;  Best_cap_HFC:=cap_HFC;  Best_cap_HST:=cap_HST;
Best_Inc_EL:=vec_INC(iterpar);
display Incumbent;
endif;

!check_sol;
z_incen(j).nonvar:=0;
break when loopcount > Max_Iter or sp_ElapsedTime>108000 [s]
 or abs(UB(iterpar)-LB(iterpar) )<epsilon ;
endrepeat;

display diff, zpar_iter;
sp_ElapsedTime := CurrentToMoment( [tick], sp_StartTime );
cap_HFC.nonvar:=0; activate_HFC.nonvar:=0;
z_incen(j).nonvar:=0;
P_pv_MAX.nonvar:=0;
```

Figure 5.1.8.2

The solution method adopted was the same as in “A bi-level approach for last-mile delivery with multiple satellites” by Maria Elena Bruni, Sara Khodaparasti, Guido Perboli.

The origin of bi-level optimization problems dates back to the works of von Stackelberg and Peacock (1952) on game theory and, in particular, leader–follower games. The leader, that has information about the follower’s objectives, takes decisions first and communicates them to the follower, which reacts to the decision of the leader optimizing its own objective (Colson et al., 2007). As a result, the leader’s optimization problem is a nested problem, where the feasible set is partly determined by a second optimization problem (Dempe et al., 2019). This approach has been successfully applied to tackle decision making problems with a hierarchical nature in various fields, such as supply chain, energy sector, transportation network design, revenue management, to mention a few (Kleinert et al., 2021).

The bi-level model formulation allows to explicitly model the interaction between the follower or lower level (operators and energy providers) and the leader or upper level (policy authorities therefore the decision-makers).

6. *Outcome*

In AIMMS, results refer to the output values or data produced by the model after it has been solved or run. These results are typically the values of variables, parameters and objectives that have been calculated during the optimization or simulation process. Results help users understand how the model behaves and can be analyzed to make decisions or adjustments.

AIMMS allows you to view the results dynamically, offering flexibility to explore different scenarios. These results are key to interpreting the model's performance and ensuring it aligns with the objectives set in the beginning.

The bi-level model presents a high degree of complexity due to its hierarchical structure since the iterations and relations between the upper and lower-level decision-making processes introduces significant computational challenges. The interdependence of these two levels often results in a highly constrained optimization problem which requires advanced solution techniques to ensure the feasibility and convergence of the problems.

The development of the solution approach required a lot of computations and extensive trial to refine the methodology and ensure effectiveness.

Therefore, the presentation of the experimental results and managerial insights is deferred to future research.

7. *Conclusion*

In the transition towards a more sustainable and efficient energy system, Integrated Energy Systems play a significant role. These systems integrate multiple energy sources—such as electricity, heat, and hydrogen—to improve efficiency, reduce waste, and lower carbon emissions. Rather than managing energy sectors independently, an integrated approach allows for better resource optimization and enhances system reliability.

One of the key benefits of Integrated Energy Systems is their ability to balance supply and demand across different sectors. For instance, surplus electricity from solar panels can be stored in batteries or converted into hydrogen for later use. Likewise, heat produced by industrial processes or power plants can be recovered and repurposed for district heating, rather than being lost. By managing energy more intelligently, these systems help maximize the value of renewables and decrease reliance on fossil fuels.

Another advantage is increased resilience. Traditional energy networks can struggle with fluctuations in supply, particularly with variable sources like wind and solar. By integrating multiple energy carriers, IES can provide backup solutions and ensure a more stable supply, even during peak demand or periods of low renewable generation. This flexibility makes them a crucial part of the transition to a low-carbon energy system.

Despite their advantages, widespread adoption of Integrated Energy Systems still faces obstacles. A major challenge is the lack of strong incentives and supportive policies. While many governments encourage renewable energy development, there is limited research on how to effectively design incentives for green energy production and clean technologies implemented within an integrated framework.

To bridge this gap, future research should focus on developing policies that encourage businesses and consumers to invest in Integrated Energy Systems. This includes exploring efficient subsidy models, creating market-driven mechanisms for renewable energy trade and assessing the long-term economic benefits of IES.

For future studies a key gap in the literature concerns the impact of regional policy variations on IES adoption. While the study provides an optimized framework, it does not fully address the complexities of heterogeneous regulatory environments, such as differences in tax incentives, feed-in tariffs, and emission pricing mechanisms across countries. Future research should explore how different policy designs affect the scalability and feasibility of IES in diverse geographical contexts.

Despite significant advancements in IES research, several knowledge gaps persist. Future studies should focus on developing dynamic optimization models that account for energy price variability, evaluating the effectiveness of policy incentives across different regulatory frameworks. Addressing these gaps will be essential for the widespread adoption of IES in a decarbonized energy landscape.

In conclusion, Integrated Energy Systems have the potential to transform the energy landscape by making it cleaner, more efficient, and more resilient. However, their success depends on well-designed policies and incentives that promote their adoption. Addressing these gaps in both research and real-world applications will be crucial to advancing the energy transition and building a more sustainable future.

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