# THÈSE

Pour obtenir le grade de

## DOCTEUR DE L'UNIVERSITE GRENOBLE ALPES

Spécialité : **Génie Industriel, Conception et Production**

Arrêté ministériel : 25 mai 2016

Présentée par


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Préparée au sein du **LSET au CEA Liten**
Dans **l'École Doctorale I-MEP2 : Ingénierie – Matériaux, Mécanique, Environnement, Energétique, Procédés, Production**

# Méthodes de modélisation et d'optimisation technico-économique pour la planification de systèmes multi-énergies

# Techno-economic modelling and optimisation methods for the planning of multi-energy systems

Thèse soutenue publiquement le **14 décembre 2021**, devant le jury composé de :

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# Remerciements

Cette thèse fait suite à une première expérience au LSET. Cette expérience m'a offert l'opportunité et donné l'envie d'aller plus loin. D'excellentes conditions étaient alors réunies. Je pense en particulier à mon entourage professionnel et personnel. Je remercie donc toutes les personnes que j'ai côtoyé pendant ces trois belles années (ainsi que les précédentes).

Je souhaite tout d'abord remercier mes encadrants. Merci Alain d'avoir été si disponible et bienveillant au jour le jour, d'avoir autant travaillé à ce que les conditions techniques soient (aussi) au rendez-vous. Merci pour tes grandes qualités d'écoute. Merci Cyril pour ta pertinence, merci de m'avoir toujours aidé à prendre du recul et d'avoir été là autant que tu le pouvais. Merci Pierre pour ta grande pédagogie, ton soutien et ton enthousiasme pour cette thèse. Merci Bernard d'avoir dirigé ces travaux, d'y avoir contribué avec tes idées, tes qualités humaines et ton juste professionnalisme. Un grand merci à vous quatre donc, qui avez montré de l'intérêt pour ce sujet, et qui m'avez accordé tout ce temps. Nos échanges ont toujours été sincères, ouverts et passionnants : c'était un réel plaisir de travailler avec vous.

Mes remerciements vont également aux membres du jury. Merci à Christophe Berenguer, Safia Kedad-Sidhoum, Bruno François, Christophe Rapine et à Fabien Perdu. Merci pour le temps que vous avez consacré à ce travail. Merci pour votre regard, vos remarques attentives et pertinentes. Merci pour votre précieuse approbation, qui vaut plus qu'un diplôme à mes yeux.

Je souhaite remercier l'ensemble des membres de mon laboratoire, et en particulier l'équipe Grenobloise avec qui j'ai eu grand plaisir à travailler, échanger, festoyer. Merci à tous les (anciens) habitants du bureau des ‘‘précaires’’ à savoir Amélia, Hemant, Pimprenelle, Quentin, Sacha, Sophie, Yannis, et tous ceux qui y ont séjourné, même quelques semaines. Merci pour les rires et la complicité. Merci également à Cécile, Julie, Elise, Florent, Gilles, Hélène, Roland, Stéphanie, Philippe, Pierre-André, Valérie, Vincent, mais aussi à Cédric et Stéphane, ainsi que Benoit, Boris et Hugo. Merci pour les précieuses pauses café, les petites attentions sucrées/salées, les après-travail. Merci aux Chambériens et à leur hospitalité autour de barbecues solaires. Merci à tous les autres collègues du CEA dont j'ai croisé la route. Merci à Arthur pour nos échanges, et merci à Joséphine, Eglantine et Sarah pour votre aide.

Je remonte en arrière pour exprimer ma reconnaissance à tous les professeurs et enseignants qui ont (souvent) fait de ma scolarité un plaisir. Je pense en particulier à Danièle Gibbons, sans qui mes études supérieures auraient été autrement plus difficiles. Merci pour la passion et la rigueur avec lesquelles tu as enseigné.

Un grand merci à tous mes amis, les plus proches comme les plus éloignés dans le temps et dans l'espace. Je pense aux amis de longue date : Anaëlle, Camille, Cassandre, Corentin, Gibii, Julie, Louise, Lucile, Marion, les Maximes, Sam, Sylvain et tous les autres pour leur fraîcheur. Je remercie bien sûr les copains de l'INP avec qui j'ai tant partagé : Alice, Amani, Camille, Hugo, Jeanne, Lucie, Marine, Martin, Tarik et ceux que j'ai perdu de vue. Merci à cette équipe (encore un peu) Grenobloise que j'affectionne particulièrement : Amélia, Hemant, Julie, Nelly, Pacco, Pierre, Quentin, Sacha, Z et Zoé. Merci aux musiciens qui m'ont aidé à décompresser : JB, Joachim, Maël, Thomas, Luigi, Mathieu et Sophie. Merci à tous ceux que j'ai rencontré au fil de l'eau : Antoine, Eugénie, Marie-Mélina, Maxime, Nicolas et tous les autres.

Merci Anna pour ta tendresse et tes argumentaires animés.

Je termine en remerciant ma famille. Merci à mes parents qui nous ont tant donné, soutenu et exprimé leur fierté. Merci Maman, Papa pour votre amour. Merci Valentine, notre complicité m'est si précieuse. Merci Emilou de m'emplir de fierté. Merci Grand-Mère, Mamie pour toutes vos attentions, merci JC pour ton humour. Merci Cath pour ta bonne humeur contagieuse, merci Marco pour ta patience et ta générosité. Merci aussi à toute ma famille plus éloignée, avec une pensée particulière pour ma tante Odile et mes cousins Clément, Robin et Lucas. J'ai toujours tant de plaisir à vous rendre visite. Merci Serge pour l'exemple que tu as été.

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# Introduction

Le changement climatique constitue un défi colossal. Parmi les impacts des activités humaines sur son environnement, le changement climatique est celui qui représente, en retour, la plus grande menace pour les êtres humains [1]. La taille de ce défi est aussi due à son universalité. Bien que chacun contribue et soit affecté par le changement climatique de manière inégale [2–4], chacun est partie prenante. La planète Terre avec son climat est notre plus grand bien commun, et l'ampleur du défi nécessite d'agir à toutes les échelles possibles [5].

Le constat scientifique est sans équivoque : atténuer le changement climatique nécessite une réduction rapide et conséquente des émissions de gaz à effets de serre [1]. Le principal levier consiste à changer notre manière de produire et de consommer de l'énergie [6]. En effet, cette énergie provient majoritairement du pétrole, du charbon et du gaz [7], sources émettrices de $CO_2$. Pour réduire la consommation de ces ressources, trois stratégies existent :

- La sobriété, qui consiste à changer nos modes de vie pour réduire notre besoin et consommer moins d'énergie finale (baisser le thermostat du radiateur par exemple).
- L'efficacité énergétique, qui consiste à assurer un besoin en consommant moins d'énergie primaire (utiliser une chaudière à haut rendement, ou isoler thermiquement un logement par exemple).
- Remplacer l'usage d'énergies primaires carbonées par des sources moins carbonées (utiliser une chaudière à bois plutôt qu'une chaudière consommant du fioul par exemple).

Non sans oublier le premier point, nous nous concentrons maintenant sur les deux derniers. L'efficacité énergétique peut être améliorée en travaillant sur les processus qui consomment et/ou transforment l'énergie, en mutualisant les ressources et les besoins, en utilisant des énergies fatales ou de récupération, et en recherchant la complémentarité entre vecteurs énergétiques (électricité, chaleur, froid, gaz, *etc.*). Les sources d'énergies peu carbonées incluent l'énergie hydraulique, géothermique, nucléaire, solaire, éolienne *etc*. Ces deux dernières ne peuvent être pilotées, et leur production n'est pas toujours en phase avec la demande. Ce déphasage nécessite le recours à la flexibilité d'autres moyens de production (hydrauliques, nucléaires, fossiles), voire à des sources de flexibilité supplémentaires comme le stockage d'énergie [8].

Travailler sur l'efficacité énergétique et le remplacement d'énergies primaires carbonées par des sources moins carbonées peut se faire à plusieurs échelles. Cette thèse concerne l'échelle locale : industries, quartiers, villes ou territoires. En revanche, les méthodes citées et développées par la suite ne sont pas exclusivement réservées à cette échelle. Nous parlerons de systèmes énergétiques pour désigner les principaux composants technologiques qui, utilisés ensemble, permettent de produire, convertir, stocker et transporter de l'énergie vers un consommateur. Quelques exemples : un réseau de chaleur urbain, un processus industriel couplé à une production d'énergie locale, une production d'hydrogène et d'électricité pour alimenter une flotte de véhicules.

La conception (ou l'éco-conception) de systèmes énergétiques passe par plusieurs étapes. La Figure 1 illustre les étapes typiques d'un tel projet, jusqu'à la gestion opérationnelle du système. Cette thèse concerne les étapes de faisabilité et de préconception.

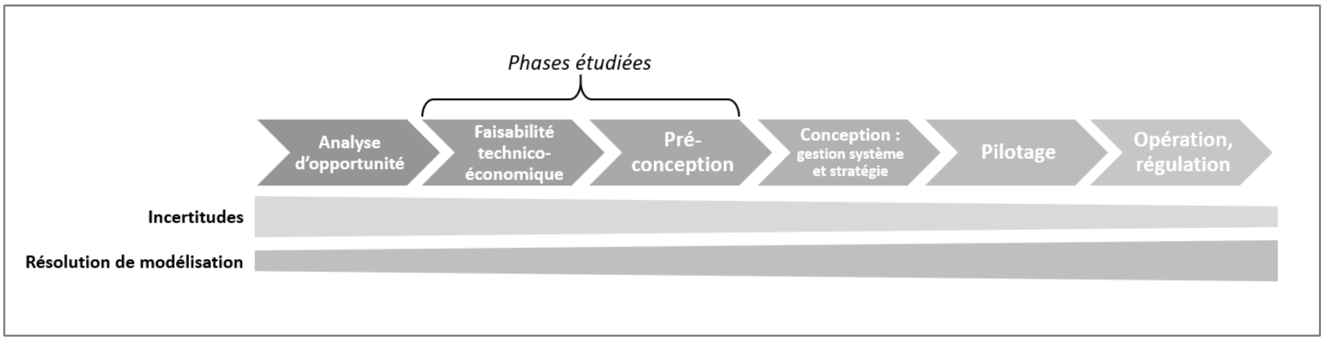


*Figure 1 : Etapes d'un projet de conception et d'utilisation d'un système énergétique*

La question de la viabilité de ces projets est une question complexe. Cette complexité provient d'une part de la diversité et de la multitude d'acteurs concernés, potentiellement dissociés : concepteurs, investisseurs, conseillers experts, opérateurs, fournisseurs, ou encore usagers. La dimension politique, d'abord présente pour des questions d'emploi ou d'accès à l'énergie est aujourd'hui essentielle pour considérer la dimension écologique dans de tels projet. Cette dernière est éminemment complexe, de par son étendue à toute la durée de vie du projet et de par la multitude d'indicateurs qu'elle englobe [9]. Simultanément, la durée de vie des projets, la diversité des ressources et les incertitudes quant à leur accessibilité future rend l'équation économique difficile à résoudre. Finalement, la complexité technique s'intensifie avec l'utilisation de ressources intermittentes ou fatales, et la recherche de complémentarité entre vecteurs énergétiques.

L'étude technico-économique de systèmes énergétiques traite des deux derniers aspects, et peut intégrer une partie de la dimension écologique sous la forme de contraintes où de pénalités financières sur les émissions de $CO_2$. Ces études nécessitent d'évaluer le fonctionnement du système sur plusieurs dizaines d'années pour trouver un compromis entre les coûts d'opération et les coûts d'investissement. Cette évaluation se fait en simulant / optimisant l'opération du système à chaque heure, avec un horizon d'anticipation plus ou moins long (un jour, une semaine ou un an par exemple). Il y a donc plusieurs échelles de temps à traiter. De plus, ces systèmes techniquement complexes peuvent inclure un grand nombre de composants, obéir à des règles de marché élaborées ou encore dépendre de paramètres incertains.

La modélisation mathématique est donc nécessaire et fait l'objet d'un compromis difficile à trouver entre les temps de calculs pour fournir des solutions, la pertinence (ou précision) des indicateurs et la complexité du modèle. Cette dernière peut rendre son élaboration plus couteuse et son interprétabilité plus difficile. La simplicité du modèle est donc une qualité essentielle [10].

L'objet de cette thèse est d'apporter des réponses à des questions au cœur de ces problématiques : Comment faire usage des méthodes disponibles pour l'étude et la planification technico-économique de systèmes multi-énergies ? Peut-on compléter le panel existant avec de nouvelles méthodes pertinentes ?

Ce manuscrit de thèse se présente sous la forme de plusieurs articles publiés ou en cours de soumission dans des journaux scientifiques. Les Chapitres 1, 2 et 4 correspondent à trois articles. Le Chapitre 3 est une note technique qui a été soumise avec l'article correspondant au Chapitre 2. Les chapitres sont donc rédigés en anglais, et introduits par un paragraphe en français.

Le Chapitre 1, un état de l'art, dresse un tableau des méthodes existantes au travers de leurs utilisations. Le Chapitre 2 présente deux nouvelles méthodes pour évaluer et optimiser le fonctionnement de systèmes énergétiques. Les deux méthodes se distinguent de par leur capacité à utiliser des horizons d'anticipation longs (typiquement un an), tout en représentant dans le détail le fonctionnement du système à l'échelle horaire. Le Chapitre 3 teste ces deux méthodes sur un ensemble de cas élémentaires supplémentaires. Puis, le Chapitre 4 illustre sur un cas d'étude l'impact d'hypothèses de modélisation et revient sur l'intérêt de complexifier un modèle pour améliorer la finesse des résultats, les temps de calculs, ou valider/invalider les hypothèses initiales. Finalement, la Conclusion résume les travaux réalisés pour répondre aux deux questions posées. Elle complète également les réponses aux questions en synthétisant les options méthodologiques disponibles en fonction des objectifs de l'étude et des difficultés calculatoires rencontrées.

# Chapitre 1

Ce premier chapitre constitue l'état de l'art de cette thèse. L'état de l'art est basé sur une grille de lecture originale. L'objectif est de donner une vision large et synthétique des méthodes de simulation et d'optimisation qui peuvent être utilisées dans le cadre d'études technico-économiques. Ces études permettent de mieux comprendre, concevoir et planifier l'évolution des systèmes énergétiques. Cet état de l'art concerne en particulier les méthodes utilisées à l'échelle industrielle, urbaine, ou territoriale, bien que des méthodes utilisées à des échelles supérieures puissent être pertinentes à l'échelle locale, et inversement. Ce chapitre permettra de mieux se saisir des questions motivant les études, des hypothèses de modélisation, des algorithmes utilisés et des difficultés calculatoires engendrées. Ces aspects sont interdépendants et cet état de l'art permet aussi d'en comprendre les articulations. Ce travail est un préambule à l'élaboration de méthodes innovantes et pertinentes. Il est d'autant plus important que la littérature concernant la modélisation et la simulation de systèmes énergétiques est riche et foisonnante.

L'article qui suit a été publié dans l'International Journal Of Energy Research :

*Cuisinier E, Bourasseau C, Ruby A, Lemaire P, Penz B. Techno-economic planning of local energy systems through optimization models: a survey of current methods. Int J Energy Res 2020:4888–4931. https://doi.org/10.1002/er.6208.*

Les références bibliographiques de ce chapitre et des chapitres suivants sont synthétisées dans une seule et même section Bibliographie à la fin de ce manuscrit. De même, les annexes sont regroupées en fin de document.

# Techno-economic planning of local energy systems through optimisation models: a survey of current methods.

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Abstract:

Energy system planning is a difficult task, since it involves long-term decision-makings with multiple dimensions: technical, economic, social, ecological, and political. The rise of distributed and multi-energy systems including new technologies has further increased this complexity. Techno-economic studies based on optimisation models have recently received much attention in the literature. They are essential to grasp energy systems complexity and provide decision support. This work targets methodological issues related to local systems while comparing them with methods used at larger scales. First, a new framework providing a comprehensive vision of added values and limits of optimisation models is presented. Then, the main methodological trends as well as several undertaken research paths are identified based on the analysis of more than sixty research papers. The review results are summarised in a complete and concise table. Finally, future research topics are discussed including the operational facets of investment optimisation models in case of high intermittent energy shares, flexibility issues and long-term operational decisions. The results provide useful information to modellers or researchers that look for appropriate and state-of-the-art optimisation methods, or aim to deepen current research paths. Hence, they will facilitate the planning and development of energy systems for the future.

Highlights:

- New framework to assess needs and methods for techno-economic local energy system planning
- Detailed survey of more than sixty papers including original methodologies
- Identification of main methodological trends, focuses and future challenges
- Key insights to better understand various methods: their added value and limits

Key words: Local energy systems, planning, optimisation, simulation, investment

# Glossary

## Abbreviations

| Abbreviation | Meaning |
|---|---|
| **AC** | Alternative Current |
| **ACh** | Absorption Chiller |
| **CAPEX** | Capital Expenditures |
| **CCHP** | Combined Cooling Heat and Power |
| **CE** | Capacity Expansion |
| **CHP** | Combined Heat and Power |
| **DER** | Distributed Energy Resources |
| **DES** | Distributed Energy System |
| **DH** | District Heating |
| **DHC** | District Heating and Cooling |
| **DR** | Demand Response |
| **EA** | Evolutionary Algorithm |
| **EC** | Electric Chiller |
| **EFOM** | Energy Flow Optimisation Model |
| **EPM** | Expansion Planning Models |
| **ESOM** | Energy System Optimisation Model |
| **EV** | Electric Vehicle |
| **FACTS** | Flexible AC Transmission Systems |
| **GA** | Genetic Algorithm |
| **GE** | Generation Expansion |
| **GHG** | Greenhouse Gases |
| **GSA** | Global Sensitivity Analysis |
| **HC** | Hydrogen Chain (electrolyser + H2 storage + fuel cell) |
| **HP** | Heat Pump |
| **ICE** | Internal Combustion Engine |
| **IE** | Intermittent Energy |
| **LP** | Linear Programming |
| **MC** | Monte Carlo |
| **MES** | Multi-Energy System |
| **MILP** | Mixed Integer Linear Programming |
| **MP** | Mathematical Programming |
| **MPC** | Model Predictive Control |
| **OPEX** | Operational Expenditures |
| **PWA** | Piece Wise Approximation |
| **PSO** | Particle Swarm Optimisation |
| **PV** | Photovoltaic cells (solar panels) |
| **RO** | Real Options |
| **SD** | Standard Deviation |
| **SES** | Smart Energy Systems |
| **ST** | Solar Thermal collectors |
| **TRA** | Trust Region Algorithm |
| **TS** | Thermal Storage |
| **UC** | Unit Commitment |
| **VPP** | Virtual Power Plant |
| **WT** | Wind Turbines |

# Definitions

| Expressions | Definition used in this paper |
|---|---|
| **Local energy systems** | Individual buildings, industrial energy intensive or production sites, micro grids, stand-alone systems, smart energy systems, district heating and cooling, cities and territories below national scale. Such systems are often distributed and/or multi-energy systems e.g. involving electricity, heat and gas as means to store and convert energy. |
| **Techno-economic studies** | Studies where several technologies are modelled in a more or less simplified fashion and considered together to provide a systemic view. Used to perform economic evaluation or optimisation of the system where environmental externalities can be included as constraints, objectives or simply accounted by the mean of metrics derived from life cycle analysis for instance. |
| **A model** | A simplified representation of one or several aspects of reality. |
| **A formalism** | A formal language used to build models in a non-ambiguous way. |
| **A paradigm** | A coherent set of models used in conjunction. |
| **An algorithm** | A non-ambiguous sequence of instructions or operations to solve a problem. |
| **Simulation** | Use of a model to observe results of hypothetical actions on it. |
| **Optimisation** | Use of a model including decision variables to derive their optimal values when minimizing or maximizing one or several objectives under given constraints by the mean of algorithms. |
| **A method** | A set of coherent actions and processes to answer (a) given question(s) (including possible formalisms and algorithms definitions to perform simulation and / or optimisation). |
| **An approach** | A general trend of methods. |
| **A tool** | A computer program used to build models with a possible given formalism and method(s). |
| **Stochastic optimisation** | Where the optimisation objective is to maximize or minimise the expected outcome. |
| **Robust optimisation** | Where the optimisation objective is to minimise the worst possible outcome (with possible restrictions on over-conservative solutions). |

# 1. Introduction

Global environmental concerns are pushing us toward a cleaner life style in a general sense. Among these concerns, global warming stands as a major issue and most developed countries have set greenhouse gases reduction objectives after the Paris agreements [11]. The energy sector plays a major role in European emissions; hence, the energy transition towards clean and renewable energy systems is one of the keys to limit environmental impacts. The energy transition calls for **long-term planning** at national levels. One related challenge is to identify evolution targets to reach efficient systems with respect to the economics and the environmental. These systems must adapt to greenhouse gases emission constraints, as well as evolving economic, climate, regulation, technological landscape and load environments. Increasingly, national targets spread at local scales so local actors are facing need for long-term energy system planning as well: [12] and [13] explore such issues at the urban level. **Local energy systems** (see Definitions) cover a wide range of systems including buildings, industrial energy intensive or production sites, micro grids, stand-alone systems, smart energy systems, district heating and cooling, cities and territories below national scale. With the decentralization nature of energy systems through DER (Distributed Energy Resources) and with the emergence of SES (Smart Energy Systems) (described respectively in [14] and [15,16]), systems become promisingly more efficient and increasingly complex. They typically include more technologies and energy vectors to become "multi-energy". This goes along with the penetration of IE (Intermittent Energies) that brings non-controllable and uncertain energy productions.

Planning the design and the evolution of such systems is thus a challenging task. A way of providing decision support is through **techno-economic studies** (see Definitions). Techno-economic studies often rely on simulation or optimisation models (as defined in [17]). This survey focuses on **optimisation models** (see Definitions), where several technologies are modelled in a more or less simplified fashion and considered together to provide a systemic view. The model is then used to perform economic optimisation of the system where environmental externalities can be included as constraints, objectives or simply accounted by the mean of metrics derived from life cycle analysis for instance. Figure 2 summarises the scope of this survey.

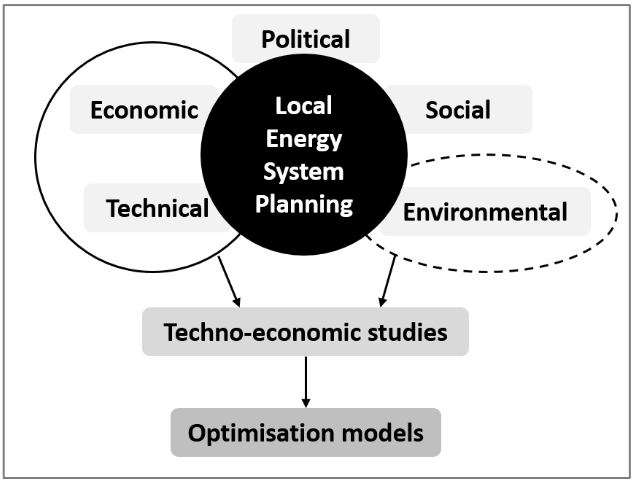


*Figure 2: Scope of this survey.*

## 1.1 Modelling needs for energy planning

In line with the energy landscape evolution, the modelling task is to represent local energy systems which faces intermittencies on both load and production sides. Hence, dynamic models are often privileged with hourly or sub-hourly time steps. These systems can include **different energy carriers** (electricity, gas, heat or biomass for example). Multi-energy systems offer greater opportunities to reach better technical, economic and environmental performances, as stated in [16,18]. Technologies include **production, conversion and storage units** from daily to seasonal storage and must be modelled with a suitable amount of details. Modelling specific **market conditions** might be of concern as well. Finally, the modeller must keep in mind **various sources of uncertainties** and can include them in the modelling (and optimisation) process. Uncertainties can lie in boundary conditions, in the model parameters or even in the model itself. They are due to uncertain data on emerging technologies, stochastic intermittencies or prospective long-term hypothesis for instance.

Most of time, techno-economic studies aim to answer the following question: What investments to undertake? At an early planning stage, many design choices remain open, leading to **complex optimisation problems**. Moreover, planning studies can look forward up to fifty years. This raises the question of how the system should evolve with respect to the context i.e. what investments to realise now and in the coming years. Finally, the objective of such studies can be twofold: coming up with theoretically performant solutions for a given environment (e.g. [19]), or learn on innovative energy system behaviours to provide useful insights (see [20], [21] or [22] for instance).

Therefore, there is a need for approaches that can properly represent local energy systems (as described above), and provide decision support for planning needs. In order to make the best use out of current methods or develop new ones, **a clear view of current practices is needed**.

At this stage, a distinction must be made between tools (computer programs used to build models such as EnergyPlan, TIMES, OSeMOSYS or DER CAM for example), and their underlying modelling and simulation / optimisation method (i.e. the formalism used and the possible optimisation algorithm).

## 1.2 Literature on energy system planning

Energy system planning studies have recently received much attention at local, national, and even up to European scale. Papers either focus on trying out new methods (e.g., [23,24]) or investigate specific case studies (e.g., [25,26]) or both. Large-scale studies address energy sectors interactions or focus on power systems. The latter include operational details [27]. Local scale studies cover a more diverse number of cases, including microgrids [28], stand-alone systems [29], multi or smart energy systems [30], DH (District Heating) [24] or DHC (District Heating and Cooling), single buildings [31] or production sites [32].

Many reviews on tools, methods and practices for planning studies can be found in the literature. They often provide guidelines to select an appropriate tool for various energy systems, based on overall criteria (see [33–36]). The Open Energy Modelling Initiative community brings a general overview of current “open” approaches [37]. On the side of large-scale energy system planning, methodological reviews are available: [38] classifies approaches into three categories: optimisation, equilibrium and alternative. They spell out their added value and limits.  References [39], [40] and [27] focus on methods to include operational details in energy planning models including IEs, while [41] discusses electricity network models for energy system planning. They help providing clear vision and deep understanding of current practices and bring light on today challenges. On the side of local scale energy system planning, [12] reviews current urban planning practices and computer tools, they argue that building activities should be co-optimised with energy systems.

In [42], authors develop a general framework to review ESOMs (Energy System Optimisation Models) at the municipal level. Reference [43] gives a general review of six planning tools for community scale system. Reference [18] focuses on MES (Multi-Energy Systems), describing related concepts such as Energy Hubs (initially introduced in [44]), microgrids and VPPs (Virtual Power Plants). Tools, evaluation methodologies and performance assessment criteria are covered as well. A review on optimisation methods used in various energy fields is provided in [45]. Finally, [46] proposes a selection process to identify suitable tool at the community scale.

## 1.3 Contributions

To our knowledge, existing reviews and surveys on techno-economic planning of local energy systems partially analyse the underlying methodologies or are limited to generic tools and models, ignoring a part of the wide spectrum of approaches used in the literature.

We propose a **survey of current optimisation methods** that includes original research works. The scope is described as follows. Systems considered are complex due to multiple energy carriers, technologies, IEs, storages and involve multiple operational and/or investment decisions. We choose not list all possible optimisation methods that could be used. Instead we look at current tools, generic models and original methods found in the energy planning literature that are actually in use to address these problems. Although this work is intended to bring light for local scale techno-economic studies, we broaden the scope to some methods used at larger scales that stand between bottom up investment optimisation models (as defined in [47]) like TIMES, and operational optimisation models like PLEXOS (we further refer to bottom up optimisation models). They can further inspire methodological improvements for local scale methods, especially since recent literature question their ability to capture operational details [39,48–53]. Such methods benefit from abundant literature and were long time-tested to perform energy system planning (including long-term planning over multiple year periods). Furthermore, they often rely on similar formalisms as methods used at local scales (i.e. mathematical programming). Although this work is not intended to be fully exhaustive, we hope to bring light on current practices by restricting the research to papers published after 2006 that present studies with existing or original methods.

First, this paper delivers a comprehensive vision of possible added values and limits of optimisation models by the mean of an original framework. The framework identifies the different optimisation questions (i.e. what is to be optimised), the feedback level (i.e. how far it answers the optimisation question) and discusses the various modelling facets of energy systems (Section 2). We particularly reflect on the capability of a given method to accurately model local energy systems and provide decision support to the modeller. Second, we review more than sixty recent publications through the framework lens to identify main methodological trends, modelling and computational issues as well as specific state of the art approaches (Section 3). Third, reviewed papers are summarised in a complete and concise table, bringing substantial information on current literature (Table 3). Finally, possible research paths for the future are discussed.

# 2. The analysis framework

This section presents the analysis framework proposed to perform the survey. The framework is summarised on Figure 3, which shows a schematic view of a techno-economic approach. First, we introduce the Energy System Investment Planning (ESIP) problem to characterize the optimisation problem underlying in energy planning studies (Section 2.1). Then we question the capability of a method to provide decision support for ESIP studies at local scales at each step of the process. Three axes are identified: the richness of the feedback provided by the method (Section 2.2), the relevancy and accuracy of the model considered (Section 2.3), and the optimality and robustness of the optimisation method (Section 2.4). The model relevancy and accuracy are broken up into several facets: the investment decision facet and the operational facet. The latter includes technological units and networks, spatial, temporal, operational decisions and market facets. This way we hope to provide a comprehensive vision to better grasp various approaches found in the literature.

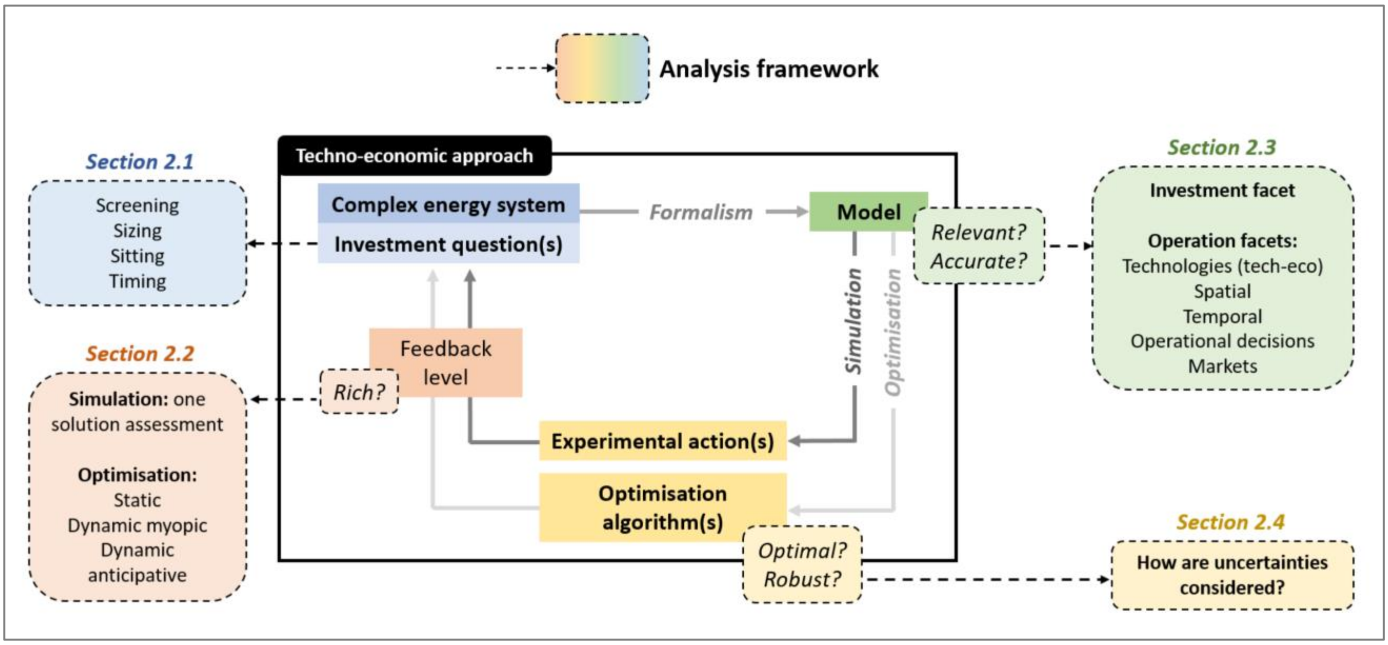


*Figure 3: Summary of the analysis framework based on the approach processes. The approach capability to provide valuable feedback is questioned at each step.*

## 2.1 The Energy System Investment Planning (ESIP) Problem

One way to provide decision support for energy system planning is to see it as an optimisation problem, where investment decisions in various technologies must be made. This analysis prism is common in energy system modelling, and optimisation methods have been increasingly used in the past decades (as shown in [45]).

We define the general **Energy System Investment Planning (ESIP) problem** as follows. The energy can take various forms: electrical, thermal, kinetic, potential (chemical, gravitational, *etc*.). The ESIP problem comprises various energy systems in a broad sense, including MES, microgrids, SES, DHC, stand-alone systems, power systems, DER, single buildings, industrial energy systems, *etc*. These systems classically involve energy production, storage, conversion and consumption units. The investment related problem can address various sub-questions:

- “What technology to invest in?”, if several technologies are in competition or can be used in symbiosis;
- “How much?”, when one must decide the installed capacity of a technology;
- “Where to install it?”, if a detailed spatial representation is used;
- “When to install it?”, when considering the system design evolution or in a Real Option (RO) thinking (see [54]).

We respectively refer to the **screening**, the **sizing**, the **sitting** and the **timing (with possible RO thinking)** problems. ESIP problems can be structured into two stages: the **investment facet** and the **operational facet**. Since finding a good design is tightly linked to the way the system will be operated. In other words, a balance has to be found between CAPEX (Capital Expenditures) and OPEX (Operational Expenditures). Hence, there is a need to simulate how the system will operate to assess if a design solution is of interest (see Figure 4). Since the main objective is to optimise investments, the more accurate the operation simulation, the better the resulting investment solution.

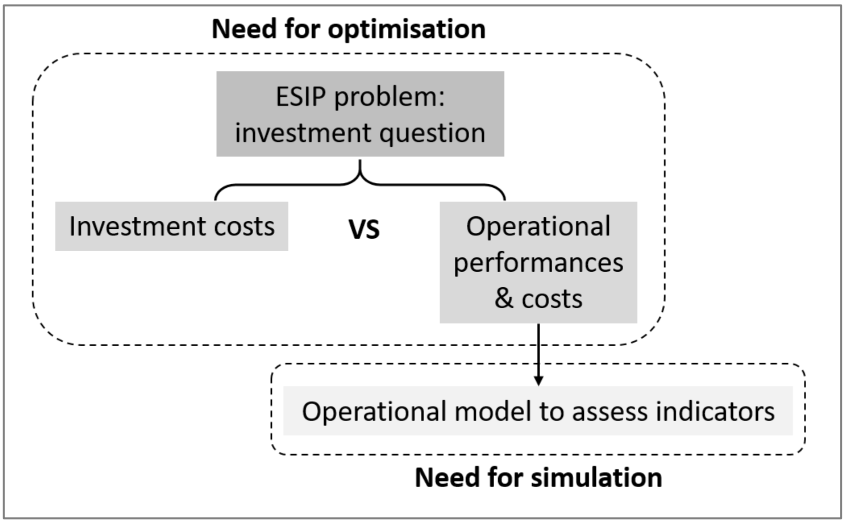


*Figure 4: The need for operation simulation when optimising investment decisions.*
**Energy System Investment Planning*

## 2.2 The feedback levels from simulation and optimisation

We first make a difference between the different feedbacks that a method can provide to the modeller. At the lower stage, the method can only **feedback the system operation simulation**. It must be clarified that optimisation models can be used as simulators (in this case they optimise operational decisions only). We can then talk about simulation models in terms of how they are used, while they are optimisation models in terms that they include optimisation variables. Although simulation can already provide key insights for energy system planning (investment optimisation can be done “by hand” through experimental decisions), it has a limited interest when it comes to finding an optimised design within a large search space. This is the case of the EnergyPlan tool [55] or the Balmorel tool used in mode Balbase1 or Balbase3 [56] for instance. As a consequence, simulation models are sometimes used as black boxes (so called “slave models”) along with metaheuristics to optimise the system design and sometimes the system evolution (as in [57]). Such metaheuristics optimisation algorithms can also directly be included in the energy planning tool as the iHOGA tool [58] or the Odyssey tool [59]. Hence, a step further is to optimise investment decisions.

The investment optimisation can be done considering an existing system or starting from scratch. We also distinguish between **static, dynamic myopic and dynamic anticipative investment optimisation** (as described in [48], see Figure 5).

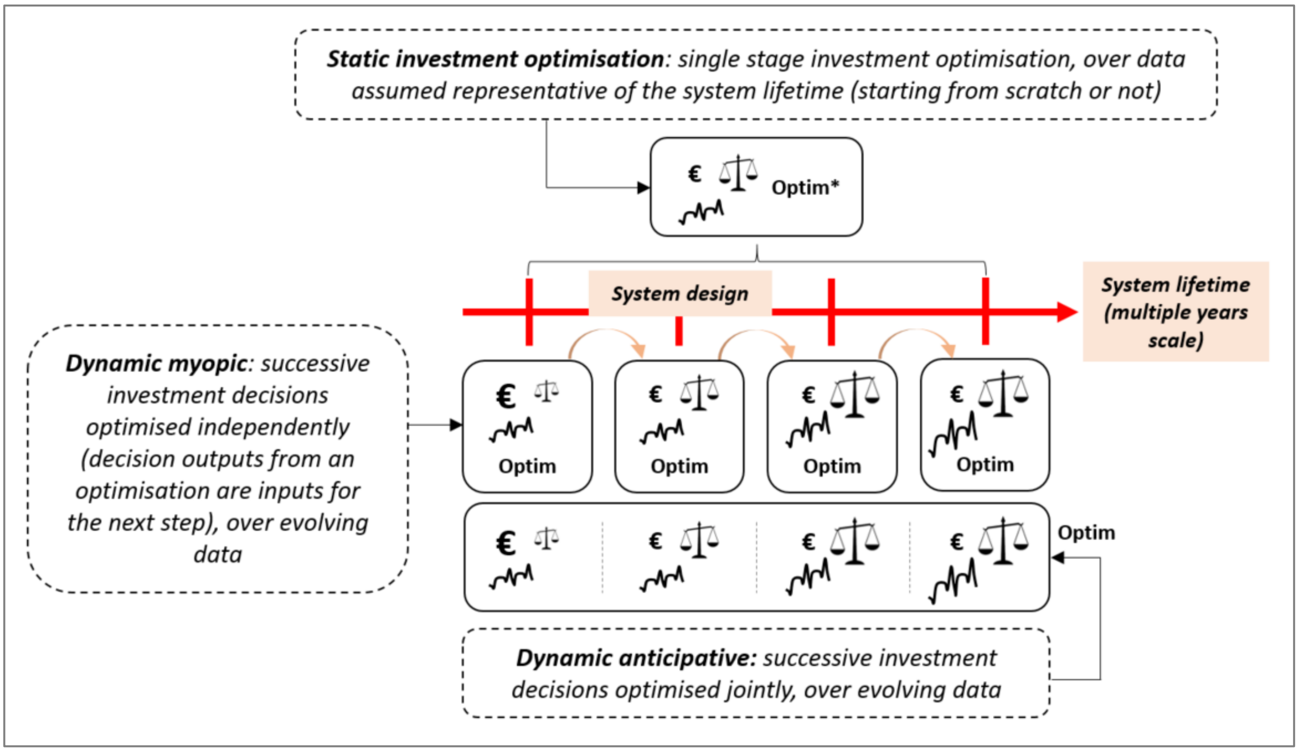


*Figure 5: Illustration of different feedback levels when optimising investment decisions. Dynamic optimisation bring further insights, dynamic anticipative optimisation implies further computation challenges.*
**Optimisation*

In the static case, a single investment decision stage is optimised. A single target year is often considered as representative of the system lifetime (e.g. [56] and [60,61], references further discussed in Section 3). Such approach can also be referred as a "snapshot" investment optimisation [62].

One can also optimise the investment in a dynamic fashion over several years and investment stages. This enables to adapt the system design under an evolving environment (loads, jurisdiction, markets, weather, *etc.*). Each investment decision stage considers previous investments as inputs. The investment optimisation can be myopic, which is equivalent to running static investment optimisations iteratively. This approach is used in the ReEDS tool [63], the Perseus tool [64] and the Balmorel tool [56].

In contrast, dynamic investment optimisation can be anticipative, i.e. all investment decisions are optimised jointly. Large-scale, multi-sectors energy models like TIMES [65] (or so called "equilibrium models") rely on such approaches. However they can be seen as simulation models as pointed out in [38]. Indeed, the optimisation formalism is actually used to simulate the energy system economics under a given scenario. This way, energy policies can be assessed. At smaller scales, investment optimisation directly supports decision-making. Therefore, dynamic investment optimisation can bring further insights compared to static approaches as argued in [66].

The leap from static to dynamic myopic investment optimisation is quite straightforward from the problem complexity perspective. In contrast, dynamic anticipative investment optimisation introduce a more challenging computational burden. Running dynamic myopic investment optimisation might lead to lock-in situations where an investment was made at a particular investment decision stage that is obsolete in the future, implying sink costs. Comparing solutions from a dynamic myopic investment optimisation with multiple static investments can reveal such lock-in risks. Dynamic anticipative investment optimisation concludes on the optimal investment pathway to follow. Hence, the latter potentially provides a higher feedback level to the modeller.

## 2.3 The model relevancy and accuracy: keys to meaningful assessments

Techno-economic studies build on their ability to model technologies in a systemic perspective to reach performant and technically feasible solutions. Hence, the ability of the model to accurately represent key aspects of technical reality is of high relevance to raise valuable insights. We further describe accuracy levels for both investment and operational facets.

### 2.3.1 The investment facet

The investment facet represents how investment decisions are made and how it affects investment costs and/or equipment performances.

Models based on continuous variables are limiting, although they can be suitable for technologies such as batteries, PVs (Photovoltaic cells) or when considering large-scale capacities. Including discrete decisions opens larger modelling possibilities. Size or scale effects on investment costs can then be modelled (sometimes referred as “lumpy investment”, e.g. [67]). One can also include a size dependency on conversion performances or minimum working power (see [23] for example). Finally, long-term learning effects can be relevant in case of dynamic investment optimisation over multiple years [67].

### 2.3.2 The operational facet

The operational facet represents how the system dynamically operates. We distinguish several facets: the techno-economic, the spatial, the temporal facets, and the way operational decisions and markets are modelled. They are further detailed below.

<u>The techno-economic facet, including technological units and networks</u>

Technology units must be described with a suitable level of detail. Table 1 shows a quick summary of aspects that can be included with **continuous** and **discrete** variables under a MP (Mathematical Programming) formalism. Discrete variables provide more modelling options but tend to increase computation costs. Since they bring more combinatorial complexity in the optimisation problem. UC (Unit Commitment) models illustrate the variety of technological operational features that can be envisaged using linear and discrete MP formulations (see [69–73], further discussed in Section 3). In [23], authors also use some accurate modelling features (size dependencies of component efficiencies). Different MP formulations can be used to model similar behaviours. Tight and compact formulations can be found in the literature (see [74,75]): they ensure higher computational efficiency.

*Table 1: Technology units and network models under mathematical programming formalism. Examples of aspects that can be modelled with continuous and binary variables.*

<table>
<tr><th>Variables Needed</th><th>Technology facets</th><th>Electric network facets</th><th>Heat network facets</th><th>Others facets</th></tr>
<tr><td>Continuous</td><td>Maximum working power<br>Linear costs<br>Multiple inputs or outputs<br>Maximum ramps up and down<br>Ramp costs and overconsumption<br>Curtailment on IEs, including costs<br>Planned production or maintenances<br>Constant efficiencies<br>Unmet load costs<br>Ramping flexibility requirements<br>Spinning reserves<br>Linear emissions or environmental impacts</td><td>Flow capacity<br>Linear losses<br>DC approximation [41,76]</td><td>Flow capacity with constant temperatures and linear losses<br><br>Variable temperature and constant mass flow [71,77].</td><td>Energy contracts: utility purchase, injection<br><br>Systemic constraints: ramping flexibility requirements, spinning reserves, linear emissions or environmental impacts</td></tr>
<tr><td>On/off status (binary variable)</td><td>Minimum working power<br>Fixed working costs or consumption<br>Minimum on and off times<br>Fixed working power<br>Minimum working temperature</td><td colspan="2"></td><td rowspan="3">More specific utility purchase or injection rules (price thresholds for instance)</td></tr>
<tr><td>Multiple status (binary variables)</td><td>Piecewise efficiencies or costs (continuous variables can be used under proper convexity/concavity conditions)<br>Discretized working powers</td><td>AC (Alternative Current) approximation [78]</td><td></td></tr>
<tr><td>Start-up and shut-down status (binary variables, on/off status are needed)</td><td>Start up or shut down costs or overconsumption (continuous variables can be used under proper convexity/concavity conditions)<br>Maximum number of start up or shut down<br>Maximum start up or shut down ramps</td><td colspan="2"></td></tr>
</table>

Networks are often modelled as **linear energy flows formulations**, including flow capacities, and sometimes linear losses. Non-linear aspects of electric networks can be approximated with a **DC (Direct Current) linear approximation** under certain assumptions including small voltage angle differences, high resistance / reactance ratio, and per-unit system voltage magnitudes close to 1.0 (see [78]). DC approximation is often used as a compromise between accuracy and computation burden, especially for transmission systems [41]. However, DC approximation assumptions become invalid for distribution systems [76]. Non-linear formulations are then needed, involving more computational burden under MP formalisms [78].

Concerning heat networks, linear approximations with variable temperatures and constant mass flow were proposed (e.g. [71,77]), even if such considerations can show little impact for low temperature levels [77]. Linear formulations with constant temperatures are often used [24,28,61,72] (references further discussed in Section 3). Efficiencies can still be modelled as functions of supply and return temperatures so that the latter can be externally optimised [79]. More accurate formulations also involve non-linear equations: in [80], an approximated linearized optimisation model coupled to a non-linear simulation model is used.

The spatial facet

The spatial facet usually ranges between **single node** (thus ignoring networks) and **multi-nodes** representations. Although this might be of little concern for small-scale systems, it becomes an issue when spatial aggregation is needed for computational or data availability reasons. At the same time, appropriate spatial resolutions are needed if one wants to capture network related issues or the distributed nature of solar and wind generation for instance. Reference [27] discusses this issue for large-scale power systems. This aspect will be further addressed in Section 3.2.4.

The temporal facet

When it comes to model the system dynamics, a temporal framework is needed. For energy planning studies, a **one-hour time step** is used most of time, capturing energy load and production fluctuations while keeping reasonable data set sizes. We further distinguish models based on a **full time horizon** (usually a year), and models based on aggregated data sets.

Aggregated data sets were introduced to reduce the operational problem size, and thus the problem complexity. To this effect, discrete operational decisions involve discrete variables proportionally to the length of the time horizon. **Duration curves, time slices, typical days or weeks (i.e. representative periods)** are commonly used. The **duration curve** is the most restricting method since it does not retain chronology between time steps (a duration curve represents the given curve sorted by decreasing ordinate values). The other methods rely on a system optimisation over a smaller data set considered as representative of the system operation over its lifetime (usually some days or weeks). In a sense, it is a hypothetical extension of the full time horizon optimisation over a single year. **Time slices** sometimes include time steps of variable size depending on the time of the day (up to six hours steps in the night, one-hour steps in the peak periods). **Typical days or weeks** usually keep a one-hour time step.

Methods for building these aggregated data sets are numerous. Reference [49] compares the integral method (aggregation by average, a classic time slices approach) with the method consisting of selecting representative days or weeks in the whole data set with a given weight. Methods to select appropriate periods and assign them proper weights were recently discussed and designed in the literature (see [81–87]). Limits of such methods were also pointed out: [88] highlights concurrency and continuity problems. Concurrency problems arise when correlations between different time series are lost in the process. Continuity problems concern possible lack of consistency of the system state between two time steps. In [85], authors state that consistent criterion for selecting representative periods is lacking, although the duration curve approximation is often used.

The number of representative periods to consider is a trade-off between representativeness and computational burden. References [23] and [89] explore this aspect on a case study. Twelve periods are often used in ESOMs (as mentioned in [27,39]), while forty-eight were considered necessary in [90]. In [19], it is shown that a higher resolution is needed when looking at low $CO_2$ emissions systems.

The temporal representation becomes more challenging if one wants to take into account long-term (i.e. seasonal) constraints or storages. Since, representative periods retain chronology within themselves but not between themselves [27]. Thus it becomes harder to consider the long-term dimension without modelling the full time horizon. This aspect will be further discussed in Section 3.2.5.

The operational decisions facet

Operational decisions can be made under two main different methods / paradigms. The first one assumes that the system operational decisions follow pre-defined expert rules. Such rules take the following form: "if the battery state of charge is above a certain threshold: discharge it in priority to meet the load" for instance (strategy I in [91]). Approaches relying on this paradigm are latter called simulation-based optimisation approaches. They often come with the "**myopic assumption**", meaning that operational decisions are made without considering the future of the system and its environment. It ignores load or weather predictions for instance, which can be limiting. In addition, such rules can be difficult to write for complex systems and can lead to sub-optimal operational decisions. The second paradigm is to leave the operational decisions in the hand of optimisation algorithms. This is often performed through MP formalism and corresponding algorithms, although it can also be done by other methods like dynamic programming or metaheuristics. This approach often relies on the "**perfect foresight assumption**", meaning that the optimisation algorithm makes decision with perfect knowledge of the future like loads and weather forecasts. When looking at systems where operational decisions are supposed to be made by a single stakeholder, this can refer to MPC (Model Predictive Control). For large-scale, multi-sectors energy models like TIMES, they represent energy markets operations. Indeed, they are often supposed to maximize the total surplus or minimise overall costs, which simulates the market behaviour under perfect competition (and perfect foresight) assumptions. In both cases, the perfect foresight assumption is limiting since it overestimates weather, load and market forecast capabilities.

The market facet

Markets or energy contracts can be more or less challenging to include in the model. Besides, what is meant by "market facet" strongly differs between large scale and small scale energy models.

For large scales, multi-sectors models like TIMES, market mechanisms are captured by the MP formalism and associated optimisation methods to derive optimal transactions between many actors. Relying on economy theory, such models can simulate a (partial) supply-demand equilibrium under the perfectly competitive (and perfect foresight) market assumptions. They consider price-elastic end-use demand curves as well as supply curves (using convexity/concavity properties for linearization [65]). The total surplus is maximised so the market equilibrium is reached. Others consider fixed energy demands and satisfy them at minimum costs, see [92] for instance. More detailed market representations including multiple actors and / or imperfect markets, or day-ahead and balancing steps involve **multi-level problems** that can be much more challenging to solve as described in [93].

At local scales, when stakeholders access energy markets, incentives or energy contracts should be explicitly modelled. Linear formulations can easily capture constant or variable energy prices on the spot market. Including discrete variables can further model annual utilization times or threshold effects for example. Here again, more detailed models lead to multi-level problems (see [94], Section 3.2.3 for instance).

## 2.4 Optimality and robustness: including uncertainties

When relying on optimisation approaches, the modeller often needs to assess the robustness of obtained solutions (through sensitivity analysis). A step further is to look directly for robust solutions through the optimisation process. By “robust” one can have in mind that “the solution remains good” when the model inputs are changed. “Good” can be defined in two possible ways: good in average or good in worst cases. The first can be achieved by stochastic optimisation, the second by robust optimisation. Both objectives can be in competition: hybrid methods help to reach trade-offs. With more hindsight, one would like the obtained solution to “remain good” in real life conditions. While the model inputs correspond to parametric uncertainties, the latter considerations also include structural uncertainties as defined in [95] (see also endogenous and exogenous uncertainties as defined in [96]).

We further refer to three types of uncertainties: those related to the purely operational problem (optimise operational decisions for a given design), those related to the investment problem (with operation simulation) and the lasts concerning the system environment evolutions. A quick overview is given in Table 2 including methodological options observed during the survey process (Section 3). More details are given Sections 3.2.1 and 3.2.2. Risk based methods are reviewed in [97].

*Table 2: Examples of uncertainties related to techno-economic planning of energy systems (problem-based classification).*

| ***Uncertainty type*** | **Dynamic investment problem (system environment evolutions)** | **Static investment Problem** | **Purely Operational Problem** |
|---|---|---|---|
| ***Description*** | Load trends, jurisdictions, technology breakthroughs, costs and performances (learning effects), energy costs & weather trends. | Operational & investment facets modelling (structural).<br><br>Technology parameters (OPEX, CAPEX, lifetime, replacement costs, efficiencies), input data series (parametric). | Forecast errors (loads or weather) & technology failures (parametric). |
| ***Time scale*** | Several years to tens of years | One year to several years | Daily to one year |
| ***How they can be considered (parametric uncertainties)*** | Mainly deterministic scenario runs [98]. | Uncertainty propagation or sensitivity analysis.<br>Monte Carlo scenarios with stochastic / robust optimisation) (see Section 3.2.1). | Monte Carlo scenarios with two-stage stochastic optimisation (for forecast errors) (see Section 3.2.2.). |

For the purely operational problem, the goal is to be as performant as possible by reducing uncertainties and including them in the optimisation process. In particular, methods including stochastic optimisation were utilised to include forecasting errors (see [94] for instance). When moving to the investment problem, the issue for the operational facet is different: it should represent how the system will be operated, including forecasting errors. It was recently argued that energy planning optimisation approaches should include the fact that operational systems, especially with high IE shares, face uncertainties [27,93]. Moving from the perfect foresight to the imperfect foresight hypothesis by modelling the actual forecasting errors reduces structural uncertainties. Parametric uncertainties for investment problems can be addressed by various means (see Table 2). They include uncertain technology parameters and input data series like solar and wind generation that show significant inter-annual variability [88]. Finally, uncertainties related to the system environment evolution (sometimes referred as “deep uncertainties”) are most of time ignored or considered by testing different deterministic scenarios, although recent search investigates ways to better account for it (see [98]).

# 3. Survey of optimisation methods for energy system planning

We propose a survey of current optimisation methods for local energy system planning. As discussed in Section 1.3, we include a short overview of bottom up optimisation models used at larger scales. The survey is summarised in Table 3.1 to 3.14 (end of Section 3). These tables classify several ESIP studies performed with generic or specific methods. All papers discussed in Section 3 that can be found in Table 3.1 to 3.14 are annotated by *. More generic tools and models are also cited for illustrative purposes as well as further references. This survey is intended to be complementary with previously cited reviews that discuss other criteria (sector or technologies considered, availability, openness or development platform for instance) or consider different scopes (see Section 1.2.2).

The organisation of Section 3 is summarised in Figure 6. The following information is retained from each paper: the system considered, a general description of the simulation / optimisation method, the type of problem(s) considered (sizing, sitting, screening, timing), the investment feedback level, the investment facet, the operational facets and how uncertainties where considered (or not). Since this survey focuses on ESIP problems, the term "uncertainties" here refers to parametric uncertainties related to the investment problem (as defined in Section 2.1). The operational facet is broken up into further categories as discussed in Section 2.3.2. Key aspects of techno-economic facets are raised (original formulations, use of integer variables, non-linearities, *etc*.).

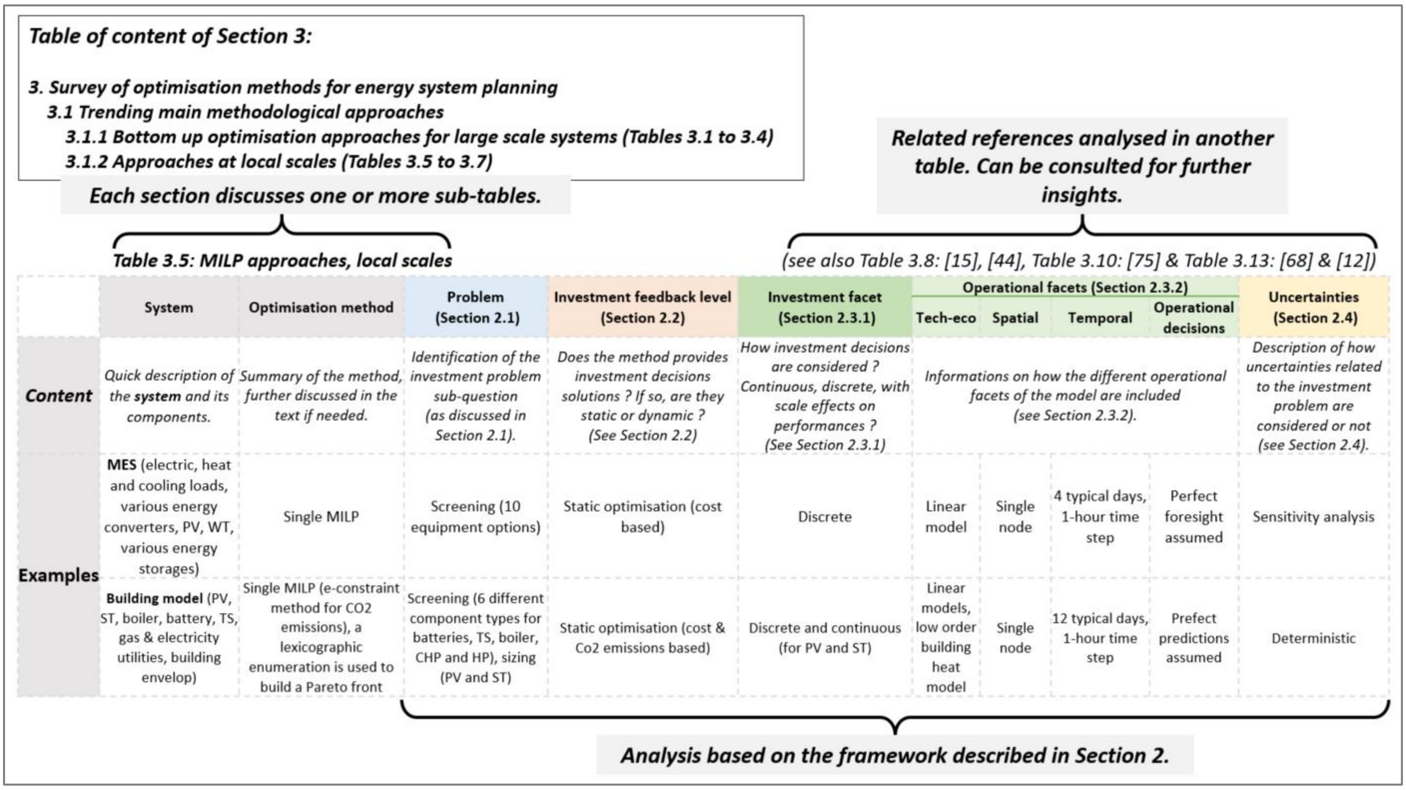


*Figure 6: Description of the organisation of Section 3: how to read it with Table 3.*

Figure 7 gives a simplified summary of the analysis framework described in Section 2 on a concise spider graph. Spatial considerations, treatment of investment uncertainties and representations of markets are excluded for sake of clarity. The different "levels" on the graph are defined by a general order of interest for local energy planning through techno-economic studies. Main identified methodological trends are mentioned in Section 3.1 and their typical capabilities are displayed on Figure 8. As mentioned in Section 1.3, methods used at larger scales were included in the analysis for their potential interest at local scales. Clearly, each methodological trend can be more or less suited depending on the scale and the aim of the study. Here the aim is to understand and summarise what they generally take into account and how they would perform within the scope of local planning studies. Methodological capabilities shown in Figure 8 represent a typical use of corresponding approaches (illustrative references are provided).

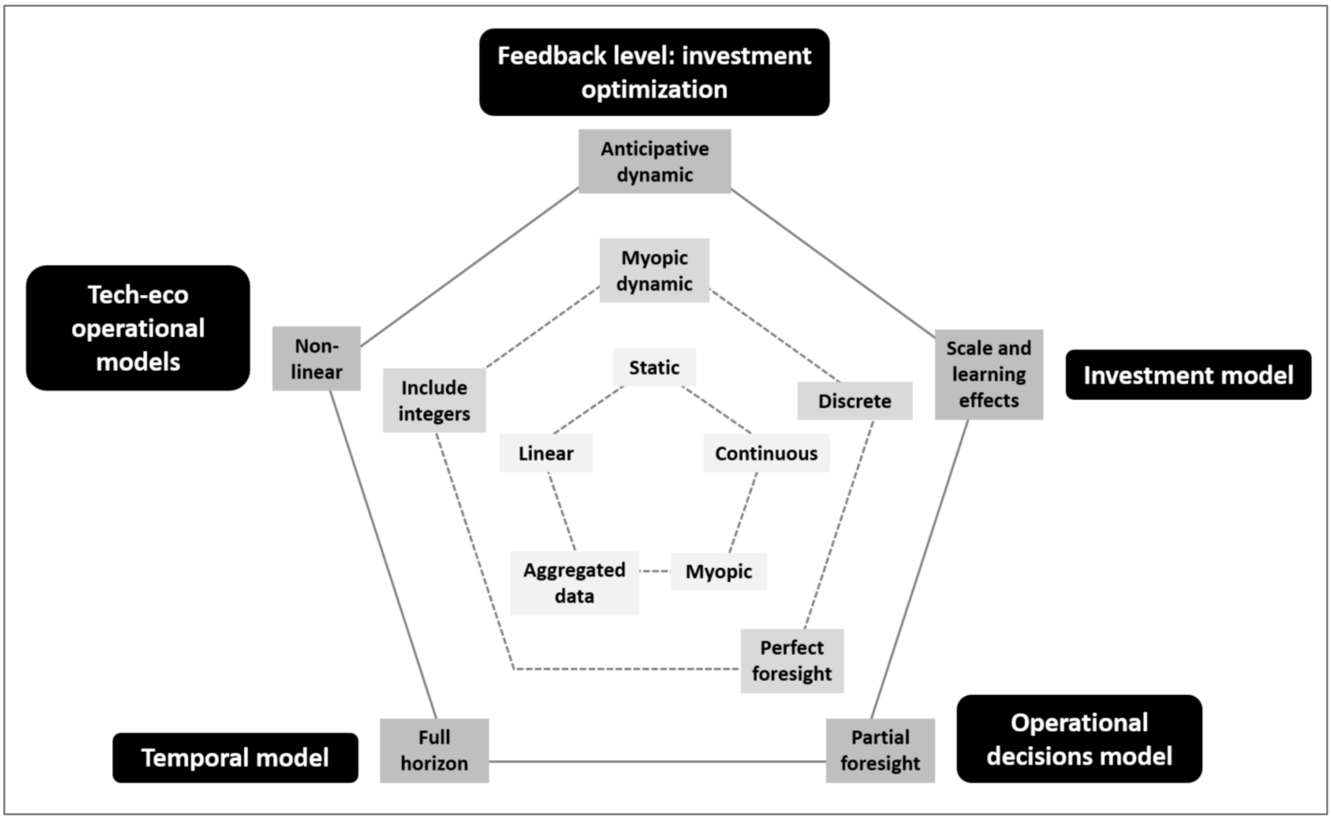


*Figure 7: Schematic simplified visual of the proposed framework (excluding spatial, market facets and investment uncertainties).*

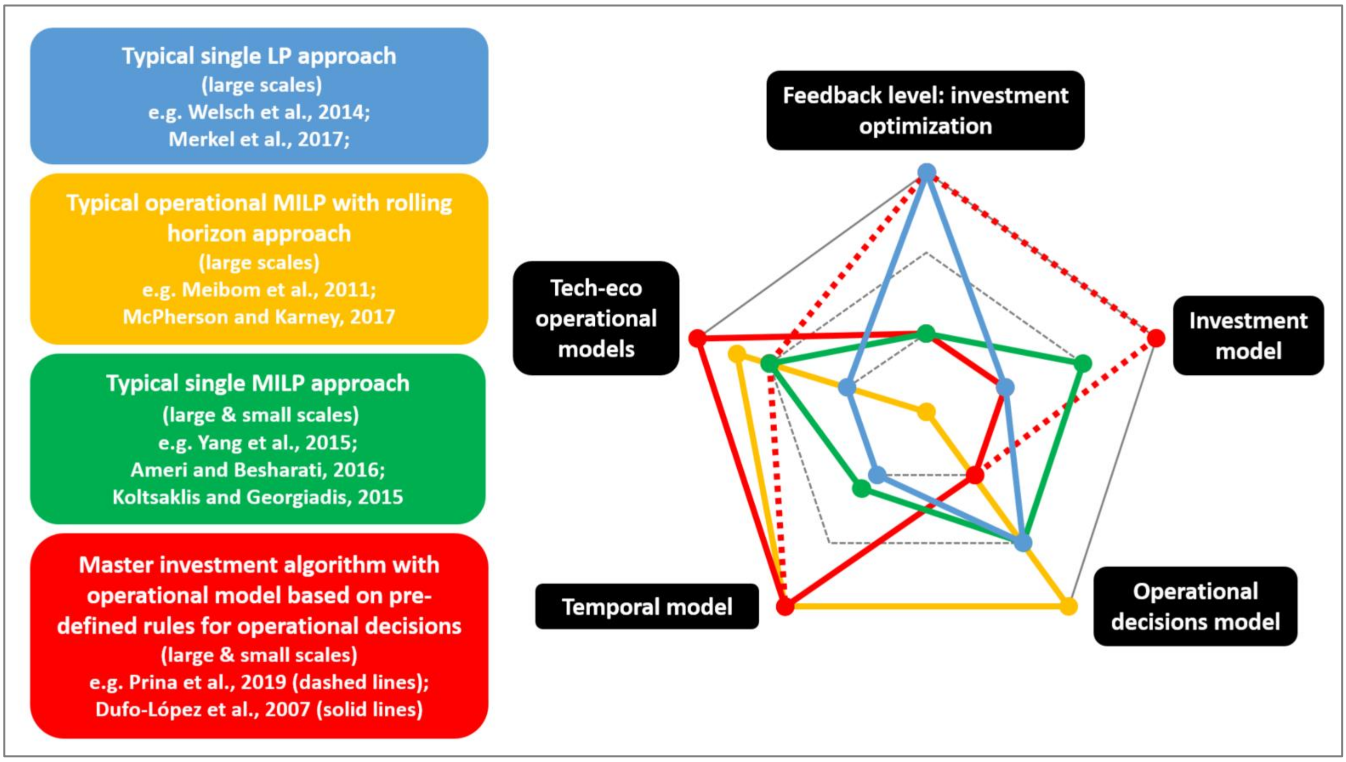


*Figure 8: Illustration of the four "main trends" in energy system planning within the simplified framework.*
** Linear Programming*
*** Mixed Integer Linear Programming*

Such capabilities can be further extended on various aspects like uncertainties, spatial and temporal granularities, or markets modelling for instance (see Section 3.2). However, it could be more or less challenging depending on the chosen approach. For instance, extending the investment options search space might be more impacting for master investment algorithms like metaheuristics, but the later can be more suited to explore discontinuous options. On another hand, extending time and space granularity, increasing the information feedback level, or solving multi-level problems is generally more challenging for MILP (Mixed Integer Linear Programming) than LP (Linear Programming) approaches since MILP includes integer variables (as a general rule of thumbs: the more integer variables the more challenging the problem is to solve). Finally, purely operational MILP approaches can further push the accuracy boundaries since the operational problem could be temporally broken up within the rolling horizon approach.

## 3.1 Trending main methodological approaches

### 3.1.1 Bottom up optimisation approaches for large scale systems (Table 3.1 to 3.4)

Energy planning studies for large-scale systems (national and above) are numerous. Several approaches can be seen in the literature. Main trends of bottom up optimisation approaches used at large scales are summarised below.

Operational MILP approaches (i.e. UC models, Table 3.1):

Purely operational MILPs are usually quite accurate (see Figure 8). They optimise operational decisions over several hours or days. They are often used within a rolling horizon approach to simulate a full year or to update available information for purely operational purposes. We typically refer to well-known UC models (sometimes called UCED for Unit Commitment and Economic Dispatch) like PLEXOS (e.g. [99]*) or LUSYM [73] where UC decisions are included (start-up and shut-down decisions). The SILVER model [100]* includes a price setting module and a real time optimal power flow module. These models are mostly used for power systems but also for DH systems (see [74] for instance). In [101]*, authors consider wind generation and load as stochastic inputs within their UC model (Monte Carlo scenarios for day-ahead decisions); they formulate a MILP with a rolling horizon approach to simulate the system operation. The EUCAD model [102] was used with POLES (a top-down simulation model at global scale) to consider power systems operations. Such models can be used as simulators when it comes to investment decisions.

LP approaches (Table 3.2):

LP approaches (see Figure 8) are typically used in energy modelling tools like TIMES [65] (a complete implementation of the TIMES model at the European scale can be found in [103]), PERSEUS-RES-E [64]* or open source licensed tools like OSeMOSYS [92]. The OSeMOSYS model was used in [49] and [104]*, some improvements are documented in [105–107] and [108]* for instance. OSeMOSYS was recently upgraded to perform stochastic uncertainty analysis by the mean of Monte Carlo simulation (uncertainty propagation) [96]. ReEDS [109] is another example of such modelling tools, although it has a stronger focus on the electric network facet (with a DC approximation) with high spatial details. These models are often used with a time slice or representative period approach, but full time horizon can be considered as well [104]*. The Balmorel tool [56] proposes four running modes which corresponds to different trade-offs between temporal resolution and feedback level.

Such models are typically referred as ESOMs, EPMs (Expansion Planning Models) or EFOMs (Energy Flow Optimisation Model) for general energy systems (from energy extraction to end-uses) and CE (Capacity Expansion) or GE (Generation Expansion) models for power or DH systems. We further use the ESOM & CE designations. LP approaches are most of time used for large-scale systems even if they can be adapted for smaller scales: the EnergyScope TD model [110] was recently designed for urban and regional energy planning studies. It models multiple energy sectors and targets fast computation times to stay suited for uncertainty applications.

LP approaches consider load or weather predictions; they usually rely on a perfect foresight hypothesis. Some of these tools or models perform myopic dynamic or static investment optimisation like ReEDS or EnergyScope TD respectively. On the other hand, others like TIMES or OSeMOSYS can easily optimise several investment decision stages over multiple decades in a predictive fashion. Hence, they can show how the system optimally evolves along with its environment (jurisdiction, load and energy prices trends, *etc*.) so that decision makers can experiment various energy policies. Finally, one advantage of the LP approach is the easiness of performing a sensitivity analysis by the interpretation of dual variables. In the case of ESOMs simulating supply-demand equilibrium (see Section 2.3.2), one can derive marginal value pricing of commodities for instance [65].

Main drawbacks are poor modelling accuracy, especially due to the restriction to linear equations. The lack of technical accuracy of large scale LP models has been recently discussed [39,48–53] as well as options to overcome such issues like soft or hard link between ESOMs / CE models and UC models. Reference [69] compares a soft-link model with an integrated model and argue that short-term constraints should not be neglected. In [111]* an extended TIMES model at a national level is soft-linked with a residential building stock and energy demand model and with an optimisation model for pre-dimensioning decentralized heat systems. Another soft-linking example can be found in [99]*.

MILP approaches (Table 3.3):

MILP formulations (see Figure 8) can also be used to optimise investment decisions at large scales [61,69,112]*. The IMRES model [70]* is an example of such approaches. MILP formulations can be seen as a form of trade-offs between ESOMs / CE models and UC models [16]. They usually perform static or myopic dynamic investment optimisation and use aggregated data (representative days for instance) to reduce computational burden. Indeed, computation times can be very high for large systems or for detailed models. For instance, the MILP used in [70]* takes around ninety hours to converge (the optimality gap was not specified).

MILP investment approaches are often used at smaller scales: more details are given in Section 3.1.2.

The case of Energy Plan (Table 3.4):

Previous approaches rely on a MP formalism. The Energy Plan tool follow a different paradigm: it is an energy simulation tool where operational decisions are made based on pre-defined expert rules. Alone, Energy Plan cannot optimise investment decisions. It was used by [152]* as a black box with a metaheuristic to optimise several investment decisions stages in a dynamic anticipative fashion (see Figure 8). Energy Plan can perform full year operation simulation at the hourly level; however, the operational decision facet of the model does not take weather or load predictions into account.

Similar approaches are used at smaller scales; see Section 3.1.2 for more details.

### 3.1.2 Approaches at local scales (Table 3.5 to 3.7)

MILP approaches (Table 3.5):

MILPs are very popular in the literature, especially at local scale. They were used for various cases including power systems, DES (Distributed Energy Systems), buildings, MES, *etc*. Problems studied include screening, sizing and sitting questions. The use of binary or integer variables is justified by various aspects for both operational facet (see Table 1) and investment facet. DER CAM is a commercial tool based on this approach. It is used in [113]* and [28]*, another example can be found in [114]. Open licensed tools like OMEGAlpes [115] and Oemof [116] also rely on MILP formulations.

As LP models, investment MILP models consider load or weather predictions, and rely on perfect foresight hypothesis. They usually perform static investments (a single investment optimisation stage) and use aggregated data (typically representative days) to reduce computational burden. See [25,30,117–119]*. On the other hand, [120]* uses a MILP formulation to perform dynamic anticipative investment optimisation with a high level of technical details. The temporal facet is restricted to two typical days per year to limit computational costs. Another example of dynamic investment optimisation based on a MILP formulation can be found in [66], where both myopic and anticipative approaches are tried out. A main drawback of this formalism is the restriction to linear models as pointed out in [121]. Here, authors compare results from a MILP formulation for the system sizing with operational performances based on a detailed dynamic thermal-hydraulic model. They find an error of 5.1% in the energy mix.

MILP models were also used at larger scales: see Section 3.1.1.

Master investment algorithms with slave operational models (Table 3.6 and 3.7):

A possible approach is to separate the investment and the operational problems with master algorithms which optimise investment decisions by the mean of a slave operational model. Such master algorithms often rely on exhaustive search, heuristic or metaheuristic approaches. Metaheuristics enable various investment considerations (with discrete decisions); however the search space of investment options is a sensitive parameter that affect computation times.

Simulation models coupled with pre-defined expert rules for operational decisions are often used as slave operational model (Table 3.6). We can refer to simulation-based optimisation models. PSO (Particle Swarm Optimisation) or GA (Genetic Algorithm) are commonly used metaheuristics (e.g. [32,122,123]*). Examples of tools are: Energy Pro [124]*, HOMER [125], iHOGA [58] and Odyssey [59]. The two last include their own master investment optimisation algorithm. Main advantages are quick simulation times, thus easiness of considering full time horizons (one year or more with hourly or sub-hourly time steps) and potentially highly accurate techno-economic facets (non-linear). Quick simulation times enable trying out different investment decisions rapidly [124]*. Reference [126] provides a review of such approaches. Their main drawback is that they often impose a myopic operational facet.

In [127]*, authors propose an approach based on artificial neuronal networks to speed up calculations further. A surrogate model (an artificial neuronal network) approximates a simulation model (physical model with pre-defined operational rules). A steady e-state evolutionary algorithm optimises sizing decisions and uses the surrogate model to build a Pareto front which is with the original model in a second stage. The author first trains the surrogate model on several data sets and re-trains it for data sets with different characteristics (load, solar and wind data). The system architecture is kept constant. Although computations were sped up, costs and benefits of such approaches should be assessed while keeping in mind training cost relative to the computation time saved (simulation models with pre-defined operational rules usually already run fast).

Master investment algorithms can also be used with MP approaches for operational simulation (see Table 3.7). However, this approach is less common and was not reported in Figure 8 for sake of clarity. Reference [128]* uses a master algorithm for sizing decisions (efficient global optimisation based on the Kriging method) with various black box models for operation simulation and optimisation. This way they compared TRA (Trust Region Algorithm), PSO, dynamic programming and a MILP (with a simplified storage representation) coupled with the TRA (with the original storage representation). Finally, the KEO model [129]* is a UC model that is soft-linked to an energy-economic model built on Excel to evaluate long-term scenarios for both power and district heating systems.

## 3.2 Approaches with specific focuses

Section 3.1 aimed to depict main trends in energy system planning optimisation approaches. Many of the reviewed papers extend these approaches or develop alternative ones to focus on particular issues (including uncertainties, market mechanisms, spatial and network details *etc.*). These papers are presented here, including concise descriptions of their optimisation approaches.

### 3.2.1 Including investment parametric uncertainties in the optimisation process (Table 3.8 and 3.9)

Without timing optimisation (Table 3.8):

MP formulations were used to account for parametric uncertainties related to the investment problem. In [130]*, authors performed a stochastic optimisation of a stand-alone power system based on multiple daily scenarios for load and wind production with a MILP formulation. A MILP is also used in [26]* to account for uncertain solar generation over typical weeks. In previous cases, problems are reformulated in their equivalent deterministic version. In [131]*, uncertain load, solar and wind as well as OPEX and CAPEX are considered. They used an operational LP model with a rolling horizon for operation simulation. Architectures and sizing are then investigated over Monte Carlo scenarios by exhaustive search. Finally, [19]* uses a single MILP with typical days coupling methods. They first perform a sensitivity analysis on temporal resolution to derive the number of typical days needed. They later characterize uncertainty sources to derive scenarios on loads and PV generation. They optimise the system design for each scenario and evaluate the design operational performances on every other scenario. They define robustness and optimality metrics and compute their correlations with the maximal daily thermal demand and annual energy demand. This way they define a "robust" scenario on which the system design is finally optimised and compared with "average" and "worst case" scenarios.

In another paradigm, [132]***** uses the Odyssey simulation tool as a black box and perform a hybrid robust and stochastic optimisation of a stand-alone power system. Most influential parameters are first determined with a general 2-stage sensitivity analysis (based on the Morris method and the Sobol sensitivity indexes); the system size is then optimised with a GA (hybrid stochastic/robust optimisation with selected uncertain parameters). More details can be found in [133].

At a larger scale [60]* develops a robust formulation while considering a target year with a monthly time steps. Here again, a GSA (General Sensitivity Analysis) helps deriving the most influential parameters. The proposed robust MILP formulation includes protection parameters that can be tuned to avoid over-conservative solutions: the formulation of [134] is extended to account for multiple uncertain parameters multiplying single decision variables.

With timing optimisation (RO approaches) (Table 3.9):

Other methods also consider such uncertainties with a focus on the economic benefits to perform investment timing flexibility: they allow differing investments as uncertainty decreases (to avoid sink costs for instance). These methods rely on the so-called RO approach. In [53]*, authors optimise battery and generators capacity along with transmission lines and installation of FACTS (Flexible AC Transmission Systems) devices with a stochastic/robust multi-stage MILP. They perform anticipative dynamic investment optimisation over a PV prices scenario tree. In [135]* a method is proposed to optimise investment decisions for a DES with energy prices and demands evolving under uncertainty. They start by performing an exhaustive search for the system design using a MILP to simulate the system operation (under all possible demand and prices scenarios). In a second step, they formulate a multi-stage stochastic MILP to optimise the investment decisions timing using the pre-computed operational costs. The RO thinking is also applied in [136]*. Here again, the investment decisions timing is optimised. The investment facet is built in an original way: investments decisions follow pre-defined expert rules which parameters are optimised with a multi-stage stochastic MILP (solved with a Lagrangean decomposition). The authors point out that such approach might be more intuitive for decision makers who rely on heuristics rules rather than on advanced mathematical concepts. They apply it to a hybrid waste-to-energy system with a simple static economic facet. Finally, [137]* uses a multi-stage stochastic LP model to optimise investments in power systems with unfolding uncertainty on gas prices, they also rely on a static simplified economic facet. Other examples of the RO approach can be found in the literature (e.g. [138,139]). A review focusing on smart grids and low carbon systems can be found in [54].

### 3.2.2 Reducing structural uncertainties by considering imperfect forecasts (Table 3.10)

Some methods have a strong focus on the operational facet. They typically consider imperfect load, weather or price forecasts. This reduces structural uncertainties for the investment problem (see Section 2.4). In [140]*, authors consider stochastic wind generation inputs modelled with a Weibull probability density function. Operational decisions are taken by a dynamic program in a RO fashion. Reference [90]* presents a LP model that considers sub-hourly power adjustments with uncertain wind generation and demand fluctuations as well as forecast errors. It enables the sizing of storage and thermal units (static investment) and includes ramp and reserves margins. In [141]*, a two-stage stochastic MILP is used: at first stage, day-ahead start up decisions are optimised based on Monte Carlo scenarios for wind production. Decisions related to flexible equipment are taken in a second stage, after scenario realization. The problem is reformulated as an equivalent full deterministic MILP and relies on a rolling horizon approach. They additionally rely on an approximated value function method (based on Bellman's equation) to consider the value of storage and non-decommissioned production units at the end of the optimisation horizon. This approach draws on the Markov Chain formulation previously used to build Monte Carlo scenarios. The value function is based on a linear formulation with a coefficient adjusted by a learning procedure. Sizing optimisation (batteries and wind turbines) is performed with a response surface method using the value function as a surrogate model. Finally, [22]* uses a two-stage stochastic LP ("DS" model) to model day-ahead market and include balancing costs (under a perfect market assumption). They explore the impact of imperfect wind forecasts and short-term variability modelling on the investment problem results.

### 3.2.3 Market oriented approaches (Table 3.11)

Other studies focus on modelling energy markets (including imperfect forecasts or not). In [142]*, authors model deregulated electricity and heat markets for a power and heat energy hub. They propose a bi-level MILP recasted in a single level formulation to model a single leader versus multi-follower Stackelberg game. The heat and electricity market clearing sub-problems are convex, hence replaced by their Karusk-Kuhn-Tucker conditions. Perfect foresight is assumed but the model could be extended to account for imperfect forecasts. Although designed for operational decisions optimisation, [94]* proposes a model for the day-ahead market (solved every day) and balancing market (solved every hour) with bidding decisions (written as two two-stage stochastic LPs). They consider perfect foresight only one hour ahead for VRE generation and twenty-four hours ahead for the heat load. Stochastic scenarios are used otherwise. A rolling horizon approach allows simulating the full system operation. Finally, [93]* spells out MP formulations for CE problems (investment decisions optimisation). They account for perfect and imperfect markets (non-cooperative sequential game between a collusion of producers making expansion decisions to maximize profits and a market operator who minimises the energy cost). They also account for perfect and imperfect forecasts with two sub-cases: efficient market (day-ahead decision while considering balancing scenarios) and inefficient market (day-ahead decision without considering balancing scenarios). Some formulations are multi-level (possibly stochastic) optimisation problems that can be reduced to single level (deterministic) optimisation problems under simplifying assumptions (discrete investment decisions, linear models).

### 3.2.4 Spatial and network oriented approaches (Table 3.12)

Spatial representations were not discussed in detail in most investigated papers. Reference [24]* proposes a spatial clustering and optimisation method for a district heating investment problem. An intra-cluster optimisation is performed by a MILP based heuristic: network options are explored by a minimum spanning tree algorithm from multiple starting points (buildings). Then, a MILP optimises investment decisions for energy production means (with a 2% relative gap) before a final MILP optimises operational decisions (0% relative gap). An inter-cluster network optimisation is performed in a second step. In [79]* and [82,143,144], EAs (Evolutionary Algorithms) are used for investment decisions coupled to slaves modules. The first module is a thermo-economic simulation model that compute parameters including operation expenses, emissions, technical constraints and reference stream values. The second module is a MILP that optimises operational decisions. The last module computes indicators like the system efficiency, the total annual cost and $CO_2$ emissions. The Geneva canton is clustered into thirteen nodes. The complete system is modelled by three layers: the global layer, the DHC networks (heat cascading) layer and local layer. Network temperatures are discretized into multiple temperature streams in the MILP model. Heat networks modelling options are further discussed in [71,77]: they propose a linear approximation accounting for temperature variations with constant mass flow rates. They apply their formulations to UC models for district heating. On the side of electric networks, [78]* proposes three optimisation methods for DES with an AC model for distribution networks. The "combined method" consists in a GA algorithm used as a master algorithm to optimise investment decisions. A slave MILP optimises operational decisions including an in-house linearized AC model, more accurate than the classic DC approximation. The full AC steady-state power flow model is then computed for every time step to detect voltage and current violations (based on the Newton-Raphson method with Matpower, MATLAB). The voltage and current violations are accounted by the GA master algorithm via penalty costs. For further insights about electric networks modelling and optimisation, see [41,76].

### 3.2.5 Considering long-term operational issues (Table 3.13)

Considering long-term aspects like seasonal storages or annual constraints can lead to computational challenges. Since the operational optimisation horizon is then necessarily extended. Methods were proposed to optimise investment decisions while considering long-term operational issues. References [23,83]* draw on the approach consisting of a single MILP model (for investment and operational decisions) solved over representative periods (days). They further extend it by proposing representative periods coupling methods. The computational efficiency of such approaches is used in [19]* to consider load and weather data series uncertainties in the design phase (see Section 3.1.2). The coupling method proposed in [23]* is implemented in the model EnergyScope TD [110]. Long-term issues are also considered in [141]* via a value function method (see Section 3.2.2, Table 3.9). In [145]*, a MILP with a rolling horizon approach including long-term constraints for optimising operational decisions is proposed. They include them by utilising a simplified representation for long-term operation decisions while keeping a detailed model for upcoming decisions. In [146]*, authors use a long-term model that provides storage level objectives to a short-term model (unidirectional link). The long-term model uses a coarse temporal representation while the short-term model optimises decisions at the hourly level. Finally, [147]* proposes a rolling horizon approach where a MILP is solved iteratively over one week. Yearly constraints (primary energy savings and efficiency) are considered on past, current and future performances. Future performances are first estimated based on typical weeks. The model is run over several years until yearly constraints are satisfied: future performances estimations are updated based on of the previous year simulation.

### 3.2.6 Tackling computational challenges (Table 3.14)

ESIP problems can be very challenging to solve, they are usually NP-hard. In [148], authors show that the synthesis problem (i.e. the investment problem) of decentralized energy systems is strongly NP-hard. Some papers reviewed focus on computational issues and propose alternative approaches. The widely used MILP approach is usually challenging due to integer or binary variables (as stated in [68]*).

Data aggregation methods are a straightforward way to tackle computational challenges: it reduces the problem size. The use of representative periods is widespread in the literature. In [149]*, modellers propose a data aggregation differing from representative periods that allows accounting for inter-day storages: they aggregate similar time steps (load, solar or wind generation) instead.

It is pointed out in [150]* that time series aggregation deteriorates the solution quality, especially for storage optimisation. They explore a solving method for complex problems including seasonal storages: a MILP model is solved by computing lower and upper bounds until a certain optimality gap. The model producing upper bounds optimises sizing and operational decisions on aggregated data (typical days) followed by a MILP optimising operational decisions only on full data. A branch-and-cut commercial solver produces lower bounds, as well as an in-house algorithm based on data aggregation and relaxations. A Bender decomposition approach with Pareto optimal cuts is used in [130]*. Reference [68]* proposes another decomposition method: an upper level MILP with discrete investment decisions optimises the full problem with relaxed operational decisions variables to get a lower bound. Then, they optimise independent operational problems for each time period separately (lower level) to obtain upper bounds. A similar approach is suggested with typical periods at the upper level. They propose extra lower/upper bounding strategies as well as an ordering strategy for solving lower level problems so that the lower bound increases faster. Both previous approaches rely on the fact that only investment decision variables link the operation variables of each time step in a single optimisation problem. In [72]*, a heuristic method to solve a MILP problem formulation in three steps is developed. At first, a full year optimisation on aggregated time steps (more than two hours) is performed, it uses a LP approach for the operational facet (ramps are also excluded). The building envelope retrofits and ST (Solar Thermal collectors) sizes are fixed after this first step. Then a full year optimisation with an hourly time step fixes other technology sizes, here again the operational facet is simplified. In the last step, the system operation is optimised over a full year with an hourly time step and operational considerations such as on/off status and ramps. Finally, [151]* uses EAs as master algorithms for investment decisions, a MILP is used as a slave operational model. The MILP is firstly solved with a 10% relative gap to obtain a lower bound for design solutions, it is then run with a 1% relative gap if the solution is promising, i.e. the lower bound is significantly lower than the current best solution. It is solved on three representative weeks independently. Different solving strategies based on integer variable relaxations are tested for investment decisions.

***Table 3.1: Operational MILP, large scales*** *(see also Table 3.2: [99])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [100] | **Ontario province (Canada) power system** (nuclear, gas, hydro, wind, biofuel and solar, electric network, electric load, DR[b], EV[c], pumped hydro storages) | **SILVER** model, three stages:<br><br>-Day ahead economic dispatch setting prices (marginal cost, assuming generation assets are price-setters)<br><br>-Day ahead UC model<br><br>-Real time optimal power flow dispatch | Operation simulation only | | | Linear models (depending on the different stages): on/off status, start-up/shut-down status (and costs), ramps, minimum up and down times, availability of EV, DR linear model<br><br>Networks: DC linear electrical network model (500, 230 and 115kV lines) | Several (missing information) | 24-hour optimisation horizon, 1-hour time step | Partial foresight 24 hours ahead (forecast errors built by an hyperbolic distribution (wind and solar) | NA |
| [101] | **Irish power system** (storages, WT[d], peat, hydro, pumped hydro, tidal stream, peak production, GTs, transmissions with Great Britain modelled in an aggregated way) | Scenario tree building tool + operational model:<br><br>stochastic MILP + rolling horizon (day-ahead and re-scheduling decisions on a 3-hour horizon)<br>(**Wilmar** tool extension) | Operation simulation/optimisation only (year 2020), different portfolios simulated | | | Linear model: on/off and start-up status, costs, reserves, minimum working power, up and down times, ramps, opportunity value of having online units and storage levels at the end of the optimisation horizon. PWA[e] for fuel consumption curves<br><br>Networks: Linear energy flow model including losses | 21 nodes | 36 hours horizon | Perfect foresight assumed over 3 hours. Before: MC[f] multi-stages scenario trees (with a regressing moving average and a SD[g] depending on the forecast horizon) are used for load and wind generation forecast errors as well as forced outages. The MC simulations include spatial correlations. | NA |

[a] *Combined Heat and Power*
[b] *Demand Response*
[c] *Electric Vehicle*
[d] *Wind Turbines*
[e] *Piecewise Approximation*
[g] *Standard Deviation*
[f] *Monte Carlo*

*Table 3.2: LP based approaches, large scales*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [64] | **Europe energy system** (energy vectors & materials including pollutants and GHG[a]) | **Perseus-RES-E** (Single LP) | Sizing | Dynamic myopic optimisation from 2000 to 2020 (cost based optimisation, investment every 5 years) | Continuous | Linear model including ramp costs and limits, reserve capacities<br>Networks: energy flow with losses | 15 regions | 4 typical years, 8 typical days for each year divided in time slots (2 to 6-hour time step) | Prefect predictions assumed | Multiple deterministic scenarios |
| [99] | **Irish power system** (gas, coal, peat and WT generation, hydro pump storages) | The **Irish TIMES** model (single LP) is used for investment decisions (generation portfolio) which are provided as inputs to the **PLEXOS** model (operational MILP) | Sizing | Static investment optimisation, 2020 is used as a target test year (cost based) | Continuous | TIMES model: linear, supply cost and demand elasticity curves<br>PLEXOS: on/off status, minimum working power, on/off times, start-up/shut-down status, ramps | Missing information | PLEXOS: 30-minutes time step, 24 hours horizon (full year simulation by rolling horizon) | TIMES: perfect foresight assumed<br>PLEXOS: random outages generated by MC simulations | TIMES: multiple deterministic scenarios |
| [104] | **Large scale power system** (4 different conventional production technologies: base, mid, peak and high peak) | Single LP | Sizing | Static optimisation (cost based) | Continuous | Linear models including ramps, operation reserves, must-run constraints and periodic maintenance | Single node | Full year horizon, 1-hour time step | Perfect foresight assumed | NA |
| [108] | **Ireland power system** (WT, PV, storage and various power plants) | **OSeMOSYS** (single LP) including fashioned operational constraints | Sizing, timing | Dynamic anticipative optimisation on 40 years (cost based, investment every 5 years) | Continuous | Linear model with fashioned operational constraints: operating reserve, minimum working power, wind availability, $CO_2$ emissions constraints | Single node | 12 typical days: day, night and peak time for 4 seasons, 1-hour time step | Perfect foresight assumed | NA |
| [111] | **German residential heat system and power system** (HP[b], biomass boilers, micro CHP, gas boiler, ST, several heat demand classes) | Enhanced **TIMES** (single LP) model (TIMES-HEAT-POWER) with inputs from a residential building stock model (providing final energy demand scenarios) and pre-dimensioning for decentralized heat systems (MILP) | Sizing, timing | Dynamic anticipative optimisation from 2015 to 2050 (cost based, investment every 5 years) | Continuous | TIMES model: aggregated power system, differentiated heat system (140 heat classes)<br>Decentralized heat system: MILP model | Single node | TIMES model: 8 typical days with 2 to 6-hour time step, total of 48 time slices.<br>Decentralized heat system optimisation: 9 typical weeks, 15-minutes time step | Perfect foresight assumed | Multiple deterministic scenarios |

[a] *Green House Gases*
[b] *Heat Pump*

***Table 3.3: MILP based approaches, large scales***

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [61] | **Great Britain power and heat systems** (power units, heat and electricity networks and loads, daily TS[a], WT, PV) | Single MILP | Sizing (power units, TS, WT, PV), penetration level of district network VS end use heating technologies, electricity network reinforcements and district heating network investments | Static optimisation, year 2030 (cost based) | Cost function based on preliminary estimates for district heating, linear investment in electricity network reinforcement, linear model for production means | Linear model: ramps, on/off status and start-up status (start up and fixed working costs), operating areas for CHP + demand side management model (within a day), pre-heating, carbon constraint<br><br>Networks: DC linear electrical network model, sub-hourly frequency regulation and reserve constraints. Linear heat network energy flow model including linear losses | 4 regional nodes | Typical days, 1-hour time step | Perfect foresight assumed | Deterministic |
| [69] | **French power system** (nuclear, coal and gas turbine generations, WT and PV) | Single MILP with integer clustering method: binary variables of similar production unit are aggregated into a single integer variable. Different flexibility metrics, method for selecting typical weeks based on dynamic programming. | Sizing, timing | Dynamic anticipative or myopic (missing information) optimisation on 10 years (cost based, investments every year (emission targets) | Continuous | Linear model including reserves, ramps, on/off and start-up/shut-down status, minimum up and down times, minimum working power | Single node | Each year is represented by 4 typical weeks, 1-hour time step | Perfect foresight assumed | 12 deterministic scenarios |
| [70] | **Power system** (power plants, storage including hydraulic, electric load, PV and WT) | **IMRES** model: single MILP | Screening (for power plants only), sitting if multi-nodes | Static optimisation (cost based) | Discrete | Linear model: on/off, start up and shut down status used for minimum working power, minimum up and down time constraints, up and downward reserves, $CO_2$ emissions constraint, hydro storage linear model, ramps, demand side management | To be defined | To be defined | Perfect foresight assumed | Deterministic |
| [112] | **Greek power system** (lignite, natural gas, coal and oil production units, hydro, WT, PV, biomass) | Single MILP | Sizing, screening (8 technology options), timing | Dynamic myopic optimisation from 2014 to 2030 (cost based optimisation, investments every year) | Discrete | On/off, start-up status (including hot, warm, cold status, (de)synchronization and soak times), minimum up/down times, ramps, reserves, 4 marginal cost blocks for imports and exports<br><br>Networks: linear energy flow model | 5 nodes | 12 typical days, 1-hour time step | Prefect predictions assumed | Deterministic |

[a] *Thermal Storage*

***Table 3.4: Master investment algorithms + slave operational models with pre-defined expert rules for operational decisions, large scales***

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [152] | **Italian energy system** | EnergyPlanOpt TP: sequential simulations with **EnergyPlan** + metaheuristic for sizing (MOEA) | Sizing (PV, WT and batteries) | Dynamic anticipative optimisation on 30 years, investments every years ($CO_2$ emissions and cost based) | Continuous investment, including learning effects | Missing information | Missing information | Full year operation simulation | Myopic: pre-defined decision rules | Deterministic scenarios |

***Table 3.5: MILP approaches, local scales*** *(see also Table 3.8: [19], [26], [130], Table 3.10: [140] & Table 3.13: [23] & [83])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [25] | **CCHP[a] and DHC systems** (electric grid, GT, boiler, ACh[b], EC[c], PV, heat recovery stream generator, compression chiller, heat and cooling networks) | Single MILP | Screening, sizing (including networks architectures) | Static optimisation (cost based) | Continuous and discrete | On/off status for minimum working powers and affine performances<br>Networks: Linear energy flow linear model, include losses | 7 nodes (each is a CCHP system) | 2 typical days, 1-hour time step | Prefect predictions assumed | Deterministic |
| [28] | **Microgrid** (electric, heat and cooling loads, ICE[d], batteries, PV, gas boiler, EC, ACh, electric and heat networks) | Single MILP (**DER CAM** model) | Sitting, screening and sizing (8 equipment options) | Static optimisation (cost based) | Continuous and discrete investments | Linear models for technologies, electricity market model including a binary variable (purchase decision)<br>Networks: DC linear electrical network model, linear heat network energy flow model including losses | Single node case<br>and multi-node case<br>(5 nodes, 4 buildings) | 36 typical days, 1-hour time step | Perfect foresight assumed | Deterministic |
| [30] | **MES** (electric, heat and cooling loads, various energy converters, PV, WT, various energy storages) | Single MILP | Screening (10 equipment options) | Static optimisation (cost based) | Discrete | Linear model | Single node | 4 typical days, 1-hour time step | Perfect foresight assumed | Sensitivity analysis |
| [113] | **A campus** (PV, electric grid, batteries, loads, diesel generator) | Single MILP (**DER CAM**) combined with the Distribution Engineering Workstation (**DEW**) tool in a second stage | Sizing (DER CAM output) and sitting (4 cases assessed with the DEW tool) | Static optimisation (cost based) | Continuous<br>investments | Not detailed (DER CAM tool to assess power system violations and losses).<br>Networks: Not detailed (DEW tool) | 25 nodes | 24 typical days, 1-hour time step | Perfect foresight assumed | NA |
| [117] | **Building model** (PV, ST, boiler, battery, TS, gas & electricity utilities, building envelop) | Single MILP (e-constraint[e] method for $CO_2$ emissions), a lexicographic enumeration is used to build a Pareto front | Screening (6 different component types for batteries, TS, boiler, CHP and HP), sizing (PV and ST) | Static optimisation (cost & $CO_2$ emissions based) | Discrete and continuous (for PV and ST) | Linear models, low order building heat model | Single node | 12 typical days, 1-hour time step | Prefect predictions assumed | Deterministic |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| [118] | **MES** (electricity, heat and cooling loads, electricity & gas resources, energy converters and storages) | Single MILP (energy hub concept) | Screening (including hubs ports connections selection) | Static optimisation (cost based) | Discrete | Linear model | Single node | 5 typical days, 1-hour time step | Perfect foresight assumed | Sensitivity analysis on equipment availability |
| [119] | **Urban DES** (main thermal power plant, electric (low and medium voltage), heat (steam and hot water) and cooling distribution networks, distribution stations, electric, heat and cooling loads) | Single MILP | Sitting, screening, sizing (13 equipment options, networks architectures) | Static optimisation (cost based) | Discrete | Linear models for technologies with on/off status (minimum working power & affine efficiency)<br><br>Networks: Linear energy flow model | 10 nodes (2 possible nodes for power plant sitting, 3 nodes for distribution station sitting) | 3 typical days, 2 hour time step | Perfect foresight assumed | Deterministic |
| [120] | **Ward-Hale 6-bus system and iEEE 118 bus system** (various generation and storages technologies, grid imports, loads, electric network) | Single MILP | Screening and sitting (10 generation options and 10 storage options for both cases) | Dynamic anticipative investment optimisation (cost based) | Discrete | On/off and start-up/shut-down status are considered to model minimum working power, start-up/shut-down costs and minimum up and down times. Includes a linear loss of load probability constraint and ramp constraints.<br><br>Networks: DC linear electrical network model | 6 and 118 nodes | 2 typical days, 1-hour time step | Prefect predictions assumed | Deterministic |
| [121] | **Biomass and power to heat production plant** (biomass boiler, heat pump, heat storage, gas boiler backup, network heat load, $CO_2$ emissions and renewable energy ratios from the electricity grid for 3 countries) | Single MILP for sizing optimisation, MILP + rolling horizon + numerical simulator (**Standard Modelica and DistrictHeating Modelica libraries**) for assessment of operational performances | Sizing | Static optimisation (cost based, 3 e-constraints on $CO_2$ emissions, biomass availability and on renewable energy ratio) | Continuous (the storage sizing includes a two-part piecewise linear formulation) | Sizing: on/off and start-up/shut-down status are considered to model minimum working power minimum up and down times. Includes 3 yearly e-constraints.<br><br>Operation: similar MILP formulation, coupled to detailed dynamic thermal-hydraulic model. | Single node | Full year horizon, 2-hour time step for sizing, 15 minutes time step for the operation simulation | Prefect predictions assumed over a year for sizing, over 1 day for the operation simulation | Deterministic |

[a] *Combined Cooling Heat and Power*
[b] *Absorption Chiller*
[c] *Electric Chiller*
[d] *Internal Combustion Engine*
[e] *The e-constraint method is an alternative way to perform multi-objective optimisation: extra objectives are included in the form of constraints. For instance, a certain limit on yearly $CO_2$ emissions can be set. This enables the user to obtain one point of a Pareto set.*

***Table 3.6: Master investment algorithms + slave operational models with pre-defined expert rules for operational decisions, local scales*** *(see also Table 3.8: [132])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [32] | **Wind farm** (WT + batteries + forecasted total output to the grid) | Several operational models used: pre-defined decision rules, fuzzy strategy and artificial neural network for battery control. Exhaustive search and GA are used for sizing and operational decision rules setting. | Sizing (battery: capacity and power) | Static optimisation (cost based, including unmet forecasted output within 4% and 90% of time) | Continuous | Linear model | Single node | 282 days, 10 time step | 1-hour forecast considered | Deterministic |
| [91] | **Stand-alone hybrid energy system** (PV + HC[a] + battery + electric load) | 3 control strategies + **Matlab simulink** used for sizing | Sizing (PV, FC, electrolyser, batteries & hydrogen storage capacity) | Static optimisation (technical criteria based) | Continuous | Physical model, non-linear | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | Deterministic |
| [122] | **Stand-alone hybrid system** (PV, battery, diesel generator, HC, WT, Hydro, electrical load) | Master GA for sizing + physical model with operational decision rules (a GA optimises operational decision rules parameters) | Sizing (full system) | Static optimisation (cost based) | Discrete | Physical model, non-linear | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | Deterministic |
| [123] | **Stand-alone hybrid system** (PV, WT, diesel engine, HC, electric load) | Master PSO for sizing + physical model with operational decision rules | Sizing (full system) | Static optimisation (cost based, C02 emissions and unmet load are included with the e-constraint method) | Continuous | Physical model, non-linear | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | Sensitivity analysis on economic parameters |
| [124] | **DH network** (78000 people) (gas, fuel, biomass or waste boilers, CHP) | Operation simulation with **Energy Pro** + exhaustive search for sizing | Sizing (heat storage, heat pump and ST) | Static optimisation (cost based) | Discrete | Energy Pro model (includes start-up costs, minimum working power, minimum operating hours, start-up time, shut-down time) | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | Deterministic (3 electricity price scenarios tested + sensitivity analysis) |
| [127] | **DES** (PV, WT, battery, internal combustion generator, electric load) | Master metaheuristic for investment optimisation with a slave surrogate model (artificial neuronal network) for operation simulation<br><br>See Section 3.1.2 | Sizing (PV, WT, battery, internal combustion generator) | Static optimisation (cost and grid integration level based) | Continuous | Linear | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | Deterministic |

*[a] Hydrogen Chain (Electrolyser – Gas Storage – Fuel Cell)*

***Table 3.7: Master investment algorithms + slave LP or MILP operational models*** *(see also Table 3.12: [78] & [79])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [29] | **Islanded microgrid**: **CAES** (daily storage, WT, PV, diesel engine) | Master GA for sizing + operational MILP | Sizing (CAES, PV, WT, diesel engine) | Static optimisation (cost based) | Discrete | Linear model: linear CAES storage model (including compression and expansion stages), on/off and start-up variables for start-up costs, ramps, operational reserves | Single node | 6 typical days, 1-hour time step | Prefect predictions assumed | Sensitivity analysis on operating reserve and cost parameters |
| [31] | **Hospital** (CHP, boiler, HP, electric grid, electric, heat and cooling loads) | Exhaustive search for screening and sizing + operational MILP followed by a financial analysis | Screening (architecture and technologies), sizing | Static optimisation (cost based) | Discrete | Discrete model, on/off variables, each module is either off or working at full power. Includes operating reserve constraint. | Single node | 6 typical days, 2-hour time step | Perfect foresight assumed | Deterministic |
| [153] | **CCHP microgrid system**, **hospital case study** (electric, heat and cooling loads, various energy converters, PV, storages) | 4 architectures tested: master GA for sizing and screening + operational MILP | Screening, sizing | Static optimisation on 2 criteria: $CO_2$ emissions and cost | Continuous and discrete investments | Linear model | Single node | 36 typical days, 1-hour time step | Perfect foresight assumed | Deterministic |
| [128] | **Microgrid** (PV and fly-wheels, electric grid) | Efficient Global Optimisation (based on Kringing method) for sizing + various operational optimisation algorithms: Trust Region Algorithm, PSO, dynamic programming, and MILP with simplified model (storage losses) + correction with original model and Trust Region algorithm | Sizing | Static optimisation (cost based) | Continuous | Piecewise linear approximation of storage losses, binary variable for grid penalty costs | Single node | 1 day, 1-hour time step (repeated for 365 days) | Prefect predictions assumed | Deterministic |
| [129] | **Munich DH network** (CHP[a], biogas, geothermal & heating plants) | Energy-economic model built on Excel ("EW" model) soft-linked (bi-directional) with a UC model (**KEO**) | Various analysis managed by the EW model (prices, investment, expansion planning, sales decline scenarios *etc*.) | | | UC model (ramps, on/off and start-up/shut down variables for minimum up and down times, start-up priorities, minimum working power *etc*.) | Missing information | Rolling horizon with a 5 days horizon | Perfect foresight over 5 days | NA |

*Table 3.8: Focus on investment uncertainties, without timing optimisation*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [19] | **Urban MES** (energy hub with PV, ST, HC, batteries, HP, gas convertors, boiler, TS, gas & electric grids, heat and electric loads) | Single MILP with a typical days coupling method run on a robust scenario<br><br>See Section 3.2.1 | Sizing, screening | Static optimisation (cost based, with e-constraints on $CO_2$ emissions) | Piecewise linear investments with fixed costs | Linear model, on/off status for conversion technologies, affine efficiencies with size dependency, minimum working power with size dependency | Single node | Typical days (from 3 to 48) coupled with storage equations (method 'M1') or full year for continuous variables and typical days for binary variables (method 'M2'), 1-hour time step | Perfect foresight assumed | Considering uncertain ambient temperature, solar irradiance to compute uncertain PV outputs and to derive uncertain loads with EnergyPlus (including other uncertain building-related parameters). 1440 scenarios used in total. |
| [26] | **MES** (gas turbines, CHP, boiler, batteries, TS, HP, PV, gas and electricity grids, electric and heat loads) | Two-stage stochastic MILP: screening and sizing at first stage, operation at second stage over different scenarios. Problem solved with a single MILP equivalent deterministic formulation. | Screening, sizing | Static optimisation (cost based, with e-constraint method for $CO_2$ emissions) | Discrete | Linear model: on/off status for minimal working power, ramps, capacity requirements, binary variable for energy shortage + $CO_2$ emissions constraint | Single node | 3 typical weeks, 1-hour time step | Perfect foresight assumed | Uncertain PV production considered (10 MC scenarios for each typical week) |
| [60] | **Swiss energy system** (energy resources, mobility, storages, industrial heat, centralized DHN, decentralized heating, energy loads) see reference for further details | GSA followed by a robust MILP formulation.<br><br>See Section 3.2.1 | Screening and sizing of technologies (see reference for further details) | Static optimisation for the 2035 target year (cost based) | Continuous and discrete | Linear energy model | Single node | Full year horizon, monthly time step | Static model | Discount rate, technology lifetime, investment and operation costs, costs of resources (considered in the robust optimisation after GSA) |
| [130] | **Stand-alone power system** (WT, batteries, electric load and grid, thermal generators) | MILP + Bender's decomposition and use of Pareto-optimal cuts. | Sizing (number of batteries, WT and transmission line capacity units) | Static optimisation (cost based) | Discrete (integer variables) with fixed cost (binaries) | Linear model with on/off status for fixed operational costs | Single node | 4 typical days, 1-hour time step | Perfect foresight assumed | Multiple scenarios for each typical day (demand and wind production scenarios) with varying SD and mean. |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| [131] | **Microgrid** (WT, PV, battery, biomass CHP, classic CHP, biomass gasifier, internal combustion engine, gas storage, boiler, heal and electricity loads) | 5 architectures tested, exhaustive search for WT and PV sizing, rolling horizon with a LP model for operation optimisation over MC scenarios | Screening for the system architecture and sizing (WT and PV) | Static optimisation (cost based) | Continuous | Linear model, including ramps | Single node | 1 day, 1-hour time step | Perfect foresight assumed over the 4 hour horizon of the rolling horizon model | Uncertain loads, PV and WT production considered (1000 daily scenarios) as well as OPEX and CAPEX + sensitivity analysis on battery capacity, electricity and gas prices and loads |
| [132] | **Stand-alone power system** (electric load, PV, batteries, HC) | GSA followed by a master GA for robust / stochastic investment optimisation with an operation simulation tool.<br><br>See Section 3.2.1 | Sizing (all items) | Static optimisation , two objectives: cost and unmet load minimization | Continuous | Non-linear polynomial efficiencies, electrolyser & fuel cell replacements based on utilisation (**Odyssey** tool) | Single node | Full year horizon, 1-hour time step | Myopic: pre-defined decision rules | All technologies techno-economic parameters, 24 parametrical parameters in total |

*Table 3.9: Focus on investment uncertainties: with timing optimisation (RO approaches)*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [53] | **Power system test case** (WT, PV, electrical network, battery, quad-booster transformer) | Stochastic / robust multi-stage MILP | Sizing (batteries, generators) and screening / sitting (network architecture and FACTS devices), timing | Dynamic anticipative optimisation (cost based optimisation) | Continuous and discrete | Linear model including ramps, linear FACTS (flexible AC transmission system) device model.<br><br>Networks: DC model | 3 nodes | 1 typical day, 1-hour time step | Perfect foresight assumed | Scenario tree on the PV prices |
| [135] | **DES** (gas & electrical grids, CHP, boiler, EHP, TS, electric & heat load) | Multi-stage stochastic MILP with pre-computed operational costs.<br><br>See Section 3.2.1 | Timing (CHP, EHP, TS) | Dynamic anticipative optimisation over 15 years, investments every 5 years | Discrete | Linear models with on/off status (minimum working power), including ramps | Single node | 6 typical days, 1-hour time step | Perfect foresight assumed | Uncertain electricity, gas prices & demand evolution unfolding through the scenario tree (1600 scenarios) |
| [136] | **Hybrid waste to energy system** (anaerobic digester and gasifier, gas turbine) | Multi-stage stochastic MILP optimizing investment decision rules parameters.<br><br>See Section 3.2.1 | Timing | Dynamic anticipative optimisation over 9 years (with imperfect foresight) | Investment decision rules with parameters, continuous investments every year (anaerobic digester and gasifier) | Economic linear model | NA | Static | Static | Uncertain amount of two waste types evolution every year (unfolding through the scenario tree) |
| [137] | **Distributed generation, national power system** (gas engine, WT, PV) | Multi-stage stochastic LP on a scenario tree | Timing (gas engine, WT and PV penetrations) | Dynamic anticipative optimisation over 20 years (with imperfect foresight) | Continuous | Economic linear model | NA | Static | Static | Uncertain gas prices evolution (unfolding through the scenario tree) |

***Table 3.10: Considering imperfect forecasts*** *(see also Table 3.1 & Table 3.11: [93] & [94])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [22] | **Power system** (WT, gas, nuclear & coal) | Several models, description of the "DS" model: A two-stage stochastic LP for day ahead and real time markets. Solved as a single deterministic LP. Forecast errors are modelled via an ARMA time series model with decaying autocorrelation. | Sizing (starting from scratch) | Static optimisation (cost based) | Continuous | Linear model including ramps | Single node | 1 to 100 typical days, 1-hour time step | Imperfect wind forecast considered (24 hours ahead). 1000 wind scenarios are generated and then reduced to 10 with a reduction method. | Deterministic |
| [90] | **IEEE 24-bus test system** (power thermal units, storage, demand response, electrical network, WT) | Single LP with chance constraint programming.<br><br>See Section 3.2.2 | Sizing for storage and thermal units (capacity and ramping capability) | Static optimisation (cost based) | Continuous | Linear models including ramps at both time scales for thermal units + ramp reserve capabilities for regulation level (within the 5-minutes time steps)<br><br>Networks: DC model | 24 nodes | Two scales: 1-hour time step and 5-minute time step, 48 typical days | Imperfect foresight considered: uncertain inputs and their forecast errors are estimated and incorporated at intra hour time step. | Deterministic |
| [140] | **Hybrid generation plant** (WT + diesel generator + electrical load) | Exhaustive search for sizing + dynamic programming for operational decisions (RO approach) | Sizing (number of WT) | Static optimisation (cost based) | Discrete | Linear model with on/off status | Single node | Full year horizon, 1-hour time step | Imperfect foresight considered for wind generation (modelled by a Weibull distribution) | Deterministic |
| [141] | **Microgrid** (WT, batteries, inflexible and flexible production units, electricity grid) | Two-stage stochastic MILP with dynamic programming for operation optimisation. Surrogate model for investment optimisation.<br><br>See Section 3.2.2 | Sizing (battery and WT) and system operation optimisation | Static optimisation (cost based) | Discrete | Linear model with on/off and start-up/ shut down binary variables to account for fix, start up and shut-down costs, lost demand cost, ramps. | Single node | Full year horizon, 1-hour time step | Perfect foresight 24 hours ahead for WT generation, stochastic scenarios otherwise (10 different for each day) | Deterministic |

**_Table 3.11: Market oriented approaches_** *(see also Table 3.10: [22])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [93] | **Danish power system** (inflexible and flexible generation, WT, electric load) | Different models for various market and forecast assumptions are spelled out.<br>See Section 3.2.3 | Sizing (WT) | Static optimisation (cost based) | Discrete (in order to recast the multi-level problem as a single-level problem) | Linear (so that the lower-level problems satisfy the linearity constraint qualification to recast the multi-level problem as a single-level problem)<br>Network: energy flow model | Two nodes | Full year horizon, 1-hour time step | Imperfect foresight considered (24 hours ahead imperfect forecasts) | Deterministic |
| [94] | **DH: heat production with participation on electricity day-ahead and balancing markets** (heat load, CHP, gas boilers, ST, PV, WT, TS, gas grid, electric boiler) | 2 two-stage stochastic LPs consecutively solved in a rolling horizon approach.<br>See Section 3.2.3 | Operation simulation/optimisation only, considering day-ahead market bids & balancing markets. | | | Linear model including a penalty cost model for bid deviations (prohibiting speculation) | Single node | Rolling horizon for both LPs (3 days ahead and 12 hours ahead), 1-hour time step | Perfect foresight 1 hour ahead for VRE generation and 24 hours ahead for heat load, stochastic scenarios otherwise | NA |
| [142] | **IEEE 33-bus test system coupled to a 32-node district heat network** (electric & heat markets, HP, CHP, batteries, TS, gas grid, heat and electric loads) (Each energy hub can consume or offer electricity and only consume heat) | Single leader VS multi-follower Stackelberg game: bi-level MILP recasted as a single MILP.<br>See Section 3.2.3 | Operation simulation/optimisation only, considering an energy hub participating into day-ahead markets for heat and electricity operated by two different operators (pay-as-bid agreement). | | | Linear models | IEEE 33-bus<br>power distribution network and a 32-node district heating model | 3 typical days, 1-hour time step | Perfect forecast (imperfect forecasts could be included by a scenario approach) | NA |

***Table 3.12: Spatial and network oriented approaches***

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [24] | **DH: centralized production means with heat network and decentralized production means** (PV, CHP, boiler, TS) | Clustering method + intra-cluster optimisation by MILP based heuristic + inter-cluster network optimisation in a second step. See Section 3.2.4 | Screening, sizing, sitting (production means and heat network) | Static optimisation (cost objective and $CO_2$ emissions objective) | Continuous investments with minimum installed capacity and fixed cost | Linear models for technologies with on/off status (minimum working power). Networks: linear heat network energy flow model including losses | 221 buildings grouped in 13 clusters and 25 outliers | Typical days linked by a storage constraint, 1-hour time step | Perfect foresight assumed | Deterministic |
| [78] | **DES test case** (5 residential buildings seen as energy hubs: TS, PV, GB, CHP, heat and electric load, gas and electric grids (constant prices)) | 3 methods compared including a master GA for investment optimisation, a MILP for system operation optimisation and an AC steady state power flow model. See Section 3.2.4 | Sizing | Static optimisation (cost and $CO_2$ emissions based) | Continuous with fixed costs | Linear models for technologies (LP), building consumption modelled with **EnergyPlus** Networks: AC non-linear model and in-house linearized AC model (includes a piecewise linear approximation to account for the current magnitude) | 5 nodes (residential buildings) | 12 typical days, 1-hour time step | Perfect foresight assumed | Deterministic |
| [79] | **Geneva canton, Switzerland** (hypothetical case, multiple investment options: centralized and decentralized options are tested over different scenarios) | EA for investment optimisation coupled to slave modules: See Section 3.2.4 | Sizing (including minimum sizes for technologies, $CO_2$ taxes) and screening (networks architecture, flow rates, supply and return temperatures) | Static optimisation (cost, efficiency and $CO_2$ emissions based) | Continuous and discrete (technologies, resources selection, $CO_2$ taxes and networks connections) | MILP model: linear, including on/off status and material, power and heat streams DHC networks: linear energy flows including multiple temperature intervals through the definition of streams and layers | A clustering algorithm is used to define 13 integrated zones modelled in 3 layers (global, DHC networks and local streams), | 8 typical days, 1-hour time step | Perfect foresight assumed | Deterministic |

***Table 3.13: Including long-term operational issues*** *(see also Table 3.10: [141] & Table 3.14: [149])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [23] | **Urban MES** (energy hub with PV, ST, HC, batteries, HP, gas convertors, boiler, TS, gas & electricity utilities, heat and electric loads) | Single MILP with a typical days coupling methods | Sizing, screening | Static optimisation (cost based with e-constraints on $CO_2$ emissions) | Piecewise linear investments with fixed costs | Linear model, on/off status for conversion technologies, affine efficiencies with size dependency, minimum working power with size dependency | Single node | Typical days (from 3 to 72) coupled with storage equations (method 'M1') or full year for continuous variables and typical days for binary variables (method 'M2'). 1-hour time step | Perfect foresight assumed | Deterministic |
| [83] | **3 systems: CHP system** (gas & electricity utilities, CHP, gas boiler, TS, heat & electric loads), **residential system** (electricity utility, PV, HP, electric heater, heat storage, heat & electric loads), **island system** (WT, back up, PV, HC, battery, electric load) | Single MILP with a typical days coupling method | Sizing | Static optimisation (cost based) | Continuous with fixed cost | Linear model | Single node | 12 typical days, coupled with storage equations, 1-hour time step | Prefect predictions assumed | Deterministic |
| [145] | **CCHP system** (boilers, CHP, ACh, turbo chiller, heat and cold storages, gas and electricity grids, electric, heat and cooling loads) | MILP + rolling horizon (24 hours shifting). A 48 hour horizon + 6 typical days represent the rest of the year and are (re)computed at every stages of the rolling horizon | Operation simulation only | | | Annual considerations (annual peak power price, grid prices reduced above a certain annual utilization time), linear model (convex performance curves are linearized) | Single node | 2 days + 6 typical days representing the rest of the year + critical time steps accounting for extreme data, 1-hour time step | Perfect foresight over 2 days | NA |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| [146] | **Heat supply system** (seasonal sensible TS, ST, HP, heater, heat load) | A long-term model (LP) setting storage level targets (non-linear penalty cost if not satisfied) to a short-term model (greedy heuristic optimisation with a rolling horizon) | Operation simulation only | Linear models, binary variable for short-term storage decision (fixed input/output flows) | Single node | Long-term model: full year horizon, daily time step.<br><br>Short-term model: few days horizon, 15-minute time step | Perfect foresight for the short-term model, imperfect foresight for the long-term model | NA |
| [147] | **Hospital distribution system** (electricity grid, low and high temperature thermal grids, boilers, heat storage, ICEs, time dependent demands, electricity available from the grid, electricity prices and ambient temperature) | MILP + rolling horizon. A one week horizon is used with future estimations based on typical weeks or on the previous year simulation (see Section 3.2.5) | Operation simulation only | Linear model, on/off and start-up status with related costs and constraints, polynomial efficiencies, yearly constraints on primary energy saving and on the system efficiency | Single node | The full year horizon is simulated, typical weeks are used at the first iteration. | Perfect foresight over the one week horizon | NA |

***Table 3.14: Tackling computational challenges*** *(see also Table 3.12: [24] and Table 3.8: [130])*

| Reference | System | Optimisation method | Problem (Section 2.1) | Investment feedback level (Section 2.2) | Investment facet (Section 2.3.1) | Operational facets (Section 2.3.2) | | | | Uncertainties (Parametric, Section 2.4) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Tech-eco** | **Spatial** | **Temporal** | **Operational decisions** | |
| [68] | **Gas turbine CHP system** (GT generator, waste heat recovery boilers, gas fired boilers, electric compression refrigerators, steam absorption refrigerators, 6 buildings with electric, steam and cold loads) | Single MILP solved by computing lower and upper bounds until a certain optimality gap.<br><br>See Section 3.2.6 | Screening, sizing (4 options for each technology) | Static optimisation (cost based) | Discrete | Linear model with on/off status | Single node | Full year horizon, 1-hour time step | Perfect foresight assumed | Deterministic |
| [72] | **DH system** (boiler, HP, electric heater, ST, TS, building envelop retrofit, heat load, electricity grid) | MILP based heuristic solved in 3 steps.<br><br>See Section 3.2.6 | Sizing (boiler, HP, electric heater, ST, TS, building envelop retrofit) | Static optimisation (cost based) | Scale effects (linear piecewise function) | Linear model including ramps, on/off status, temperature-dependent COP, $CO_2$ emissions constraints<br><br>Networks: energy flow model (linear losses) | Missing information | Full year horizon, 1-hour time step | Perfect foresight assumed | 9 scenarios tested with specific design and operation constraints in, each scenario |
| [149] | **European power system 2030** (base and peak power generations, WT, PV, intraday and inter-day storages, hydro, transmission lines) | Single LP model with a time aggregation approach based on a clustering algorithm: time steps with similar load, WT and PV productions are aggregated (chronology between time steps is retained). | Sizing (starting from scratch, power generation, WT, PV, storages , hydro and transmission lines) | Static optimisation (cost based) | Linear | Linear model including ramps (UC constraints were excluded for simplicity)<br><br>Networks: energy flow model (linear losses) | 28 bus network (one country is represented by one bus) | Full year horizon, variable time step (1-hour or more) defined by the clustering algorithm | Perfect foresight assumed | Deterministic |
| [150] | **Small MES** (Absorption chiller, boiler, CHP, compression chiller, electric boiler, HP, PV, WT, electric storage, cold and heat (seasonal) storage) | MILP model solved by computing lower and upper bounds until a certain optimality gap.<br><br>See Section 3.2.6 | Sizing | Static optimisation (cost based) | Continuous | Linear model with on/off status for minimum working power | Single node | Full year horizon, 1-hour time step | Perfect foresight assumed | Deterministic |
| [151] | **CHP units network** (GT, ICE, boiler, steam cycles, heat storage, electric and heat load, electric grid) | Master EAs for investment decisions with slave MILPs for operation simulation.<br><br>See Section 3.2.6 | Screening, sizing (20 to 30 investment variables) | Static optimisation (cost based) | Discrete and continuous variables, non-linear costs (scale effects) | On/off status, performance curves (linearized with PWA, concave and not concave), including two-degree-of-freedom units with PWA | Single node | 3 typical weeks (CA algorithm developed), 1-hour time step | Perfect foresight assumed | Deterministic |

# 4. Discussion

This survey offers a wide and detailed picture of current optimisation methods used for techno-economic analysis of energy system planning. One can note that despite their expansion in other research topics, artificial intelligence techniques were not often observed. A possible explanation is that energy system planning is an exploratory task while artificial intelligence performs well in known situations.

At local scales, a wide variety of approaches was observed. A first observation is the less recent use of simulation-based optimisation approaches (Section 3.1.2). Mainly since the decisions rules hardly apply to complex systems and have to be adapted by hand when one needs to evaluate several architectures. In addition, they can lead to sub-optimal operations (due to their myopic assumption) and lose relevance for systems with high IE shares, storages, or when investigating production and demand flexibility. In such systems, operational performances issues are important to include at investment planning stages [22].

On the opposite side, the increasing complexity of energy systems has led to the common use of optimisation approaches relying on mathematical programming formalisms (Section 3.1.2). At small scale, **MILP formulations** is a straightforward way to optimise investments and operational decisions under the assumption of an effective control of the future system i.e. with perfect forecast of load and production fluctuations. They often rely on energy models. This accuracy level might be considered adequate for this type of study although some technical aspects are sometimes deepened within the limits of linear formulations: DC approximations for electric networks or further discrete constraints and costs for production and conversion technologies for instance. This is an important limitation of MILP approaches, since non-linear formulations are needed for rigorous consideration of physical aspects. More generally, MILP formulations face inherent computation burdens that particularly increase with the use of integer variables i.e. with technological / economic details, and with spatial / temporal dimensions. This is the case of on/off, start-up/shut-down or other non-linear behaviours of operational decisions. These aspects are often considered as essential to account for the system flexibility to obtain technically feasible solutions. In parallel, computational burdens strongly increase with stochastic optimisation when accounting for operational or investment uncertainties, or when considering market mechanisms. This often leads to multi-stage problems (Sections 3.1.1-3).

Some authors explored further strategies including **decompositions methods and heuristics to solve tough MILP problems** (Section 3.1.6). Researchers could benefit from further crossings between energy system planning literature and operational research applied in other industrial areas. However, these strategies are often problem specific and require more resources. As a consequence, many approaches rely on time series aggregation in the form of representative periods (see Section 2.3.2). Options to reduce complexity while keeping complete temporal data include rolling horizon approaches. They further account for more realistic operational decisions (with limited foresight). However these approaches cannot optimise investment decisions alone. In addition, simulation times must be kept short if one wants to evaluate multiple investment options (see [131] for instance).

Such considerations elaborate on the following challenge: provide substantial investment decision support while relying on **realistic operational models**. This topic is a current concern on the side of optimisation models for large scale energy system planning since the integration of IEs [27,39,40]. If the LP approach is widely applied at large scales, researchers recently questioned flexibility related assumptions for large shares of IEs. Efforts are driven toward these issues (see Section 3.1.1) and can further inspire energy system planning at smaller scales.

With the penetration of IEs, the system flexibility is a growing issue. Modelling **flexibility** is challenging, even more when considering seasonal storages or other long-term operational issues (Section 3.2.5). The use of **aggregated data** alleviates computation burden but has an impact on flexibility strategies as argued in [49] and [150]. This was also observed in [110]. Moreover, the quality of the approximation is data and problem specific so it may have variable performances [88]. They also found higher discrepancies when looking at high IE shares. Hence there is a need for optimisation models that rely on full temporal data to properly consider flexibility issues. Such models should include long-term operational issues like seasonal storage.

Another key aspect for flexibility assessment is the **weather related uncertainties**. Most reviewed studies considered perfect foresight hypothesis, which becomes limiting in case of high IE shares. Indeed, data series uncertainties and forecast errors become increasingly important. Perfect foresight hypothesis also become limiting when considering long-term operational issues like seasonal storages since it increases the operational optimisation horizon. In such cases, forecast assumptions must be challenged.

# 5. Conclusion & perspectives

Future energy systems are expected to rely on **multiple energy vectors** [16,154] and **multiple scales** (countries, regions, cities, individual actors). Long-term energy system planning is now needed at both large and local scales [12,13]. This is in line with a decentralised tendency of energy systems [14] and can be supported by **techno-economic studies based on optimisation models**. Such models must relevantly describe energy systems and optimise investment decisions to expose useful insights and decision support to the user. Literature about ESIP (Energy System Investment Planning) optimisation is abundant and a clear view of current modelling methods used for this subject is far from evident. We proposed a **survey of current optimisation methods**. Unlike existing reviews on local energy system planning, this survey goes deeper into modelling methods. This is done through an **original analysis framework** that questions their modelling accuracy and the feedback level they provide for local investment planning studies. The analysis reviews substantial information relative to the systems studied, the method used, the problems considered, the feedback levels and the modelling assumptions.

We first summarise main methodological trends that include operational and investment optimisation models based on mathematical programming formalisms as well as black box models used with metaheuristics to optimise investment decisions.

Then we identify current research paths: including parametric uncertainties, structural uncertainties related to the forecast assumptions, market mechanisms, spatial representations, long-term operational and computational issues.

We finally discuss added values, limits and particular consideration of systems flexibility in current models. Indeed, with a **growing integration of IEs** [155], the systems **flexibility becomes a critical issue**. Current flexibility assumptions are now being challenged for large scales energy systems. When looking at local scales, such issues are amplified. Flexibility constraints and ability of short and long-term storages should be modelled, while keeping **realistic foresight assumptions** and **accurate temporal representations** accounting for realistic operational constraints. Such research orientations are expected to raise **tough optimisation problems**, which already pushes researchers to explore original methods. Concurrently, including uncertainties in the optimisation process to reach robust solutions will further increase computational challenges.

# Chapitre 2

Le chapitre précédent a permis de comprendre les enjeux relatifs à la modélisation et à l'optimisation de systèmes énergétiques pour des études technico-économiques. Il en ressort le besoin de simuler et d'optimiser ces systèmes sur la base de modèles opérationnels plus précis, en tenant compte d'hypothèses plus réalistes. Cela implique de représenter plus finement les technologies avec leurs contraintes techniques, utiliser des séries temporelles complètes, et tenir compte des limites dans la capacité du pilotage à prévoir et optimiser le fonctionnement du système.

Le choix est fait de s'intéresser aux méthodes basées sur le mécanisme d'horizon glissant. En effet, le mécanisme d'horizon glissant est déjà utilisé pour piloter des systèmes énergétiques existants et est inspiré du principe du contrôle prédictif. De plus, utiliser un tel mécanisme permet de faire interagir différentes briques méthodologiques (module d'optimisation, de prévisions, simulateur, *etc*.), ouvrant la porte à l'exploration d'hypothèses plus fines concernant les aspects technologique, économique, décisionnel, ou encore temporel. Finalement, cette approche permet de découper temporellement le problème d'optimisation et donc d'utiliser des variables entières sans faire exploser les temps de calcul. En effet, si l'on cherche à résoudre un problème opérationnel au pas de temps horaire sur un an, l'utilisation de variables entières en augmentera fortement la complexité.

Les approches classiques en horizon glissant utilisent généralement un horizon d'optimisation tronqué (quelques jours), pour ne pas retomber sur les difficultés calculatoires rencontrées lorsque l'on résout le problème complet en une fois. Cependant, lorsque les décisions opérationnelles court terme dépendent de décisions lointaines (si le système inclue un stockage saisonnier par exemple), l'horizon tronqué conduit à de mauvaises solutions.

Le deuxième chapitre propose une approche pour inclure ces décisions opérationnelles long terme dans l'optimisation court terme. Les pas de temps lointains sont agrégés pour maîtriser les temps de calcul. Deux méthodes d'agrégation sont présentées.

L'utilisation d'horizons glissants permet de simuler l'opération du système. Ce simulateur pourra être utilisé avec un algorithme maître (de type métaheuristique par exemple) pour optimiser la conception du système. La vitesse d'exécution du simulateur sera alors une qualité recherchée au même titre que la pertinence de ses résultats.

L'article qui suit a été publié dans le journal Energy :

*Cuisinier E, Lemaire P, Penz B, Bourasseau C, Ruby A. New rolling horizon optimization approaches to balance short-term and long-term decisions: an application to energy planning. Energy 2022; 245. https://doi.org/10.1016/j.energy.2021.122773.*

Les renvois au Chapitre 1 correspondent à la référence [156].

Abbréviations utilisées au Chapitre 2 :

| Abbréviation | Expression complète |
| --- | --- |
| **CF** | Cost Function |
| **D** | Demand |
| **FP** | Flexible Production |
| **IFP** | Inflexible Production |
| **LTS** | Long-term Storage |
| **RH** | Rolling Horizon |
| **RP** | Representative Period |
| **STS** | Short-term Storage |

# New rolling horizon optimisation approaches to balance short-term and long-term decisions: an application to energy planning

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Abstract:

The planning of complex systems such as energy systems calls for multiple and recurrent operational decisions depending on the present situation as well as future trends. Such decisions can be optimised with rolling-horizon approaches where most immediate decisions are fixed, based on current previsions, while next decisions are made at further optimisation steps with updated information. In this paper, we focus on cases where long-term decisions have to be balanced with detailed short-term decisions to insure operational realism. On such problems, standard rolling horizon approaches are hard to solve due to the substantial increase of the temporal dimension. To overstep this issue, we propose new approaches to balance short and long-term decisions. Two modelling approaches, based on aggregated time steps, are proposed and tested on an energy production problem where energy can be stored seasonally. Approaches are compared to benchmarks approaches, and a sensitivity analysis is performed. Both approaches show promising savings and correspond to different compromises between simplicity, computation time and performance.

Highlights:

-New rolling horizon approaches with an extended planning horizon are proposed.

-Detailed short-term decisions and long-term decisions are optimised jointly.

-Approaches rely on an adaptive time step aggregation method.

-Approaches are tested on a complex heat production problem with seasonal storage.

-Solutions are improved with no / limited increase of computation times.

Key words: rolling-horizon, energy planning, optimisation, predictive strategy, MILP

# 1. Introduction

This paper proposes new rolling horizon approaches to deal with **dynamic operational problems** that include both **short and long-term decisions**. We particularly focus on cases where immediate short-term decisions must be modelled with a detailed discretization of time, whereas long-term decisions must be anticipated but cannot be taken in advance due to poor quality of **forecast** information. The new approaches are illustrated on a typical **energy planning problem** where energy production decisions depend on **seasonal variations**; however, this energy planning problem can be substituted by any production planning problem where short and long-term decisions must be balanced.

**Rolling horizon** (RH) approaches are common in decision making [157,158] and are particularly relevant to solve recurrent, dynamic or multi-period problems where some immediate decisions must be made and available data can be up-dated through time. The idea is to solve the problem over a chosen planning horizon and using current forecasts, but to fix and effectively apply only a part of the optimised decisions. Then, for the next step, the system state as well as forecasts are updated, as in real life situations, and the problem is solved again on the shifted planning horizon. Relying on a RH can also help to divide a large optimisation problem into smaller ones. In [159,160], authors compare the solving of energy planning problems over the entire problem horizon with RH approaches.

RHs are particularly applied in the energy sector. They were traditionally used to solve so-called unit commitment problems, where the set-up and the power dispatch of energy production units must be decided [74]. A RH based method is applied in [80] to optimise operations in a district heating system. In [161], authors develop a three level RH framework for power systems and evaluates the impact of forecast accuracy. In [94], authors use a RH approach to optimise energy market bids and balancing market decisions in a stochastic framework. [162] uses a RH approach to optimise operations in an electric microgrid (i.e. electricity purchased, produced, stored, consumed and sold). In [163–165], authors optimise electric network operations. They rely on RH algorithms to optimise day and intra-day decisions. They investigate various models that consider the stochastic nature of the intermittent energy productions and of the demand. Authors from [166] use a RH model as a reference to evaluate several mathematical programming formulations dedicated to the design and operation optimisation of an energy system. Further examples can be found in [121,195,167].

In the previous examples, RHs consider short planning horizons with detailed time discretization. For instance, energy system modelling often requires an hourly discretization of time. In cases of long-term planning needs (typically when energy systems include seasonal storage), short planning horizons are limiting: a hourly planning horizon of 48 hours can fail to provide an effective use of a seasonal storage for instance. On the other hand, increasing it to 8760 hours can lead to **untractable optimisation problems**. One could drop the RH approach and solve the problem as a single mathematical program with heuristics or decomposition techniques. However, this would require the perfect foresight assumption while the RH approaches enable to consider imperfect forecasts and information updates. Furthermore, RH approaches can include interactions of the decision model with other parties. Hence, this paper focuses on RH applications where short-term decisions should be optimised along with long-term ones. In such cases, there is a need to consider decisions over different time scales and to optimise them jointly.

This challenge was recently discussed in the energy system literature. Authors in [146] use a RH to optimise a heat supply system that includes a seasonal storage. The RH includes a few days planning horizon with seasonal storage level targets at each RH cycle. The economic objective is penalised if targets are not met. However, the penalty price is still to be found. In [168], large scale hydro-thermal systems are optimised with a RH mechanism. The long-term hydro storage is managed by introducing a value for the stored water at the end of the planning horizon. However, the computation of this value is not detailed. Finally, authors from [141] simulate a microgrid with a RH. The value of storage and set-up units at the end of the planning horizon are given by a value function. The latter is estimated by solving a simplified version of the infinite horizon problem with dynamic programming.

The need for a long-term planning horizon can also occur from annual constraints or objectives like energy efficiency/savings, peak power prices, or environmental emission limits for instance. In [145], authors consider annual network charges based on an energy use threshold. They use a RH with a planning horizon based on time aggregation by representative days on the long-term. In [147], a RH is used to optimise the system operation and reach energy efficiency and energy saving targets. They rely on long-term estimations based on representative weeks. Contrarily to [145], the computations had to be done solved several times with updated estimations to reach the targets. In both cases, the continuity between aggregated periods is not kept, so such methods cannot be used if long-term decisions are path-dependent: in case a long-term storage for instance.

Finally, authors from [169] focus on the long-term degradation of batteries while optimising their daily operation in a RH model. They develop a specific parametric model to anticipate future costs of the battery deteriorating modes.

**Contributions:**

Few researches were found that deal with the cases where detailed short-term decisions must be optimised along with long-term decisions. This type of challenge is relevant in the field of energy research. Methods proposed in [146,168] rely on key arbitrary values. Methods from [145,170] do not keep continuity between long-term decisions. Hence, they are not applicable if long-term strategies are path dependent. The method from [169] is technology specific and [141] provides one heuristic method. Given the related problems complexity, **heuristics** relying on future data approximations are of interest. Different heuristics can provide different **compromises** between **computation times, performances and simplicity**. Furthermore, this can vary over the application case. Hence, authors contribute to this research gap by proposing two news approaches.

Both approaches rely on an **adaptive time-step aggregation**. They do not need the modeller to provide a value for long-term moves. Furthermore, both can keep the continuity between state variables over the long term and ensure short computation times. The first one stands out for its easiness of application and short computation times with a case-dependent solution quality. The second for its potential to reach better solutions. The proposed approaches are illustrated on an energy production planning problem and can be extended to other domains.

The paper is organised as follows. We first introduce the problem studied (Section 2). Then, Section 3 describes the proposed approaches. Results are shown and discussed in Section 4 and a sensitivity analysis is performed on the two best versions of the models (Section 5).

# 2. Problem formulation

This section presents the problem used to illustrate the proposed methodologies. It is a heat production case study: heat production units and storage must be managed to supply a network that delivers heat to dwellings corresponding to 5000 inhabitants. The time varying heat demand (D) must be supplied at each period (units considered are actually energy units). It can be supplied with two production means: an Inflexible (but cheap) Production (IFP) and a Flexible (but expensive) Production (FP). They respectively correspond to a biomass boiler and a gas boiler. Additionally, two storage units can be used: a Short-Term Storage (STS) and a Long-Term Storage (LTS). The latter has a higher capacity but lower performances.

The mathematical description of the problem is further detailed. This model is supposed to perfectly represent the real life problem. The mathematical formulation is described on a discrete horizon $H = \{1, \dots, \Theta \in \mathbb{N}^*\}$. The time step size (in hours) is given by $dt$ and ensures units consistency. Variables are written in bold, continuous variables in capital letters and binary variables in small letters. In order to represent units consistency, $X$ corresponds to units/hour and $E$ to units. Parameters and variables are detailed below.

Production units:

- The FP unit is only defined by its unitary production cost in euros/unit $C^F$, with no constraint on the produced quantity. Variable $\boldsymbol{X_t^F} \in \mathbb{R}^+$corresponds to the production of the FP at $t$ in units/hour.

- The IFP is characterised by a minimum and a maximum production capacity in units/hour ($Xmin^I$ and $Xmax^I$), a maximum change of its production rate in units/hour ($Xr^I$), a minimum on time in hours (i.e. if turned on, the IFP must be kept on over at least $Tmin^I$ time steps), a unitary production cost in euros/unit ($C^I$ ), a fixed production cost in euros/hour ($Con^I$) and a set-up cost in euros ($Cset^I$). Variable $\boldsymbol{X_t^I} \in \{0 \cup [Xmin^I, Xmax^I]\}$ corresponds to the production of the IFP at $t$ in units/hour, $\boldsymbol{y_t^I} \in \{0,1\}$ equals 1 if the IFP is on at $t$, 0 otherwise and $\boldsymbol{z_t^I} \in \{0,1\}$ equals 1 if the IFP is being set-up at $t$, 0 otherwise.

Storage units:

Storage units (STS and LTS) are respectively defined by a maximum capacity in units ($Emax^S$,$Emax^L$), a storing efficiency ($\eta^S$, $\eta^L$) corresponding to the percentage of units that are actually stored during the storing operation (the rest is lost), losses in units lost/unit stored/hour ($\delta^S$, $\delta^L$) and a similar stock/destock capacity in units/hour ($Xmax^{SL}$). Associated variables are the stored quantity in units ($\boldsymbol{E_t^S} \in [0, Emax^S]$ and $\boldsymbol{E_t^L} \in [0, Emax^L]$) and the stock and destock rates in units/hour ($(\boldsymbol{Xout_t^S}, \boldsymbol{Xout_t^L}, \boldsymbol{Xin_t^S}, \boldsymbol{Xin_t^L}) \in [0, Xmax^{SL}]^4$) at time step t.

Demand**:**

The demand ($X_t^D$in units/hour) has seasonal variations with higher values in winter and intermediate seasons than in summer. It also varies weakly, and daily due to external temperatures and sociological aspects.

The mathematical formulation of the problem is as follows:

| | | |
|---|---|---|
| $Min$: | $\sum_{t\in H}(C^F \boldsymbol{X_t^F} + C^I \boldsymbol{X_t^I} + Con^I \boldsymbol{y_t^I}) * dt + Cset^I \boldsymbol{z_t^I}$ | *E1* |
| $Such\ that$: | | |
| $\forall\ t \in H$: | $X_t^D = \boldsymbol{X_t^F} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t^S} - \boldsymbol{Xin_t^S} + \boldsymbol{Xout_t^L} - \boldsymbol{Xin_t^L}$ | *E2* |
| | $\boldsymbol{E_t^S} = \boldsymbol{E_{t-1}^S} * (1 - \delta^S dt) + \left(\eta^S \boldsymbol{Xin_t^S} - \boldsymbol{Xout_t^S}\right)dt$ | *E3* |
| | $\boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt) + (\eta^L \boldsymbol{Xin_t^L} - \boldsymbol{Xout_t^L})dt$ | *E4* |
| | $\boldsymbol{X_t^I} \leq Xmax^I \boldsymbol{y_t^I}$ | *E5* |
| | $Xmin^I \boldsymbol{y_t^I} \leq \boldsymbol{X_t^I}$ | *E6* |
| | $\boldsymbol{y_t^I} - \boldsymbol{y_{t-1}^I} \leq \boldsymbol{z_t^I}$ | *E7* |
| | $\boldsymbol{X_t^I} - \boldsymbol{X_{t-1}^I} \leq Xr^I$ | *E8* |
| | $\boldsymbol{X_{t-1}^I} - \boldsymbol{X_t^I} \leq Xr^I$ | *E9* |
| $\forall\ t \in \{Tmin^I, \dots, \Theta\}$: | $\sum_{t'=t+1-Tmin^I}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I}$ | *E10* |
| $\forall\ t \in \{1, \dots, Tmin^I - 1\}$: | $\sum_{t'=1}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I}$ | *E11* |
| $\boldsymbol{E_0^L} \leq \boldsymbol{E_\Theta^L}$ | | *E12* |

The objective *E1* is to minimise the sum of all costs. *E2* ensures that the demand is satisfied. *E3* and *E4* are the balance equations for both storage units. *E5-E6* set the minimum capacity of the IFP and fixes $\boldsymbol{y_t^I}$. *E7* fixes $\boldsymbol{z_t^I}$. *E8-E9* limit the changes in the IFP production rate. The minimum on/off times of the IFP are given by *E10-E11*. Finally, *E12* states that the final LTS level is at least equal to its initial level. This last constraint is only used if H corresponds to a year ($\boldsymbol{E_0^L}$ is set to 0 otherwise). Other variables are set to 0 if $t = 0$.

We assume that the problem we address is fully described by the above model. This problem can be solved iteratively over $H$ in a rolling horizon fashion (see next section). However, with the possibility to store units over the long term with the LTS, the optimal operation of the system for a given RH cycle can only be found by setting the length of $H$ equal to a year. With an hourly time step, $H$ would include 8760 periods which highly increases the problem dimension. To overcome this issue, new approaches are proposed in Section 3.

# 3. Proposed rolling horizon approaches to solve the optimisation problem

This section describes the approaches proposed in this paper. They enable to solve the problem presented in Section 2 in a RH fashion by considering long-term future decisions while optimizing short-term ones.

Figure 9 describes the RH approach as well as the additional notations used in this paper. The problem is solved over a chosen planning horizon with available forecasts. Optimised decisions are effectively applied over the fixed horizon ($FH$). At the next cycle, $H$ is shifted by the length of $FH$. The system state as well as forecasts are updated before the problem is solved again on $H$. This process goes infinitely.

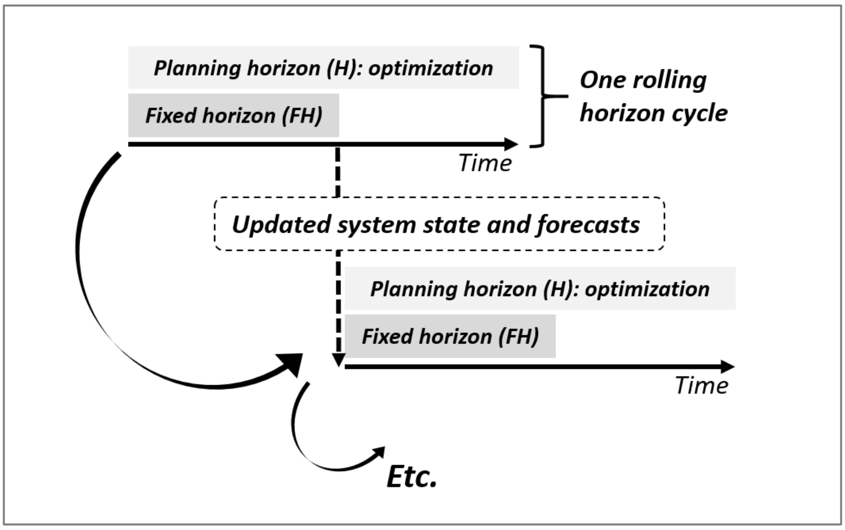


*Figure 9: Rolling horizon principle.*

As mentioned previously, the possibility to store units over the long term extends the planning horizon length, leading to computational issues. In order to make this extension possible, we introduce the idea of short and long-term horizons with aggregated time steps. The horizon of the original model ($H$) is divided into $SH = \{1, \dots, \theta - 1\}$ and $LH = \{\theta, \dots, \Theta\}$ where $\theta \in H$ ($H = SH \cup LH$). The time step size of the original model ($dt$) is kept over $SH$ while it is increased over $LH$. Time step aggregations were already used in other fields of energy system analysis [171,172]: time steps with similar values are aggregated to reduce the problem size. Here, aggregations are made on the more distant time steps for which uncertainty increases i.e. the more distant, the bigger the aggregation. Hence, the time step size $dt$ is now dependent on $t$: $dt_t$. The approach enables a long-term vision up to a year or more while limiting the total number of time steps. Furthermore, the aggregation is adapted to the immediate decision need: upcoming decisions are accurately modelled while long-term ones are reduced to necessary variables. This way, short and long-term decisions are reconciled.

The slicing (i.e. the values of $\theta$ and $dt_t$) is arbitrary and is to be defined by the modeller. It is problem dependant. One could further define a hypothetical medium-term horizon for instance. An example of slicing is given Figure 10. This slicing naturally fits the problem of Section 2 with its actual data (see Section 4). The time step size is adapted to the forecast accuracy. Different versions of this slicing will be tested in the numerical experiments (Section 4).

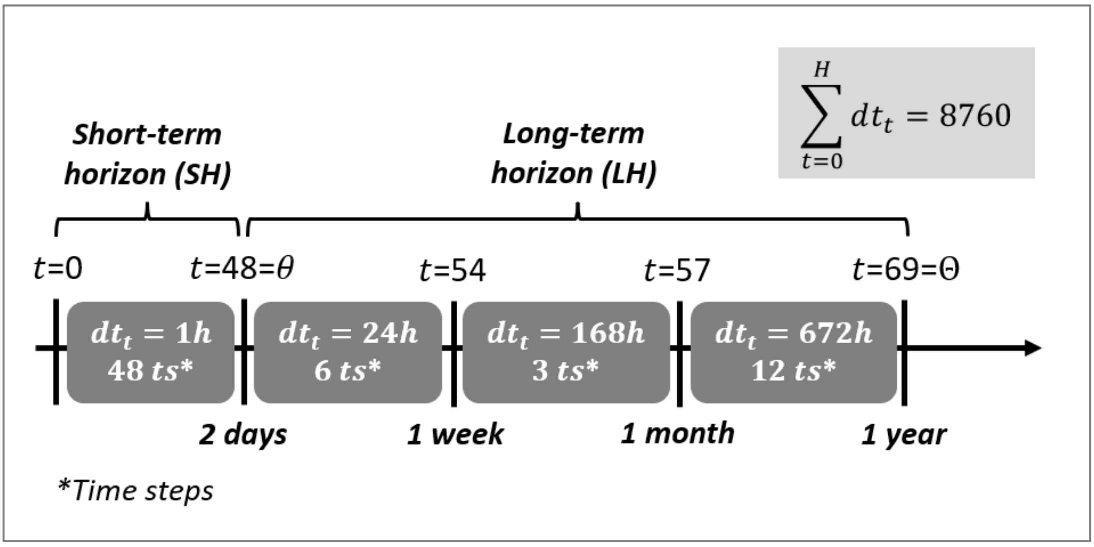


*Figure 10: Planning horizon including a long-term vision with aggregated time steps*

In all cases, the original MILP formulation of the problem of Section 2 is kept over $SH$, which includes $FH$. Hence, *E2*, *E5* and *E6* are satisfied as well as *E3*, *E4*, and *E7-E11* within $FH$. The RH mechanism ensures that *E3*, *E4* and *E7-E11* are satisfied between each $FH$. Finally, *E12* is satisfied because $\boldsymbol{E_0^L}$ is set to 0. Hence, the solution provided by the RH is a solution of *E2-12*.

Two models are proposed for $LH$ to capture long-term data and decisions. The optimisation is then carried out on both horizons jointly in order to keep consistency between short and long-term decisions.

## 3.1. Aggregation by Means and Relaxation: the Mean model

This approach uses means of the demand over $LH$ as an aggregation of future data. The demand $Xmean_t^D$ over the current time step $t$ of size $dt_t$ is the mean of the original demand over this time step. Two formulations are presented for the problem over $LH$.

### 3.1.1. Linear formulation: the original Mean model

Here, the original MILP formulation given by *E1-E11* is kept but integer variables are set to zero over $LH$. Variables on $LH$ represent the means of the original continuous variables over the aggregated period. This new formulation is given below. Changes are marked in blue and new equations are indexed by "*E.X1*". We assume that $n^I < \theta$ .

<u>The Mean model is as follows:</u>

$Min$:

$$\sum_{t\in H}(C^F\boldsymbol{X_t^F} + C^I\boldsymbol{X_t^I}) * dt_t) + \sum_{t\in SH}(Con^I\boldsymbol{y_t^I} * dt_t + Cset^I\boldsymbol{z_t^I}) \qquad E1.1$$

$Such\ that$:

$\forall\ t \in H$:

$$Xmean_t^D = \boldsymbol{X_t^F} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t^S} - \boldsymbol{Xin_t^S} + \boldsymbol{Xout_t^L} - \boldsymbol{Xin_t^L} \qquad E2.1$$

$$\boldsymbol{E_t^S} = \boldsymbol{E_{t-1}^S} * (1 - \delta^S dt_t) + (\eta^S\boldsymbol{Xin_t^S} - \boldsymbol{Xout_t^S})dt_t \qquad E3.1$$

$$\boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + (\eta^L\boldsymbol{Xin_t^L} - \boldsymbol{Xout_t^L})dt_t \qquad E4.1$$

$\forall\ t \in SH$:

$$\boldsymbol{X_t^I} \leq Xmax^I\boldsymbol{y_t^I} \qquad E5.1$$

$$Xmin^I\boldsymbol{y_t^I} \leq \boldsymbol{X_t^I} \qquad E6.1$$

$$\boldsymbol{y_t^I} - \boldsymbol{y_{t-1}^I} \leq \boldsymbol{z_t^I} \qquad E7.1$$

$$\boldsymbol{X_t^I} - \boldsymbol{X_{t-1}^I} \leq Xr^I \qquad E8.1$$

$$\boldsymbol{X_{t-1}^I} - \boldsymbol{X_t^I} \leq Xr^I \qquad E9.1$$

$\forall\ t \in \{Tmin^I, \dots, \theta - 1\}$:

$$\sum_{t'=t+1-Tmin^I}^{t}\boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \qquad E10$$

$\forall\ t \in \{1, \dots, Tmin^I - 1\}$:

$$\sum_{t'=1}^{t}\boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \qquad E11$$

$$\boldsymbol{E_0^L} \leq \boldsymbol{E_\theta^L} \qquad E12$$

### 3.1.2. Including set-up costs: the Mean-SetUp model

In a second formulation, we propose the inclusion of set-up costs over $LH$. This is because set-up costs can be preponderant (see Section 4), thus there might be an interest in setting-up the IFP for longer than the length of $SH$. This is done by including the second part of *E4*, *E5-E7*, as well as set-up costs in the objective on $LH$. The model including the set-up costs is called Mean-SetUp. Contrarily to the Mean model, the Mean-SetUp model is expected to better manage a potential cycling of the IFP. The MILP formulation of the Mean-SetUp model is given below. Changes compared to the Mean model are shown in blue and new equations are indexed by "*E.X2*".

<u>The Mean-SetUp model is as follows:</u>

$Min$:

$$\sum_{t\in H}((C^F \boldsymbol{X_t^F} + C^I \boldsymbol{X_t^I}) * dt_t) + Cset^I \boldsymbol{z_t^I}) + \sum_{t\in SH}(Con^I \boldsymbol{y_t^I} * dt_t) \qquad E1.2$$

$Such\ that$:

$\forall\, t \in H$:

$$Xmean_t^D = \boldsymbol{X_t^F} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t^S} - \boldsymbol{Xin_t^S} + \boldsymbol{Xout_t^L} - \boldsymbol{Xin_t^L} \qquad E2.1$$

$$\boldsymbol{E_t^S} = \boldsymbol{E_{t-1}^S} * (1 - \delta^S dt_t) + \left(\eta^S \boldsymbol{Xin_t^S} - \boldsymbol{Xout_t^S}\right) dt_t \qquad E3.1$$

$$\boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + (\eta^L \boldsymbol{Xin_t^L} - \boldsymbol{Xout_t^L}) dt_t \qquad E4.1$$

$$\boldsymbol{X_t^I} \leq Xmax^I \boldsymbol{y_t^I} \qquad E5$$

$$\boldsymbol{y_t^I} - \boldsymbol{y_{t-1}^I} \leq \boldsymbol{z_t^I} \qquad E7$$

$\forall\, t \in SH$:

$$\boldsymbol{X_t^I} \leq Xmax^I \boldsymbol{y_t^I} \qquad E6.1$$

$$\boldsymbol{X_t^I} - \boldsymbol{X_{t-1}^I} \leq Xr^I \qquad E8.1$$

$$\boldsymbol{X_{t-1}^I} - \boldsymbol{X_t^I} \leq Xr^I \qquad E9.1$$

$\forall\, t \in \{Tmin^I, \dots, \theta - 1\}$:

$$\sum_{t'=t+1-Tmin^I}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \qquad E10$$

$\forall\, t \in \{1, \dots, Tmin^I - 1\}$:

$$\sum_{t'=1}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \qquad E11$$

$$\boldsymbol{E_0^L} \leq \boldsymbol{E_\Theta^L} \qquad E12$$

Although the Mean-SetUp model is expected to perform better than the Mean model, both models rely on an approximation of future costs. This approximation is based on means and on a lightened version of the original problem formulation. These models are expected to give lower bounds for the original problem over $T$ and to underestimate future costs. In particular, the use of means leads to ignore oscillations, which are costly to the system. This justifies the elaboration of a second method described in the next section.

## 3.2. Aggregation by Representative Periods and Cost Functions: the RpCf model

In order to overcome the mentioned limits of the Mean model, we introduce the RpCf (Representative periods and Cost functions) model. It relies on an aggregation of future data by representative periods (RPs). RPs could be used directly over $LH$ with the original MILP formulation, as performed in [145]. However, this can highly increase computation times and the continuity between time steps is lost. Hence we propose a new approach.

First, $\tau$ is introduced as the current step of the RH process. Hence, the couple $(t, \tau)$ describes one actual period of time. The proposed RpCf approach relies on a pre-computation of operational costs in function of a variable which describes the long-term evolution of the system state: $c_{t,\tau}$. In our case this variable is the variation of the state of the LTS: $\boldsymbol{\Delta_t} = \boldsymbol{E_t^L} - \boldsymbol{E_{t-1}^L}$. Note that $c_{t,\tau}$ could have been defined as dependant of $\boldsymbol{E_t^L}$ and $\boldsymbol{E_{t-1}^L}$. Using $\boldsymbol{\Delta_t}$ instead loses information but reduces (pre-)computation times.

Hence, future system costs are estimated depending on the quantity moved to the LTS (possibly negative) over all periods of the $LH$. The functions $c_{t,\tau}$ are called the cost functions (CFs) and are defined for all periods $t$ and for all steps $\tau$.

Similarly to Section 3.1, we present two versions of the RpCf model: a first one without including set-up costs over $LH$, and a second one that includes them.

### 3.2.1. The original RpCf model

Assuming that functions $c_{t,\tau}$ are known, the problem is formulated as follows. Changes to the original MILP formulation are shown in blue and new equations are indexed by "EX.3".

<u>The RpCf model is as follows:</u>

$Min$:

$$\sum_{t \in SH} (C^F \boldsymbol{X_t^F} + C^I \boldsymbol{X_t^I} + Con^I \boldsymbol{y_t^I}) * dt_t + Cset^I \boldsymbol{z_t^I}) + \sum_{t \in LH} \left( c_{t,\tau}(\boldsymbol{\Delta_t}) \right) \quad E1.3$$

$Such\ that$:

$\forall\, t \in SH$:

$$X_t^D = \boldsymbol{X_t^F} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t^S} - \boldsymbol{Xin_t^S} + \boldsymbol{Xout_t^L} - \boldsymbol{Xin_t^L} \quad E2.3$$

$$\boldsymbol{E_t^S} = \boldsymbol{E_{t-1}^S} * (1 - \delta^S dt_t) + (\eta^S \boldsymbol{Xin_t^S} - \boldsymbol{Xout_t^S}) dt_t \quad E3.1$$

$$\boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + (\eta^L \boldsymbol{Xin_t^L} - \boldsymbol{Xout_t^L}) dt_t \quad E4.3$$

$$\boldsymbol{X_t^I} \leq Xmax^I \boldsymbol{y_t^I} \quad E5.1$$

$$Xmin^I \boldsymbol{y_t^I} \leq \boldsymbol{X_t^I} \quad E6.1$$

$$\boldsymbol{y_t^I} - \boldsymbol{y_{t-1}^I} \leq \boldsymbol{z_t^I} \quad E7.1$$

$$\boldsymbol{X_t^I} - \boldsymbol{X_{t-1}^I} \leq Xr^I \quad E8.1$$

$$\boldsymbol{X_{t-1}^I} - \boldsymbol{X_t^I} \leq Xr^I \quad E9.1$$

$\forall\, t \in \{Tmin^I, \dots, \theta - 1\}$:

$$\sum_{t'=t+1-Tmin^I}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \quad E10.1$$

$\forall\, t \in \{1, \dots, Tmin^I - 1\}$:

$$\sum_{t'=1}^{t} \boldsymbol{z_{t'}^I} \leq \boldsymbol{y_t^I} \quad E11$$

$$\boldsymbol{E_0^L \le E_\Theta^L} \qquad E12$$

$$\forall\, t \in LH: \qquad \boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + \boldsymbol{\Delta_t} \qquad E13.3$$

Equation *E13.3* is the storage balance equation over $LH$. With *E4.3*, it ensures continuity between the LTS states over $H$. One can note that the problem over $LH$ is a shortest path problem.

The CFs are naturally included in the MILP formulation as piecewise linear functions. The CFs are estimated by solving the original problem over one or several RPs of the period $t$, for all $\tau$ and for various values of $\Delta$. The method for estimating the CFs is detailed in Appendix A for a given horizon slicing. In the case of the problem given in Section 2 and the data used in Section 4, the CFs are very close to piecewise linear functions and are convex. Slopes of the linear parts correspond to the marginal cost of the last called production unit (IFP or FP). Hence they are easily included in the MILP formulation. However, non-convex and non-linear functions would be more costly to handle.

Contrarily to the mean approximation, costs estimations based on RPs do not ignore the hourly oscillations which are costly to the system. Furthermore, costs are estimated based on the original problem formulation as opposed to the Mean model where a linear approximation is used.

### 3.2.2. Side effects and inclusion of set-up costs:

The RP-FC-SetUp model computations of CFs are subject to side effects depending on the STS and the IFP states at the beginning of the RP. In particular, set-up costs can be preponderant (see Section 4) and ignoring them over could lead to sub-optimal solutions. Hence, similarly to the Mean-SetUp approach, we extend the RP-FC approach so that set-up costs are anticipated over the long term. This is done by computing CFs for both assumptions:

- The IFP is already set-up at the beginning of the RP ("On" assumption).
- The IFP is off at the beginning of the RP ("Off" assumption).

Hence, two sets of CFs are obtained: $c^{on}$ and $c^{off}$. This information is included in the model as follows. Changes compared to the formulation of the RpCf model are shown in blue and new equations are indexed by "EX.4".

We remind that $SH = \{1, \dots, \theta - 1\}$ and $LH = \{\theta, \dots, \Theta\}$.

The RpCf-SetUp model is as follows:

$Min$:

$$\sum_{t\in SH}(C^F \boldsymbol{X_t^F} + C^I \boldsymbol{X_t^I} + Con^I \boldsymbol{y_t^I}) * dt_t + Cset^I \boldsymbol{z_t^I})$$

$$+ c_{\theta,\tau}^{on}(\boldsymbol{\Delta_\theta^{on}}) + c_{\theta,\tau}^{off}\left(\boldsymbol{\Delta_\theta^{off}}\right) + \sum_{t\in LH\backslash\{\theta\}}\left( c_{t,\tau}^{on}(\boldsymbol{\Delta_t})\right) \quad E1.4$$

$Such\ that$:

$\forall\, t \in SH$:

$$X_t^D = \boldsymbol{X_t^F} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t^S} - \boldsymbol{Xin_t^S} + \boldsymbol{Xout_t^L} - \boldsymbol{Xin_t^L} \quad E2.3$$

$$\boldsymbol{E_t^S} = \boldsymbol{E_{t-1}^S} * (1 - \delta^S dt_t) + \left(\eta^S \boldsymbol{Xin_t^S} - \boldsymbol{Xout_t^S}\right)dt_t \quad E3.1$$

$$\boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + (\eta^L \boldsymbol{Xin_t^L} - \boldsymbol{Xout_t^L})dt_t \quad E4.3$$

$$\boldsymbol{X_t^I} \le Xmax^I \boldsymbol{y_t^I} \quad E5.1$$

$$Xmin^I \boldsymbol{y_t^I} \le \boldsymbol{X_t^I} \quad E6.1$$

$$\boldsymbol{y_t^I} - \boldsymbol{y_{t-1}^I} \le \boldsymbol{z_t^I} \quad E7.1$$

$$\boldsymbol{X_t^I} - \boldsymbol{X_{t-1}^I} \le Xr^I \quad E8.1$$

$$\boldsymbol{X_{t-1}^I} - \boldsymbol{X_t^I} \le Xr^I \quad E9.1$$

$$\forall\, t \in \{Tmin^I, \dots, \theta - 1\}: \quad \sum_{t'=t+1-Tmin^I}^{t} \boldsymbol{z_{t'}^I} \le \boldsymbol{y_t^I} \quad E10.1$$

$$\forall\, t \in \{1, \dots, Tmin^I - 1\}: \quad \sum_{t'=1}^{t} \boldsymbol{z_{t'}^I} \le \boldsymbol{y_t^I} \quad E11$$

$$\boldsymbol{E_0^L} \le \boldsymbol{E_\Theta^L} \quad E12$$

$$\forall\, t \in LH\backslash\{\theta\}: \quad \boldsymbol{E_t^L} = \boldsymbol{E_{t-1}^L} * (1 - \delta^L dt_t) + \boldsymbol{\Delta_t} \quad E13.4$$

$$\boldsymbol{E_\theta^L} = \boldsymbol{E_{\theta-1}^L} * (1 - \delta^L dt_\theta) + \boldsymbol{\Delta_\theta^{on}} + \boldsymbol{\Delta_\theta^{off}} \quad E14.4$$

$$\boldsymbol{\Delta_\theta^{on}} \le \boldsymbol{y_{\theta-1}^I} Emax^L \quad E15.4$$

$$\boldsymbol{\Delta_\theta^{off}} \le (\boldsymbol{1} - \boldsymbol{y_{\theta-1}^I})Emax^L \quad E16.4$$

Equation *E14.4* is the storage balance equation exclusive to time step $\theta$. *E15.4-E16.4* ensure the consistency between the CFs $c^{on}$ and $c^{off}$ with the state of the IFP at $\theta - 1$. This way, the continuity between the IFP states is kept up to $\theta$.

Since the information about the state of the IFP is lost after $\theta$, CFs computed with the "On" assumption are used afterwards (*E1.4*). This is because future costs are overestimated otherwise, which can lead to unused stored units and costly solutions. This model is called the RP-FC-SetUp model. It is expected to perform better than the RP-FC model since continuity between the IFP states is kept between $SH$ and $LH$.

# 4. Comparison of all approaches: computational experiments

In this section, the proposed approaches are compared on the basis of the problem described in Section 2. The problem corresponds to a heat production case study: heat production units and storages must be managed to supply a network that delivers heat to 5000 inhabitants. Other production planning problems where short and long-term decisions must be balanced could be used as well. The data are shown Table 4.

*Table 4: Data of the heat production problem.*

| Element | Parameter | Notation | Value |
|---|---|---|---|
| **Flexible Production (FP), gas based** | Capacity (units/hour) Cost (euros/unit) | N.A. | Uncapacited |
| | Cost (euros/unit) | $C^F$ | 66.8 (See Appendix D for details) |
| **Inflexible Production (IFP), biomass based** | Capacity (units/hour) | $Xmax^I$ | 3 |
| | Minimum capacity (units/hour) | $Xmin^I$ | 1.2 |
| | Maximum change in production | $Xr^I$ | 1.2 |
| | Variable cost (euros/unit) | $C^I$ | 33.3 (See Appendix D for details) |
| | Fixed cost (euros/unit) | $Con^I$ | 10 |
| | Set up costs (euros) | $Cset^I$ | 500 |
| **Short-term Storage (STS)** | Capacity (units) | $Emax^S$ | 30 |
| | Efficiency | $\eta^S$ | 0.98 |
| | Losses (units/unit stored /hour) | $\delta^S$ | 0.00021 (0.5% per day) |
| | Stock/destock capacity (units/hour) | $Xmas^S$ | 3 |
| **Long-term Storage (LTS)** | Capacity (units) | $Emax^L$ | 1500 |
| | Efficiency | $\eta^L$ | 0.97 |
| | Losses (units/unit stored /hour) | $\delta^L$ | 0.00042 (1% per day) |
| | Stock/destock capacity (units/hour) | $Xmas^L$ | 3 |
| **Demand (D)** | Demand profile (units/hour) | $X_t^D$ | See Appendix C for details |

## 4.1. Experiments procedure

The same heat demand profile le is used over both horizons $SH$ and $LH$. This way, only biases on the data aggregation method and on the models themselves are accounted for. Other demand profile les as well as imperfect forecasts will be tested in Section 5.

1. The RH process is parametrized as follows: for all computations, the Fixed Horizon (*FH*) is set to 24 hours, and three different planning horizons are tested, as defined by Figure 11. *H1* and *HM* are respectively a simplified and a truncated version of *H2*.

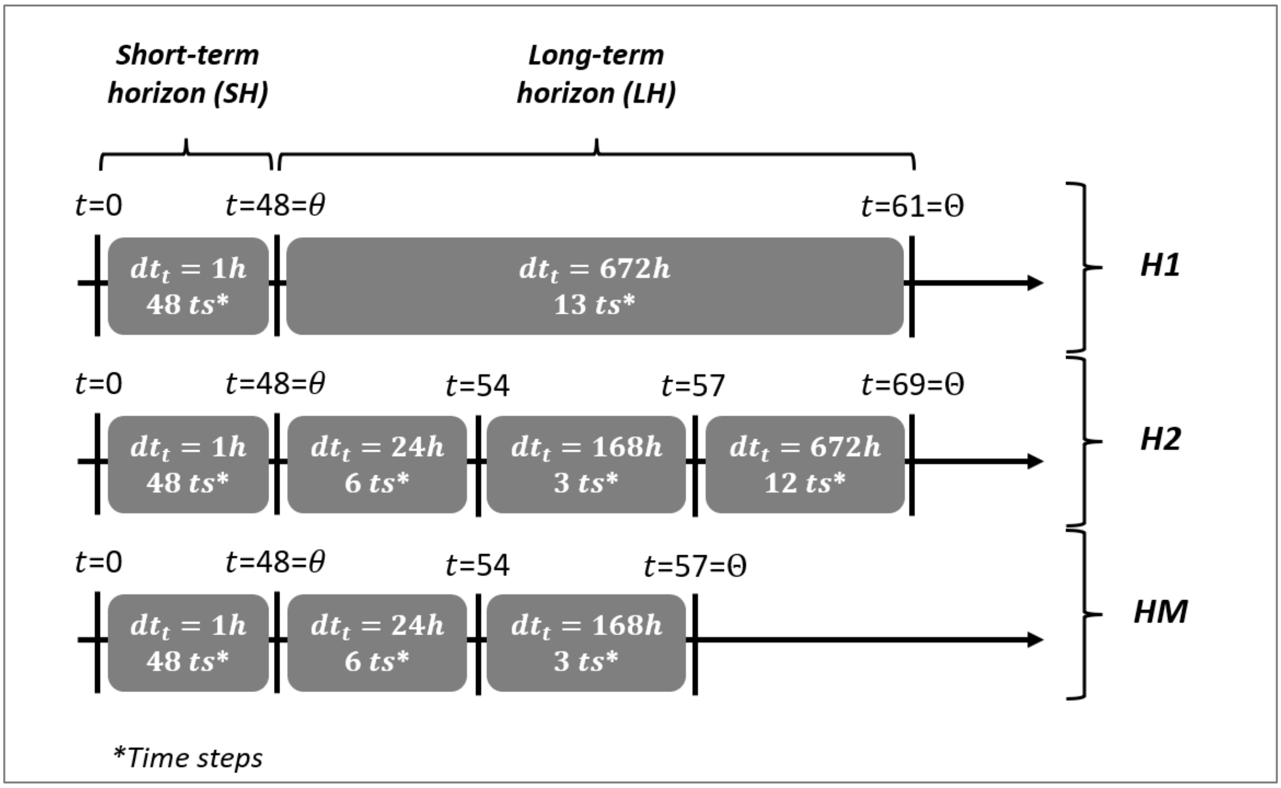


*Figure 11: Planning horizon H1, H2 and HM*

Two extra computations are performed to provide benchmark references:

- A “Cicada” approach where the problem is solved based on a similar RH mechanism as previous approaches, except that the planning horizon $H$ is limited to $SH$. This approach is used as a benchmark where forecasts are limited to 48 hours. As mentioned in Section 2, given the seasonal variations of the demand and given the possibility to store units over the long term with the LTS, the optimal solution might only be found by solving the problem over a year. Hence the Cicada strategy suffers from the so-called truncated horizon effect as de ned in [173]. Storage units are emptied and the IFP is turned o at the end of $H$. The *FH* of 24 hours limits these side effects but is not sufficient to ensure an efficient long-term strategy.

- A “One Shot” optimisation of production decisions where the problem (original formulation, *E1*-*E12*) is solved over a year in a single optimisation (with an hourly time discretization). This is used as a benchmark where the hourly demand is perfectly known over the whole year, which over-estimates forecast abilities and under-estimate the system operating costs. Given the problem size, only the lower and upper bounds are obtained.

All approaches are evaluated over a year. Solutions retained correspond to solutions on the *FHs* of the RH process over a year (see Figure 12). Since the yearly strategy over the LTS might evolve if more years are simulated, models are run until it converges. In practice, this is the case after one or two years.

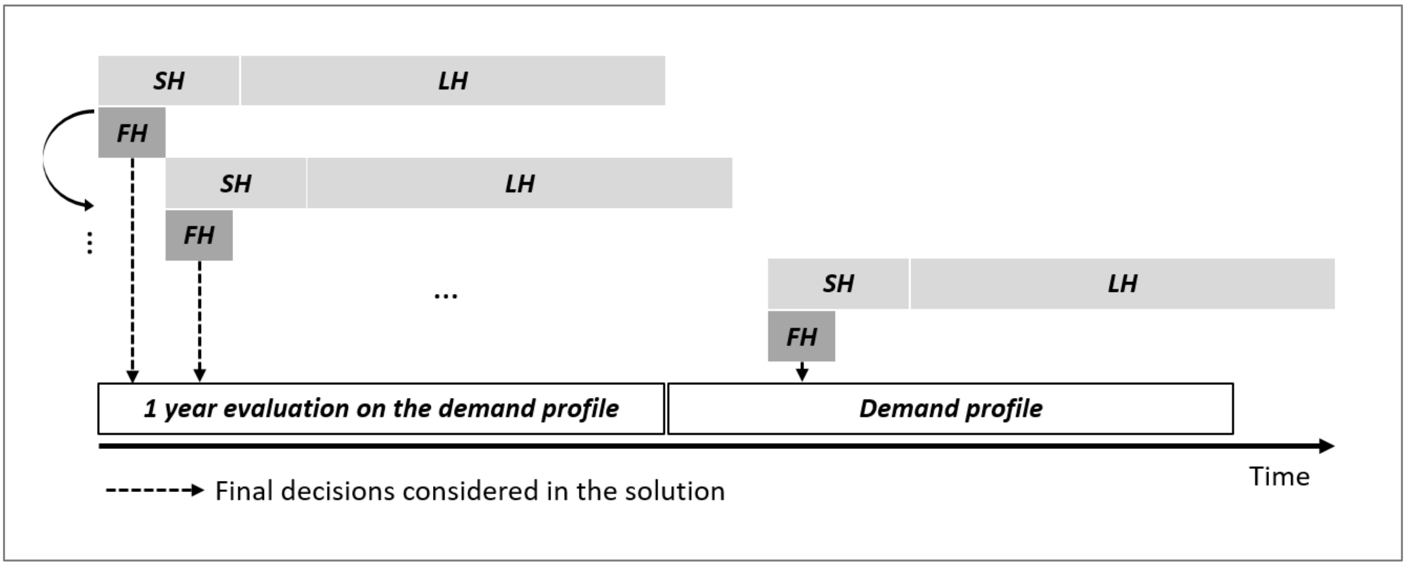


*Figure 12: Evaluation process*

## 4.2. Computational environment

Computations are performed within the PERSEE environment (see Figure 13). PERSEE is a modelling software dedicated to techno-economical assessment and design of energy systems at local, industrial and territorial scales, while optimizing their operating costs. It has been developed in CEA (Centre Energie Atomique et Energies Alternatives) since 2018 on the basis of past experiences from the Odyssey [194] and the PEGASE platforms [174]. It relies on the MILP formalism which is widely applied to deal with problems related to energy-system planning [156]. PERSEE provides a graphical user interface that allows one to model the system by assembling MILP model contributions from a C++ library, building the whole optimisation problem. Multiple carriers can be used including electricity, heat or materials (gas, fuel, biomass *etc*.). Variables can describe energy, mass, power or mass flows. The net present value is used as the objective function. It accounts for capital and operating expenditures, replacement, purchase and sales costs as well as possible carbon emission penalties. It becomes an operating cost function when the system operation only is considered. Following up [156], PERSEE models have been written to be compliant with several time discretizations including representative periods and time dependent aggregated time steps.

The problem is solved by one of the solvers available through a multi-MILP-solver interface (OSI open source, CPLEX, GUROBI *etc*.) As part of the PEGASE platform, PERSEE is able to control fine simulators, digital twins or real systems using model predictive control. PEGASE is compliant with the FMI-Cosimulation 2.0 norm. Both PERSEE and PEGASE are expected to be open source by 2022, in the frame of the starting CEA Trilogy project.

In this paper, the 12.9.0 version of the CPLEX solver [175] was used on an Intel Xeon Gold 6154 CPU with 2 processors of 3 GHz. The installed RAM is 96 GB. Threads used were limited to 8 threads except for the One Shot optimisation where all threads were used with a limit of 40 hours. In all cases, the final relative gap was set to $10^{-6}$.

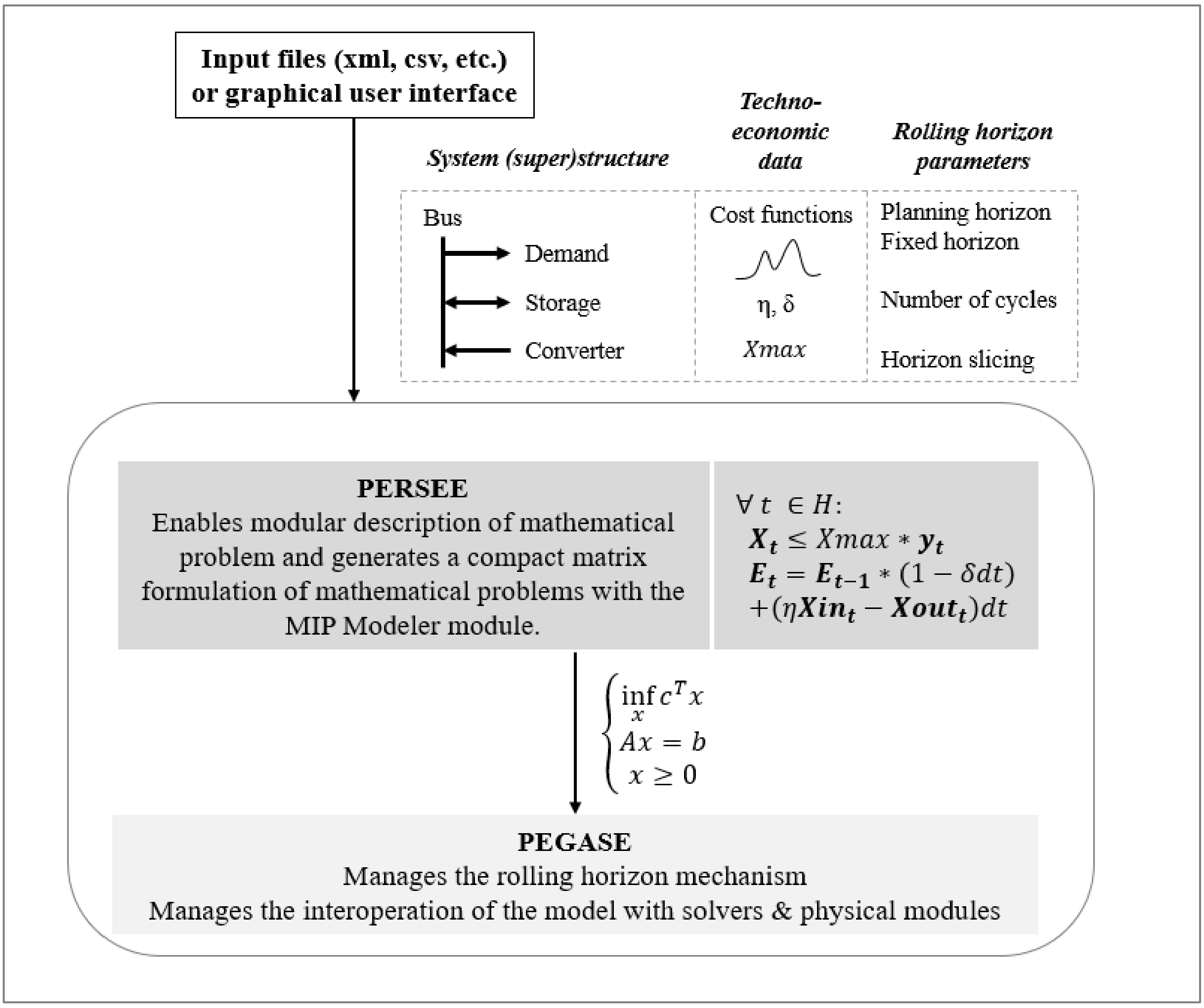


*Figure 13: Schematic description of the modelling environment*

## 4.3. Results

### 4.3.1. Economic performances and computation times

Results are given in Table 5. The final relative gap with upper and lower bounds are given for the One Shot optimisation. Savings are defined as the difference between the total costs of the Cicada approach with the total costs of another approach. This way, only compressible costs are considered. Savings of Table 5 are displayed on Figure 14.

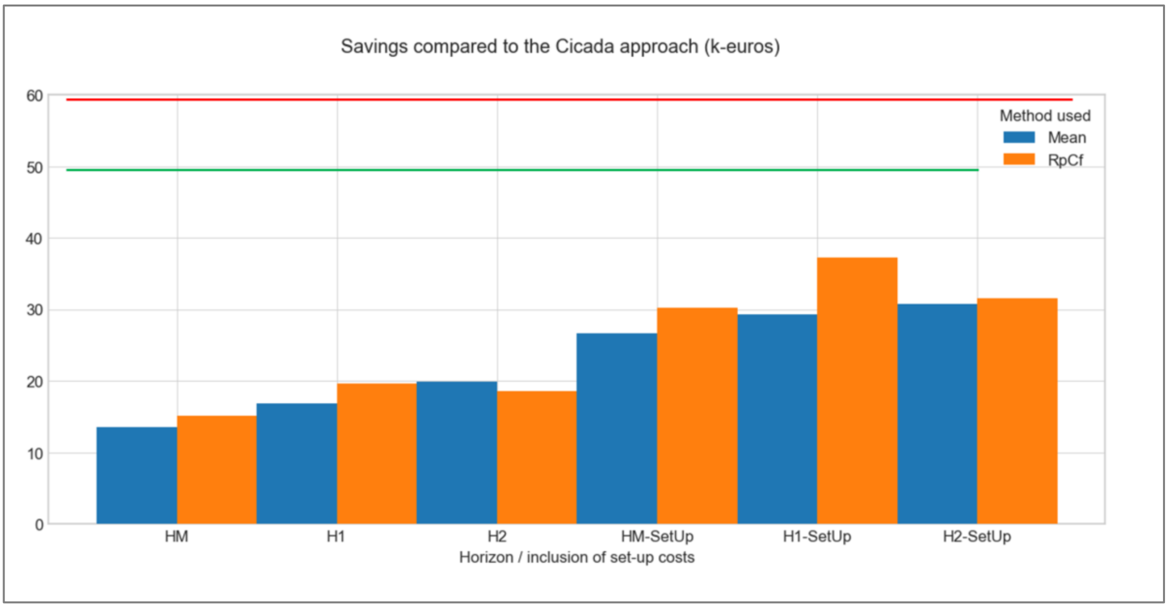


*Figure 14: Savings of all approaches compared to the Cicada approach (k-euros), with upper bound (red) and lower bound (green) of the One Shot optimisation.*

*Table 5: Results*

| Model | Planning horizon | Total cost (euros) | Savings compared to the Cicada approach (euros) | Simulation computation time (sec) | Cost functions computation time (sec) |
|---|---|---|---|---|---|
| **Mean** | *H1* | 847 755 | 16 887 | 36 | 0 |
| **Mean-SetUp** | | 835 340 | 29 302 | 33 | 0 |
| **Mean** | *H2* | 844 700 | 19 942 | 33 | 0 |
| **Mean-SetUp** | | 833 924 | 30 718 | 34 | 0 |
| **Mean** | *HM* | 851 083 | 13 559 | 40 | 0 |
| **Mean-SetUp** | | 837 918 | 26 724 | 40 | 0 |
| **RpCf** | *H1* | 844 948 | 19 694 | 95 | 353 |
| **RpCf-SetUp** | | 827 315 | 37 327 | 95+95* | 695 |
| **RpCf** | *H2* | 846 071 | 18 571 | 202 | 9 331 |
| **RpCf-SetUp** | | 833 064 | 31 578 | 253 | 18 64 |
| **RpCf** | *HM* | 849 442 | 15 200 | 130 | 8 9701 |
| **RpCf-SetUp** | | 834 456 | 30 186 | 131 | 17 945 |
| **Cicada approach** | | 864 642 | 0 | 32 | 0 |
| **One Shot optimisation** | | Lower bound: 806 435 | 58 207 | 40 hours Final relative gap: 1.03% RAM used: 56 GB | 0 |
| | | Upper bound 814 863 | 49 779 | | |

**Only case where the computations converged after two years instead of one year.*

### 4.3.2. Solutions

The solutions for the benchmark Cicada approach, for models Mean, Mean-SetUp, RpCf, RpCf-SetUp with horizon *H1* and for the One Shot optimisation are described here (Figure 15 to Figure 20). For each figure, the upper graph shows the elements of the balance equation E2, while the lower graph shows the state of both storages. All graphs start on the first of July.

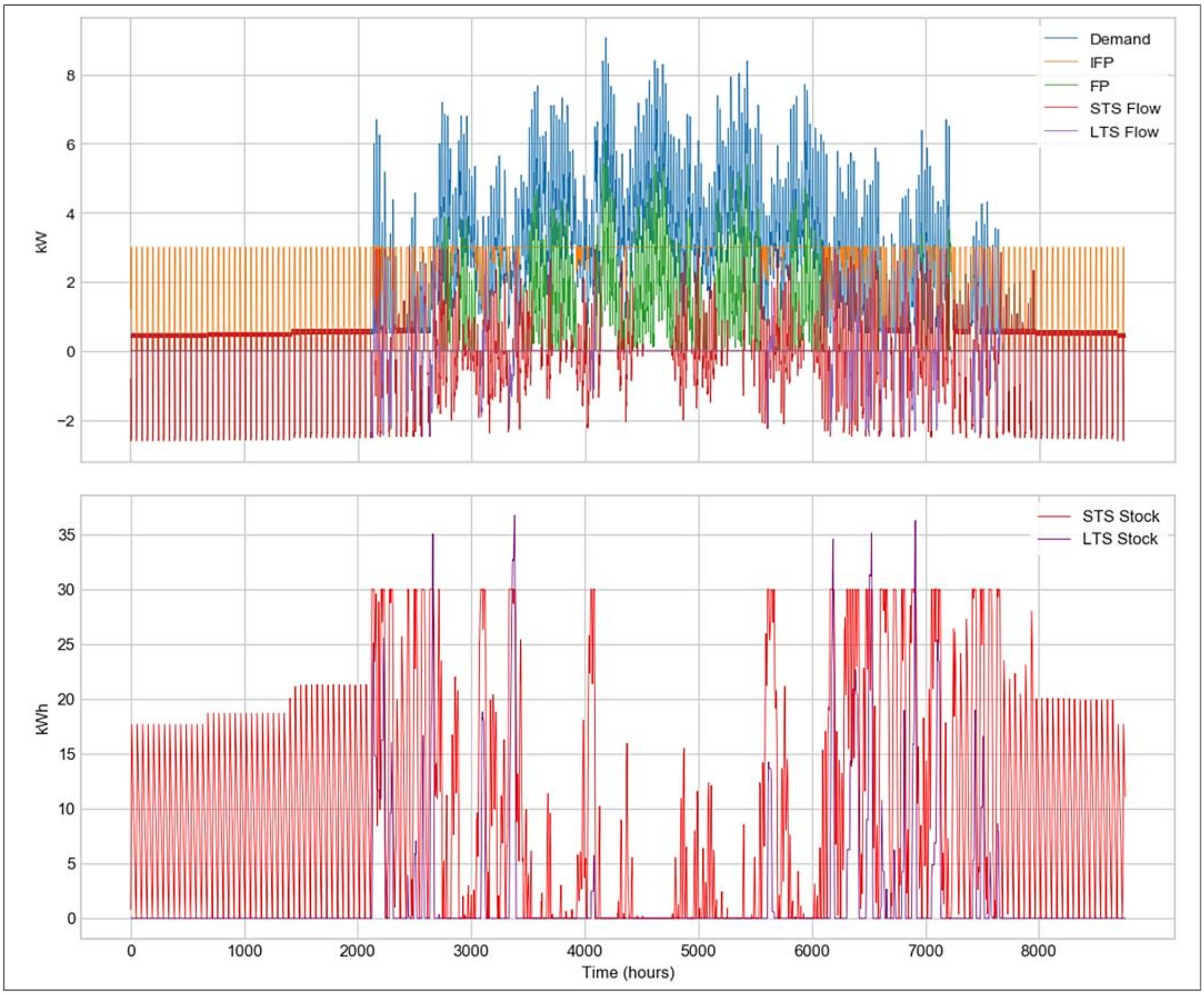


*Figure 15: Results for the benchmark Cicada approach.*

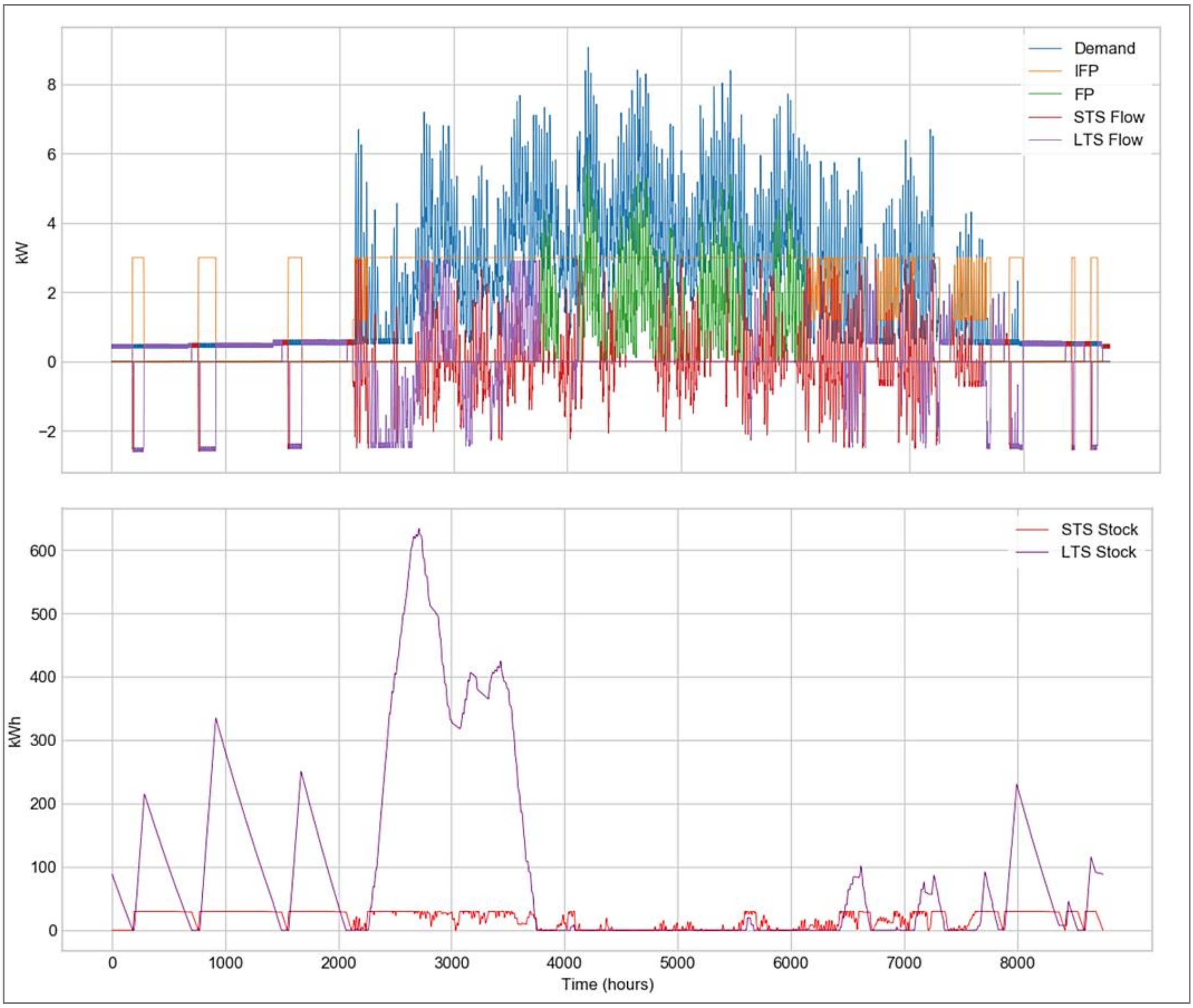


*Figure 16: Results for the One Shot optimisation.*

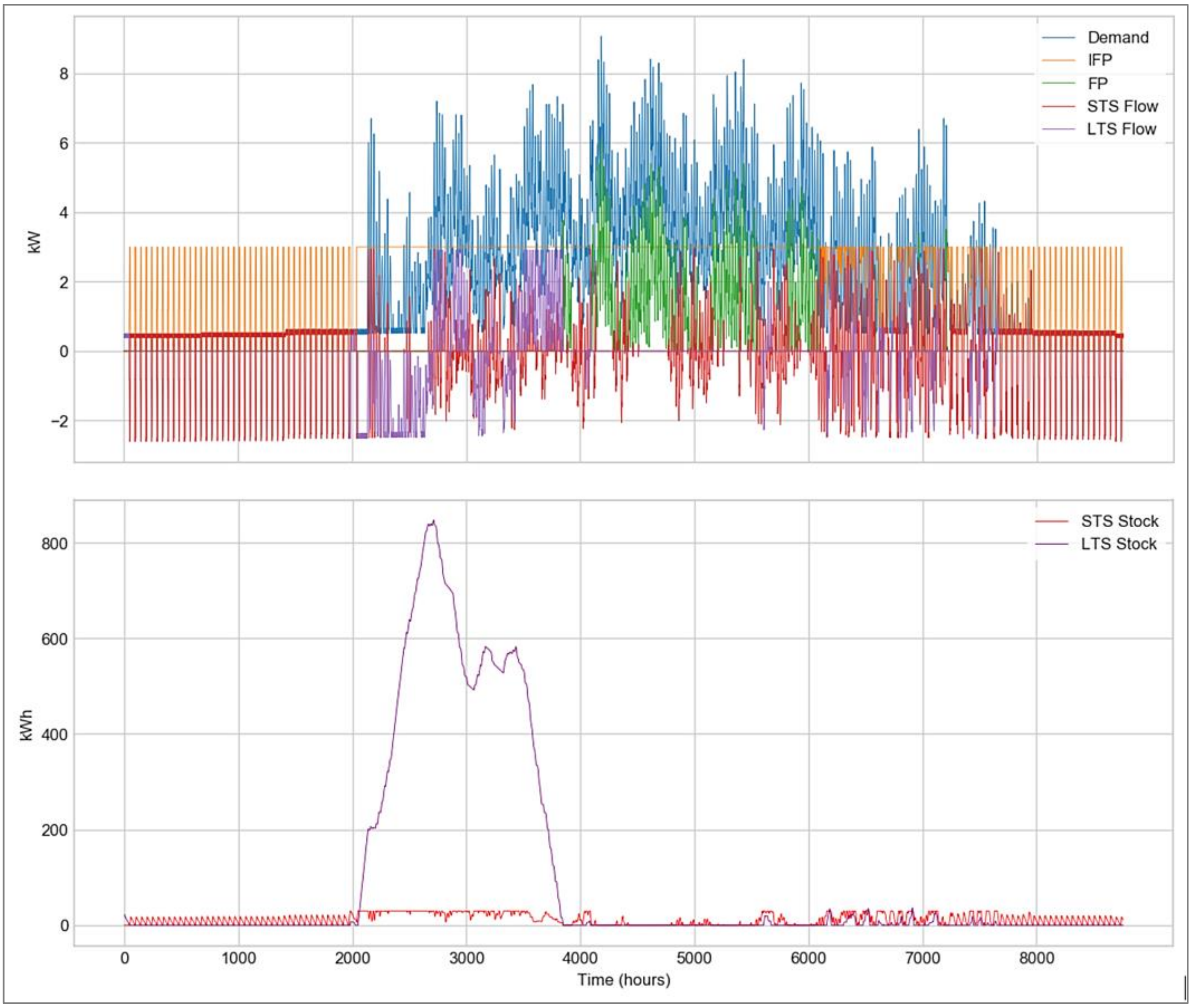


*Figure 17: Results for the Mean model, with horizon H1.*

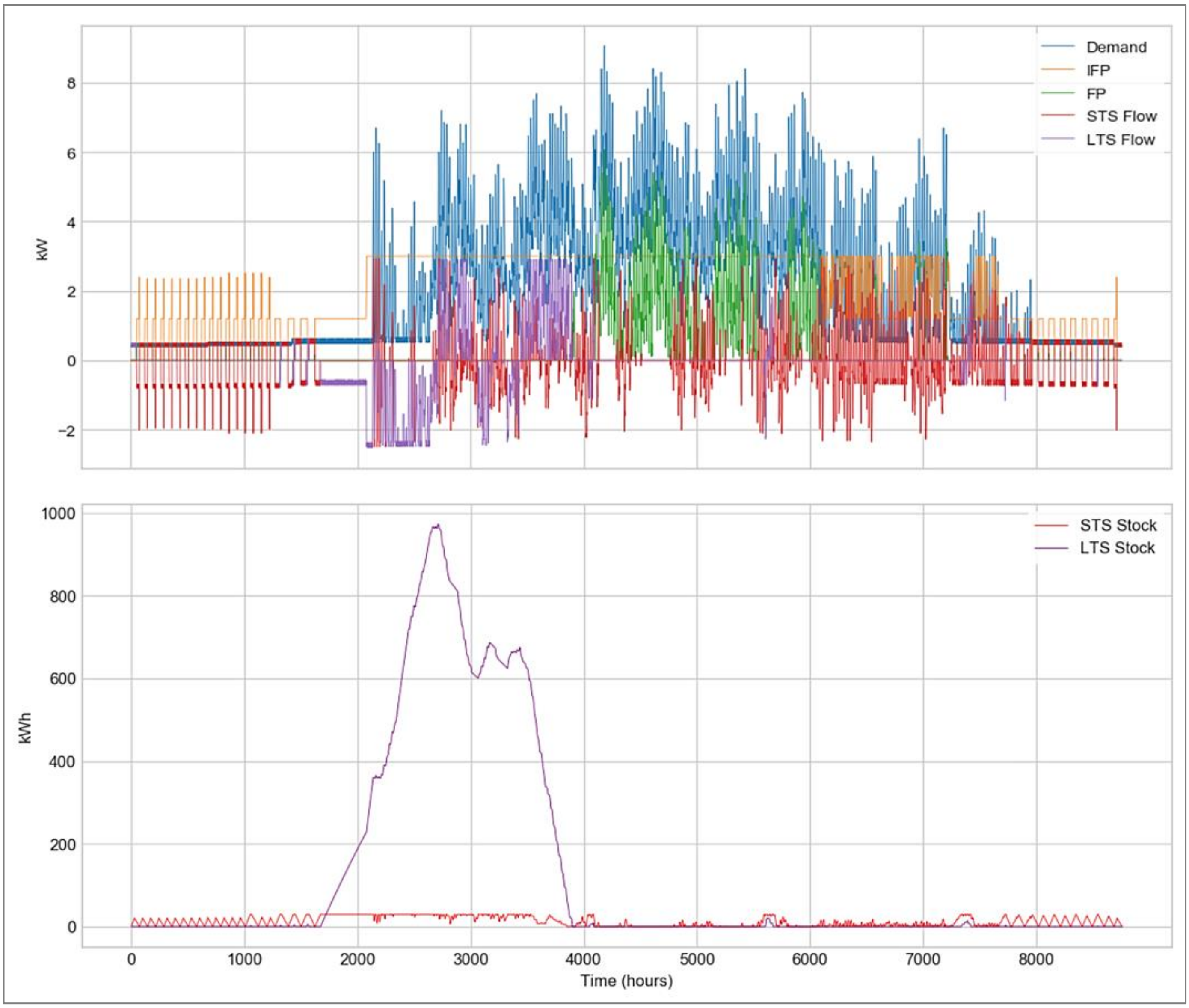


*Figure 18: Results for the Mean-SetUp model, with horizon H1.*


*Figure 19: Results for the RpCf model, with horizon H1.*

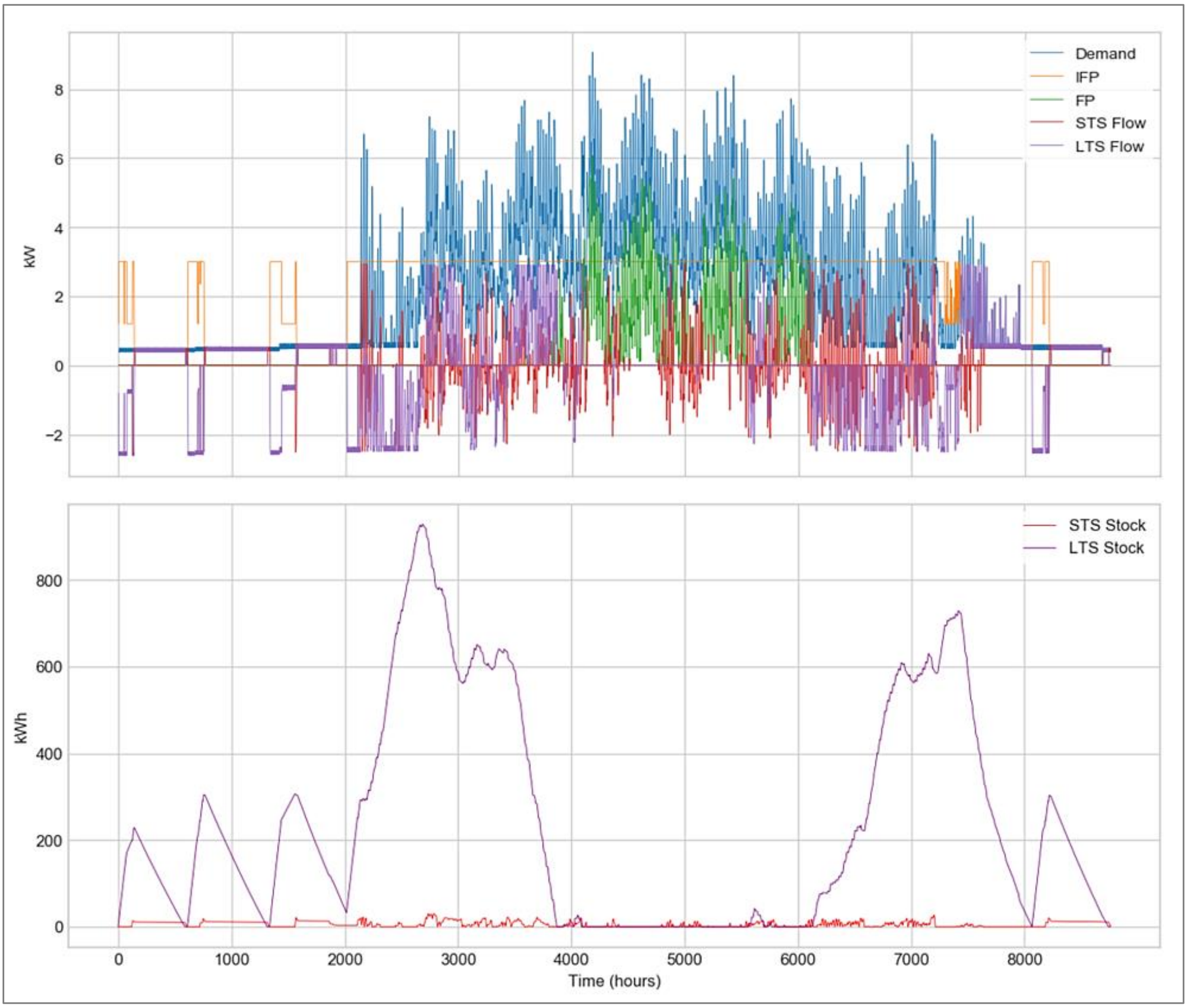


*Figure 20: Results for the RpCf-SetUp model, with horizon H1.*

The Cicada approach shows nearly no use of the LTS. It makes the IFP cycling a lot. This is due to the fact that it does not anticipate set up costs after 48 hours.

In the One Shot optimisation solution, the IFP is started up only few times during the summer to limit set-up costs. The storage is filled up to 650 units before the heating season.

The Mean model makes the IFP cycle as much as the Cicada approach before the heating season (the same phenomena occurs with *H2* and *HM*). It makes use of the LTS (which is not the case with *HM*) but stores more than the One Shot optimisation. This is because it does not anticipate the destocking flow capacity of the LTS and the demand flows lower than the IFP capacity. Hence the stored quantity is held longer than expected which implies more losses.

The Mean-SetUp model makes longer cycles with the IFP (the same phenomena occurs with *H2* and *HM*). It stands far from the cycling strategy of the One Shot optimisation because the minimum capacity of the IFP is not considered on the LH. Hence, future costs are under-estimated. The inclusion of set-up costs also adds a phase where the IFP is used at minimum capacity (before the heating season).

The RpCf model also makes the IFP cycle a lot (to a lesser extent that the Cicada or the Mean models). It also stores less units before the heating season, which is an improvement compared to the Mean model.

Finally, the RpCf-SetUp model has an efficient cycling strategy on summer which is comparable to the One Shot optimisation. The model also stores units at the end of the heating season, contrarily to the One Shot optimisation. One explanation is that the approximation with RPs led to an overestimation of future costs on these periods.

## 4.4 Discussion and recommendations

Solutions quality:

All approaches bring savings compared to the Cicada benchmark approach (see Figure 14). In most cases, RpCf approaches yield better solutions than Mean approaches. The difference is more significant with *H1*. These savings are also significant compared to the upper and lower bounds obtained by the One Shot optimisation. The difference with the One Shot optimisation is due to the model approximations and to the aggregation of future data.

Computation times:

Table 5 shows the computation times for the different approaches (Appendix B provides further information on the convergence of the One Shot optimisation). The inclusion of a long-term horizon with the Mean and Mean-SetUp approaches does not significantly impact computation times. Computation times with *HM* increased because the relative gap was not adapted to the horizon length (the objective is optimised down to the euro for horizons *H1* and *H2* while it is optimised down to the tenths of euro on the *HM* horizon which is over-qualitative). On the other hand, computation times are three times higher for the RpCf models on *H1*. It further increases when moving to *H2* and *HM* horizons. The RP-CF-SetUp model with *H2* needed a second year of simulation to converge: the first year ended with a higher storage level than what it started with. Regarding the CFs building computation times, they can easily be reduced by using binary search techniques or parallel computations for instance. Computation times are relatively high for horizons *H2* and *HM* because CFs are computed for every day and week of the year, while *H1* only requires CFs for every period of 4 weeks.

What modelling aspects to include in the long-term model:

Long-term models that include set-up costs give better savings. This is due to the high set-up costs: there is an interest in setting up the IFP for longer than the SH. Further applications should include decisions that have a potential long-term impact in the long-term model. Concerning the Mean models, the problem formulation to use as a long-term approximation can be case dependent. In this case, inclusion of the IFP minimal capacity was not fruitful for instance. It led to an overestimation of future costs and units were stored for no use. A formulation that under-estimates future costs will at least perform better than the Cicada approach. This is true for Mean models on this case study because oscillations of the system are costly.

Choice of planning horizons:

Concerning Mean approaches, the longer and the more detailed the planning horizon the better the results. This is not true for the RpCf model which yields a better solution with *H1*. This can be explained because the continuity of the IFP discrete states is kept between $SH$ and $LH$ but it is lost after the first time step of $LH$. Hence, the RpCf-SetUp model benefits from the large time steps of *H1*. Therefore, the choice of the planning horizon can depend on the approach used.

# 5. Sensitivity analysis

In this section, we perform a sensitivity analysis for models RpCf-SetUp and Mean-SetUp. We choose to keep the same *LH* in both cases. Hence, *H1* is used because it led to significantly better results with the RpCf-SetUp model. The objective is to test the robustness of the two best approaches on similar horizons. Both models are tested with different assumptions on the data used in Section 4, and on the quality of the demand forecast.

## 5.1 Sensitivity on the data

We first test both models on different data sets. We cross two data modifications:

- A change in the FP costs: 44.4, 55.6, 66.8 and 78.0 euros/unit are tested. A cost of 66.8 was used in Section 4 and a cost of 44.4 corresponds to the case where no CO2 emission penalties are considered (see Appendix D for details).
- A change in the profiles used for the demand, which corresponds to different meteorological scenarios. Three demand profiles A, B and C are considered (details are provided in Appendix C). Profile A was used in Section 4.

The savings compared to the Cicada model are compared for all tests, see Figure 21. Both models have steady and consistent behaviour. They bring important savings on other pro les, showing reassuring stability. The exception occurs when the FP costs are low. In fact, potential saving heavily depends on the FP costs. This is because an important part of the savings comes from an efficient management of the IFP during the summer and intermediate seasons. If the FP costs are lowered, it is used during the summer instead of the IFP. In addition, the small difference between the FP and IFP costs lowers the interest in the storage of units at the beginning of the heating season. This makes the RpCf-SetUp model slightly less performing than the Cicada model: units are stored but losses exceed the savings over the FP use (see Figure 22). This is due to an over-estimation of future costs which can come from the data aggregation with representative periods.

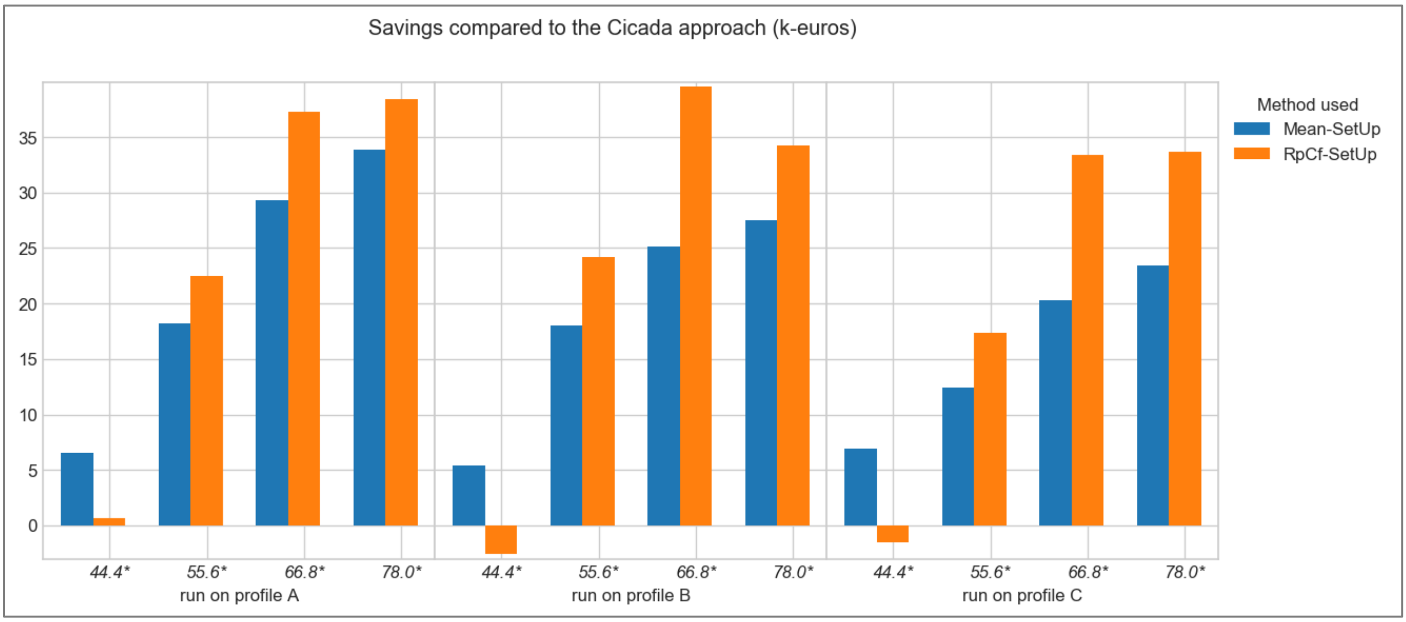


*Figure 21: Savings of models RpCf-SetUp and Mean-SetUp on horizon H1, for different costs of the FP, on demand A, B and C (k-euros).*
**Costs of the FP.*


*Figure 22: Solution of the RpCf-SetUp model in case where the FP cost is 44.4 euros and the demand profile B is considered..*

## 5.2 Sensitivity on the quality of forecasts

Up to now, the same profiles for the demand were used for both short-term and long-term horizons. The only biases came from the models used and data aggregation method (i.e. means and RPs). We now compare results when different demand profiles are considered over the long-term horizon i.e. if forecasts are inexact after 48 hours.

This is done through two test procedures. In the first procedure, the planned meteorological profile after 48 hours differs from the realised profile. However, monthly total demands are constant between the planned and the realised profile. This way, intra-month forecast errors are modeled. In the second procedure, extra-month forecast errors are considered.

### 5.2.1. Sensitivity on the forecast meteorological profile: intra-month forecast errors

In this section, tests are run with profile A, B or C as effective demands (i.e. profiles used over $SH$) and with profile A, B, C or the mean on the three profiles as forecast demands (i.e. profiles used over $LH$). Hence, the demand is still perfectly known on $SH$, but not on $LH$.

The savings (cost difference with the Cicada model) of different experiences are compared. Results are shown in Figure 23 for models RpCf-SetUp and Mean-SetUp.

A first observation is that savings are still significant and that the model RpCf-SetUp outperforms the Mean-SetUp model in all cases. Both approaches show relatively robust results with respect to the demand profile used on $LH$. As mentioned earlier, potential savings differ from one profile to another. Interestingly, the best results are not necessarily obtained when the same data is used over both $SH$ and $LH$, and the effective demand seems to be the core element (savings are bigger for A and B, smaller for C): the models do not seem to overfit the forecast data.

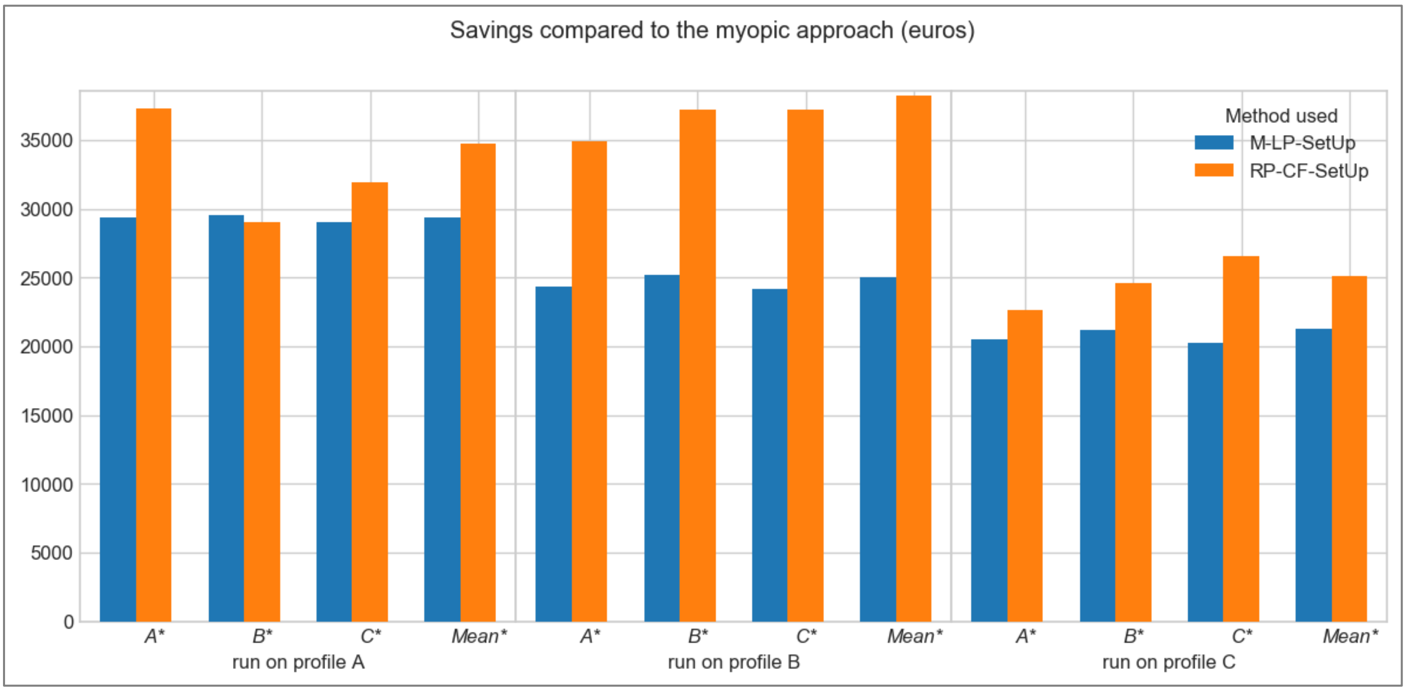


*Figure 23: Savings obtained with models Mean-SetUp and RpCf-SetUp, on horizon H1, for different demand profiles run and planned (k-euros). *Profile use as forecasted demand after 48 hours.*

### 5.2.2. Sensitivity on the forecasted meteorological profile: extra-month forecast errors

Data sets A, B and C are built from different meteorological scenarios. However, the building method supposes constant monthly total demands for all data series. In order to test our models in the case of forecast errors on total monthly demands, a second test procedure is applied. We introduce a monthly forecast error: the profile used over $LH$ corresponds to the effective profile used over $SH$ increased or decreased by a given percentage. The demand is still perfectly known over $SH$, but not over $LH$. Three cases are tested:

- The hourly demand is always overestimated by a given percentage (+X%)
- The hourly demand is always underestimated by a given percentage (-X%)

- The demand is overestimated or underestimated depending on months (+-X%, the pattern used is given in Appendix C).

The savings (cost difference with the Cicada model) of the different experiences are compared on Figure 24. All tests are performed with profile A.

Similarly to Section 5.2.1, savings are still significant and the RpCf-SetUp model remains more effective. Both models show satisfying robustness and the downgrade remains very limited as errors increase. The worst cases are when the demand is overestimated: this worsen the tendency of both models to store too many units before the heating season.

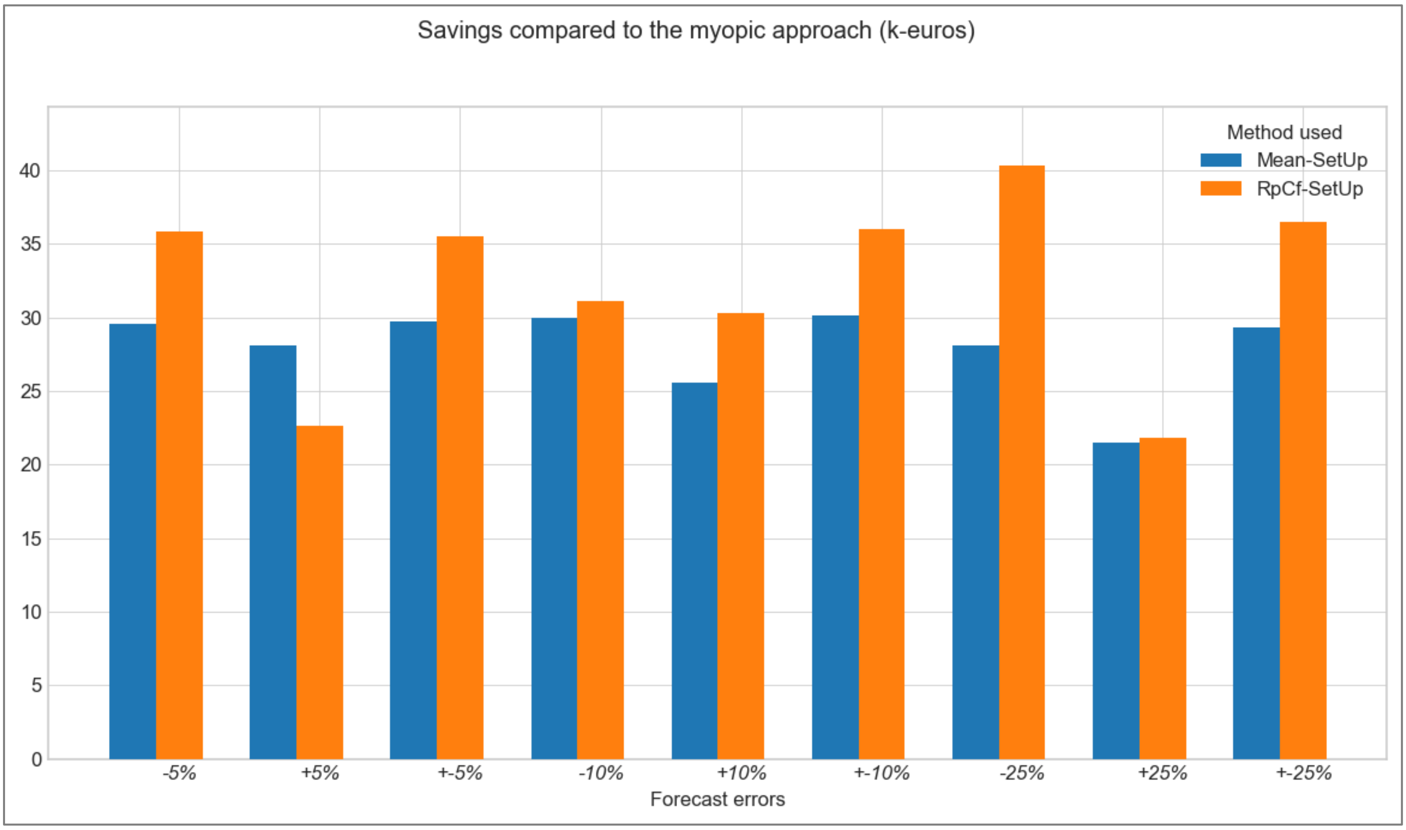


*Figure 24: Savings obtained for methods RpCf-SetUp and Mean-SetUp on horizon H1, for different errors on the forecasted demand (k-euros).*

## 5.3 Conclusion of the sensitivity analysis

The sensitivity tests show that both models bring similar significant savings with different meteorological profiles. Modifying the cost of the FP induces significant changes in the solutions costs but this is not surprising: this parameter is decisive. Hence, this does not question the models relevancy but informs us on the models behaviour for different data. In this case, the difference in the solution costs between models is lowered. Additionally, the sensitivity analysis on the quality of forecasts suggests that both models yield robust solutions, even with forecast errors. This quality is precious for planning models.

# 6. Conclusion & perspectives

**Rolling horizon** optimisation methods are relevant to **recurrent and dynamic problems** where immediate decisions must be made while they depend on upcoming ones. These decisions can **rely on forecasts** that can be updated at each optimisation step. This paper focuses on problems where detailed short-term decisions can have an impact on very distant ones and vice-versa. This highly increases the temporal dimension of the problem that has to be solved at each step. Hence, there is a need to adapt the way long-term decisions are modelled.

For this purpose, we proposed two new approaches that include long-term decisions while keeping a detailed short-term formulation and a reasonable problem size. Both approaches rely on **aggregated time steps** that are adaptive to the forecasts accuracy. In the first approach, long-term data and decisions are **aggregated as means**, with a simplified long-term model. In the second approach, long-term decisions are accounted by **cost functions**. Cost functions are estimated with **representative periods** of future data and with the original detailed model. The two approaches are described and evaluated on a case study describing a **heat production problem**. Different versions of both approaches are tested and compared with benchmark models. Finally, a **sensitivity analysis** on the data is performed.

Both models show promising performances and can be implemented to include long-term decisions in rolling horizon approaches. The first one is easy to implement and has low and stable computation times. An advantage is that the continuity between state variables is kept over the whole planning horizon. A drawback is that it can miss optimal solutions depending on the problem structure and data. The second model is more costly to apply: it requires some parameterizations and pre-computations. The continuity between the storage states is kept over the whole planning horizon while the continuity between the inflexible production states is only kept until a certain point. However, this can be sufficient and the second model still outperforms the first one with limited computation times. Both show robust performances under sensitivity analysis, but their potential generalisation to further case studies should be questioned. For this purpose, a study of the generalisation aptitude on typical cases is provided as Supplementary Material[1] with the online version of this article. Finally, all decisions with a long-term impact should be included in the long-term model, which can be more or less challenging depending on the approach. For instance, we anticipate possible computation burdens for the second approach if several long-term decisions have to be included, as this would lead to multi-variable costs functions.

Future work will include the application of the approaches to other case studies, for both optimization and simulation purposes. Other slicing for the planning horizon can be tested and the method to build cost functions can be improved to reduce computation times. Finally, the second method offers the possibility to learn on future operational costs on the basis of more accurate models. For instance, if an optimization model gives instructions to a physical simulator or a real system, the feedback can be included in the cost functions.

[1] Correspond au Chapitre 3 de ce manuscrit.

# Chapitre 3

Le précédent chapitre propose deux méthodes pour simuler et optimiser l'opération d'un système énergétique. Ces deux méthodes sont des extensions de de la mécanique classique de l'horizon glissant. Elles permettent de tenir compte de dynamiques opérationnelles long terme tout en modélisant finement des décisions court-terme au pas de temps horaire.

Ce troisième chapitre met en œuvre de ces deux méthodes sur une série de cas élémentaires, en partie inspirés par des cas d'études typiques sur les systèmes énergétiques. L'objectif est de confirmer l'intérêt de ces méthodes pour de futures applications.

Plusieurs renvois aux Chapitres 1 et 2 sont faits dans ce chapitre. Ils correspondent respectivement aux références [156] et [176].

La note qui suit a été publiée comme Supplementary Material de l'article du Chapitre 2.

L'Appendix G citée dans ce chapitre correspond à la seconde partie de ce Supplementary Material. Le format papier du manuscrit limitant sa lisibilité, elle est téléchargeable ici : https://doi.org/10.1016/j.energy.2021.122773.

Abbréviations utilisées au Chapitre 3 :

| **Abbréviation** | **Expression complète** |
|---|---|
| **CP** | Controllable Production |
| **D** | Demand |
| **IP** | Incontrollable Production |
| **N** | Network |
| **S** | Storage |

# Numerical crossed assessment of two approaches to balance short and long-term decisions in rolling horizon optimisation.

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Abstract:

This technical note is a follow-up of [176], in which we proposed two new approaches based on rolling horizon to optimise the operational control of energy systems with a balance of short-term and long-term decisions. In this note, we further validate the interest and consistency proposed approaches, by applying it on various elementary and limit cases defined by open-source data.

## 1. Introduction

Rolling horizon optimisation approaches are commonly used to solve recurrent, dynamic or multi-period problems where immediate decisions must be made while they depend on more distant ones. In some cases, immediate decisions must be modelled with a detailed time discretization while they depend on very long-term ones. In such problems, standard rolling horizon are hard to solve due to the substantial increase of the temporal dimension. In [176], authors proposed two approaches to balance short and long-term decisions : the Mean(-SetUp) and RpCf(-SetUp) approaches (see [176] for details). Both approaches were tested on an energy production planning case study where a dynamic heat demand must be supplied with various production and storage means (including seasonal storage), with promising and realistic results.

The purpose of this technical note is to further challenge the realism and adequacy of the obtained solutions, in spite of the inherent uncertainties in the modelling of the physical system and in the precision of the available data. To this extent, we experimentally check the consistency and relevance of the solutions obtained with both approaches on various elementary cases, and we check the coherence with the solutions from [176]. The elementary cases are derived from typical energy production planning elements that can be encountered in local energy systems [156] and rely on open data.

In the next sections, we describe the experimental method, present and discuss the results.

# 2. Experimental method

This section describes the experimental method used to evaluate the two approaches on various elementary case studies. Section 2.1 details the mathematical problem. The formulation is used as a starting point to define the elementary cases in Section 2.2.

## 2.1 Energy production planning problem

We now define the mathematical problem used to derive the different elementary cases. Units considered are energy units. The time varying demand (D) must be supplied at each period. The demand can be supplied with a Controllable Production (CP), and/or an Intermittent Production (IP). Energy can also be bought from an external network (N) with time dependant or constant prices. Additionally, an energy storage (S) can be used.

The mathematical description of the problem is further detailed. The mathematical formulation is described on a discrete horizon $H = [1, \dots, \Theta \in \mathbb{N}^+]$. The time step size (in hours) is given by $dt$ and ensures units consistency. Variables are written in bold, continuous variables in capital letters and binary variables in small letters. In order to represent units consistency, $X$ correspond to units/hour (power units) and $E$ to units (energy units). Parameters and variables are detailed below.

-The demand $X_t^D$ is in units/hour.

-The CP is characterised by a minimum and a maximum production capacity in units/hour ($Xmin^{CP}$ and $Xmax^{CP}$), a maximum change of its production rate in units/hour ($Xr^{CP}$), a minimum on time in hour (i.e. if turned on, the CP must be kept on over at least $Tmin^{CP}$ time steps), a unitary production cost in euros/unit ($C^{CP}$), a fixed production cost in euros/hour ($Con^{CP}$) and a set-up cost in euros ($Cset^{CP}$). Variables $\boldsymbol{X_t^{CP}} \in [0, Xmax^{CP}]$ correspond to the production of the CP at $t$ in units/hour, $\boldsymbol{y_t^{CP}} \in [0,1]$ equals 1 if the CP is on at $t$, 0 otherwise and $\boldsymbol{z_t^{CP}} \in [0,1]$ equals 1 if the CP is being set-up at $t$, 0 otherwise.

-The intermittent production $\boldsymbol{X_t^I}$ is in units/hour and has a time varying capacity $Xmax_t^I = Xmax^I * pf_t^I$ ($\boldsymbol{X_t^I} \in [0, Xmax_t^I]$).

-The energy bought on the network ($\boldsymbol{X_t^N} \in [0, +\infty[$) is in units/hour and has a time varying price $C_t^N$.

-The storage is defined by a maximum capacity in units ($Emax$), a storing efficiency ($\eta$) corresponding to the percentage of units that are actually stored during the storing operation (the rest is lost), losses in units lost/units stored/hour ($\delta$) and a similar stock/destock capacity in units/hour ($Xmax$). Associated variables are the stored quantity in units ($\boldsymbol{E_t} \in [0, Emax]$ ) and the stock and destock rates in units/hour (($\boldsymbol{Xout_t}, \boldsymbol{Xin_t}$) $\in [0, Xmax]$) at time step $t$.

Variables are set to 0 if $t = 0$. The mathematical formulation of the problem is as follows:

$Min$:

$$\sum_{t\in H}\left(C^{CP}\boldsymbol{X_t^{CP}} + Con^{CP}\boldsymbol{y_t^{CP}} + C_t^N\boldsymbol{X_t^N}\right)dt + Cset^{CP}\boldsymbol{z_t^{CP}} \qquad E1$$

$Such\ that$:

$\forall\ t \in H$:

$$X_t^D = \boldsymbol{X_t^{CP}} + \boldsymbol{X_t^N} + \boldsymbol{X_t^I} + \boldsymbol{Xout_t} - \boldsymbol{Xin_t} \qquad E2$$

$$\boldsymbol{X_t^I} \le Xmax_t^I \qquad E3$$

$$\boldsymbol{E_t} = \boldsymbol{E_{t-1}}(1-\delta dt) + (\eta\boldsymbol{Xin_t} - \boldsymbol{Xout_t})dt \qquad E4$$

$$Xmin^{CP}\boldsymbol{y_t^{CP}} \le \boldsymbol{X_t^{CP}} \qquad E5$$

$$\boldsymbol{X_t^{CP}} \le Xmax^{CP}\boldsymbol{y_t^{CP}} \qquad E6$$

$$\boldsymbol{y_t^{CP}} - \boldsymbol{y_{t-1}^{CP}} \le \boldsymbol{z_t^{CP}} \qquad E7$$

$$\boldsymbol{X_t^{CP}} - \boldsymbol{X_{t-1}^{CP}} \le Xr^{CP} \qquad E8$$

$$\boldsymbol{X_{t-1}^{CP}} - \boldsymbol{X_t^{CP}} \le Xr^{CP} \qquad E9$$

$\forall\ t \in \{Tmin^{CP}, \dots, \Theta\}$:

$$\sum_{t'=t+1-Tmin^{CP}}^{t} \boldsymbol{z_{t'}^{CP}} \le \boldsymbol{y_t^{CP}} \qquad E10$$

$\forall\ t \in \{1, \dots, Tmin^{CP}\{$:

$$\sum_{t'=1}^{t} \boldsymbol{z_{t'}^{CP}} \le \boldsymbol{y_t^{CP}} \qquad E11$$

The objective to minimise the sum of all costs is given by *E1*. *E2* ensures that the demand is satisfied. *E3* ensures that the amount of power consumed from the intermittent source does not exceed the available power. *E4* is the balance equations for the storage. *E5-6* set the minimum capacity of the CP and fixes the status $\boldsymbol{y_t^{CP}}$. *E7* fixes the state $\boldsymbol{z_t^{CP}}$. *E8-9* limit the changes in the CP production rate. The minimum on/off times of the CP are given by *E10-11*.

The problem is solved iteratively over $H$ in a rolling horizon fashion, i.e.: most immediate decisions are fixed and forecasts are updated at each rolling horizon cycle.

## 2.2 Elementary cases

We define several elementary production planning cases on the basis of the mathematical problem given in Section 2.1. Each case corresponds to the production planning problem of an energy system over one year, with an hourly time step. All cases are hypothetical and do not necessarily correspond to realistic cases (for instance, a heat demand profile can be satisfied by energy from the network with electricity spot prices). The aim is to test the Mean and the RpCf methods on various production planning problem configurations. All variations on the different hypothesis are further described, as well as the experimental plan.

Variations on the demand assumptions:

We consider two realistic demand profiles corresponding, respectively, to a **Heat** and an **Electrical** demand profiles. Both are normalised so that their mean equals 3 units/hour. Additionally, we consider five artificial demand profiles which correspond to a constant demand (**Cst**) of 3 units/hour and square wave signals with semi-annual (**Sem**), mensual (**Month**), weekly (**Week**) and daily (**Day**) frequencies with high and low values of 1 and 5 units/hour.

The heat and the electrical demand profiles are both extracted from [177]. The file used was the "USA_WA_Seattle-Tacoma.Intl.AP.727930_TMY3_BASE.csv" file and can be downloaded from the "Residential Load Data Compressed.zip" link in [177]. The heat and electricity demand respectively correspond to columns "Gas:Facility [kW](Hourly)" and "Electricity:Facility [kW](Hourly)" and were normalised so that the mean equals 3 units/hour. Profiles are shown in Figure 25.

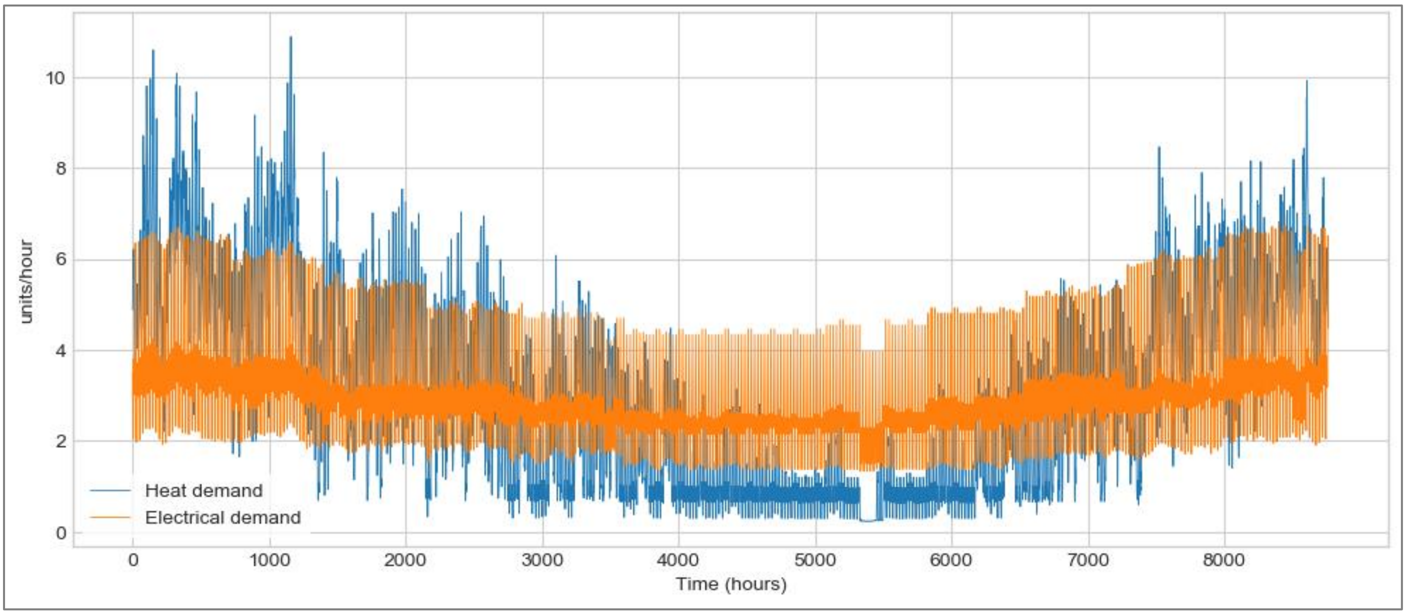


*Figure 25: Demand profiles considered (heat and electrical)*

Variations on the IP assumptions:

We consider two intermittent production profiles: a **solar** production profile and a **wind** production profile. Both were extracted from [178] (see [179] and [180] for methodological details). From the website interface, the latitude was set to 47.60038 and the longitude to -122.3301. The dataset selected was MERRA-2 (global), for year 2019, for a capacity of 6 kW. For the solar profile, the system loss was set to 0.1, the tilt parameter to 35° and the azimuth parameter to 180°. For the wind profile, the hub height was set to 80 meters and the turbine model selected was the Vestas V90 2000 model.

Profiles of the production factor $pf_t^I$ are shown in Figure 26. The production capacity $Xmax^I$ is set to 6 units/hour in both cases.

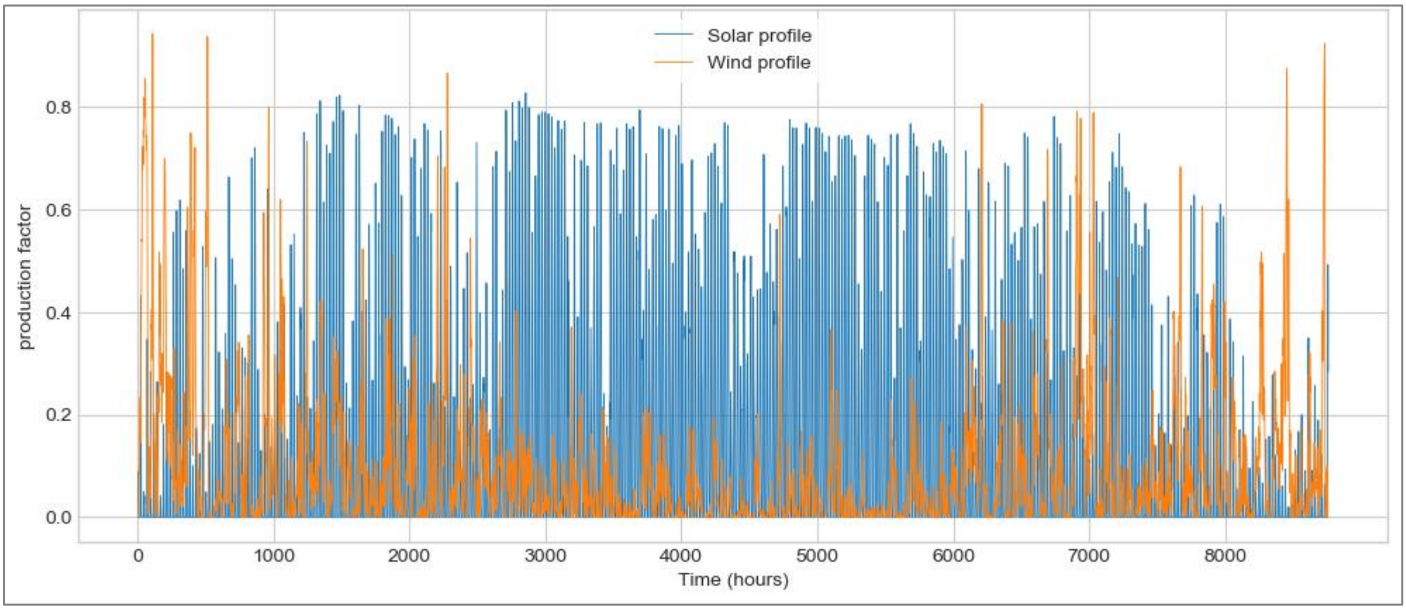


*Figure 26: Intermittent production profiles considered*

<u>Variations on the CP assumptions:</u>

We consider a case where the CP is **entirely flexible** (i.e. $Xmin^{CP} = 0, Xr^{CP} = Xmax^{CP}$ , $Tmin^{CP} = 0, Con^{CP} = 0$, $Cset^{CP} = 0$) and a case where the CP has its **flexibility constrained** (i.e. $Xmin^{CP} = 2, Xr^{CP} = 1$, $Tmin^{CP} = 12, Con^{CP} = 10$, $Cset^{CP} = 400$). In both cases, $C^{CP} = 1$ and $Xmax^{CP} = 9$. We additionally consider cases where **set-up costs are null or higher (4000 euros)**.

<u>Variations on the storage assumptions:</u>

We consider two different size: a **small size** ($Emax = 75$, corresponding to 25 hours of storage in mean) and a **large size** ($Emax = 3000$, corresponding to 1000 hours of storage in mean). In both cases, $\eta = 0.81$, $\delta = 0.0001$ and $Xmax = 4$.

<u>Variations on the network assumptions:</u>

We consider a case where the cost $C_t^N$ corresponds to the French electricity **spot price** for year 2020 and a case where it is **constant** ($C_t^N = 1000 \; \forall \, t \in H$). The French electricity spot price for year 2020 was extracted from [181] with the Python API [182] (the last day was ignored to consider a non-bissextile year). It is shown in Figure 27.

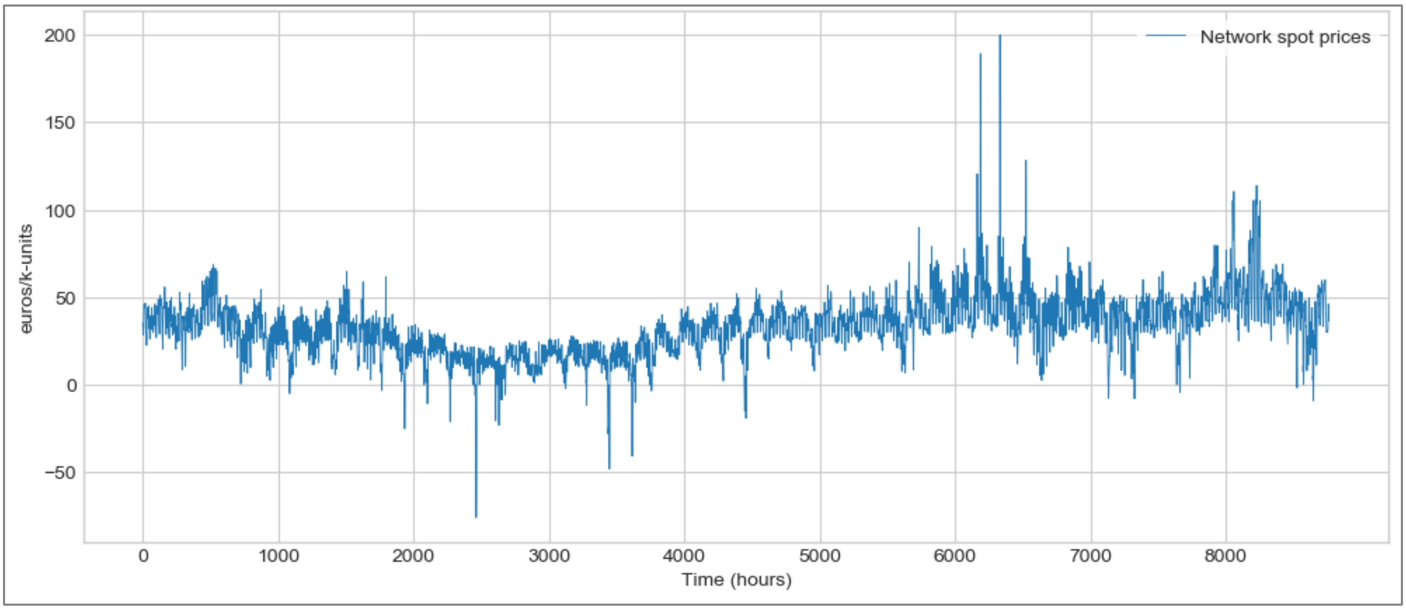


*Figure 27: Network spot prices considered*

Crossing all variations would lead to an excessive number of computations and results to interpret. The 25 architectures tested are described Table 6. If muted, the CP, storage and IP capacities are set to zero (respectively $Xmax^{CP} = 0$, $Emax = 0$ and $Xmax_t^I = 0 \; \forall \; t \; \in H$).

*Table 6: Architectures tested (X: muted elements).*

| Architecture abbreviation | Variations on the IP side: profiles tested | Variations on the CP side: | Variations on the storage side: | Variations on the network side: | Variations on the demand side: profiles tested |
|---|---|---|---|---|---|
| **Flx** | X | Flexible | X | Constant price | Heat and Electrical |
| **Flx-Wnd** | Wind | Flexible | X | Constant price | Heat and Electrical |
| **Flx-Slr** | Solar | Flexible | X | Constant price | Heat and Electrical |
| **Wnd-LrgSto** | Wind | X | Large storage | Constant price | Heat and Electrical |
| **Slr-LrgSto** | Solar | X | Large storage | Constant price | Heat and Electrical |
| **Spot-LrgSto** | X | X | Large storage | Variable spot price | Heat and Electrical |
| **Unflx-LrgSto** | X | Constrained flexibility | Large storage | Constant price | Heat, Electrical, Cst, Sem, Month, Week and Day |
| **Unflx-SmllSto** | X | Constrained flexibility | Small storage | Constant price | Heat and Electrical |
| **Unflx-HighSetUp** | X | Constrained flexibility-High Set Up costs | Large storage | Constant price | Heat and Electrical |
| **Unflx-NoSetUp** | X | Constrained flexibility-No Set Up costs | Large storage | Constant price | Heat and Electrical |

## 2.3 Evaluation process

The rolling horizon process is parametrized as follows (further details are given in [176]). For all computations, the Fixed Horizon $FH$ is set to 24 hours. The Mean and the RpCf methods are used over the horizon $H1$ which is a slicing of $H$. It keeps a detailed model over the short-term horizon ($SH$) and an aggregated model (Mean or RpCf) is applied over the long-term horizon ($LH$).

Similarly to [176], the same demand profile is used over both horizons $SH$ and $LH$. Hence, models are run with perfect forecasts. This way, only biases on the data aggregation method and on the models themselves are accounted for.

In both cases where the CP has its flexibility constrained, the Mean-SetUp and the RpCf-SetUp versions of the methods are applied (since they include important set-up costs). In cases where there is no storage, the RpCf method is not applicable. The two methods are compared to the Cicada strategy which uses the planning horizon $H1$ but without the $LH$.

All approaches are evaluated over a year. Total costs retained correspond to the sum of costs on the $FH$ of the rolling horizon process over a year. Since the yearly strategy might evolve if more years are simulated, models are run until it converges. In practice, this is the case after one or two years. Other experimental aspects are identical as in [176].

# 3. Results

All detailed results are given in Table 7 including the total costs over the simulated year, the total yearly demand and amount of units produced by the different sources. The yearly total costs are plot on Figure 28 to Figure 32 for all elementary cases and all methods. Graphs describing the solutions obtained are available in Supplementary Material[2]. The graphs are entitled with respect to the type of plot (flux or storage units), the demand profile considered, the architecture tested and the method used.

*Table 7: Results of the experimental plan*

| Demand | Architecture | Method | Total costs (euros) | Demand (units) | CP (units) | Network (units) | IP (units) |
|---|---|---|---|---|---|---|---|
| Heat | Flx | RpCf | NA | NA | NA | NA | NA |
| | | Mean | 51336 | 26281 | 26256 | 25 | 0 |
| | | Cicada | 51336 | 26281 | 26256 | 25 | 0 |
| | Flx-Wnd | RpCf | NA | NA | NA | NA | NA |
| | | Mean | 33908 | 26281 | 21715 | 12 | 27319 |
| | | Cicada | 33908 | 26281 | 21715 | 12 | 27319 |
| | Flx-Slr | RpCf | NA | NA | NA | NA | NA |
| | | Mean | 47256 | 26281 | 22176 | 25 | 24475 |
| | | Cicada | 47256 | 26281 | 22176 | 25 | 24475 |
| | Wnd-LrgSto | RpCf | 21463100 | 26281 | 0 | 21463 | 29283 |
| | | Mean | 21463100 | 26281 | 0 | 21463 | 29283 |
| | | Cicada | 21473400 | 26281 | 0 | 21473 | 29267 |
| | Slr-LrgSto | RpCf | 19483900 | 26281 | 0 | 19483 | 44906 |
| | | Mean | 19483900 | 26281 | 0 | 19483 | 44906 |
| | | Cicada | 19943500 | 26281 | 0 | 19943 | 41223 |
| | Spot-LrgSto | RpCf | 706209 | 26281 | 0 | 29405 | 0 |
| | | Mean | 710615 | 26281 | 0 | 29835 | 0 |
| | | Cicada | 750541 | 26281 | 0 | 28120 | 0 |
| | Unflx-LrgSto | RpCf | 92501 | 26281 | 27782 | 0 | 0 |
| | | Mean | 113088 | 26281 | 26777 | 0 | 0 |
| | | Cicada | 128764 | 26281 | 26977 | 0 | 0 |
| | Unflx-SmllSto | RpCf | 110238 | 26281 | 27097 | 0 | 0 |
| | | Mean | 113088 | 26281 | 26777 | 0 | 0 |
| | | Cicada | 129444 | 26281 | 27057 | 0 | 0 |
| | Unflx-HighSetUp | RpCf | 102217 | 26281 | 27781 | 2 | 0 |
| | | Mean | 115052 | 26281 | 27452 | 0 | 0 |
| | | Cicada | 456506 | 26281 | 26978 | 0 | 0 |
| | Unflx-NoSetUp | RpCf | 78716 | 26257 | 27836 | 0 | 0 |
| | | Mean | 87498 | 26281 | 27192 | 2 | 0 |
| | | Cicada | 86920 | 26281 | 27201 | 1 | 0 |
| Electrical | Flx | RpCf | NA | NA | NA | NA | NA |
| | | Mean | 26279 | 26279 | 26279 | 0 | 0 |
| | | Cicada | 26279 | 26279 | 26279 | 0 | 0 |
| | Flx-Wnd | RpCf | NA | NA | NA | NA | NA |
| | | Mean | 21643 | 26279 | 21643 | 0 | 27816 |

[2] Correspond à l'Appendix G dans ce manuscrit.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Cicada** | 21643 | 26279 | 21643 | 0 | 27816 |
| | **Flx-Slr** | **RpCf** | NA | NA | NA | NA | NA |
| | | **Mean** | 19103 | 26279 | 19103 | 0 | 43053 |
| | | **Cicada** | 19103 | 26279 | 19103 | 0 | 43053 |
| | **Wnd-LrgSto** | **RpCf** | 21445300 | 26279 | 0 | 21445 | 29283 |
| | | **Mean** | 21445300 | 26279 | 0 | 21445 | 29283 |
| | | **Cicada** | 21452200 | 26279 | 0 | 21452 | 29231 |
| | **Slr-LrgSto** | **RpCf** | 18852800 | 26279 | 0 | 18852 | 44912 |
| | | **Mean** | 18852800 | 26279 | 0 | 18852 | 44912 |
| | | **Cicada** | 18852800 | 26279 | 0 | 18852 | 44912 |
| | **Spot-LrgSto** | **RpCf** | 715964 | 26279 | 0 | 29762 | 0 |
| | | **Mean** | 721806 | 26279 | 0 | 29845 | 0 |
| | | **Cicada** | 763159 | 26279 | 0 | 28487 | 0 |
| | **Unflx-LrgSto** | **RpCf** | 113994 | 26279 | 26394 | 0 | 0 |
| | | **Mean** | 113974 | 26279 | 26374 | 0 | 0 |
| | | **Cicada** | 113977 | 26279 | 26376 | 0 | 0 |
| | **Unflx-SmllSto** | **RpCf** | 114024 | 26279 | 26423 | 0 | 0 |
| | | **Mean** | 113974 | 26279 | 26374 | 0 | 0 |
| | | **Cicada** | 113977 | 26279 | 26376 | 0 | 0 |
| | **Unflx-HighSetUp** | **RpCf** | 113984 | 26279 | 26384 | 0 | 0 |
| | | **Mean** | 113974 | 26279 | 26374 | 0 | 0 |
| | | **Cicada** | 113977 | 26279 | 26376 | 0 | 0 |
| | **Unflx-NoSetUp** | **RpCf** | 91468 | 26279 | 27718 | 0 | 0 |
| | | **Mean** | 91550 | 26279 | 27790 | 0 | 0 |
| | | **Cicada** | 91555 | 26279 | 27795 | 0 | 0 |
| **Cst** | **Unflx-LrgSto** | **RpCf** | 77139 | 26280 | 30669 | 0 | 0 |
| | | **Mean** | 113666 | 26280 | 26136 | 0 | 0 |
| | | **Cicada** | 127695 | 26280 | 29035 | 0 | 0 |
| **Sem** | | **RpCf** | 90120 | 26276 | 27540 | 0 | 0 |
| | | **Mean** | 112564 | 26276 | 26764 | 0 | 0 |
| | | **Cicada** | 120016 | 26276 | 27016 | 0 | 0 |
| **Month** | | **RpCf** | 78686 | 26276 | 28306 | 0 | 0 |
| | | **Mean** | 112848 | 26276 | 26798 | 0 | 0 |
| | | **Cicada** | 120040 | 26276 | 27030 | 0 | 0 |
| **Week** | | **RpCf** | 100369 | 26232 | 28280 | 0 | 0 |
| | | **Mean** | 113408 | 26232 | 26878 | 0 | 0 |
| | | **Cicada** | 117433 | 26232 | 27053 | 0 | 0 |
| **Day** | | **RpCf** | 115137 | 26056 | 27578 | 0 | 0 |
| | | **Mean** | 114506 | 26056 | 26905 | 0 | 0 |
| | | **Cicada** | 114559 | 26056 | 26939 | 0 | 0 |

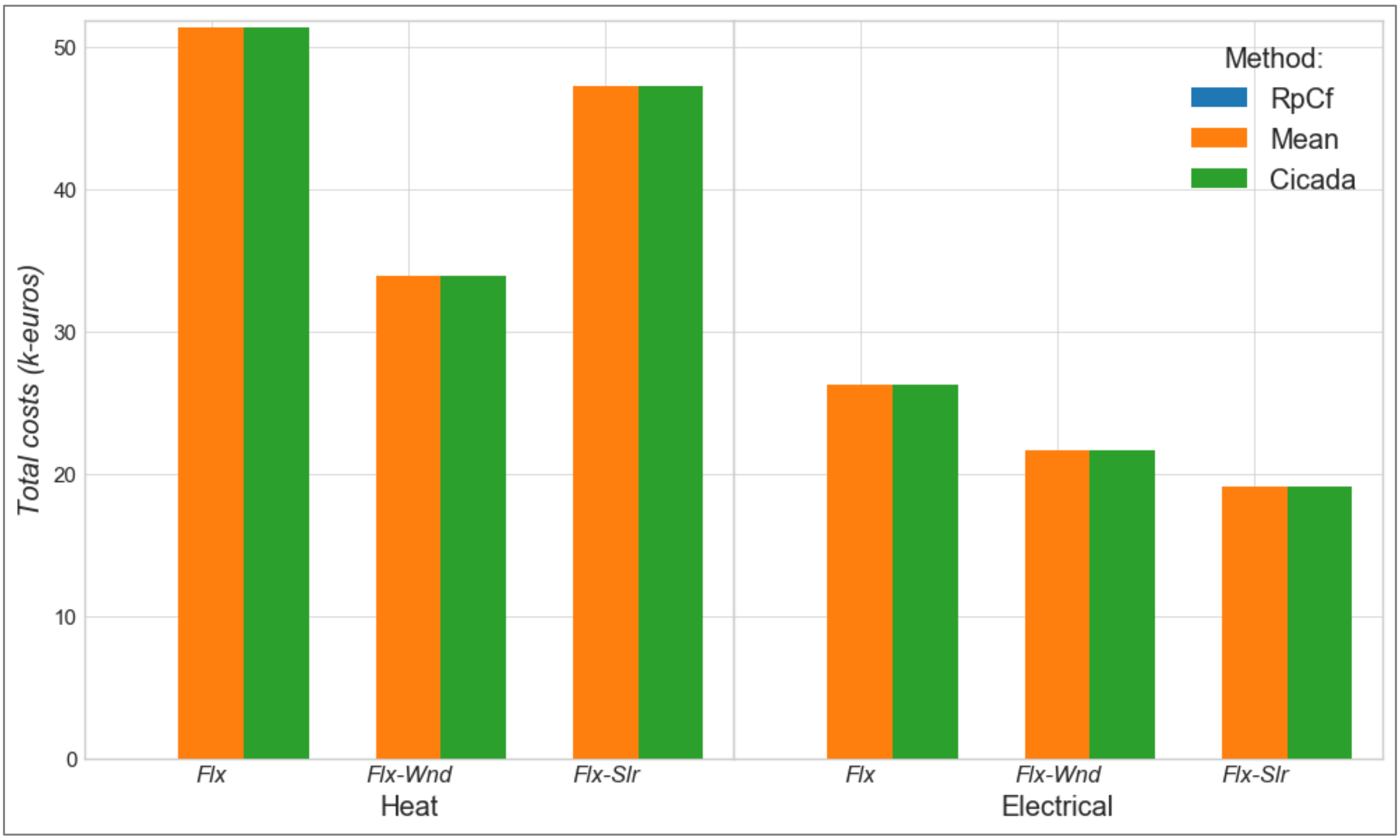


*Figure 28: Total costs for the architectures Flx, Flx-Wnd and Flx-Slr, for Heat and Electrical demand profiles*

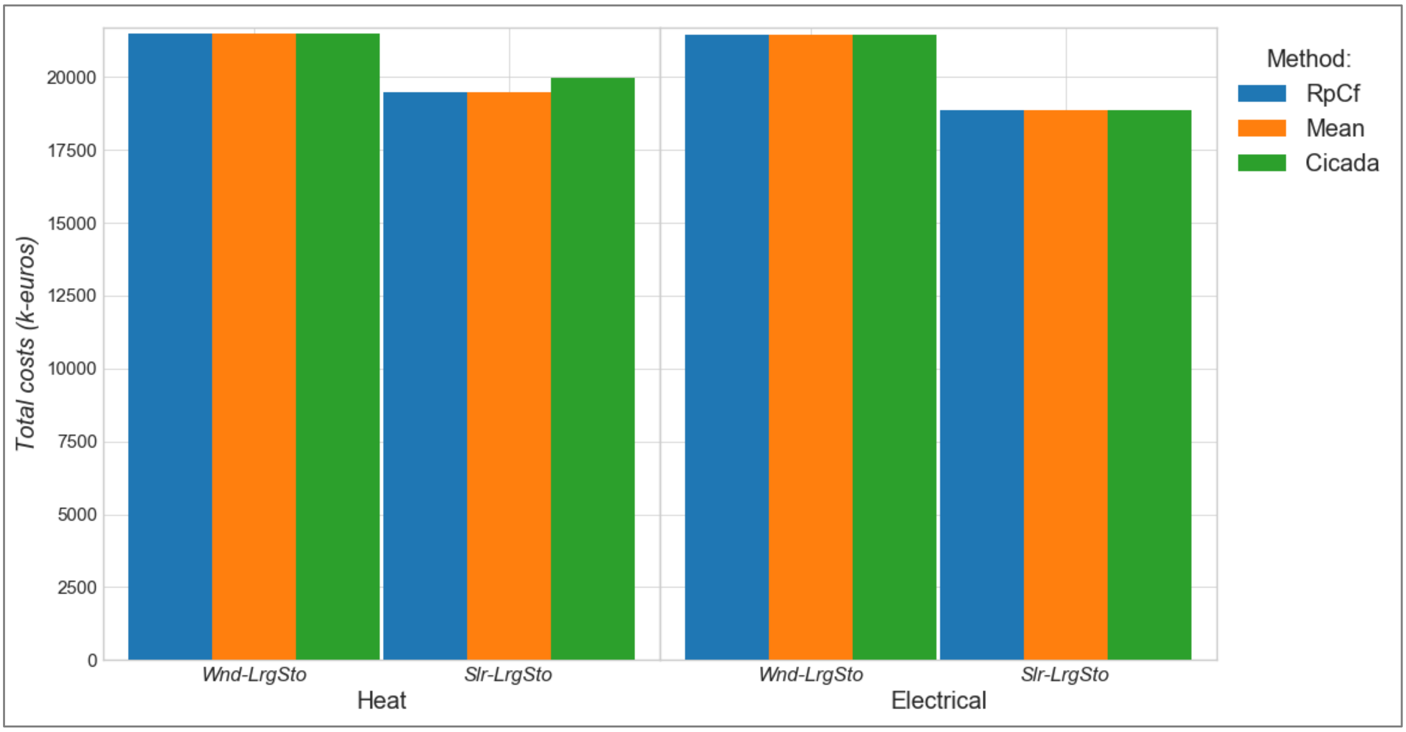


*Figure 29: Total costs for the architectures Wnd-LrgSto and Slr-LrgSto, for Heat and Electrical demand profiles*

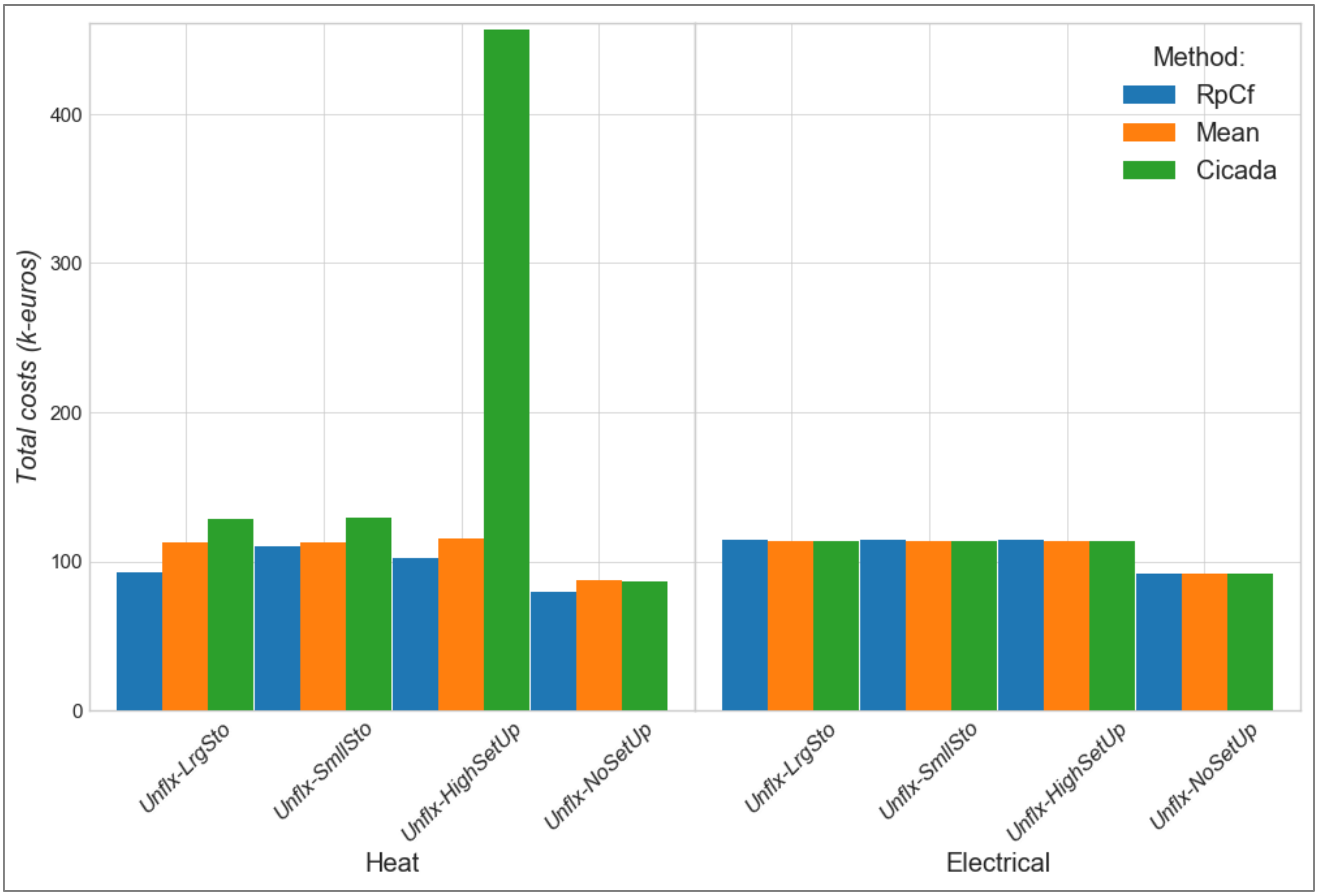


*Figure 30: Total costs for the architectures Unflx-LrgSto, Unflx-SmllSto, Unflx-HighSetUp and Unflx-NoSetUp, for Heat and Electrical demand profiles*

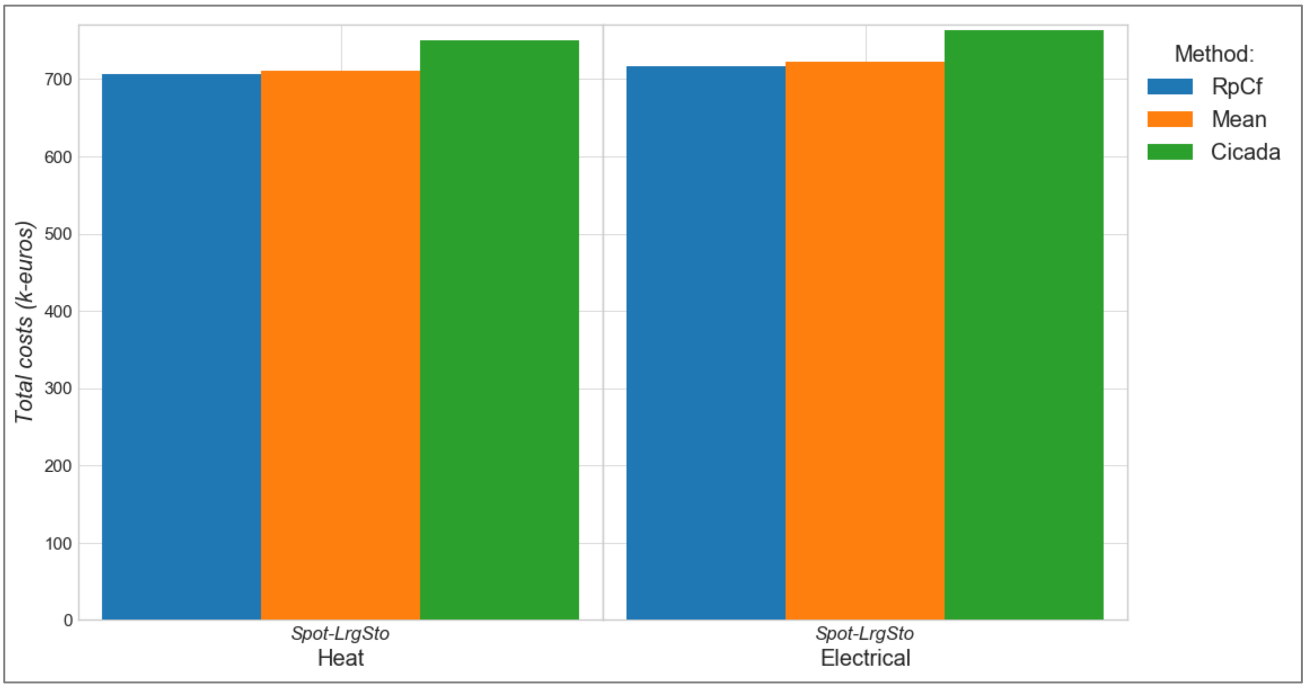


*Figure 31: Total costs for the architecture Spot-LrgSto, for Heat and Electrical demand profiles*

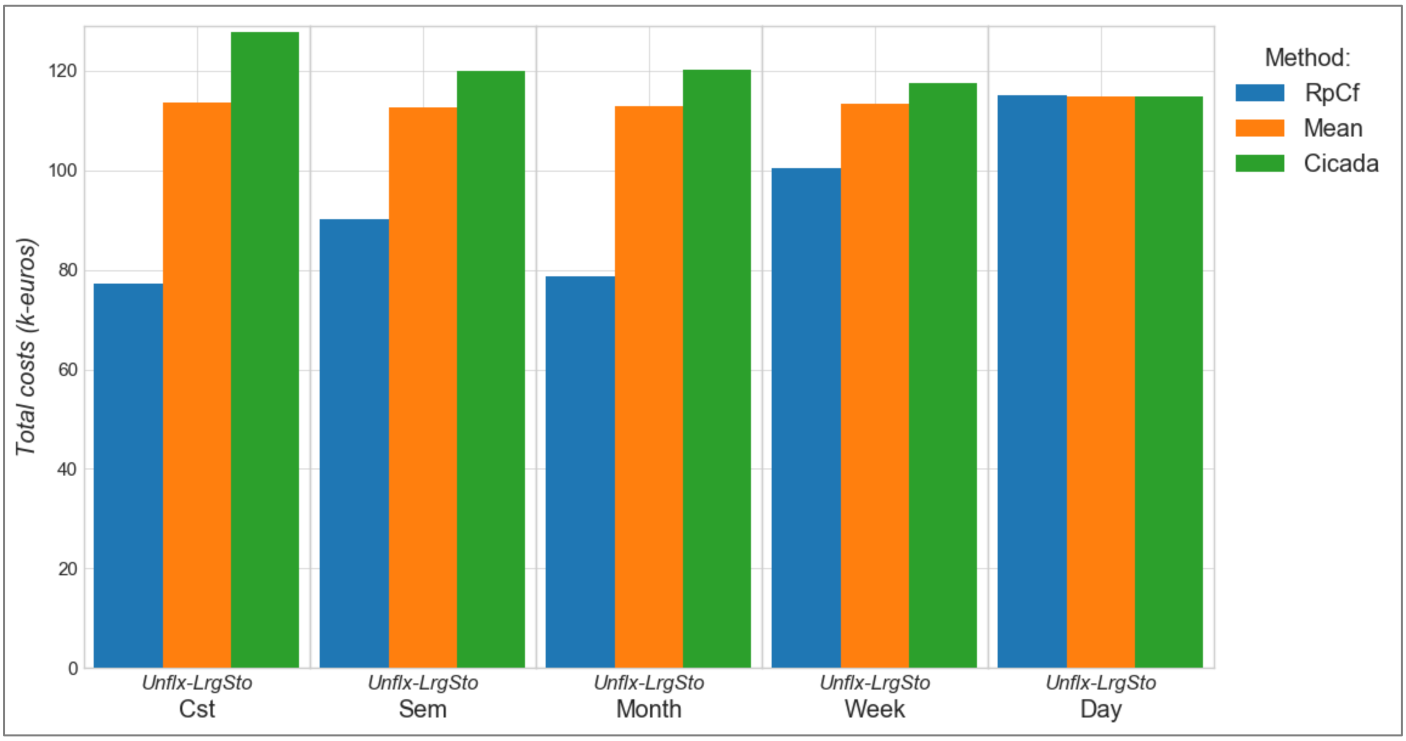


*Figure 32: Total costs for the architecture Unflx-LrgSto, for Cst, Sem, Month, Week and Dayl demand profiles*

# 4. Discussion

For cases where optimal operational decisions are obvious (the architectures Flx, Flx-Wnd, Flx-Slr, Wnd-LrgSto and Slr-LrgSto), the Mean method yields identical or better results than the Cicada method. This is consistent since these cases do not include a trade-off between short and long-term decisions. The underperforming of the Cicada method in some cases is due to the fact that it does not fill the storage at the end of the horizon even if intermittent sources are available. This shortcoming could easily be corrected with a simple heuristic (give a small economic value to the energy stored at the end of the horizon for instance).

Other cases where there could be an interest to store energy on the long term or to keep the CP turned on at the end of the *SH* horizon are (few exceptions apart) always better handled by the Mean and the RpCf methods. In most cases, the RpCf method yields the best results. This is consistent with expectations and with results from [176]. However, the RpCf method still yields sub-optimal solutions in most cases. One argument is that they can be improved by stocking units at the last moment or destocking units earlier to save on the storage losses (see the individual cases further discussed)

The cases where the Electrical demand is considered show little differences between the three methods (except when spot prices are included). This is due to the fact that the Electrical profile has lower seasonal or intra-month variations, and that it is most of time above the CP minimum capacity. Focusing on cases that include a CP with its constraints, the RpCf methods slightly underperforms other methods. Although consequences are small, the storage strategy is not fruitful and does not help on the results interpretations. Hence, the RpCf method is not recommended for cases where no particular long-term strategy is of interest.

Individual cases giving rise to discussion are further discussed, corresponding graphs can be found in the supplementary materials.

Heat demand with Unflx-LrgSto architecture:

In this case, the RpCf method anticipates the supplementary summer production costs due to the the CP constraints and makes up a stock at the end of the heating period contrarily to the Mean method. The three distinct charging steps highlight the non-optimality of the solution, partly due to the future data approximation with representative periods. Nevertheless, the strategy stays more efficient than the Mean and the Cicada strategies (see Figure 30), which operate more cycles on the CP and pay set-up costs.

Heat demand with Unflx-SmllSto architecture:

This case shows the differences in the strategies of the Cicada, Mean and RpCf methods when the demand is lower than the minimum capacity of the CP. The Mean and the RpCf methods better anticipate future costs due to the CP cycling and make better usage of the storage. Here again, the storage management of the RpCf is sub-optimal (kept full during heating season), but the method still yields better results.

Heat demand with Unflx-HighSetUp architecture:

Here the RpCf method operates in a similar way as with the Unflx-LrgSto architecture. Expensive set-up costs keeps the CP turned on at the beginning of heating season or prevent it from turning on for few units. The Mean method does not anticipate the minimum capacity constraint that impacts the summer demand satisfaction and thus does not constitute a stock. However, expensive set-up costs prevent it from turning the CP off during the summer, which fills up the stock for the beginning of the heating season. The Cicada method yields to an expensive solution with multiple CP set-ups.

Heat demand with Unflx-NoSetUp architecture:

In this case, savings can be obtained by using the CP at high capacity. The RpCf method anticipates fixed production costs on the long-term and makes better use of the storage. The Mean and the Cicada methods operate similarly, the first slighlty outperfroming the second.

Constant, and square-wave signals demand with Unflx-LrgSto architecture:

In case of a constant demand, the RpCf method charges and discharges the storage in order to save on fixed production costs of the CP, while the Mean and the Cicada methods produce at constant rates. For semestrial, monthly and weekly square wave signals, the RpCf method also makes use of the storage to reduce start-up and fixed production costs. Still, the solutions obtained are sub-optimal. This can be due to the long-term data approximation by representative periods, extrapolation of computed costs and the loss of information on the CP state after the first long-term horizon slice (see [176] for details). On the other side, Mean and Cicada methods show similar behaviour : they do not properly anticipate long-term CP constraints and costs and thus do not elaborate long-term strategies. Still, the Mean method uses less cycles on the CP, which improves the solution compare to the Cicada method. Finally, the daily square wave signals are slightly better handled by the Mean method, while the long-term strategy off the RpCf method is not efficient, similarly to cases where the Electric demand was considered.

# 5. Conclusion

This technical note aimed to verify the relevancy of the two rolling horizon methods presented in [176]. For this purpose, multiple hypothetical case studies were defined based on open data and arbitrary parameters. Both methods were tested on 24 elementary case studies including various load profiles, storages, and energy sources. All results were found consistent and confirmed the relevancy of both methods for rolling horizon optimisation in case of complex long-term operational decisions as observed in [176]. Other cases where long-term strategies are not relevant were also properly handled by the Mean and the RpCf methods, which confirms their proper parametrization. In worst cases, solutions obtained with the RpCf method were not significantly less performant but led unnecessary variations of its strategy. This makes the interpretation of results more difficult and can be due to an overlearning of the method. Fixing this issue could be a future work before practical applications.

# Chapitre 4

Les deux précédents chapitres proposent et valident l'intérêt de deux méthodes pour simuler et optimiser l'opération d'un système énergétique. Ces deux méthodes sont des extensions de de la mécanique classique de l'horizon glissant. Elles permettent de tenir compte de dynamiques opérationnelles long terme tout en modélisant finement des décisions court-terme au pas de temps horaire.

Ce quatrième et dernier chapitre illustre une nouvelle application possible de ces deux méthodes. Il revient également sur le besoin énoncé dans la conclusion du Chapitre 1. L'état de l'art a mené à la conclusion qu'il serait pertinent de s'appuyer sur des modèles opérationnels fins pour la conception de systèmes énergétiques où les questions de flexibilité sont essentielles. En particulier, ces modèles fins tiendraient compte de séries temporelles annuelles au pas de temps horaire (sans les agréger en jours types), de contraintes et coûts opérationnels spécifiques rendant compte de la flexibilité des technologies et d'hypothèses de prévisions imparfaites. Le Chapitre 4 questionne cette pertinence en illustrant l'impact de ces niveaux d'hypothèses sur un cas d'étude complexe, mêlant demandes en électricité et en chaleur au niveau d'un quartier. Les différents impacts pourront illustrer (ou non) l'intérêt d'utiliser un modèle plus fin pour améliorer la pertinence de l'étude. Un retour d'expérience sera dressé pour mieux anticiper ces problématiques sur de futurs cas.

Plusieurs renvois aux Chapitres 1 et 2 sont faits dans ce chapitre. Ils correspondent respectivement aux références [156] et [176].

L'article qui suit est en cours de soumission dans le journal Applied Energy.

Abbréviations utilisées au Chapitre 4 :

| Abbréviation | Expression complète |
|---|---|
| **CG** | Cogeneration |
| **ED** | Electric Demand |
| **ESPP** | Energy System Production Planning |
| **FB** | Fuel Boiler |
| **G** | Grid |
| **GB** | Gas Boiler |
| **HD** | Heat Demand |
| **HP** | Heat Pump |
| **HS** | Heat Storage |
| **LP** | Linear Programming |
| **MES** | Multi-Energy System |
| **MILP** | Mixed Integer Linear Programming |
| **RH** | Rolling Horizon |
| **RP** | Representative Period |
| **ST** | Solar Thermal collectors |

# Impact of operational modelling choices on techno-economic modelling of local energy systems.

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Abstract:

Many techno-economic studies of local energy systems rely on mathematical programming. This comes with several modelling choices including simplified technological and economical models, temporal and spatial resolutions or perfect foresight assumptions. These assumptions are challenged individually on different case studies in the literature. This paper evaluates and compares the impact of different modelling choices on a single case study. The system considered includes heat and electrical demands, a biomass-fired cogeneration, a heat pump, gas and fuel boilers, solar thermal collectors as well as a long-term heat storage. The modelling choices tested are the use of representative periods or not, the inclusion of flexibility costs and constraints for the cogeneration, the use of different methods to optimise operational decisions (including various rolling horizon methods), and the consideration of forecast errors or not. Results highlight the conditions under which representative periods can be used without introducing strong biases on the results. They show the consequence of neglecting flexibility costs and constraints in the problem formulation. Finally, they compare different rolling horizon strategies and conclude on the validity of the perfect foresight assumption on this case study.

Highlights:

-Usual assumptions taken when modelling energy systems with mathematical programming are assessed.

-The impact of several assumptions over different modelling facets are compared on a single case study including a long-term storage.

-The characteristics of the case study that favour (or not) the recourse to one assumption or another are highlighted.

Key words: energy systems, optimisation, MILP, representative periods, rolling horizon, flexibility, forecasts

# 1. Introduction

The Intergovernmental Panel on Climate Change calls for limiting cumulative greenhouse gas emissions of human activities in order to limit global warming [1]. Paris agreements already engaged many countries to reduce their emissions in 2015 [11]. The energy sector plays a major role in human emissions and includes local energy systems [156]. Local and smart energy systems [16,154] including distributed energy resources [14] stand as a potential way to increase energy efficiency and to lead to low carbon energy systems. Designing and simulating such systems can be a complex task which implies several modelling assumptions and choices. A multitude of modelling and optimisation methods were presented in the literature [156]. They often rely on the mathematical programming formalism but with diverse underlying assumptions. Hence, there is a need to challenge the assumptions usually undertaken.

When modelling the operation of an energy system, several modelling facets exist. Facets include the **spatial resolution, time resolution, technological and market representations, as well as how operational decisions are modelled** [156]. The technological and market representations are tightly linked to the mathematical complexity of the model. Increasing such models complexity can lead to tough optimisation problems [148]. The way operational decisions are modelled refers to how they are optimised and how errors in forecasts are considered (also referred as short-term uncertainty in [27]). Current methods based on the design and operation optimisation with a **single mathematical program assume perfect foresight** [156]. In real life applications, errors in forecasts and imperfect operational decisions occur. Hence, such methods can underestimate real life operational costs with an “over-optimised” operation of the system. In turn, this can lead to design solutions which are theoretically optimal but less performant in practice. Therefore, we distinguish three interdependent modelling issues when studying energy systems: the **computational tractability** of the model, the **performance** (economic, energetic, environmental, *etc*.) of the solutions it yields, and their **applicability in practice**.

As mentioned in [166] and [183], there is a research gap regarding the degree of model complexity that is necessary while more complex models do not necessarily yield higher performances. This paper is in line with [166] where the impact of the model complexity on its computational tractability and on its economic performances is questioned. The state of the art from [166] provides many and recent references where the impact of the spatial and temporal resolution are investigated as well as the impact of mathematical complexity of the model and the system scope (in both fields of local and large-scale energy systems). Further references can be added: in [88], the author tests multiple temporal resolution reduction methods to summarise decades of hourly solar and wind time series. Methods tested include coarser temporal resolution, heuristics and clustering methods for selecting representative days. A finding is that results are substantially altered, especially with high intermittent energy shares. On the other hand, storage options reduce the importance of high temporal resolution. Appropriate time resolution is case dependant and using representative periods (RPs) implies to set a compromise between computation times and temporal accuracy. 48 days were considered necessary in [19] for a robust design optimisation of a local MES (Multi-Energy System). Authors from [89] compare the impact of spatial and temporal resolution on the design of US regional power systems. They evaluate the impact of a coarser time resolution and of the number of representative days used. On the spatial facet, they compare an optimisation region by region with an optimisation of interconnected regions jointly. They finally compare different spatial resolutions within a region. On another note, the impact of the operational decisions modelling assumptions was investigated in [184]: the economic viability of heat pumps is evaluated for different operation optimisation algorithms and with different quality of forecasts. A finding is that both assumption levels can have important impacts on economic and energy consumption results.

**Contributions:**

Given the extensive application of mathematical programming approaches to simulate and design local energy systems, questioning the relevancy of their underlying assumptions is necessary. The impact of the different modelling choices on computational tractability and on economic performances were individually evaluated in the literature (see [166], [88], [89], [19] and literature review from [166]). Authors from [184] explored the operational decisions modelling assumptions to better evaluate the practical expected performances of optimisation models. This paper adds several contributions to this research topic:

- It evaluates the impact of the different modelling choices over operational costs on a new illustrative case study. Considering that this impact can be highly case dependant, this contributes to fill the above-mentioned research gap. The case includes electric and heat demands, as well as a large heat storage. It is a complex case that include daily and monthly time scales.
- Different modelling choices are compared together on this single case study, while previous studies evaluated impacts individually.
- It evaluates the impact of how operational decisions are modelled (including possible forecast errors), in particular in case of a large storage that implies long-term operational decisions. Methods from [176] are used.

First, we describe the illustrative case study including the mathematical formulation of the problem. Second, the different modelling facets and their respective possible assumptions are defined. Then, the experience plan and the evaluation process are described. Finally, results are presented and discussed.

# 2. Case study

The case study corresponds to the satisfaction of electrical and heat demands in the Cambridge neighbourhood of Grenoble city, France. The system structure is illustrated on Figure 33. Time varying heat and electricity demands (respectively HD and ED) must be supplied at each period. The heat demand can be satisfied through a heat network powered by solar thermal panels (ST), a heat pumps (HP) (which consumes electricity), a gas boiler (GB), a fuel boiler (FB) or a biomass back-pressure cogeneration (CG) (which produces electricity as well). The centralized heat can be stored over long periods in a heat storage (HS). Finally, if not satisfied by the CG, the ED is supplied by purchasing electricity on a grid (G) at a time dependant (spot) price. The gas, fuel and electricity prices include $CO_2$ emission costs. The $CO_2$ content of the grid is also time dependant.

The mathematical formulation of the problem is given Section 2.1. The value of parameters is given Section 2.2.

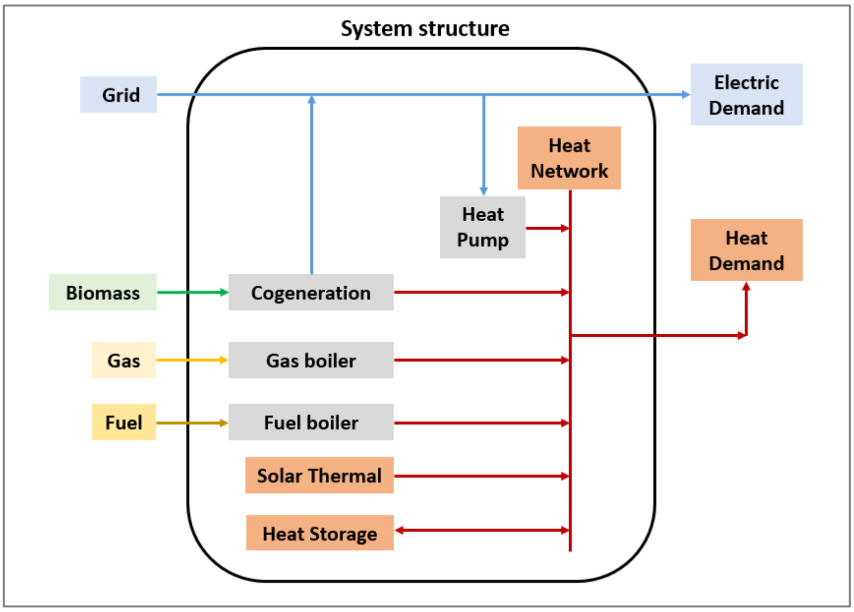



*Figure 33: Illustrative case study structure*

## 2.1 Problem formulation

The following mathematical problem defines the corresponding Energy System Production Planning (ESPP) problem. It is described on a discrete horizon $H = [1, \ldots, \Theta \in \mathbb{N}^+]$. The time step size is given by $dt$ (equal to one hour). Variables are written in bold, continuous variables in capital letters and binary variables in small letters. In order to represent units consistency, $X$ correspond to power units and $E$ to energy units. Parameters and variables are detailed below.

- The heat demand $X_t^{HD}$ and the electricity demand $X_t^{ED}$ are in kW.

- The ST production $\boldsymbol{X_t^{ST}}$ is in kW and has a time varying capacity $Xmax_t^{ST}$ ($\boldsymbol{X_t^{ST}} \in [0, Xmax_t^{ST}]$).

- The GB is characterised by a maximum production capacity in kW ($\boldsymbol{X_t^{GB}} \in [0, Xmax^{GB}]$) and a unitary production cost in euros/kWh ($C^{GB}$).

- The FB is characterised by a unitary production cost in euros/kWh ($C^{FB}$).

- The HP is characterised by a maximum production capacity in kW ($\boldsymbol{X_t^{HP}} \in [0, Xmax^{HP}]$) and an efficiency constant $\eta^{HP}$.

- The CG is characterised by a minimum and a maximum total production capacity in kW ($Xmin^{CG}$ and $Xmax^{CG}$), a maximum change of its total production rate in kW ($Xr^{CG}$), a minimum on time in hour (i.e. if turned on, the CG must be kept on over at least $Tmin^{CG}$ time steps), a unitary biomass cost in euros/kWh ($C^{CG}$), a fixed production cost in euros/hour ($Con^{CG}$) and a set-up cost in euros ($Cset^{CG}$). $\eta^e$ and $\eta^h$ respectively correspond to the nominal electricity and heat efficiencies. The ratio $\alpha = \eta^e/\eta^h$ is introduced for convenience. The CG has the ability to produce more heat by reducing its electrical production by a factor 1. $\boldsymbol{Xb_t^{CG}}$ is the amount of biomass consumed at period $t$, in kW. Variables $\boldsymbol{Xh_t^{CG}}$ and $\boldsymbol{Xe_t^{CG}}$ respectively correspond to the heat production and the electricity production of the CG at $t$ in kW, $\boldsymbol{y_t^{CG}} \in \{0,1\}$ equals 1 if the CG is on at $t$, 0 otherwise and $\boldsymbol{z_t^{CG}} \in \{0,1\}$ equals 1 if the CG is being set-up at $t$, 0 otherwise. An extra variable $\boldsymbol{Xtot_t^{CG}}$ is introduced and corresponds to the total power produced in kW.

- The electricity bought on the grid ($\boldsymbol{X_t^G} \in [0, +\infty[$) is in units/hour and has a time varying price $C_t^G$.

- The heat storage is defined by a maximum capacity in kWh ($Emax^{HS}$), a storing efficiency ($\eta^{HS}$) corresponding to the percentage of energy that is actually stored during the storing operation (the rest is lost), losses in kW lost/kW stored/hour ($\delta^{HS}$) and a stock/destock capacity in units/hour ($Xmax^{HS}$). Associated variables are the stored quantity in units ($\boldsymbol{E_t^{HS}} \in [0, Emax^{HS}]$) and the stock and destock rates in kW (($\boldsymbol{Xout_t^{HS}}, \boldsymbol{Xin_t^{HS}}) \in [0, Xmax^{HS}]^2$)) at time step $t$.

Variables are set to 0 if $t = 0$ (except for $\boldsymbol{E_0^{HS}}$). The mathematical formulation of the problem is as follows.

$Min$:

$$\sum_{t \in H}\left((C^{GB}\boldsymbol{X_t^{GB}} + C^{FB}\boldsymbol{X_t^{FB}} + C^{CG}\boldsymbol{Xb_t^{CG}} + Con^{CG}\boldsymbol{y_t^{CG}} + C_t^G\boldsymbol{X_t^G})dt + Cset^{CG}\boldsymbol{z_t^{CG}}\right) \qquad E1$$

$Such\ that$:

$\forall\ t \in H$:

$$X_t^{HD} = \boldsymbol{X_t^{GB}} + \boldsymbol{X_t^{FB}} + \boldsymbol{Xh_t^{CG}} + \boldsymbol{X_t^{ST}} + \boldsymbol{Xout_t^{HS}} - \boldsymbol{Xin_t^{HS}} + \eta^{HP}\boldsymbol{X_t^{HP}} \qquad E2$$

$$X_t^{ED} = \boldsymbol{Xe_t^{CG}} + \boldsymbol{X_t^G} - \boldsymbol{X_t^{HP}} \qquad E3$$

$$\boldsymbol{X_t^{ST}} \leq Xmax_t^{ST} \qquad E4$$

$$\boldsymbol{E_t^{HS}} = \boldsymbol{E_{t-1}^{HS}}(1 - \delta^{HS}dt) + \left(\eta^{HS}\boldsymbol{Xin_t^{HS}} - \boldsymbol{Xout_t^{HS}}\right)dt \qquad E5$$

$$Xmin^{CG}\boldsymbol{y_t^{CG}} \leq \boldsymbol{Xtot_t^{CG}} \qquad E6$$

$$\boldsymbol{Xtot_t^{CG}} \leq Xmax^{CG}\boldsymbol{y_t^{CG}} \qquad E7$$

$$\boldsymbol{y_t^{CG}} - \boldsymbol{y_{t-1}^{CG}} \leq \boldsymbol{z_t^{CG}} \qquad E8$$

$$\boldsymbol{Xtot_t^{CG}} - \boldsymbol{Xtot_{t-1}^{CG}} \leq Xr^{CG} \qquad E9$$

$$\boldsymbol{Xtot_{t-1}^{CG}} - \boldsymbol{Xtot_t^{CG}} \leq Xr^{CG} \qquad E10$$

$$\boldsymbol{Xh_t^{CG}} \leq Xmax^{CG} - \boldsymbol{Xe_t^{CG}} \qquad E11$$

$$\boldsymbol{Xe_t^{CG}} \leq \alpha\boldsymbol{Xh_t^{CG}} \qquad E12$$

$$\boldsymbol{Xe_t^{CG}} + \boldsymbol{Xh_t^{CG}} = \boldsymbol{Xtot_t^{CG}} \qquad E13$$

$$\boldsymbol{Xb_t^{CG}} = 1/(\eta^h(\alpha+1))(\boldsymbol{Xh_t^{CG}} + \boldsymbol{Xe_t^{CG}}) \qquad E14$$

$$\forall\ t \in [Tmin^{CG}, \dots, \Theta]: \qquad \sum_{t'=t+1-Tmin^{CG}}^{t} \boldsymbol{z_{t'}^{CG}} \leq \boldsymbol{y_t^{CG}} \qquad E15$$

$$\forall\ t \in [1, \dots, Tmin^{CG}[: \qquad \sum_{t'=1}^{t} \boldsymbol{z_{t'}^{CG}} \leq \boldsymbol{y_t^{CG}} \qquad E16$$

$$\boldsymbol{E_0^{HS}} \leq \boldsymbol{E_\Theta^{HS}} \qquad E17$$

The objective to minimise the sum of operational costs is given by *E1*. *E2* and *E3* ensure that both demands are satisfied. *E4* ensure that the amount of power consumed from the intermittent source does not exceed the available power. *E5* is the balance equation for the *HS*. *E6-7* set the minimum capacity of the CG and defines the states $\boldsymbol{y_t^{CG}}$. *E8* defines the states $\boldsymbol{z_t^{CG}}$. *E9-10* limit the changes in the CG production rate. *E11-12* limit the heat and electricity production of the CG so that it can trade electricity production with heat production with a factor of 1. *E13-14* define the amount of biomass consumed by the CG. The minimum on/off times of the CP are given by *E15-16*. Finally, *E17* ensures that the initial storage level corresponds to the final storage level.

## 2.2 Techno-economic assumptions

Techno-economic values of parameters used to formulate the ESPP problem are given in Table 8 and Table 9. A relatively high $CO_2$ emissions cost is considered: $C^{CO_2} = 0.2\ euros/kg$. The heat demand profile, the electrical demand profile, the production factor ($pf_t$) of the ST panels, the electricity prices $C_t^e$ and the electricity carbon content ${CO_2}_t^{grid}$ profiles are shown in Appendix E. The gas price was extracted from [185]: it corresponds to the price for non-household consumers in France in the second semester of 2020. The electricity prices profile was normalised with the electricity price for non-household consumers in France in the second semester of 2020 ([185]).

Capacities of each equipment were set after solving the investment planning problem which corresponds to the mathematical problem defined by *E1-E17* without the CG specific constraints (*E6-E10*) and with capacities as optimisation variables. The objective was modified to minimise the total actualised costs over 20 years with a discount rate of 7%. The FB was ignored at the investment phase. It can be noticed that batteries and photovoltaic solar panels were included at the investment phase but not selected by the optimiser. This step is further detailed in Appendix E. Obtained capacities were rounded.

*Table 8: techno-economic and environmental operational parameters of primary resources*

| Resources | Low heat value (kWh/kg) | Cost | CO2 content (kg/kWh) |
|---|---|---|---|
| **Gas** | $LHV^{gas} = 13.83$ | $C_{FR}^{gas} = 0.387\ euros/kg$ | ${CO_2}^{gas} = 0.243\ (3.36\ kg/kg\ CH4)$ |
| **Fuel** | $LHV^{fuel} = 12$ | $C^{fuel} = 1.09\ euros/kg$ | ${CO_2}^{fuel} = 0.340\ (4.7\ kg/kg\ Fuel)$ |
| **Biomass** | $LHV^{biomass} = 4$ | $C^{biomass} = 0.12\ euros/kg$ | ${CO_2}^{biomass} = 0$ |
| **Grid** | NA | $C_t^G = C_t^e + C^{CO2} * {CO_2}_t^{grid} euros/kWh$ <br> $C_t^e: see\ Appendix\ 1$ | ${CO_2}_t^{grid}: see\ Appendix\ 1$ |

*Table 9: techno-economic operational parameters of equipments*

| Equipment | Parameter | Value |
|---|---|---|
| GB | $\eta^{GB}$ | $0.9$ |
| | $Xmax^{GB}$ | $130\ kW$ |
| | $C^{GB}$ | $C^{GB} = (\frac{C^{gas}}{LHV^{gas}} + C^{CO2} * \mathrm{CO_2}^{gas})/\eta^{GB} = 0.07352\ euros/kWh$ |
| FB | $\eta^{FB}$ | $0.85$ |
| | $C^{FB}$ | $C^{FB} = (\frac{C_{FR}^{fuel}}{LHV^{fuel}} + C^{CO2} * \mathrm{CO_2}^{fuel})/\eta^{FB} = 0.18686\ euros/kWh$ |
| ST | $Xmax_t^{ST}$ | $Xmax_t^{ST} = Xmax^{ST} * pf_t$<br>with $Xmax^{ST} = 100\ kWc$ |
| CG | $Xmax^{CG}$ | $800\ kW$ |
| | $Xmin^{CG}$ | $160\ kW$ |
| | $Xr^{CG}$ | $160\ kW$ |
| | $Tmin^{CG}$ | $6\ hours$ |
| | $C^{CG}$ | $C^{CG} = \frac{C^{biomass}}{LHV^{biomass}} = 0.03\ euros/kWh$ |
| | $Con^{CG}$ | $1.6\ euros$ |
| | $Cset^{CG}$ | $160\ euros$ |
| HS | $Emax^{HS}$ | $70\ 000\ kWh$ |
| | $\eta^{HS}$ | $0.95$ |
| | $\delta^{HS}$ | $0.000104\ (0.25\%\ per\ day)$ |
| | $Xmax^{HS}$ | $2000\ kW$ |
| HP | $Xmax^{HP}$ | $190\ kW$ |
| | $\eta^{HP}$ | $3$ |

# 3. Experimental method

## 3.1 Modelling options compared

The aim of this paper is to evaluate the impact of the modelling choices over different energy system operational facets. The modelling options of the different facets are described here.

<u>Technological facet, two modelling options tested:</u>

- The LP option: no CG specific constraints are considered (equations E6-E10, and E15-16 are ignored, fixed production and set-up costs of the CG are set to zero). The ESPP problem is a purely Linear Program (LP).

- The MILP option: all CG specific constraints and costs are included. The ESPP problem is a Mixed-Integer Linear Program (MILP).

<u>Temporal facet, two modelling options tested:</u>

- The basic option: one year of data is considered with 1 hour time step (8760 time steps).

- The RP option: several RPs representing one year of data considered (various sizes and number are tested). The method for selecting RPs is the method from [85] ("OPT" method with the basic model)[3]. The ESPP problem formulation is kept identical but the reconstructed profiles are used instead. The reconstructed profile is built by attributing one RP to each original period so that the absolute error is minimised at each time step.

<u>Operational decisions facet, optimisation algorithms tested:</u>

- The OneShot option: perfect anticipation of future data over the year is assumed. The ESPP problem is solved as a single mathematical program.

- The Cicada and Ant options: the ESPP problem is solved in a RH fashion, the Cicada option corresponds to the usual RH solving of the ESPP problem with a planning horizon of 48 hours and a fixed horizon of 24 hours. The Ant option similar as the Cicada option, but a value to energy stored at the end of the planning horizon is attributed. This value is set to 0.7 euros/kWh, so that heat from the GB or the FB is not stored over long-term periods.

- The Mean and RpCf options from [176]: The Mean and RpCf strategies use the same problem formulation over 48 hours and approximate next data and decisions variables with aggregated time steps. This way, yearly evolutions are anticipated. The aggregation can increase with time and is defined by a slicing of the planning horizon *H*. Three planning horizons are defined: *H1*, *H2* and *H3* (see Figure 34). *H1* and *H2* were already introduced in [176]. *H3* is a compromise between *H1* and

[3] The « OPT » method with the basic model proposed in [85] selects and attributes weights to each representative periods so that the sum of the difference between the original data duration curve and the weighted representative periods duration curve is minimized. In our case study, we consider five data set (the HD, the ED, the PV and ST production factor, the grid variable price including its variable CO2 content). Each data set is normalised so that the error on its duration curve equally weights in the objective function. It can be noted that the optimised weights are not taken into account in the profiles reconstruction process.

*H2*. The Mean strategy uses average data and a simplified problem formulation over the long-term horizon. The RpCf strategy aggregates time steps by RPs, and the problem formulation is replaced by pre-computed cost functions on the long-term horizon. The horizon *H2* is not applied with the RpCf strategy: this combination was found to be less efficient in [176].

Operational decisions facet, inclusion of forecasts errors:

- The basic option: the same data sets are used as forecasts and as effective demands, PV and ST production factors, grid prices and CO2 content.

- Including forecast errors: the data sets used as forecasts after 24 hours differ from effective demands, PV and ST production factors, grid prices and CO2 content by -20% to +20%. Before 24 hours ahead, perfect forecasts are assumed.

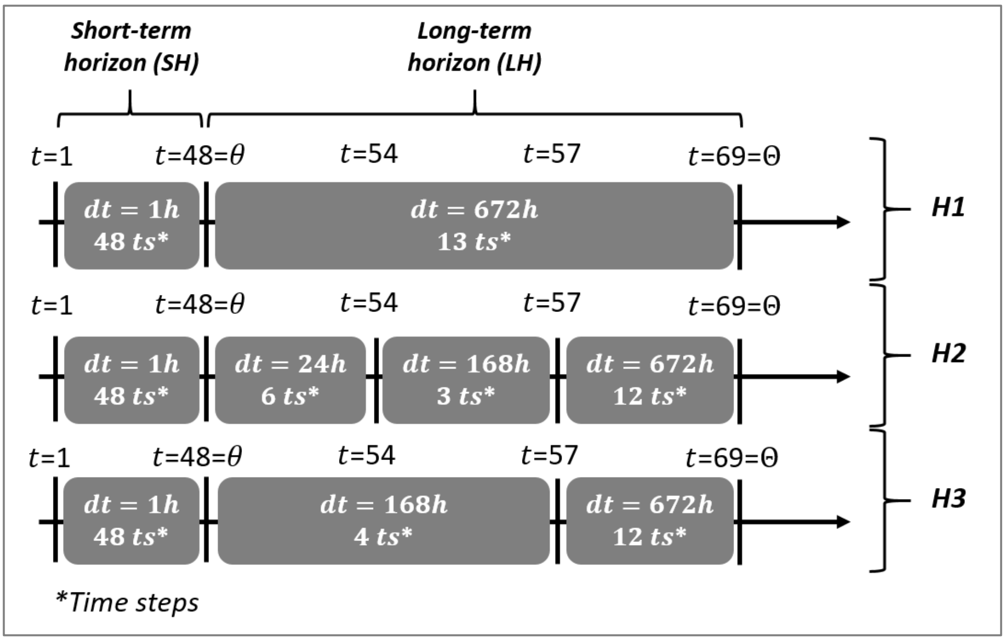



*Figure 34: Illustration of the planning horizons H1, H2 and H3*

The modelling facets and the modelling options are summarised in Table 10. We further refer to a modelling configuration as a set of options abbreviations given in Table 10. For instance, the configuration MILP-Mean corresponds to the case where all CG constraints are included and where the ESPP problem is solved in a rolling-horizon fashion with the Mean method from [176]. Also, we further use the term model to refer to a single modelling facet or a specific modelling option: for instance, "the LP model" only refers to the technological facet of the whole model. More information on the rolling horizon (RH) strategies is given below.

*Table 10: Modelling options and abbreviations*

| *Modelling facet* | Definition | Modelling option | Option abbreviation |
|---|---|---|---|
| ***Technological*** | The level of detail considered to model the CG | No CG specific constraints are considered. | LP |
| | | All CG specific constraints and costs are included. | MILP |
| ***Temporal*** | How temporally dependant data is represented | One year of data is considered with 1 hour time step (8760 time steps) | - |
| | | Several RPs of one year of data are considered to rebuild the data series (various sizes and number are tested). | RP |
| ***Operational decisions: optimisation algorithm*** | Which algorithm is used to optimise future operational decision | Perfect anticipation of future data over the year is assumed. | OneShot |
| | | The ESPP problem is solved in a RH fashion, different optimisation strategies are used (most are methods from [176]). | -Cicada<br>-Ant<br>-MeanH1<br>-MeanH2<br>-MeanH3<br>-RpCfH1<br>-RpCfH3 |
| ***Operational decisions: forecasts*** | What data is used to optimise future operational decision | The same data sets are used as forecasts and as effective demands | - |
| | | The data sets used as forecasts after 24 hours differ from the effective data sets. | - |

<u>Configurations tested and compared:</u>

Testing all possible configurations would need too many computations. In order to evaluate the impact of the modelling choices of each modelling facet, the following configurations are compared:

1. The impact of the technological model is assessed by comparing the LP-OneShot with the MILP-OneShot configuration (see Section 4.1). Given the important impact of the technological model on the costs and the solution, we further duplicate next computations for both assumptions.

2. The impact of the temporal model is assessed by comparing the LP-OneShot configuration with the LP-OneShot-RP configurations, and the MILP-OneShot configuration with the MILP-OneShot -RP configurations (with various sizes and numbers of RPs, see Section 4.2).

3. To evaluate the impact of the operational decisions model, the LP-Cicada, LP-Ant, LP-Mean, LP-MeanH2, LP-MeanH3, LP-RpCfH1 and LP-RpCfH3 configurations are compared together with the LP-OneShot configuration as a reference. We also compare the MILP-Cicada, MILP-Ant, MILP-MeanH1, MILP-MeanH2, MILP-MeanH3, MILP-RpCfH1 and MILP-RpCfH3 configurations together with the MILP-OneShot configuration as a reference (see Section 4.3).

4. Finally, the impact of the forecasts is evaluated by comparing the LP-MeanH2, LP-RpCfH3, MILP-MeanH2, and MILP-RpCfH3 configurations with and without forecast errors (these configurations yield the best results in the previous step). See Section 4.4.

## 3.2 Evaluation process

The different configurations are used to model the operation of the energy system described by *E1-E18* over one year. The configurations are compared on the basis of the total operational costs they yield over one year. This is given by *E1* in case of the OneShot model ($H = [1, \ldots, 8760]$). In case where a RH is used, the total costs retained correspond to the sum of costs on the fixed horizon of the RH process over a year. The fixed horizon corresponds to the part of decisions that are planned over $H$ and fixed before the next cycle of the RH process. It is set to 24 hours. Since the yearly strategy might evolve if more years are simulated, configurations are run until it converges. In practice, this is the case after one or two years.

In cases where the CG specific constraints and costs are included, the Mean-SetUp and the RpCf-SetUp versions of the Mean and RpCf methods from [176] are applied (since important set-up costs are included). The same demand profile is used over both short-term and long-term horizons if no forecast errors are considered. Hence, configurations are run with perfect forecasts (except in Section 4.4). This way, only biases on the data aggregation method and on the models themselves are accounted for.

A time limit of one hour was set for all computations. For cases where this limit was reached, results are presented respectively to the potential error due to the final relative gap. For instance, the MILP-OneShot configuration led to an optimisation problem with a high number of binary variables (17 520). Hence, computations were stopped after one hour with a final relative gap of 0.11%.

All computations are performed according to [176], where details can be found about the in-house PERSEE modelling environment from the LSET laboratory in CEA and about the methodology used to build the cost functions. Scripts used to build cost functions are available in [186].

# 4. Results

This section presents the impact of the modelling choices over the technological facet, the temporal facet and the operational decisions facet.

In Section 4.1, the solutions obtained for both LP-OneShot and MILP-OneShot configurations are described in detail to understand the main dynamics of the system. In next sections, the LP-OneShot and MILP-OneShot configurations are considered as references and results are expressed and compared relatively to them.

## 4.1 Impact of the technological assumptions

This section compares the OneShot-MILP configuration with the OneShot-LP configuration. Including the CG costs and constraints increases the yearly costs by almost 4 percent.

The costs breakdown given in Figure 35 shows that an important percentage of this difference is due to the CG operating costs (they are ignored with the LP option). The rest is due to an increase in the total cost of the electricity bought from the grid. This can occur because more electricity is bought on the grid and/or that it is bought at higher prices. Figure 36 provides information about the proportion of each source in the HD and ED satisfaction. Overall, the CG is less used with the MILP option (has expected: it is more expensive). Hence, it produces less electricity and less heat. In turn, the HP produces more heat, so more electricity is bought from the grid.

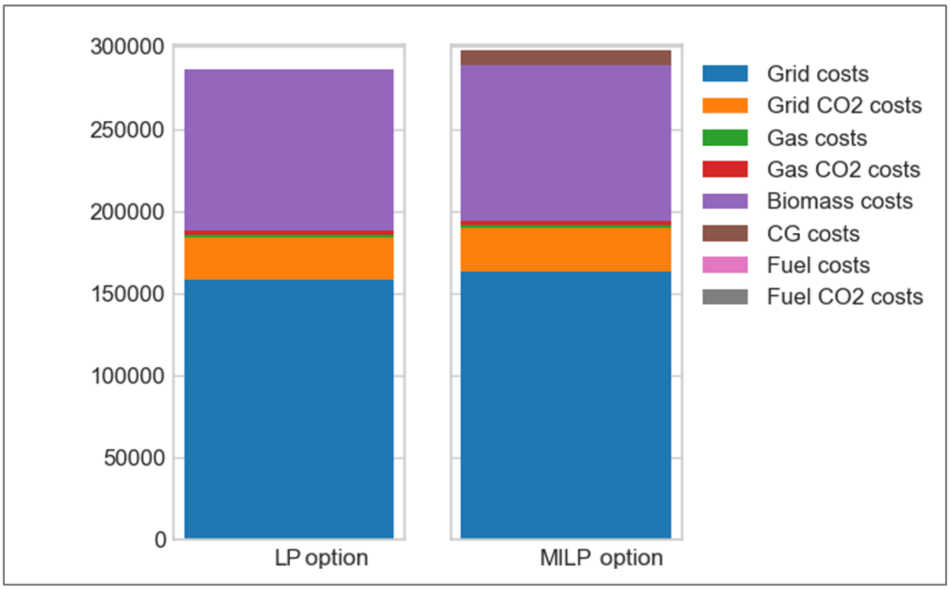



*Figure 35: Operational costs breakdown.*
*Comparison between the participation of each source in the yearly operational costs (euros) for both LP-OneShot and MILP-OneShot configurations (the ST source has no operational cost).*

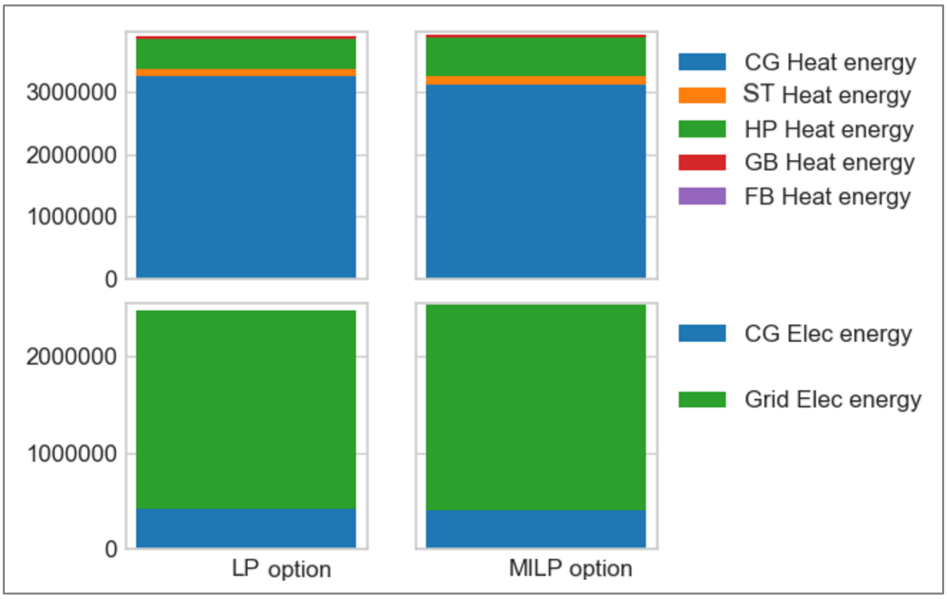



*Figure 36: Participation of each source in the HD and ED satisfaction (kWh).*
*Comparison for both LP-OneShot and MILP-OneShot configurations.*

We further describe the solutions obtained: results of the OneShot-MILP and the OneShot-LP configurations are plot on Figure 37[4] and Figure 38 respectively. Zooms on both figures are given in Appendix F, they further illustrate explanations given below.

The same strategy is used in winter, independently of the CG model: the CG and the HP are mostly used at maximum capacity. The heat storage is used to pass HD peaks. The CG trades electricity for heat before the highest HD demand peak. This is done when electricity prices are low. The GB is only used to pass the biggest HD peak. Overall, the system is highly constrained.

[4] Figure 37 shows the heat power balance, the grid prices (including the cost of CO2 emissions), the HS state and electricity balance. In other figures, only the elements necessary to interpret the results are shown for compactness purposes.

During the mid-season, the CG and the HP are used when electricity prices are high/low respectively. This strategy is enabled by the HS which is used over short and medium term periods to smooth the whole heat production. The HS also ensure that some HD peaks are passed without using the GB. The CG is not turned off with the MILP option to avoid start-up costs.

A similar price saving strategy is used in the summer when the CG is not constrained. The HS use is driven by the electricity prices. If it is constrained, this strategy enters in competition with the need to limit the number of start-ups. Hence, the CG price adaptive strategy is not always available and is only undertaken by the HP. This explains higher grid costs and higher use of the HP.

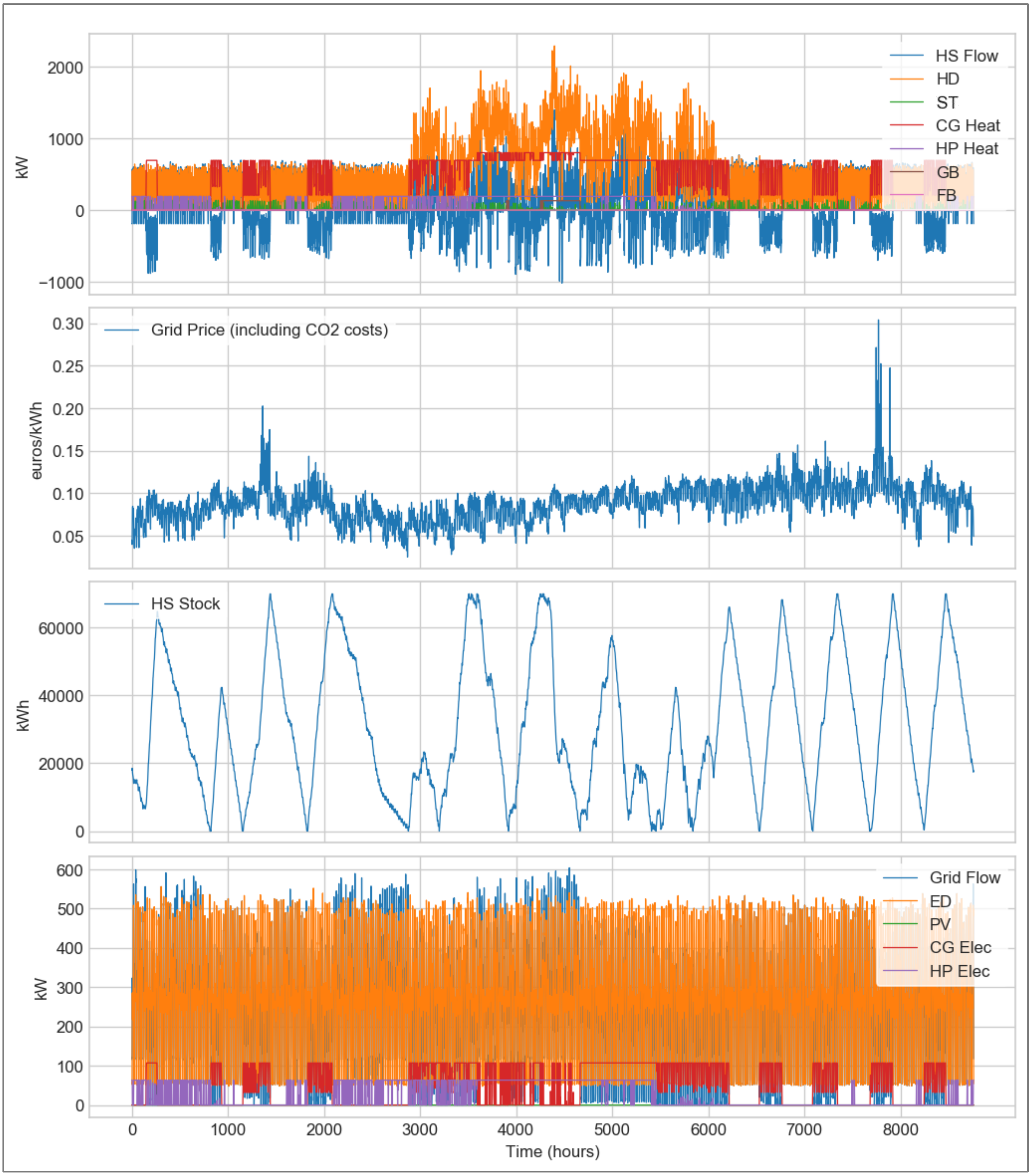



*Figure 37: Solution of the OneShot-MILP configuration: heat power balance, grid prices, HS state and electricity balance*

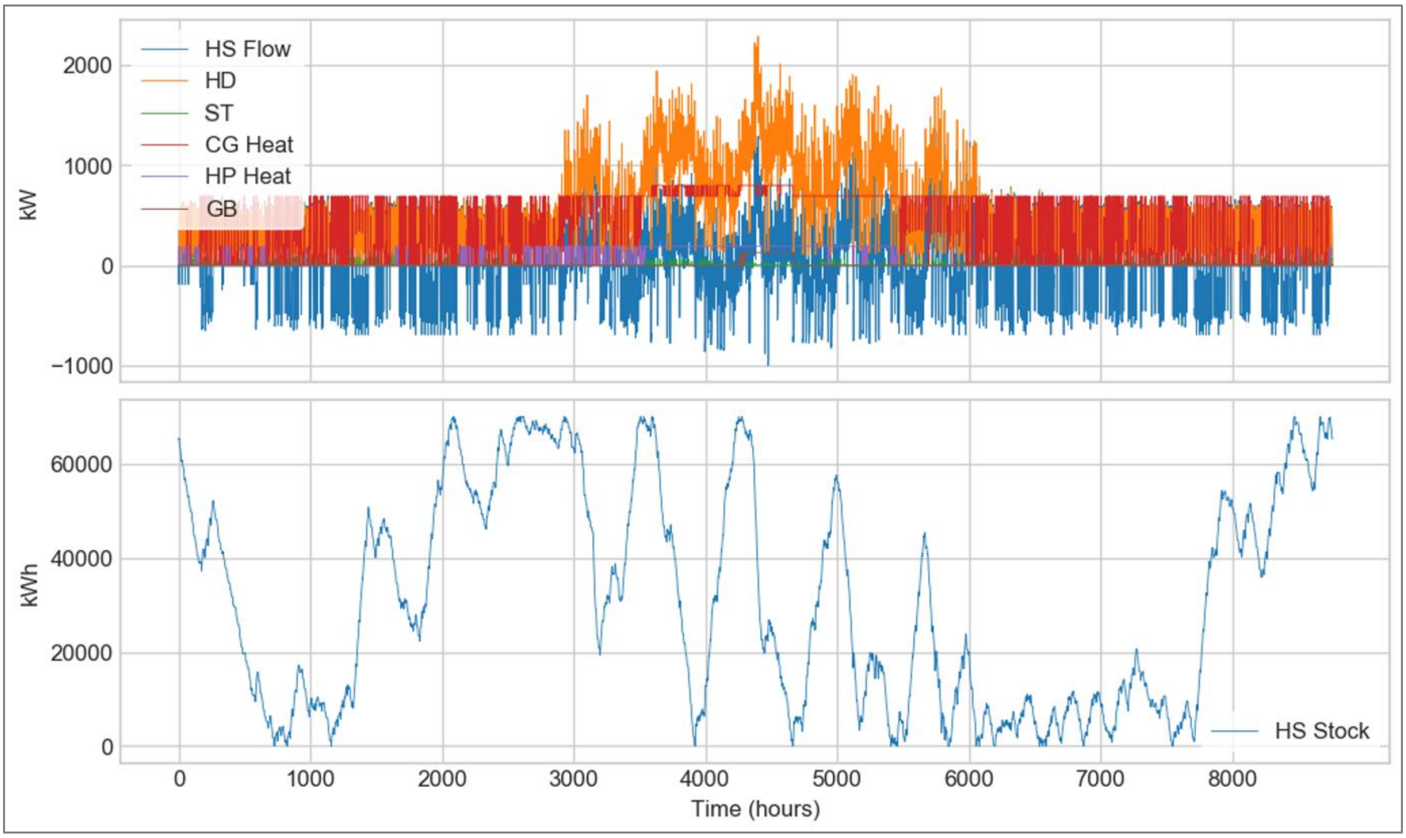



*Figure 38: Solution of the OneShot-LP configuration: heat power balance and HS state*

On the side of the economic performance, the OneShot option give the best results. The operational strategies given by the OneShot option are complex and take advantage a perfect knowledge, in particular on the electricity prices variations. One can question if such optimal operation is applicable to this extent in practice. If it is not, does it have a big impact over the total costs? This is further discussed in Sections 4.3 and 4.4.

On the side of the tractability, the MILP-OneShot configuration was surprisingly well handled by the solver despite the problem complexity: the gap was already reduced to 0.26% after 3 minutes, with an objective close to the MILP-MeanH2 configuration (see Sections 4.3). Similar computations were performed with a high capacity for the GB for which the MILP-OneShot configuration was less performant. Hence its tractability is not guaranteed.

## 4.2 Impact of the temporal assumptions

This section assesses the impact of the temporal model by comparing the LP-OneShot configuration with the LP-OneShot-RP configurations, and the MILP-OneShot configuration with the MILP-OneShot-RP configurations (with various sizes and numbers of RPs). Figure 39 (and later Figures Figure 42 and Figure 44) thus show the variation (in percent) of the LP-OneShot-RP configurations compared to the reference: the LP-OneShot configuration. Respectively, the MILP-OneShot-RP configurations are compared to the reference: the MILP-OneShot configuration.

In case of the LP option, the economic impact ranges from -6.4 to 2.1 percent of the total operational costs depending on the number and sizes of RPs used. As expected, increasing the number and the size of RPs reduces the impact, but this is not systematic. The tendency is that costs are underestimated. This could be due to the fact that extreme values are excluded when RPs are chosen (HD peaks for instance). Figure 42 shows the results when the period that includes the HD peak is imposed as a RP. In case of the LP option, this significantly improves results when RPs of one day are considered.

On the side of the MILP option, the impact ranges from -1.5 to 6.4 percent. Contrarily to the case where the LP option is used, costs tend to be overestimated. Also, increasing the number and size of RPs does not improve the results, suggesting that errors compensate. Overall, the recourse to RPs appears less stable in case of the MILP option. Figure 40 shows the costs breakdown of the MILP-OneShot reference configuration and the MILP-OneShot-RP configuration with 48 RPs of 1, 2 and 3 days: the CG costs are always overestimated (and the grid costs to a lesser extent). Figure 41 shows the heat balance and the grid prices for the case where 48 RPs of 2 days are used: contrarily to the MILP-OneShot reference configuration (Figure 37), the CG cycles more. This is because the reconstructed signal of the grid prices has a higher intra-month standard deviation. Hence, the CG strategy is modified accordingly. A similar phenomenon occurs with other sizes and numbers of RPs. This can be attributed to the fact that RPs keep the nature of the signal within themselves but not between themselves. Hence, the whole reconstructed signal has a different nature. Finally, costs are more overestimated when the HD peak is imposed as a RP and the RPs size is one day (Figure 42), suggesting that errors over different cost sources compensate less compared to Figure 39.

The RPs are often used to reduce the computation times [156]. This case study includes a large thermal storage, hence, using RPs requires methods from [23]. The method M2 is tested here: computations are run on the original data series but integer variables are gathered on the basis of RPs. This means that if two periods of the original data are represented by the same RP, integer variables are set equal on these two periods. In other words, the method M2 is a heuristic to the original problem in which the number of integer variables is reduced[5]. Figure 43 shows the computation times of this method: contrarily to the MILP-OneShot configuration (with no heuristic), the problem is solved in limited computation times. Figure 44 shows the difference in operational costs compared to the reference MILP-OneShot configuration: costs are highly overestimated. This is due to a change in the CG strategy, similarly to Figure 41. Contrarily to previous computations, there is no compensations with underestimations due to the reconstruction of the data series with RPs. Hence, on this case study, the method M2 is not fruitful. Finally, results improve when bigger RPs are used. This suggests that RPs of the size of the time constant of the CG on/off states of Figure 37 would be necessary. However, this would highly reduce the efficiency of the time aggregation.

[5] Contrarily to the problem considered in [23], the case study we consider includes constraints between time steps (other than the storage balance). These constraints are part of the CG technical constraints (*E8-9-10* and *E15-16*). Hence, method M2 was adapted: these constraints were kept within RPs but not between RPs. In particular, the CG was considered as not started up at the beginning of a RP.

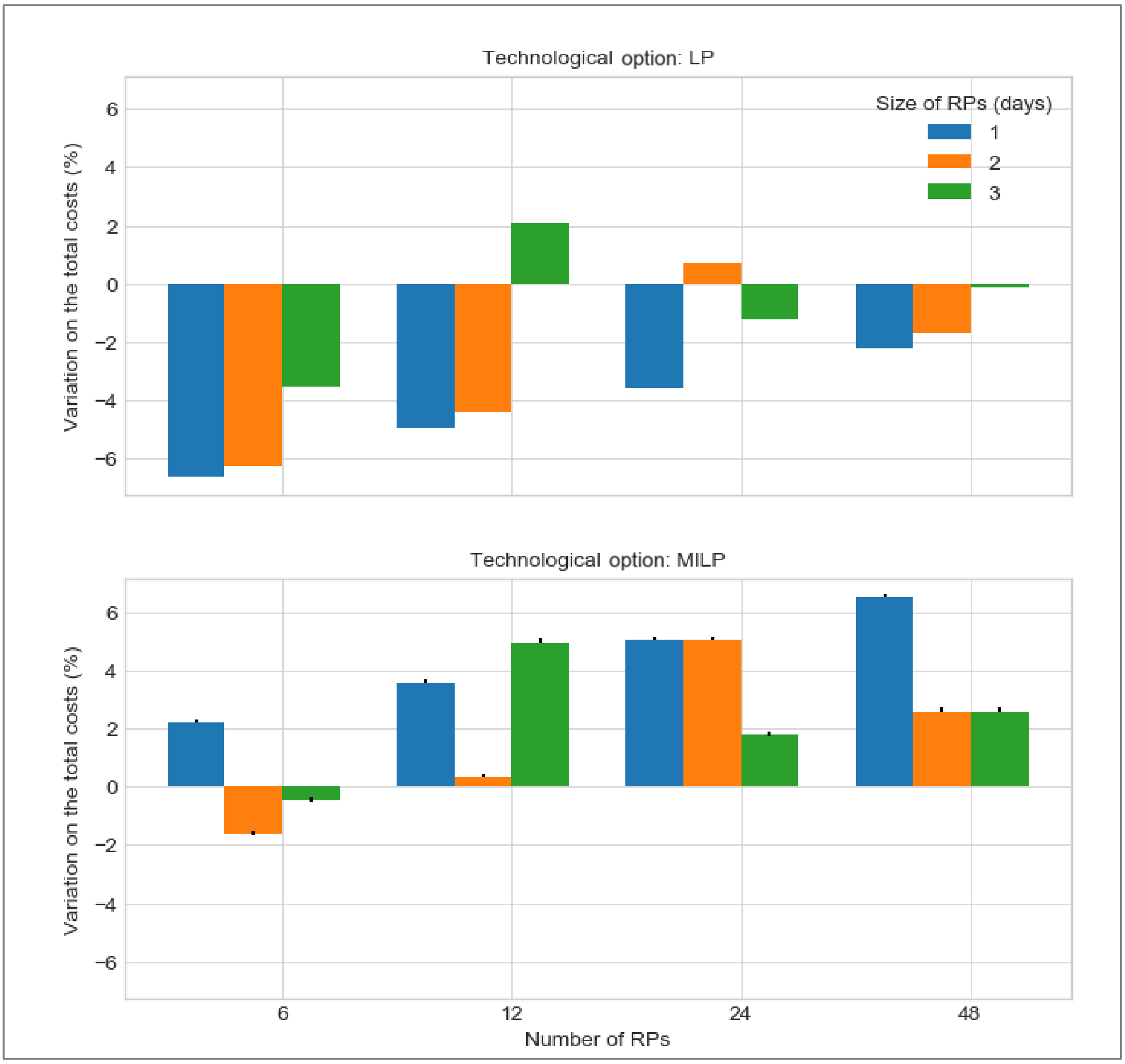



*Figure 39: Impact of the temporal aggregation.*
*Variation on the total operational costs when RP are used compared to the case where one year of hourly data is considered, for various RPs numbers and sizes, and for both LP and MILP options. Error bars are included for the latter case.*

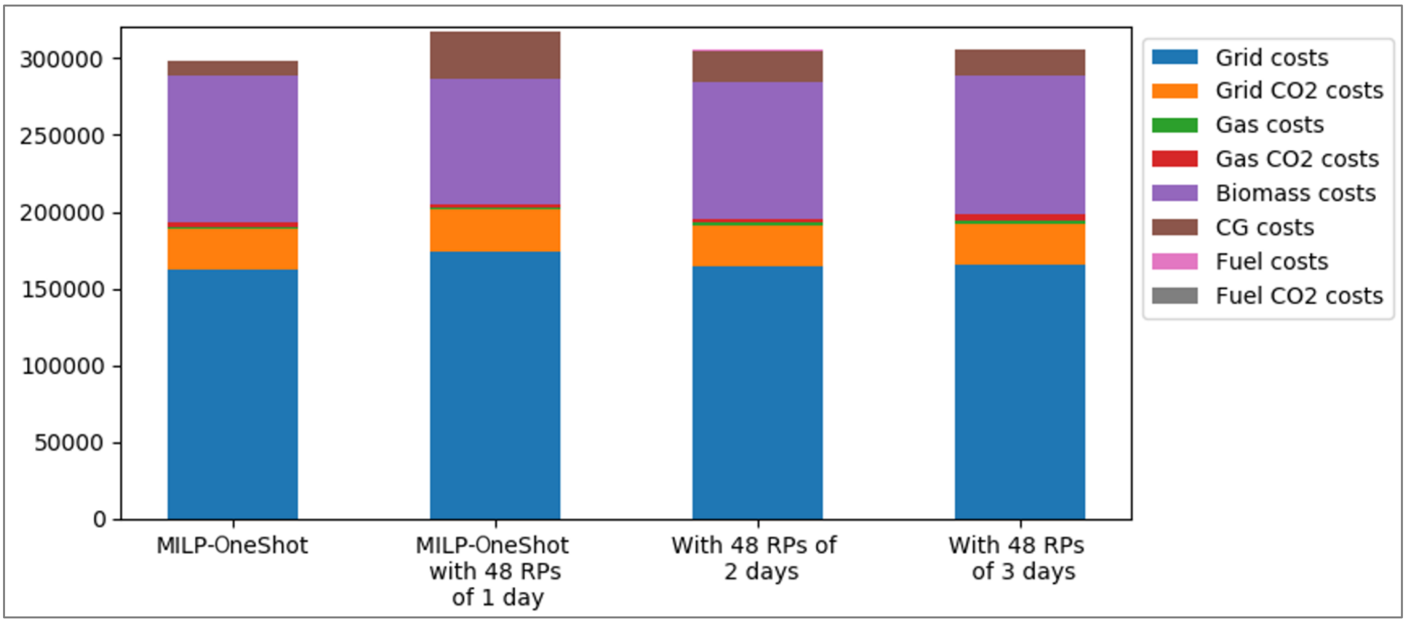



*Figure 40: Operational costs breakdown.*
*Participation of each source in the yearly operational costs (euros), comparison of the MILP-OneShot configuration with cases where 48 RPs of 1, 2 or 3 days are used.*

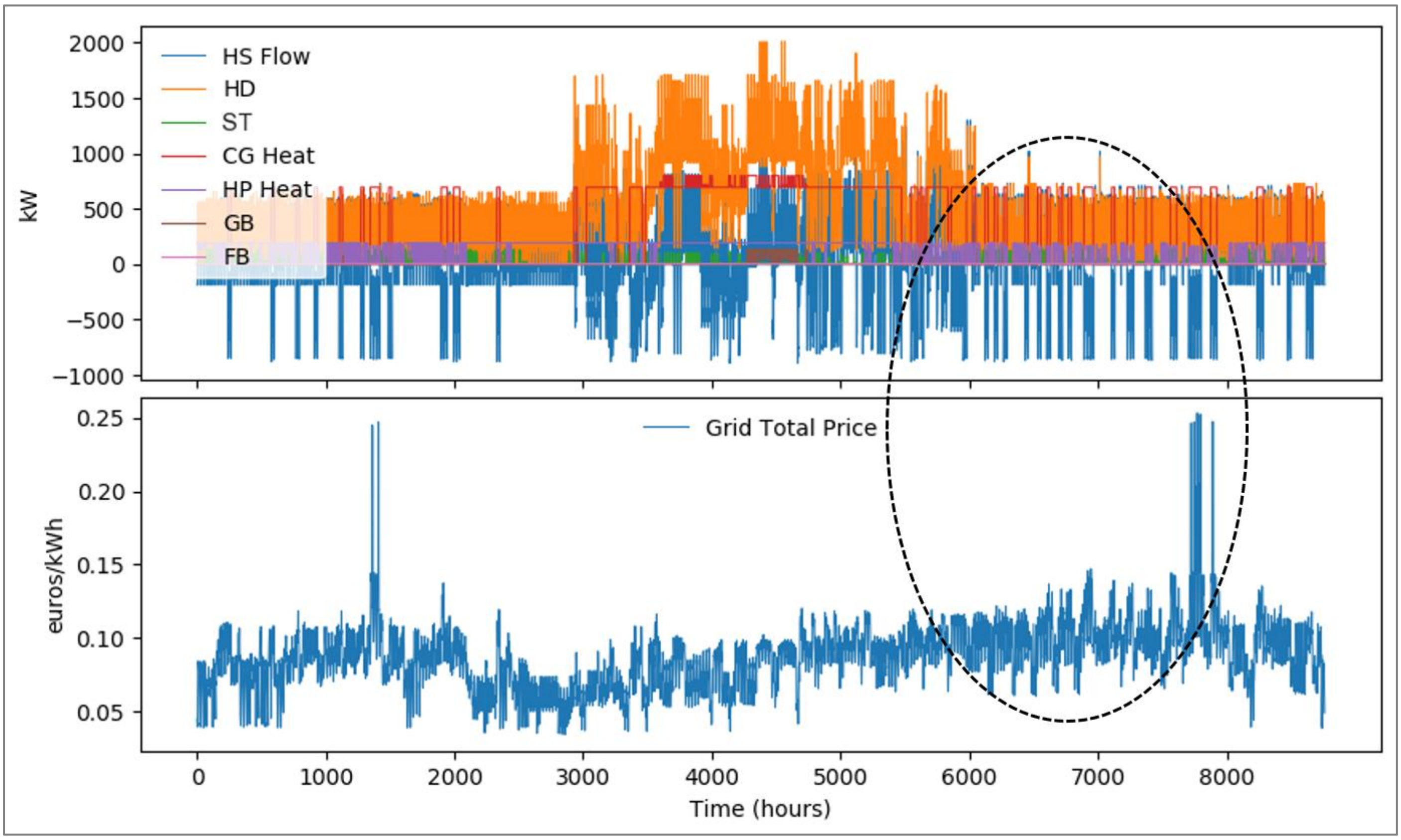



*Figure 41: Solution of the OneShot-MILP-RP configuration when 48 RPs of 2 days are used: heat power balance and grid prices*

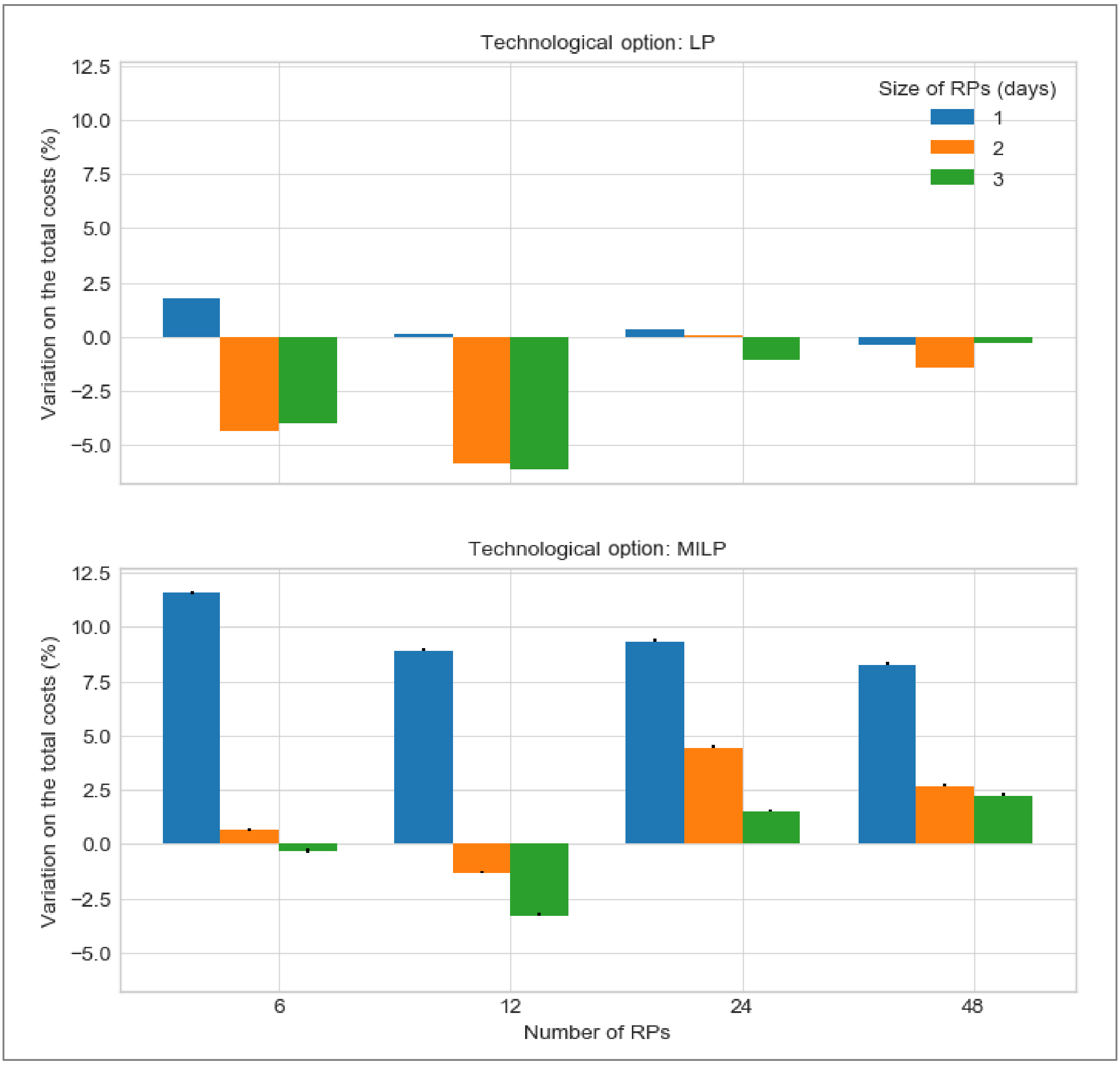



*Figure 42: Impact of the temporal aggregation.*
*Variation on the total operational costs when RPs are used compared to the case where one year of hourly data is considered, for various RPs numbers and sizes, and for both LP and MILP options. Error bars are included for the latter case.*
*Results when **HD peak period is imposed** as a RP.*

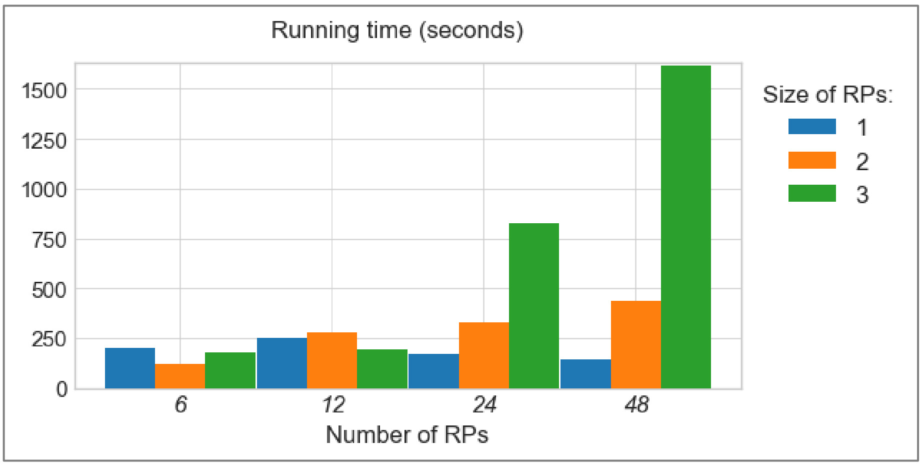



*Figure 43: Computation times of method M2 from [23], applied to our problem.*
*This is done for various number and sizes of RPs.*

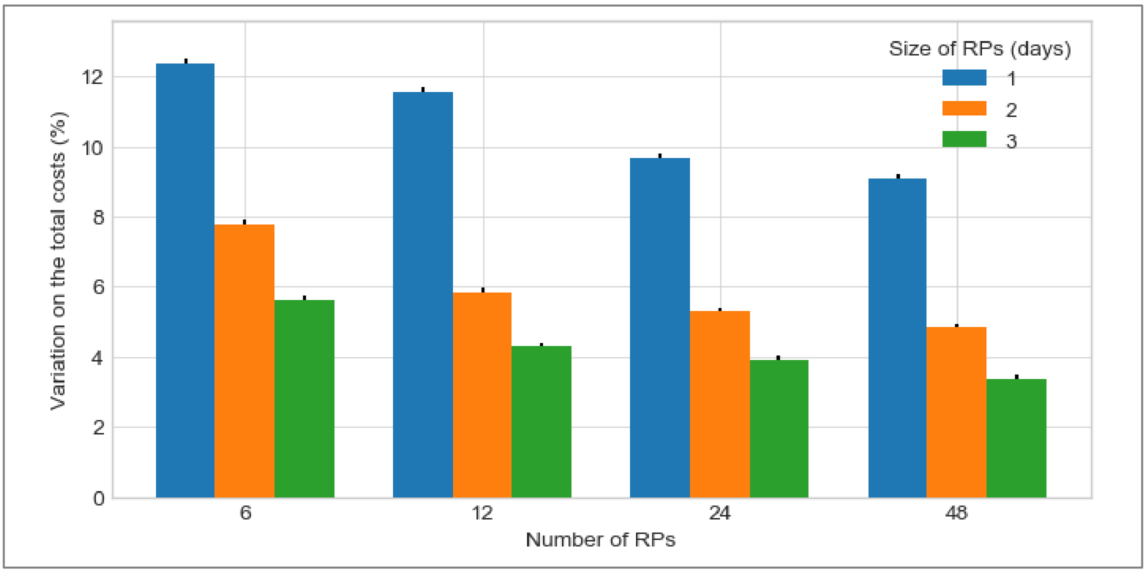



*Figure 44: Variation on the total operational costs when method M2 from [23] is used, compared to the reference MILP-OneShot configuration (original problem).*
*This is done for various number and sizes of RPs used within method M2.*

## 4.3 Impact of the operational decisions assumptions: choice of the optimisation algorithm

The impact of the operational optimisation algorithm is evaluated by comparing the LP-Cicada, LP-Ant, LP-Mean, LP-MeanH2, LP-MeanH3, LP-RpCfH1 and LP-RpCfH3 configurations with the LP-OneShot configuration as a reference. Respectively, the MILP-Cicada, MILP-Ant, MILP-MeanH1, MILP-MeanH2, MILP-MeanH3, MILP-RpCfH1 and MILP-RpCfH3 configurations are compared with the MILP-OneShot configuration as a reference. Results are expressed as percentages in Figure 45.

This impact is increased with the MILP option (i.e. when considering the CG constraints and costs in the model). Looking at the case of the Cicada option shows that the absence of long-term operational optimisation can have a high impact on economic results (see Figure 47 and Figure 48 for the MILP-Cicada and MILP-Ant solutions respectively).

If the LP option is used, results can be close to the results of the reference. Horizons $H2$ or $H3$ better capture mid-term variations and significantly improve results. In particular, the HD peak is better anticipated, which reduces the use of the FB. The LP-MeanH2 configuration gives a solution close to the one given by the LP-OneShot configuration.

If the MILP option is used, the impact is increased. The MeanH1, MeanH2 and MeanH3 options have similar strategies (see Figure 49 for the MeanH3 option): the CG is kept on during the summer. When electricity prices start to increase, it produces more and enters a lock-in situation where the HS is kept full until the heating season. This is due to the fact that future costs are averaged. Hence, the Mean options do not anticipate potential savings on the grid prices and overestimate future costs. This is similar to the Ant option. On the other side, the RpCfH3 option shows a strategy comparable to the OneShot option (see Figure 50). One difference is a lack of anticipation of the heat demand peak, which results in the use of the FB.

Finally, computation times are given in Figure 46. If one needs to reduce computation times, RH methods used here are of little help if the LP option is used. They can be interesting in case of a MILP option.

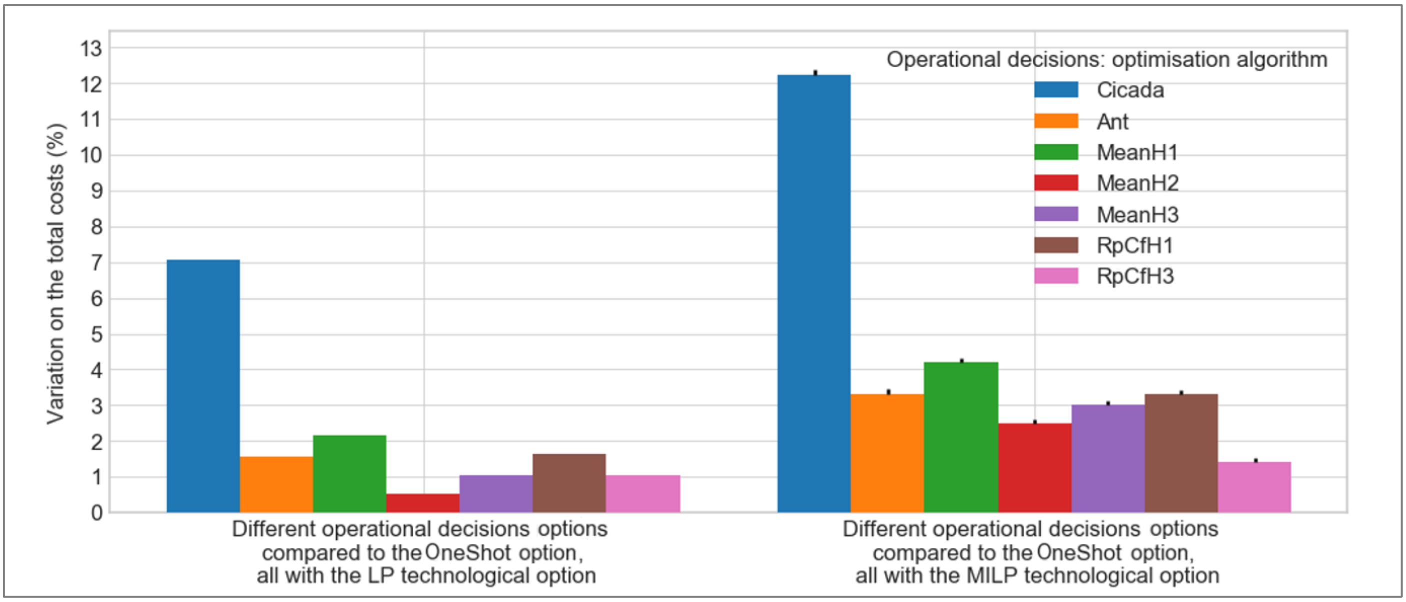



*Figure 45: Impact of the operational decisions modelling options.*
*Variation on the total operational costs of different operational decisions modelling options compared to the OneShot option, for both LP and MILP options. Error bars are included for the latter case (only the computations for the MILP-OneShot configuration reached the time limit).*

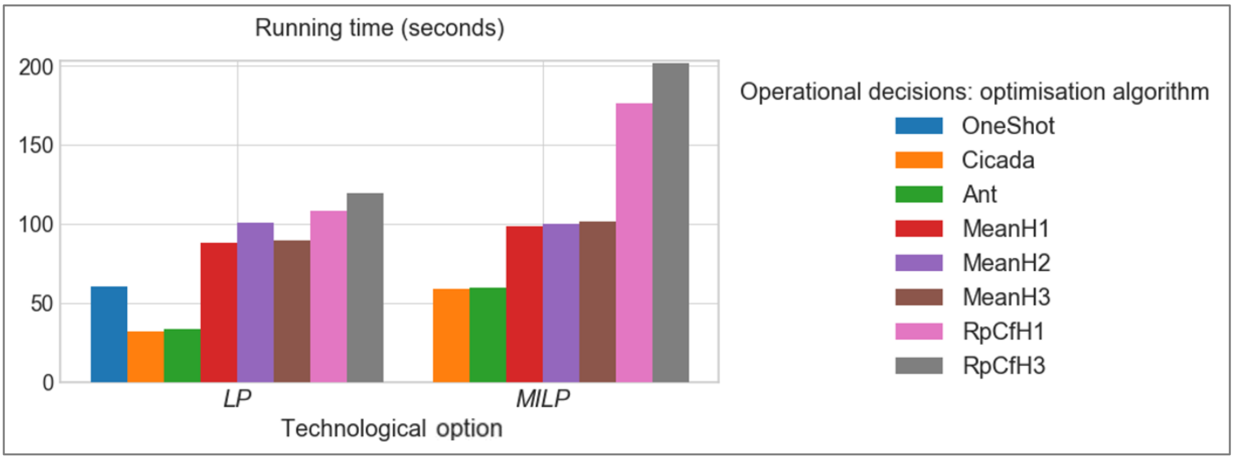



*Figure 46: Computation times (time to simulate a year) of the different operational decisions modelling options, for both LP and MILP options. The time limit of one hour was reached with the MILP-OneShot configuration.*

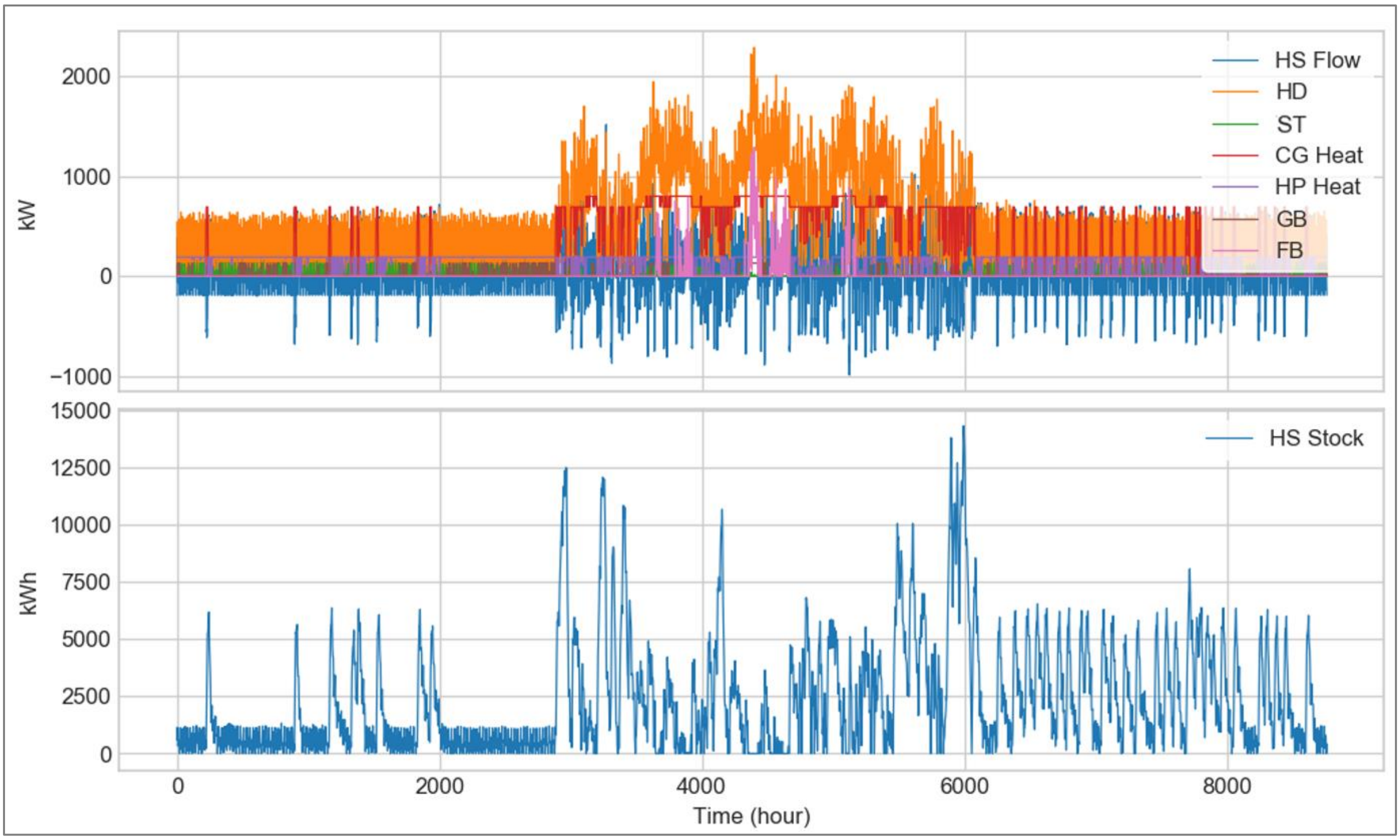



*Figure 47: Heat power and balance and storage state for the MILP-Cicada configuration.*

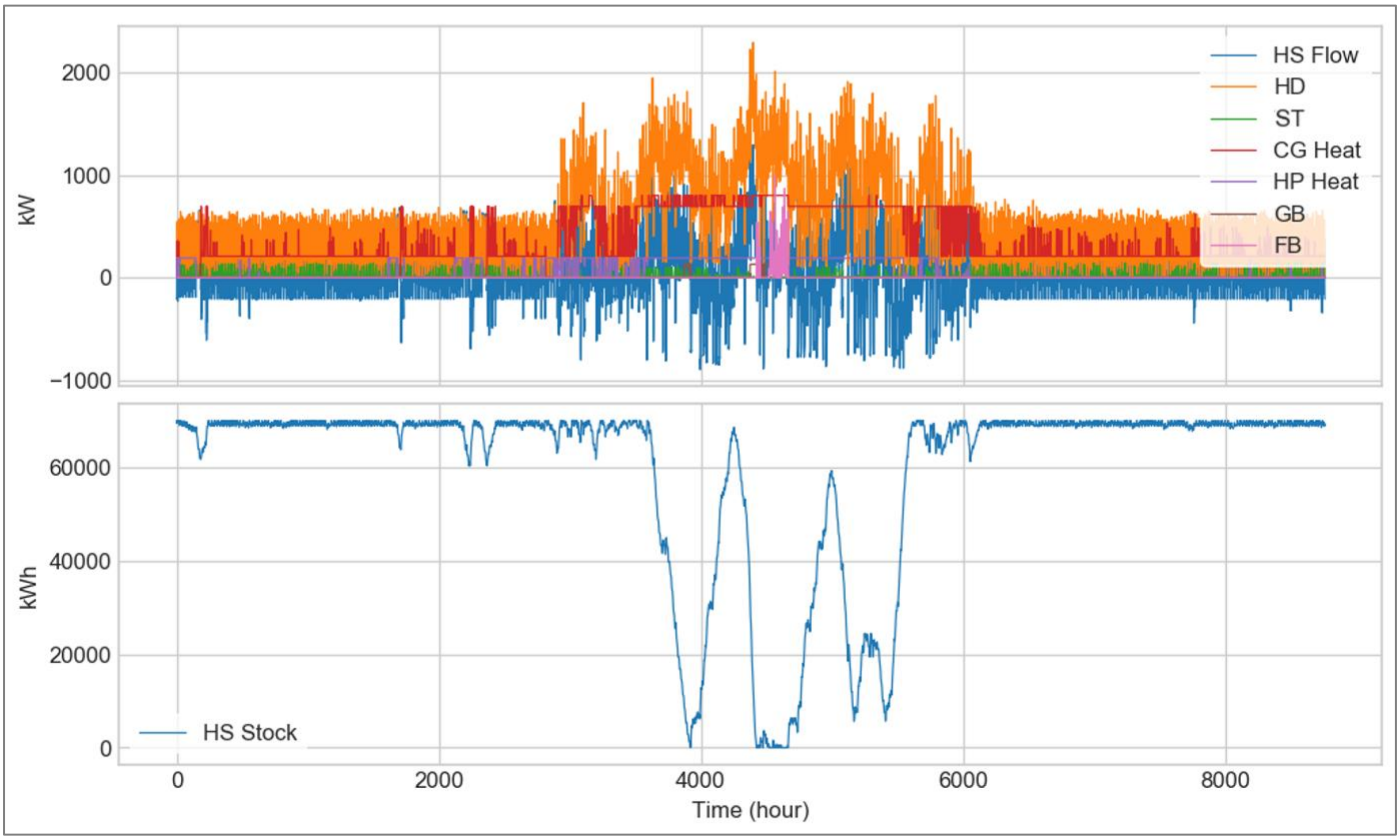



*Figure 48: Heat power and balance and storage state for the MILP-Ant configuration.*

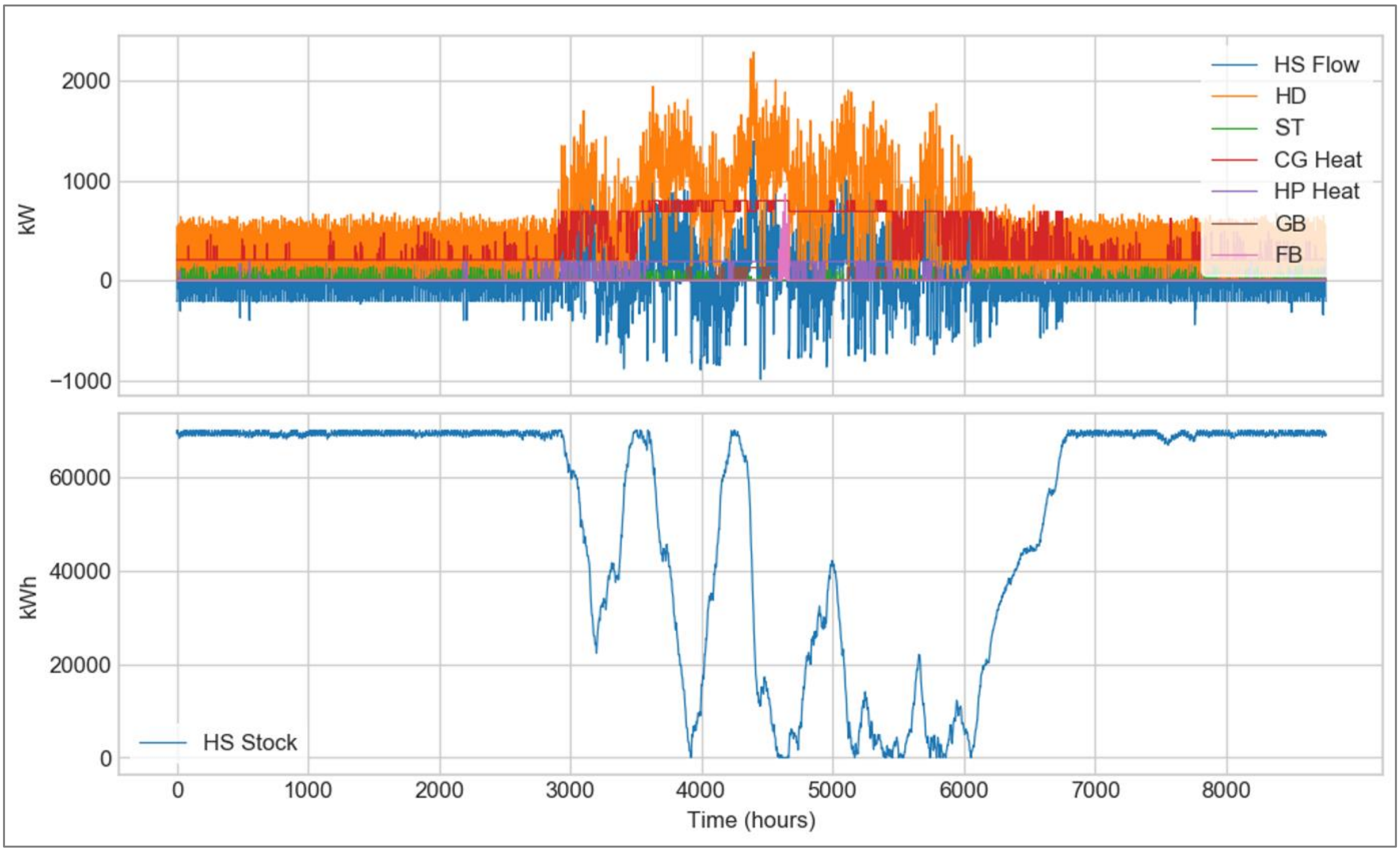



*Figure 49: Heat power and balance and storage state for the MILP-MeanH2 configuration.*

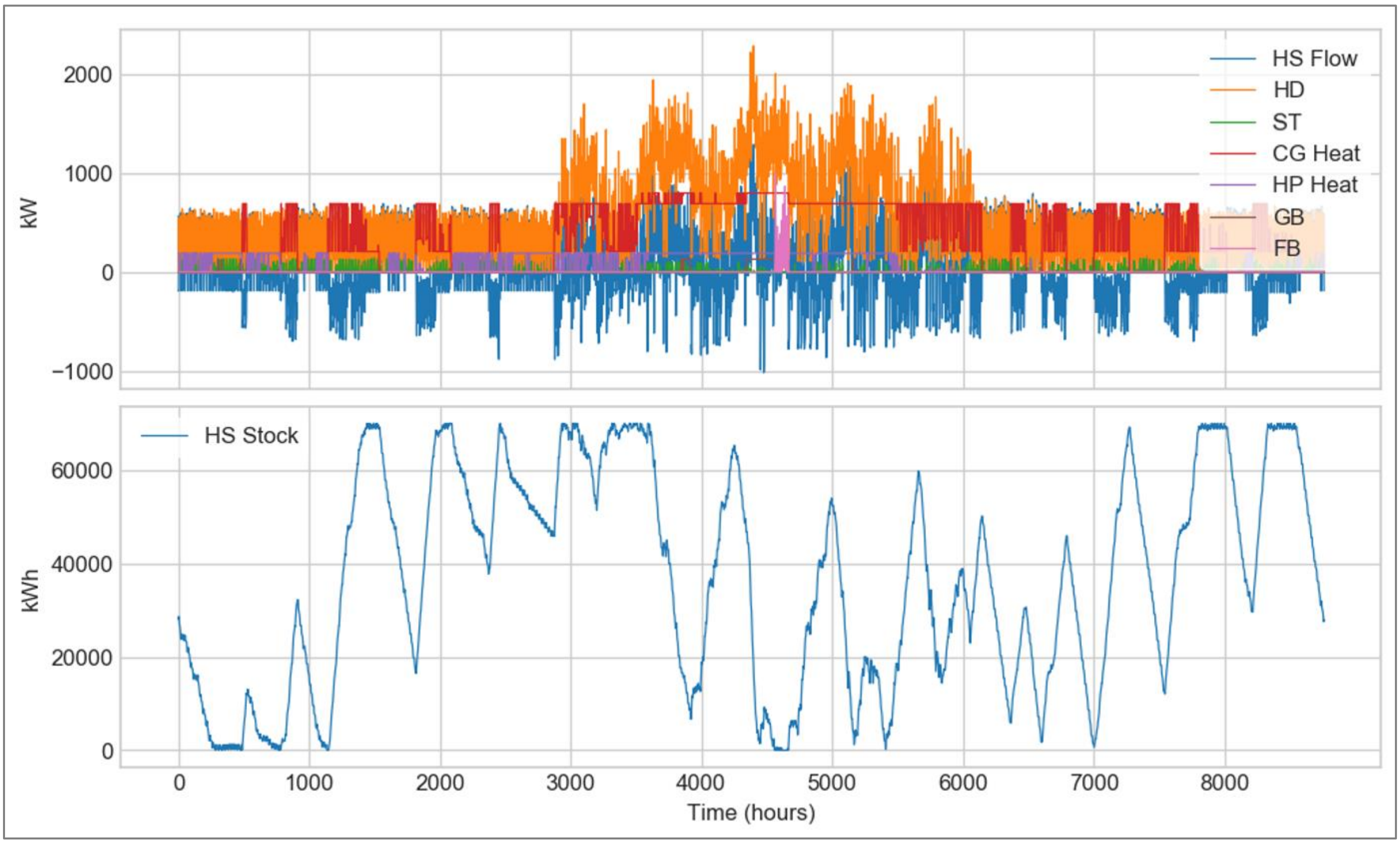



*Figure 50: Heat power balance and storage state for the MILP-RpCfH3 configuration.*

## 4.4 Impact of the operational decisions assumptions: forecast errors

The impact of the forecast errors is assessed in case of different configurations: LP-MeanH2, LP-RpCfH3, MILP-MeanH2, and MILP-RpCfH3. Figure 51 shows this impact in percent: for each case, the reference is the corresponding configuration without forecast errors. Different levels of errors are tested (over and under-estimation of 10 and 20%), for different data series.

A first observation is that, contrarily to the impact of the temporal model or the impact of the optimisation algorithm observed before, the impact is comparable when the LP or when the MILP option is used. Also, the RpCfH3 option appears more robust to HD forecast errors than MeanH2 option. Similar computations were done with the MeanH3 option: the RpCfH3 option was still more robust.

Concerning forecast errors on ED and on the production factor of the ST, impacts on the results are nearly null with the MeanH2 option. This is because within this range of errors, regardless of the forecast quality, the most part of the ED is satisfied by buying electricity on the grid (see Figure 36). Similarly, the ST production is marginal compared to the demand. Although limited, impacts are higher with the RpCfH3 option. This is because the cost functions aggregate all cost sources into a single indicator, contrarily to the Mean options.

An overestimated HD can have a positive impact. This is because the RH strategies do not store enough heat before the HD peak, which leads to gas and fuel overconsumption. Hence, overestimation of the HD compensates this bias: see Figure 52 for graphical comparison with Figure 50 (black circle). This overestimation also has a negative impact: the heat is unnecessarily hold in the storage, and gas is used instead (purple circles). Besides, under-estimating future HD leads to a higher consumption of fuel, which is more costly.

Finally, forecast errors over future grid prices and $CO_2$ content have small impacts respectively on the total costs. In case of the MeanH2 option, an overestimation slightly improves the results. This compensates the bias of the Mean options mentioned in Section 4.3. On the opposite, underestimation increases it. In case of the RpCfH3 option, over or underestimation deteriorates the results, which confirms a proper calibration.

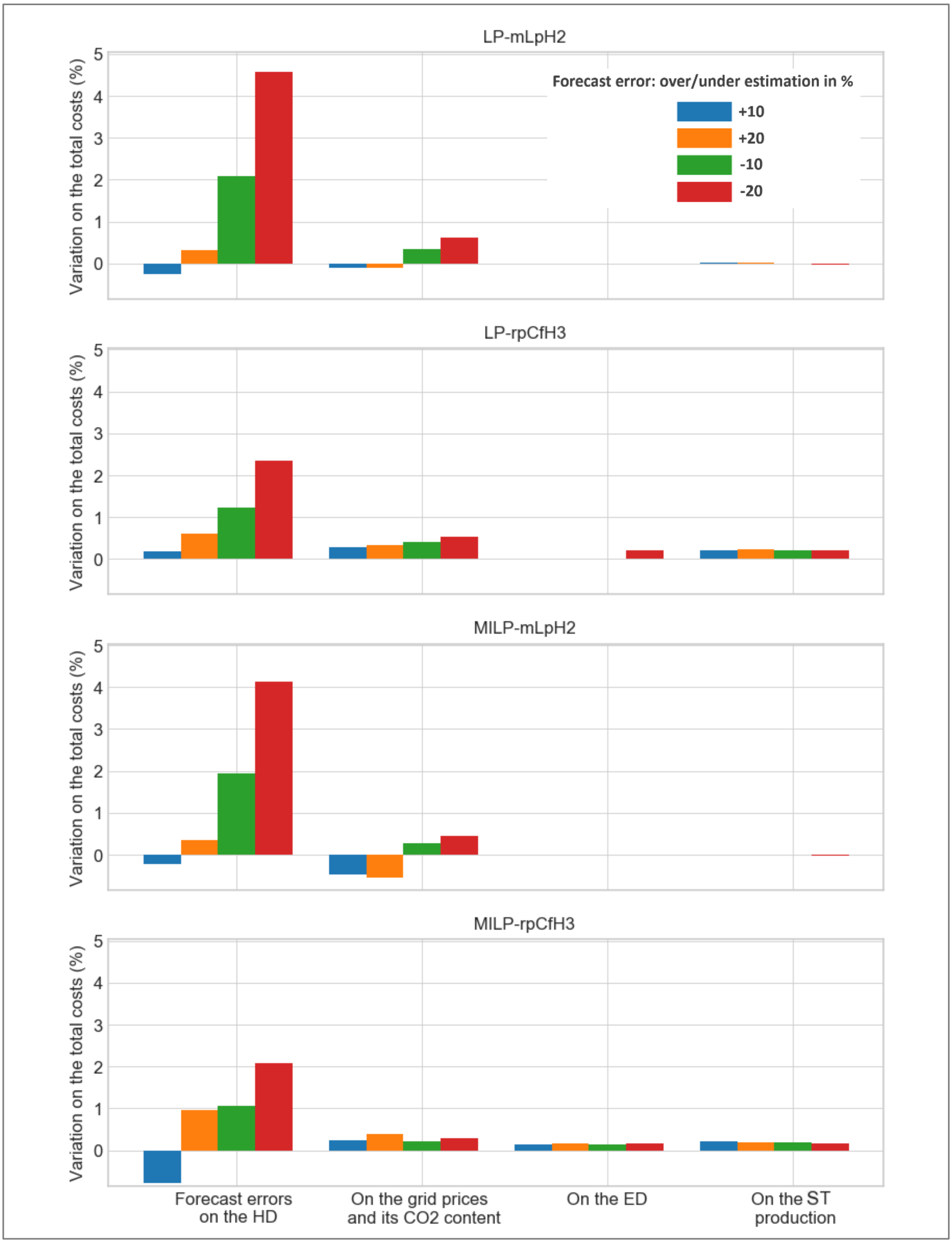



*Figure 51: Impact of the forecast assumptions.*
*Variation on the total operational costs when different forecast errors are considered (errors on the HD, the ED, the production factor of the ST, and the errors on the grid prices and $CO_2$ content together).*
*This is done for the LP-MeanH2, LP-RpCfH3, MILP-MeanH2, and MILP-RpCfH3 configurations.*

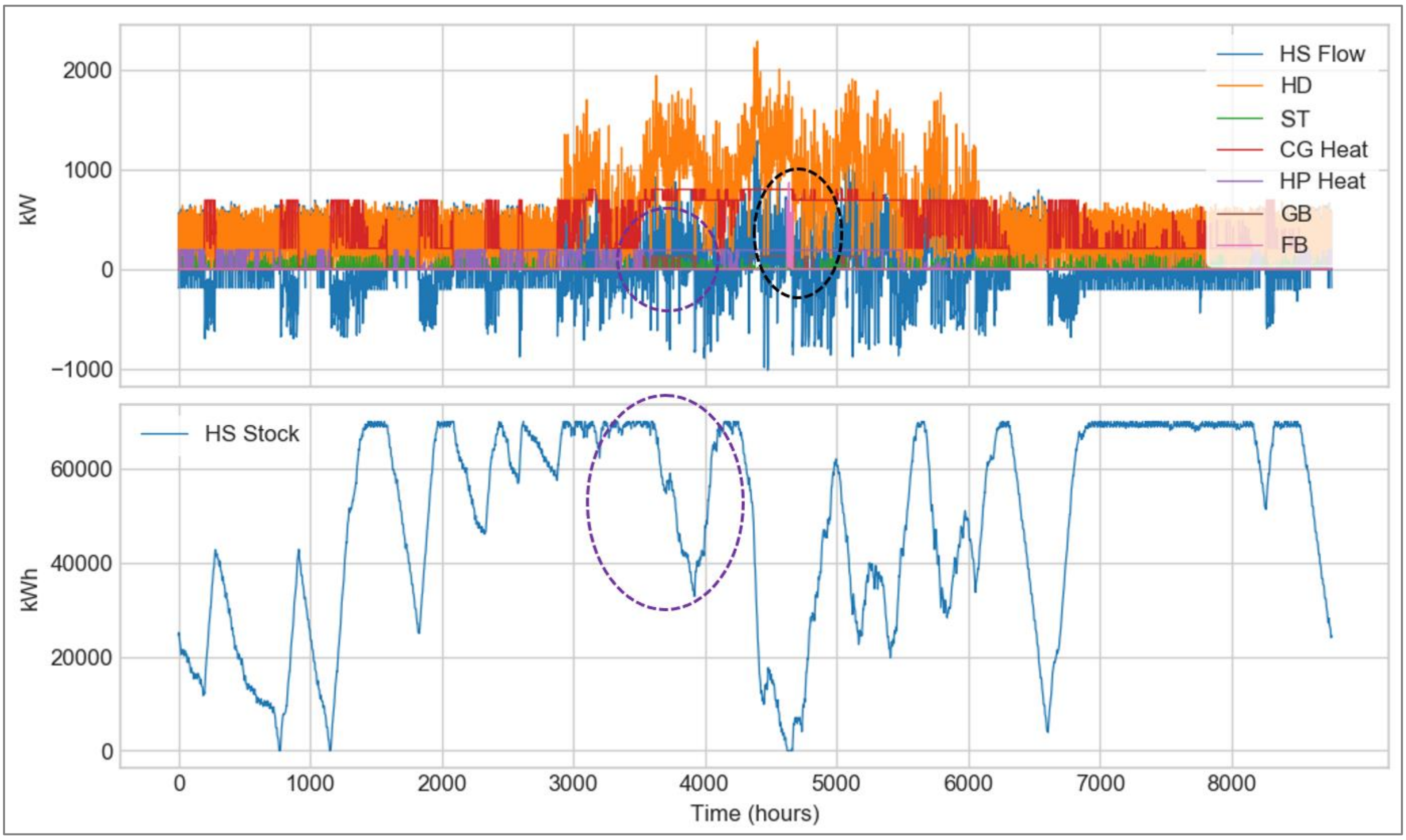



*Figure 52: Heat power balance for the MILP-RpCfH3 configuration, case where the HD is overestimated by 20% after 24h.*

# 5. Discussion

The results described in Section 4 are further discussed. They are tightly linked to the case study considered. Still, more general conclusions are outlined.

Computation times in case of the MILP option:

The MILP-OneShot configuration is surprisingly well handled by the solver despite the problem complexity: the gap was already reduced to 0.26% after 3 minutes, with an objective close to the MILP-MeanH2 configuration. Hence, the method M2 from [23] or RH methods from [176] tested on this case study are not of interest if one only needs to reduce computation times. However, the tractability of such MILP is not guaranteed. For instance, similar computations were done with a high capacity for the GB for which the MILP-OneShot configuration was less performant. Hence, methods from [23] or [176] can still be further tested for this purpose.

Assumptions on the technological facet:

On the side of the assumptions over the technological model (here the inclusion of flexibility costs and constraints for the CG), they can have an important impact over the objective (around 4 percents) and on the solution. It further conditions the impact of the temporal and the operational decisions assumptions. Hence, attention should be paid to the technological assumptions. In this case study, the difference mainly comes from the fixed costs and the start-up costs of the CG. Nevertheless, the impact of the flexibility costs and constraints is not systematic: similar computations are done with economic assumptions relevant to Denmark[6] and with a different type of CG (extraction condensing)[7]. The system sizing yield a smaller CG (580 kW) producing heat and electricity all year without being turned off. In turn, adding flexibility costs and constraints do not change significantly the solution and it do not condition the impact of other assumptions.

This can be put into perspective with recent literature on large-scale bottom up optimisation models: several works in the literature included detailed flexibility features ([70,112,187–189]). More recently, authors from [190] bring contrasts on the impact of such assumptions. They conclude that the impact can be limited on the total system costs if several sources of flexibility are considered. On the other hand, they can have a significant impact on the flexibility provider optimal sizes.

Assumptions on the temporal facet:

Moving to the temporal assumptions, results indicate that in case of simple technological assumptions, a temporal aggregation with a sufficient number and size of RPs approximates well the results. It should be noted that this case study includes four data series (the HD, the ED, the ST production factor and the grid costs including $CO_2$ emissions), which is more challenging to aggregate with RPs. Hence, authors expect the results to improve for case studies that include less data series. On the other hand, the approximation by RPs can have a higher impact if a detailed technological model is considered. In particular, this is the case if the operational strategy has medium-term dynamics. This is because RPs do not conserve the time continuity between periods.

[6] The gas price was taken equal to 0.2752 euros/kWh (extracted from [185]), and different grid prices and $CO_2$ content were used (leading to higher total prices).
[7] The extraction condensing CG is modelled with a 31% efficiency on electricity production and 47% efficiency on electrical production. It can trade heat for electricity with a ratio of 30%. Its investment cost was taken equal to 1200 euros/kW.

Assumptions on the operational decisions facet:

The impact of the operational decision modelling option is observed in Sections 4.3 and 4.4. A first conclusion is that a lack of long-term strategy can have an important impact on the operational costs. Hence, in this case, results provided by a single mathematical program with a perfect foresight assumption can only hold if an effective operational strategy is applied in practice. Further experiments on operational models elaborate on how effective the strategy should be to stick with the perfect forecast assumption of the OneShot option.

In case where the LP option is used, the sensitivity of the results to the optimisation algorithm can be limited: the MeanH2, MeanH3 and RpCfH3 options yield performances close to the OneShot option. If the MILP option is used, the impact increases and only the RpCfH3 option performs close to the OneShot option. When forecast errors are considered after 24 hours of the planning horizon, results are only significantly impacted when the HD is underestimated. On the other hand, overestimating the HD can have a positive impact or only slightly deteriorates the results. The supplementary costs caused by a lack of anticipation of the HD peak are due to the use of the FB. In practice, the GB backup is oversized (the small capacity of the GB actually comes from the over-fit of the sizing solution). Hence, the demand currently satisfied by the FB could be satisfied by the GB. For instance, in the case of the RpCfH3 option (with no forecast errors), this reduces the difference with the OneShot option to less than 1%. Given these elements, supposing that if a proper optimisation algorithm, a properly sized backup solution and conservative scenarios on the HD during the winter are used, a solution close to the OneShot option can be obtained. Hence, the perfect foresight assumption of the OneShot option seems reasonable here.

A finding is that forecast errors on the ED or on the ST production factor have very limited impact, so there is no need to put efforts on a forecast method on this side (at least after 24 hours). As mentioned earlier, this is due to the fact that the ED is mainly satisfied by the grid and the ST production is marginal. Hence, marginal forecast errors (up to 20%) do not influence the operational strategies. This **insensitivity to forecast errors can be anticipated on future case studies where the forecasts concern a marginal production or a demand that is mainly satisfied by the backup option** (here the grid).

Similarly, the forecasts on the grid prices and $CO_2$ content are not crucial at least after 24 hours. Further computations with the RpCfH3 option show that using constant values as previsions after 24 hours had nearly no impact on the final solution. Taking a step back, the MILP-OneShot configuration is run with constant total grid prices, and the variable profiles are applied a posteriori: the operational cost is only increased by 1%. Similarly, the OneShot option is run with total grid prices increased/decreased by 20% and the original profiles are applied a posteriori. This changed the solution: the CG is used instead of the HP in the summer if prices are increased and vice-versa. However, the operational costs do not increase more than 0.8 percent. This confirms that the lever on the total grid prices is small, which is consistent with the low impact of the grid prices and $CO_2$ emissions forecasts. In turn, the increase in operational costs between the MILP-OneShot configuration and MILP-MeanH1-2-3, MILP-RpCfH1 or MILP-Ant configurations is more due to the less efficient cycling strategy of the CG. This comes from the algorithm used and is less impacted by forecast errors. Cases where more benefits/costs are induced by medium/long-term temporal variations and where the system has latitude to react accordingly are expected to be more sensitive to forecasts quality.

# 6. Conclusion & perspectives

This paper investigates the impact of various modelling assumptions of local multi-energy systems on a complex case study. The modelling facets considered include the technological, temporal and operational decisions representations. The impact of the inclusion of specific flexibility costs and constraints over the objective and the solutions is evaluated, and is further crossed with other modelling assumption impacts. Full hourly temporal resolution over one year is compared with the recourse of representative periods. Single mathematical formulation with perfect foresight assumption and different rolling horizon strategies including long-term operational decisions are compared. Finally, forecast errors are included. All impacts of these different assumptions are compared together in order to validate/invalidate the corresponding assumption and further prioritize modelling efforts.

A first observation is the **potential high impact of the technological model over the objective and the solution** (operational dynamics). It further conditions the impact of the temporal and the operational decisions assumptions. Hence, attention should be given to the flexibility costs and constraints assumptions.

In case where a simple technological model is used, relying on **representative periods can well approximate operational costs** and reduce computation times. **However, operational strategies with medium-term dynamics can deteriorate the approximations yield by representative periods**. **The detailed technological model including limited flexibility of the cogeneration triggered this in this case study**.

Finally, the rolling horizon methods used can help to evaluate the impact of imperfect operational decisions (including forecast errors). In this case study, it is found that forecast errors can have relatively low impacts on the operational costs if proper operational strategy and backup are applied. Hence, the perfect foresight assumption usually taken is not invalidated here: the operational decisions are not “over-optimised” by the single mathematical program. **Overall, the impact of imperfect operational decisions model is difficult to anticipate, particularly if complex operational strategies are used**.

Future work can include the improvement of this evaluation method with more tests on the possible forecast errors. Here, only systematic over/under estimations are tested. More detailed error patterns could be used and defined with respect to actual expected forecasts accuracy. In addition, forecast errors before 24 hours could be tested.

On the side of the computational tractability, the single mathematical program handled to the solver yields a performant feasible solution in a reasonable computation time despite the problem complexity and the detailed time resolution. Cases with problems harder to solve could discard this option (when considering part-load efficiencies for instance [166]). If so, methods based on representative periods [23], decomposition methods (as reviewed in [156]) or the rolling horizon methods presented in [176] can be of interest. Future work could compare these different options.

# Conclusion

Résumé des travaux réalisés, réponses aux questions et contribution à l'état de l'art :

Cette thèse a tenté d'apporter des réponses à deux questions principales : Comment faire usage des méthodes disponibles pour l'étude et la planification technico-économique de systèmes multi-énergies ? Peut-on compléter le panel existant avec de nouvelles méthodes pertinentes ?

Le premier chapitre de cette thèse propose un état de l'art des méthodes de modélisation et d'optimisation. Cela a permis de mieux comprendre les enjeux associés, à travers un prisme d'analyse original. Il répond en partie à la première question en décrivant les méthodes existantes et leur usage en fonction du système étudié, de la question posée et de l'orientation de l'étude. Plus généralement, l'état de l'art rappelle la nécessité de bien définir les objectifs de l'étude, étape clé du processus de modélisation [10]. Ce chapitre illustre également l'usage répandu de la programmation mathématique et la diversité d'études qui l'utilisent. En effet, elle permet de représenter dynamiquement le système tout en en minimisant les coûts d'opération (et d'investissement) et en assurant le respect de bilans énergétiques et de contraintes techniques simples.

L'état de l'art met en évidence le besoin de faire appel à une modélisation plus fine de l'opération du système, en particulier si l'étude porte sur la flexibilité du système. En effet, cette flexibilité garantit l'équilibre offre/demande et est aujourd'hui étudiée au regard de l'utilisation d'énergies intermittentes, ou plus généralement de ressources moins flexibles. Cela répond donc en partie à la première question : il existe un besoin de développement de nouvelles méthodes.

Le deuxième chapitre propose deux nouvelles approches pour compléter l'éventail des méthodes existantes et tournées vers une modélisation fine de l'opération du système. Ces deux méthodes permettent de mieux tenir compte d'aspects opérationnels long terme (comme le stockage saisonnier d'énergie) dans le cadre de la mécanique d'horizon glissant. Elles offrent deux nouveaux compromis entre complexité, temps de réponse et pertinence du modèle. Le troisième chapitre valide l'intérêt des deux méthodes sur un ensemble de cas élémentaires. Cela complète la réponse à la seconde question.

Le quatrième chapitre évalue l'intérêt et les conséquences de complexifier un modèle. Cette question est illustrée sur un cas d'étude complexe qui offre un retour d'expérience pour de prochaines études. Cela poursuit la réponse déjà apportée à la première question montrant comment et sous quelles conditions des méthodes avancées peuvent aider à réduire les temps de réponse, améliorer la précision des résultats, ou valider/invalider des hypothèses. De plus, ce quatrième chapitre illustre une utilisation possible des méthodes proposées au deuxième chapitre.

Le prochain paragraphe complète la réponse à la première question en proposant une synthèse des pistes méthodologiques possibles en fonction des questions posées et des difficultés calculatoires rencontrées.

Une synthèse des pistes méthodologiques pour la modélisation et l'optimisation technico-économique :

La Figure 53 propose une synthèse pour la modélisation et l'optimisation de systèmes énergétiques dans le cadre d'études technico-économiques. La première étape consiste en un modèle écrit en programmation linéaire. Comme vu au Chapitre 1, ce formalisme est très répandu, ce qui permettra de basculer facilement sur des méthodes avancées. De plus, sa simplicité est un atout pour une première étape. Puis, différentes voies d'exploration sont possibles pour tenter d'améliorer la pertinence du modèle en fonction de l'intérêt du modélisateur. Des méthodes sont proposées à chaque étape sur la base du Chapitre 1.

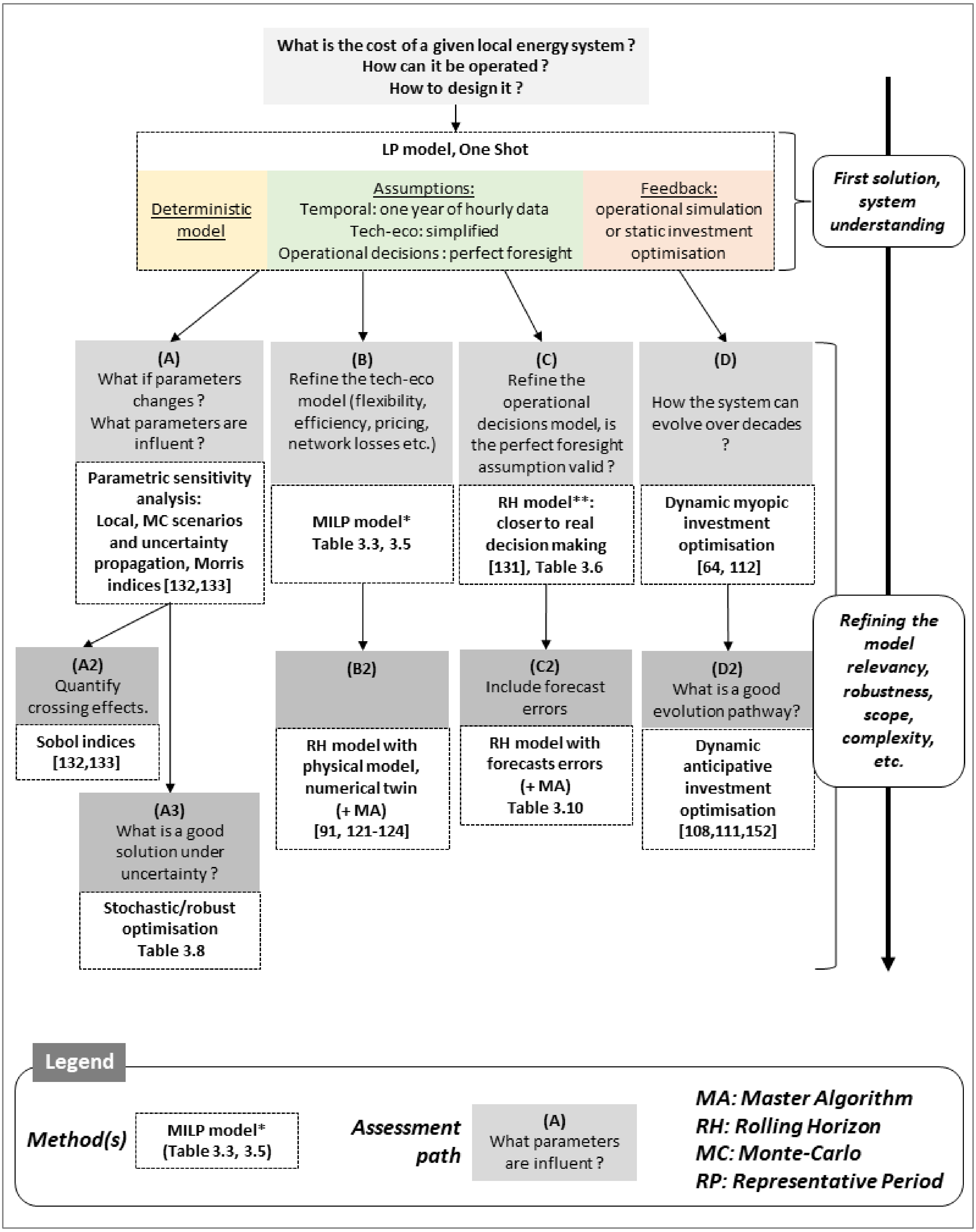



*Figure 53: Optional assessment paths when evaluating and optimising an energy system, with possible associated methods*
**See Figure 54*
***See Figure 55*

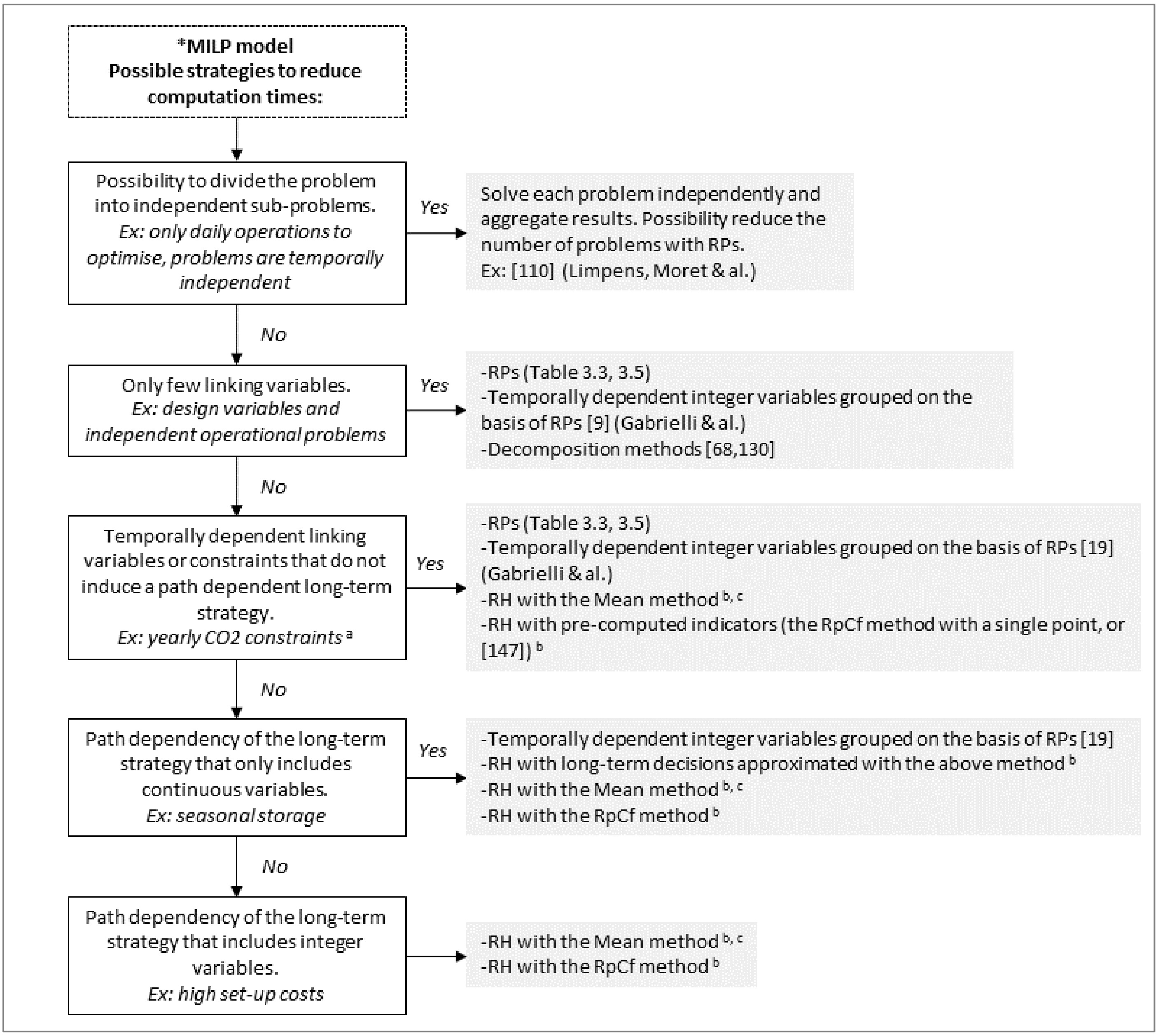



*Figure 54: Options to reduce computation times, according to the problem structure*

*[a] In case of long-term constraints or threshold, the RH might miss the target due to long-term model bias. If so, the RH can be relaunch with corrections learned from the previous try, as in [147].*
*[b] If the problem does not include design variables.*
*[c] Case dependent performances.*

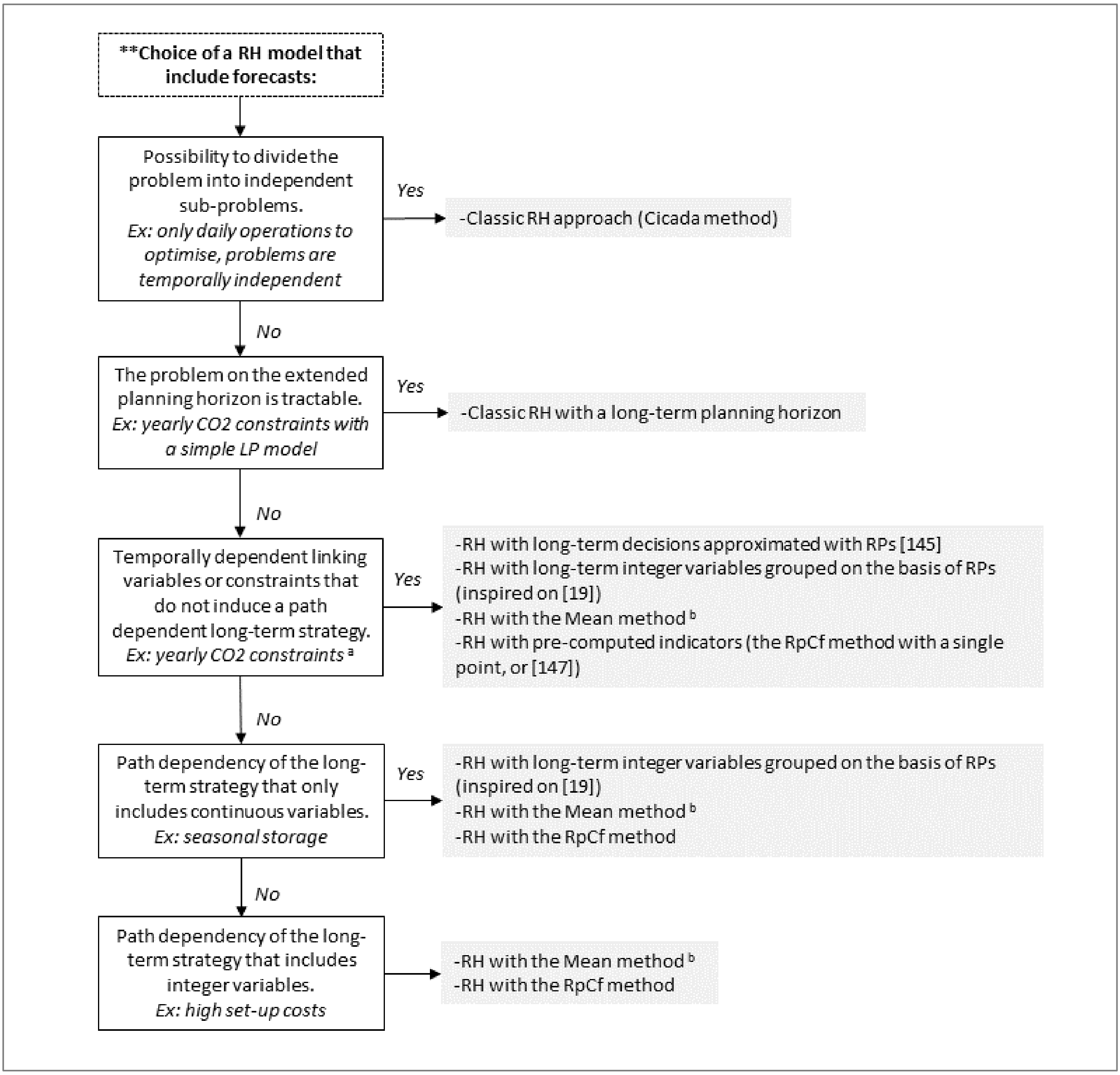



*Figure 55: RH horizon methods, according to the problem structure*

*[a] In case of long-term constraints or threshold, the RH might miss the target due to long-term model bias. If so, the RH can be relaunch with corrections learned from the previous try, as in [147].*
*[b] Case dependent performances.*

La Figure 53 suggère d'augmenter la complexité du modèle progressivement. En revanche, et même si l'analyse de sensibilité paramétrique est une excellente candidate pour une deuxième étape, rien n'impose d'explorer une voie avant une autre. Cela dépendra des objectifs du projet. Du point de vue pratique, cela dépendra aussi du temps consacré à l'étude et des méthodes et compétences disponibles. Le développement de plateformes mutualisant et validant ces méthodes est donc pertinent pour que leur temps d'appropriation ne soit pas trop important au regard du temps consacré à l'étude.

La Figure 54 et la Figure 55 complètent la Figure 53 en proposant des pistes pour réduire les temps de réponse selon la typologie du problème, sur la base des travaux menés dans cette thèse. La Figure 53 peut être complétée en commentant la faisabilité, a priori, de croisements entre les voies d'exploration :

- La voie A peut être croisée avec d'autres voies si le nombre d'évaluations et le temps de réponse du modèle ne sont pas excessifs.
- Les voies A2 et A3 nécessitant de nombreuses évaluations, il est nécessaire que le modèle ait un temps de réponse très court, comme recherché dans [110]. Le croisement de A3 avec D2 est illustré par les méthodes citées dans la Table 3.9.
- Les voies B et B2 peuvent être croisées avec les voies C et C2.
- La voie D peut être croisée avec les voies B, B2, C et C2.

La synthèse proposée par la Figure 53 n'a pas pour objectif d'être exhaustive. En effet, d'autres aspects peuvent également être approfondis comme la représentation de plusieurs acteurs échangeant selon des règles de marché (des exemples sont donnés Table 3.11). Par exemple, la fourniture d'énergie peut être assurée par différents opérateurs souhaitant maximiser leur profit. La théorie des jeux peut être utilisée pour représenter une telle situation où le fonctionnement du marché n'aboutit pas à la maximisation du bien commun (hypothèse implicite du point de départ de la Figure 53). Un autre aspect qui pourrait également être approfondi est la représentation spatiale du système. Souvent, un seul nœud est considéré. Si le système modélisé est de taille importante, ce nombre peut être augmenté pour améliorer la représentativité du modèle. Dans le cas où le nombre de nœuds devient important, des méthodes de clustering peuvent être utilisées (Table 3.12).

<u>Limites des travaux :</u>

Plusieurs limites peuvent être citées. Premièrement, l'état de l'art réalisé au Chapitre 1 n'est pas exhaustif, le temps consacré à sa réalisation étant limité. Deuxièmement, les cas d'études traités aux Chapitres 2, 3 et 4 font l'objet de nombreuses hypothèses. Par exemple, les modèles ne considèrent que des quantités énergétiques, alors que des grandeurs comme la température, la pression ou la tension permettrait de mieux tenir compte de phénomènes physiques influant sur le coût du système. L'efficacité de la pompe à chaleur modélisée au Chapitre 4 pourrait à ce titre être choisie dépendante de la température de sa source froide et de sa source chaude. Un autre exemple concerne la comptabilité des émissions $CO_2$ : seules les émissions liées à la consommation de gaz, fioul ou d'achat d'électricité sur le réseau ont été considérées. A ce calcul pourrait s'ajouter la quantité de $CO_2$ émise pendant les étapes de fabrication, ou l'étape de transport de la ressource en biomasse par exemple. Néanmoins, ces simplifications proviennent davantage de la limite de temps consacré à la modélisation et au recueil de données que de limites intrinsèques aux méthodes utilisées.

Plus généralement, la limite de ces travaux concerne l'étendue de leur pertinence sur la vie d'un projet (Figure 1). En effet, les approches présentées ont un intérêt durant les phases d'étude de la faisabilité technico-économique ou de préconception d'un système énergétique. Elles sont potentiellement trop complexes pour la phase d'analyse d'opportunité, et insuffisamment précises pour les phases de conception, pilotage et opération. Néanmoins, les méthodes basées sur le principe de l'horizon glissant (comme celles présentées au Chapitre 2) tendent à renforcer le lien entre l'étape de préconception et les étapes avales du projet.

Perspectives :

Plusieurs perspectives ont été mentionnées précédemment. Premièrement, les méthodes proposées au Chapitre 2 peuvent être appliquées à d'autres cas d'études (y compris dans d'autres domaines) pour illustrer leur intérêt ou explorer des problématiques opérationnelles difficiles à appréhender à cause de temps de calculs élevés. Par exemple, elles pourraient être appliquées dans des cas où des décisions réalisées à l'échelle de la minute doivent tenir compte de prévisions sur plusieurs jours.

Deuxièmement, les fonctions de coût pourraient être calculées sur des modèles plus fins pour améliorer leur pertinence. Par exemple, dans le cas où un module d'optimisation donne des instructions à un système réel, les fonctions de coût pourraient apprendre sur la base des coûts réels, et donc fournir un retour au modèle d'optimisation. Ce schéma est généralisable aux applications où le résultat des décisions n'est pas directement mesurable par le modèle d'optimisation.

Une autre piste citée serait l'élaboration d'une méthodologie plus complète pour évaluer l'impact des incertitudes présentes lors du pilotage du système, voire de le dimensionner en tenant compte de ces incertitudes. Ces incertitudes incluent les prévisions de séries temporelles, mais aussi l'occurrence d'évènements imprévus comme des pannes ou des augmentations soudaines du prix des ressources.

Plusieurs méthodes ont été identifiées pour aider à la résolution de problèmes difficiles incluant des variables entières. Ces méthodes agrègent les données temporelles, décomposent le problème, ou utilisent des mécanismes d'horizons glissants. De futurs travaux pourraient comparer leur efficacité sur divers cas et/ou en élaborer de nouvelles.

L'optimisation stochastique et/ou robuste de systèmes énergétiques en tenant compte de modèles opérationnels détaillés représente un challenge conséquent. Les travaux initiés dans [19] semblent pertinents sur ce point : ils permettent de choisir un scénario optimal/robuste pour dimensionner un système plutôt que de réaliser une optimisation couteuse sur un ensemble de scénarios. Cette méthode pourrait être testée et combinée à des modèles opérationnels plus fins.

La diversité des modèles et méthodes est une richesse, mais leur dispersion et leur manque d'interopérabilité est un frein à leur utilisation par les personnes en charge des études. La mise à disposition de méthodes existantes sur des plateformes intégrées pour des modélisateurs chargés d'études faciliterait leur usage. Ce travail a déjà débuté avec la plateforme PERSEE et avec de nombreux outils comparables existants (Chapitre 1, [33]). La multiplicité de ces plateformes, leurs divergences méthodologiques ou leurs hypothèses implicites peuvent constituer un frein aux dialogues entre modélisateurs et décideurs. L'émergence de standards et la transparence de ces plateformes sont des leviers possibles, au même titre que la mutualisation de données [191,192]. Les initiatives open sources [37] peuvent être gages de cette transparence. Une seconde action serait une collaboration plus étroite entre l'optimisation technico-économique et l'analyse environnementale, comme initiée dans [9]. Une intégration plus systématique d'impacts carbone issus d'analyses de cycles de vie dans les modèles d'optimisation technico-économique serait un premier pas pertinent.

# Annexes

## Appendix A: Computation of cost functions (Chapitre 2)

This Appendix details the method for pre-computing cost functions (CFs) for the horizon *H1*, for a fixed horizon of 24 hours and for the data of Table 4. As mentioned earlier, CFs ($c_{t,\tau}$) are defined for all periods $t$ and all steps $\tau$ of the RH process. However, different couples $(t,\tau)$ can describe the same actual period of time. Here, as *H1* is used and the fixed horizon is 24 hours, functions $c_{50,0}$ and $c_{49,28}$ are the same for instance. Hence, 365 functions will be needed to simulate a year.

These functions are estimated by solving the original problem over one or several representative period(s) (RP) of the actual period of time described by $(t,\tau)$, for various values of $\boldsymbol{\Delta_t}$.

The Python script used to build the cost functions is available at [186]. The script modifies the input files and calls the PERSEE software (see Section 4). Computation steps for CFs are further described in the case where *H1* is used:

1. The hourly data of the year is subdivided into 13 periods of 4 weeks. Each period of 4 weeks is approximated by one or more RPs of chosen size, based on the method proposed by [85]. If several RPs are used, the method proposed by [85] provides weights for each RP such that the weighted sum of all RP days equals the number of days in the original period. The periods selected are those that minimise the difference between the duration curves of the original data and the one of the (weighted) representative periods (a duration curve represents the given curve sorted by decreasing ordinate values). An example is given for two RPs of 2 days for a given period (Figure 56, Figure 57, Figure 58).

2. Bounds over the minimal and maximal stored quantity ($\boldsymbol{\Delta_t}$) are set as well as the number of points to be evaluated. This defines the accuracy of the CF approximation.

3. For each period and for each point defined at Step 3, the CF $c_{t,\tau}(\boldsymbol{\Delta_t})$ is evaluated by solving the original MILP formulation of the problem (given in Section 5.2.1) over the corresponding RP(s) defined at Step 2. Costs are extrapolated so that they correspond to the size of the original period (4 weeks). This is done by multiplying the RPs costs by their weight obtained at Step 2. For instance, if 4 weeks are approximated by a 2-days RP, results are multiplied by 14. In the case of (see Figure 56 and Figure 57, the 4 weeks are approximated by two 2-day RPs with different coefficients (their sum is equal to 14). The 13 CFs obtained correspond to a single $\tau$ (see Figure 59). Obtained functions are convex. Hence, they are modelled as piecewise linear functions by the mean of Special Order Set (SOS) variables [193].

4. In order to obtain all 365 CFs, the 13 CFs obtained at Step 4 are extrapolated by weighted sums.

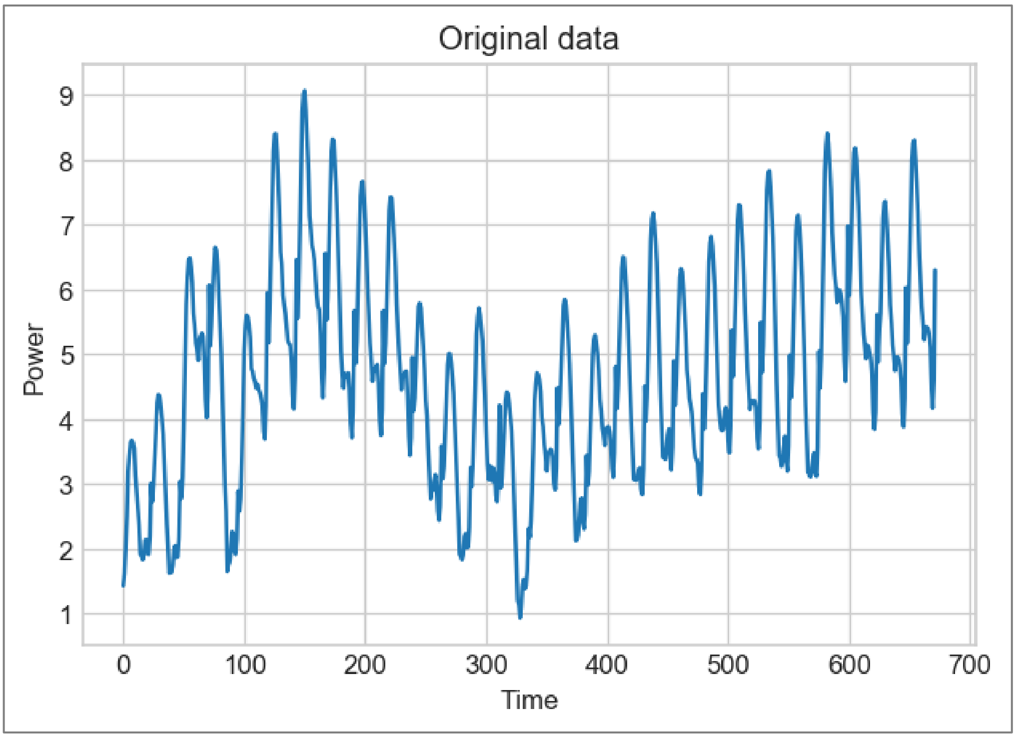



*Figure 56: Example of original data for a period of 4 weeks*

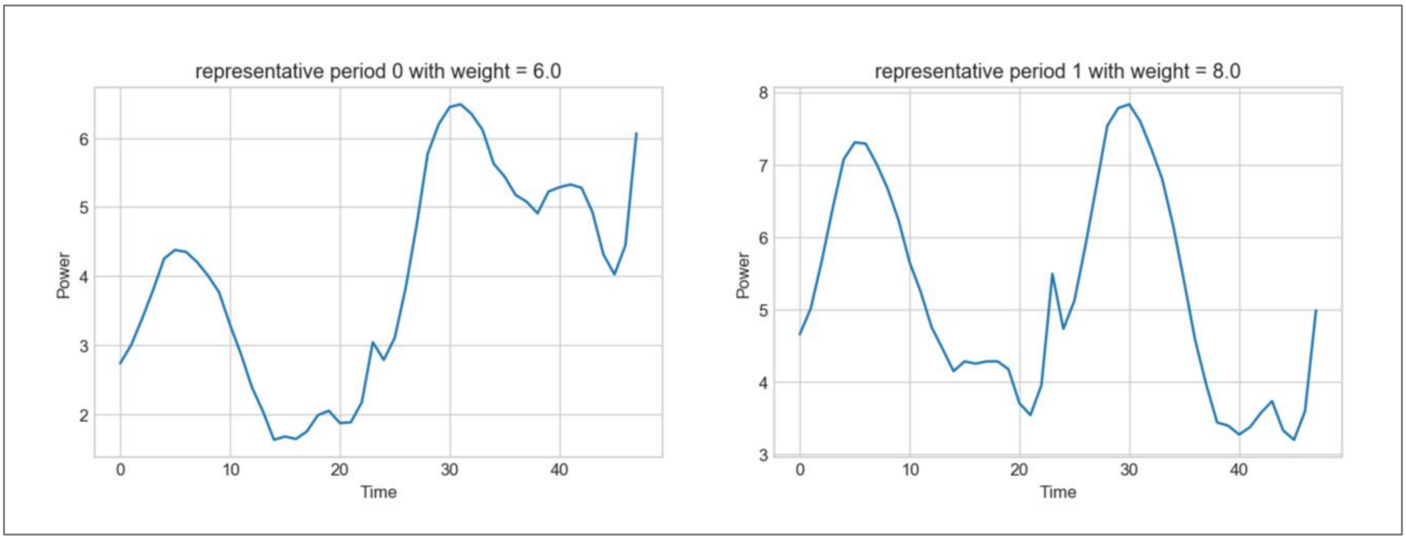



*Figure 57: Two RPs of two days for the original data*

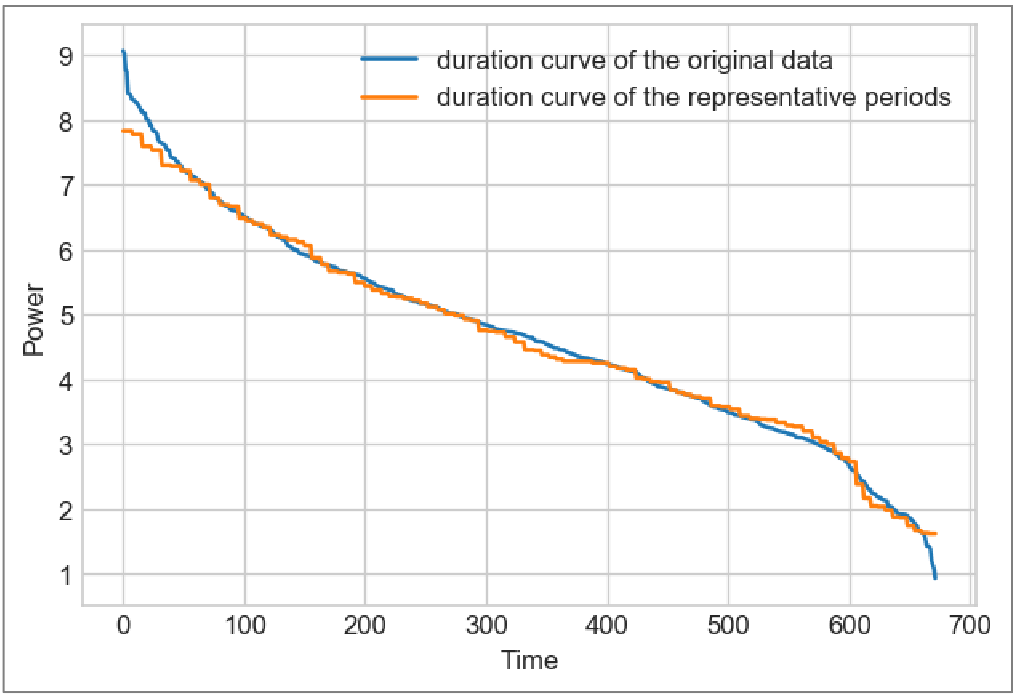



*Figure 58: Corresponding duration curves for both original RPs, the method minimises the difference between both curves.*

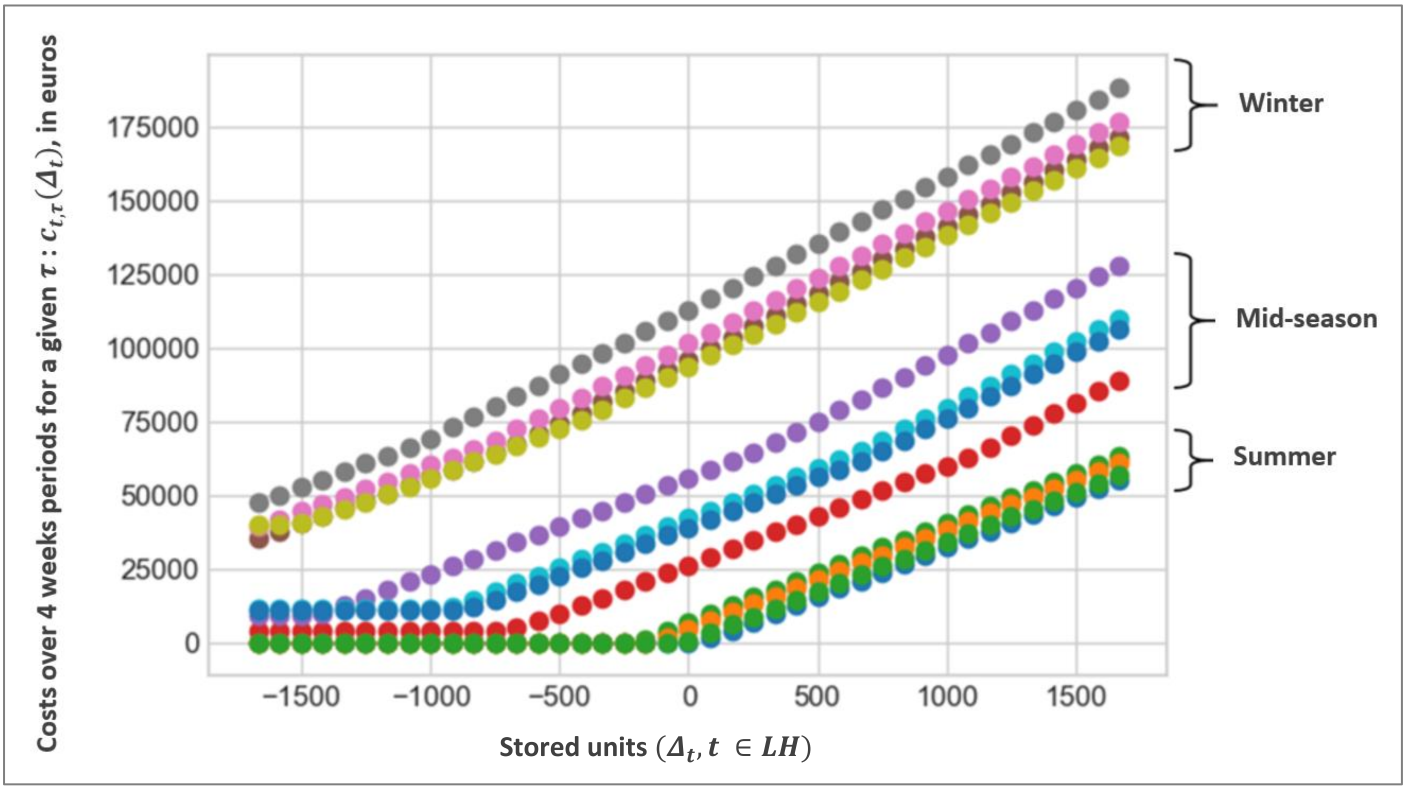



*Figure 59: Computed cost functions.*

**Alternatives for CFs computations:**

There exist other ways to compute the CFs. Here, RPs are used in order to limit the computation times. The number and size of RPs has to be set by the modeller. Ultimately, one can use the entire original data set on the given period to build the CF. Also, one could ultimately reduce $LH$ to a single time step.

Additionally, if the CF is built large periods of time, the method M2 from [23] could be used to reduce the computation time if the problem structure is similar: the is one or more long-term continuous variable(s) and integer variables with short-term significance only.

# Appendix B: Convergence of the One Shot optimisation (Chapitre 2)

Table 11 provides extra information on the convergence speed of the One Shot optimisation. Computations were stopped after 40 hours.

*Table 11: Lower, upper bounds and relative gap for the One Shot optimisation in function of the running time.*

| Time (seconds) | Lower bound | Upper bound | Gap (%) |
|---|---|---|---|
| **0** | 800 264 | 1 278 809 | 37.42 |
| **60** | 803 667 | 1 278 809 | 37.16 |
| **90** | 803 667 | 850 715 | 5.53 |
| **91** | 803 667 | 828 029 | 2.94 |
| **95** | 803 667 | 817 594 | 1.70 |
| **1000** | 804 117 | 814 578 | 1.28 |
| **40 hours** | 806 435 | 814 863 | 1.03 |

# Appendix C: Demand profiles (Chapitre 2)

The demand profiles correspond to the heat consumption of 5000 inhabitants. It is estimated by the method used in [121] with 3 different meteorological profiles: A, B and C. The monthly mean demands are the same for all profiles. Figure 60 shows the hourly heat demand pro les over a year, starting from July. At the hottest periods of the year, the heat demand only corresponds to hot water for sanitary use. This is supposed independent from the meteorological profile, hence, all profiles are similar on these periods. Profile A is used in Section 4, all are considered in Section 5.

Table 12 shows the arbitrary pattern which is used to artificially overestimate or underestimate (+-X%) the future demand, depending on the month, as explained in Section 5.2.2.

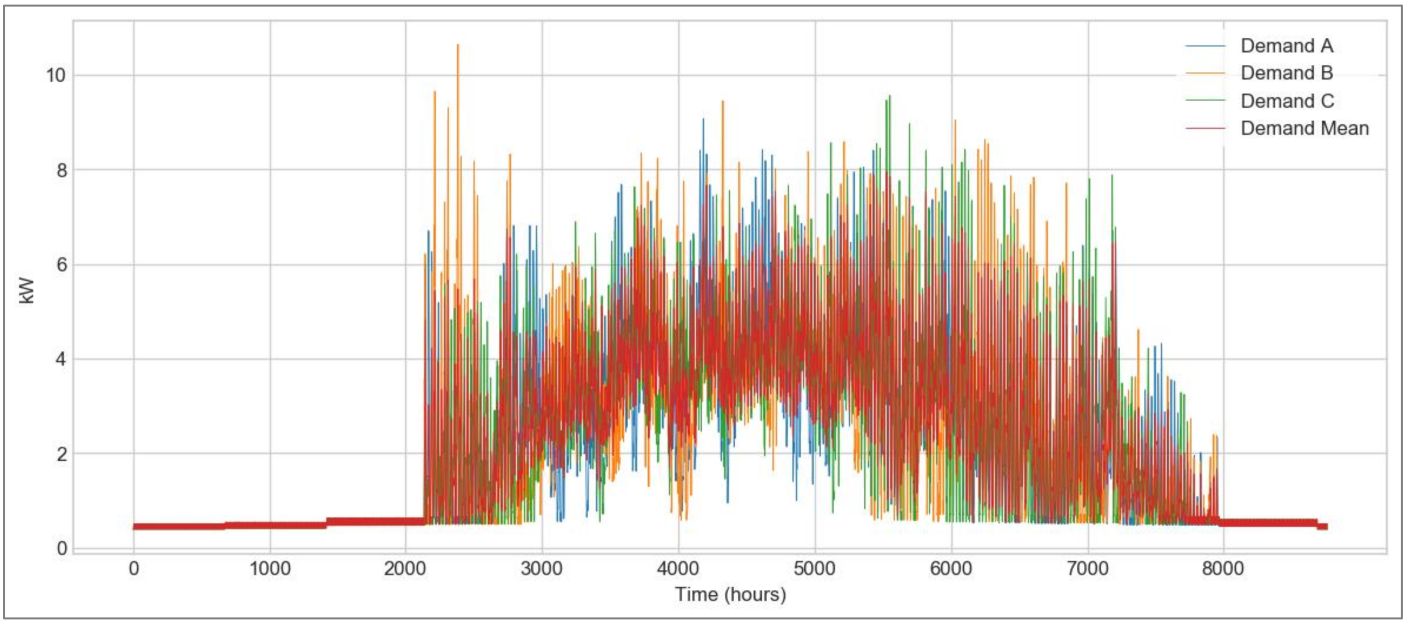



*Figure 60: Demand profiles.*

*Table 12: Pattern of cover (+) or under (-) estimation for the error term of the forecast demand.*

| Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|
| + | - | + | + | - | + | - | - | + | + | - | - |

# Appendix D: Production costs (Chapitre 2)

**Flexible production cost:**

The production cost of the FP is computed from the equation $C^F = (C^{CH4} + C^{CO_2} CO_2^{CH4}{}_{content}) / LVH^{CH4} / \eta^F$, where $C^{CH4}$is the gas cost ($0.4\ euro/kg$), $C^{CO_2}$ is the $CO_2$ emissions cost ($0.06\ euro/kg$ in Section 4), $CO_2^{CH4}{}_{content}$ is the gas $CO_2$ content ($3.36\ kg^{CO_2}/kg^{CH4}$), $LVH^{CH4}$ is the gas low heat value ($0.01\ MWh/kg$) and $\eta^F$ is the efficiency of the FP (0.9).

In Section 5, the different values tested for the FP production cost correspond to the respective $CO_2$ emissions costs of $0, 0.03, 0.06\ and\ 0.09\ euro/kg$.

**Inflexible production variable cost:**

The variable cost of the IFP is computed from the equation $C^F = C^{biomass} / LHV^{biomass} / \eta^F$, where $C^{biomass}$ is the biomass cost ($0.12\ euro/kg$), $LHV^{biomass}$ is the biomass low heat value ($0.004\ MWh/kg$) and $\eta^F$ is the efficiency of the IFP (0.9). CO2 emissions from the biomass life-cycle are supposed to be null.

# Appendix E: Sizing of the energy system (Chapitre 4)

Capacities of each equipment were set after solving the investment planning problem which corresponds to the mathematical problem defined by *E1-E17* without the CG specific constraints (*E6-E10*) and with capacities as optimisation variables:

- Parameters $Xmax^{GB}, Xmax^{CG}$ and $Emax^{HS}$ become variables $\boldsymbol{Xmax^{GB}}, \boldsymbol{Xmax^{CG}}$ and $\boldsymbol{Emax^{HS}}$**.** Variables $(\boldsymbol{Xmax^{GB}}, \boldsymbol{Emax^{HS}}) \in \mathbb{R}^+$ and $\boldsymbol{Xmax^{CG}} \in [0, XmaxCapa^{CG}]$. The limit on the CG capacity was set to take into account a limit in the biomass resource.

- Parameter $Xmax_t^{ST}$ becomes $\boldsymbol{Xmax^{ST}} * pf_t$, with $\boldsymbol{Xmax^{ST}} \in \mathbb{R}^+$.

The investment parameters are given in Table 14, the data series are shown in Figure 61. The objective was modified to minimise the total actualised costs over 20 years with a discount rate of 7%.

The FB was ignored at the investment phase. Batteries and photovoltaic solar panels were included (but not selected by the optimiser):

- The PV production $\boldsymbol{X_t^{PV}}$ is in kW and has a time varying capacity $\boldsymbol{Xmax^{PV}} * pf_t$ with $\boldsymbol{Xmax^{PV}} \in \mathbb{R}^+$(the same production factor $pf_t$ is used for the PV and ST productions).

- The batteries set is defined by a maximum capacity in kWh ($Emax^{Batt}$), a storing efficiency ($\eta^{Batt}$) corresponding to the percentage of energy that is are actually stored during the storing operation (the rest is lost), losses in kW lost/kW stored/hour ($\delta^{Batt}$) and a stock/destock capacity in units/hour ($Xmax^{Batt}$). Associated variables are the stored quantity in units ($\boldsymbol{E_t^{HS}} \in [0, Emax^{Batt}]$) and the stock and destock rates in kW ($(\boldsymbol{Xout_t^{Batt}}, \boldsymbol{Xin_t^{Batt}}) \in [0, Xmax^{Batt}]^2$)) at time step $t$. The values of corresponding parameters are given in Table 13.

The corresponding mathematical problem is further described. Changes compared to *E1-E17* are marked in blue and new equations are indexed by "*E.X1*".

$Min:$

$$\sum_{e\in\{GB,PV,ST,CG,Batt,HS,HP\}} \left(\boldsymbol{Xmax^e} * CPX^e + \sum_{y=0}^{19} \boldsymbol{Xmax^e} * OPX^e /(1+0.07)^y\right)$$

$$+\sum_{y=0}^{19}\sum_{t\in H}\left(\left(C^{GB}\boldsymbol{X_t^{GB}} + C^{CG}\boldsymbol{Xb_t^{CG}} + C_t^G\boldsymbol{X_t^G}\right) * dt/(1+0.07)^y\right)$$

*E1.1*

$Such\ that:$

$\forall\ t \in H:$

$$X_t^{HD} = \boldsymbol{X_t^{GB}} + \boldsymbol{Xh_t^{CG}} + \boldsymbol{X_t^{ST}} + \boldsymbol{Xout_t^{HS}} - \boldsymbol{Xin_t^{HS}} + \boldsymbol{\eta^{HP} X_t^{HP}} \quad E2.1$$

$$X_t^{ED} = \boldsymbol{Xe_t^{CG}} + \boldsymbol{X_t^G} + \boldsymbol{X_t^{PV}} - \boldsymbol{X_t^{HP}} + \boldsymbol{Xout_t^{Batt}} - \boldsymbol{Xin_t^{Batt}} \quad E3.1$$

$$\boldsymbol{X_t^{ST}} \le \boldsymbol{Xmax^{ST}} * pf_t \quad E4.1$$

$$\boldsymbol{E_t^{HS}} = \boldsymbol{E_{t-1}^{HS}} * (1 - \delta^{HS}dt) + \left(\eta^{HS}\boldsymbol{Xin_t^{HS}} - \boldsymbol{Xout_t^{HS}}\right)dt \quad E5$$

$$\boldsymbol{Xh_t^{CG}} \le Xmax^{CG} - \boldsymbol{Xe_t^{CG}} \quad E11$$

$$\boldsymbol{Xe_t^{CG}} \le \alpha * \boldsymbol{Xh_t^{CG}} \quad E12$$

$$\boldsymbol{Xe_t^{CG}} + \boldsymbol{Xh_t^{CG}} = \boldsymbol{Xtot_t^{CG}} \quad E13$$

$$\boldsymbol{Xb_t^{CG}} = 1/(\eta^h * (\alpha+1)) * (\boldsymbol{Xh_t^{CG}} + \boldsymbol{Xe_t^{CG}}) \quad E14$$

$$\boldsymbol{E_0^{HS}} \le \boldsymbol{E_\Theta^{HS}} \quad E17$$

$\forall\ t \in H:$

$$\boldsymbol{X_t^{PV}} \le \boldsymbol{Xmax^{PV}} * pf_t \quad E18.1$$

$$\boldsymbol{E_t^{Batt}} = \boldsymbol{E_{t-1}^{Batt}} * (1 - \delta^{Batt}dt) + \left(\eta^{Batt}\boldsymbol{Xin_t^{Batt}} - \boldsymbol{Xout_t^{Batt}}\right)dt \quad E19.1$$

$$\boldsymbol{E_0^{Batt}} \le \boldsymbol{E_\Theta^{Batt}} \quad E20.1$$

$$\boldsymbol{X_t^{GB}} \le \boldsymbol{Xmax^{GB}}, \boldsymbol{Xtot_t^{CG}} \le \boldsymbol{Xmax^{CG}}, \boldsymbol{X_t^{HP}} \le \boldsymbol{Xmax^{HP}} \quad E21.1\text{-}23.1$$

$$\boldsymbol{E_t^{HS}} \le \boldsymbol{Xmax^{HS}}, \boldsymbol{E_t^{Batt}} \le \boldsymbol{Xmax^{Batt}} \quad E24.1\text{-}25.1$$

*E1.1* now minimises the total actualised costs. *E2.1* now excludes the FB and *E3.1* includes the batteries set. *E4.1* now includes $\boldsymbol{Xmax^{ST}}$ as an optimisation variable. *E18.1* is the same equation as *E4.1* but for the PV source and *E19.1-20.1* are the same equations as *E5* and *E17* but for the batteries set. Finally, *E21.1-25.1* are the capacity constraints for all equipment.

*E1.1-25.1* describe a linear program. It was solved in 133 seconds with a commercial solver under the PERSEE modelling environment. Computational aspects are identical as in [176].

*Table 13: techno-economic operational parameters of equipments, follow up of Table 9*

| Equipment | Parameter | Value |
|---|---|---|
| **Batt** | $\eta^{Batt}$ | 0.9 |
| | $\delta^{Batt}$ | 0.00001 |
| | $Xmax^{Batt}$ | 2000 $kW$ |

*Table 14: Investment parameters*

| Equipment | Investment cost | Yearly maintenance cost (in % of the investment cost) | Maximum installed capacity |
|---|---|---|---|
| GB | $CPX^{GB} = 100\ euros/kW$ | $OPX^{GB} = 4\%$ | |
| PV | $CPX^{PV} = 750\ euros/kWc$ | $OPX^{PV} = 2\%$ | |
| ST | $CPX^{ST} = 200\ euros/kWc$ | $OPX^{ST} = 2\%$ | |
| CG | $CPX^{CG} = 800\ euros/kW$ | $OPX^{CG} = 4\%$ | $XmaxCapa^{CG} = 800\ kW$ |
| Batt | $CPX^{batt} = 220\ euros/kWh$ | $OPX^{Batt} = 2\%$ | |
| HS | $CPX^{HS} = 8.57\ euros/kWh$ below 70 000 $kWh$, 2.86 $euros/kWh$ above | $OPX^{HS} = 2\%$ | |
| HP | $CPX^{HP} = 1000\ euros/kW$ | $OPX^{HP} = 1\%$ | |

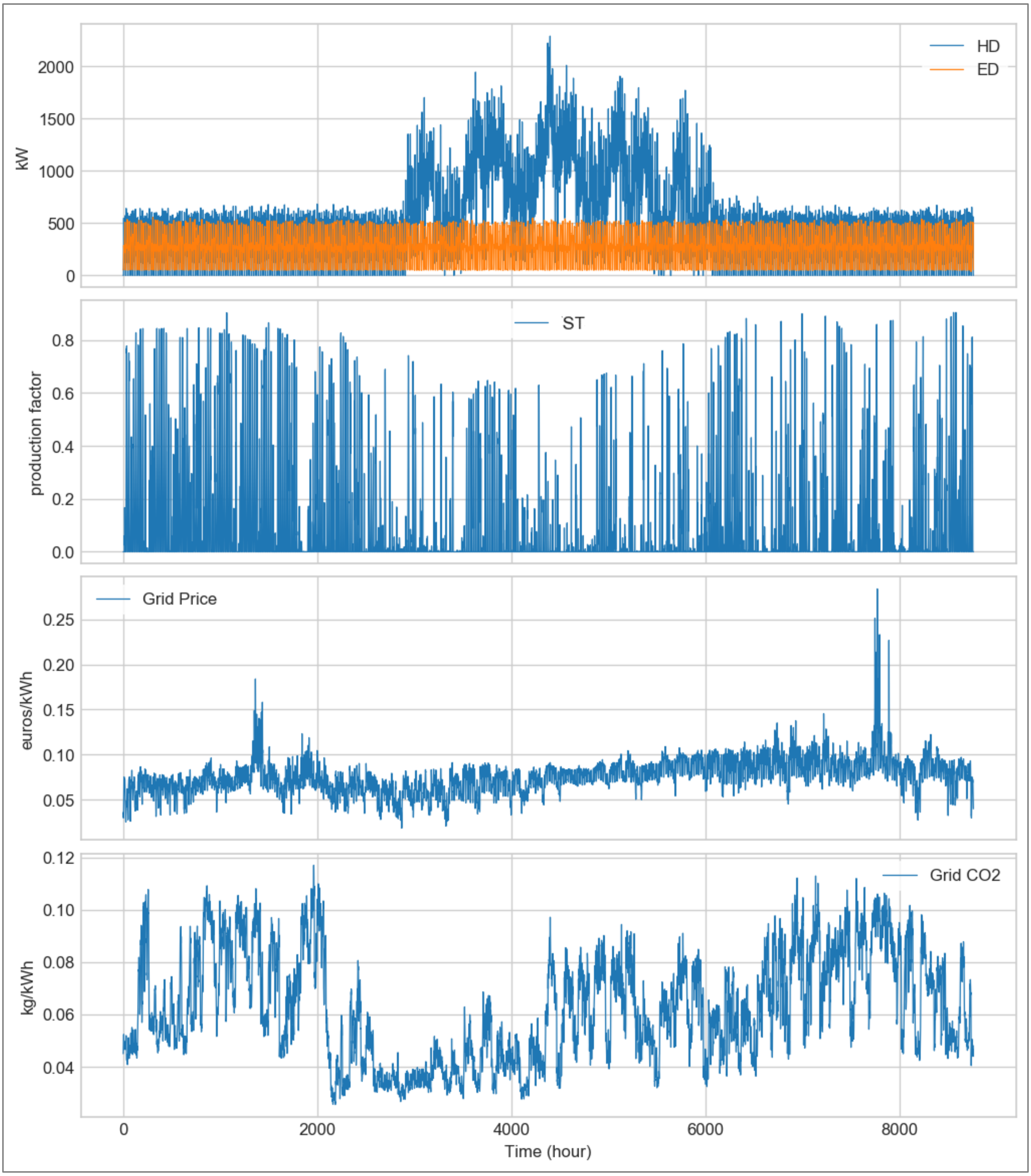



*Figure 61: Demand profiles considered, ST production factor, grid prices and grid CO2 content considered.*

# Appendix F: Zooms over optimisation strategies (Chapitre 4)

This appendix gathers zooms over Figure 37 and Figure 38.

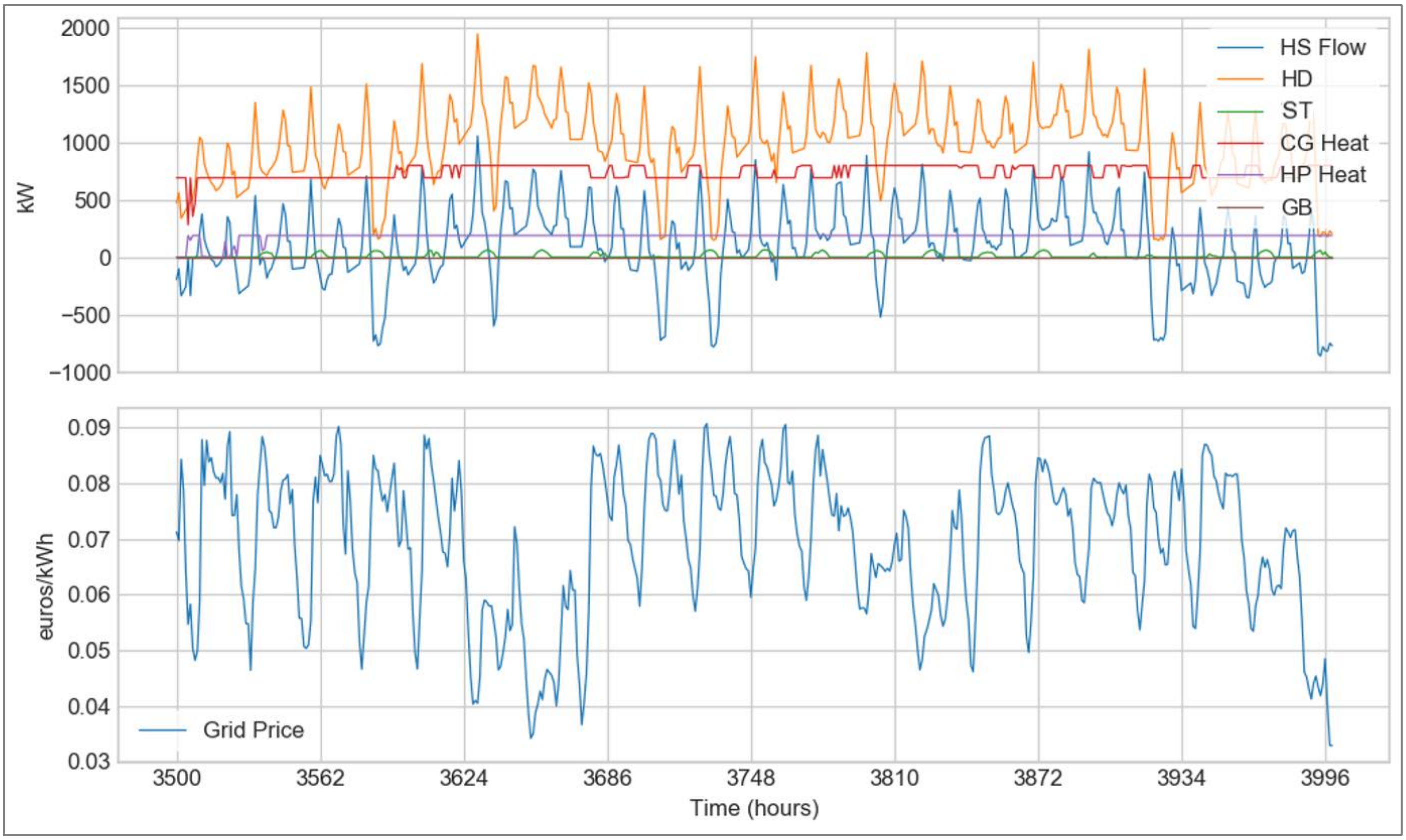



*Figure 62: Zoom on the winter period, the strategy is identical for the LP-OneShot and the MILP-OneShot configurations*

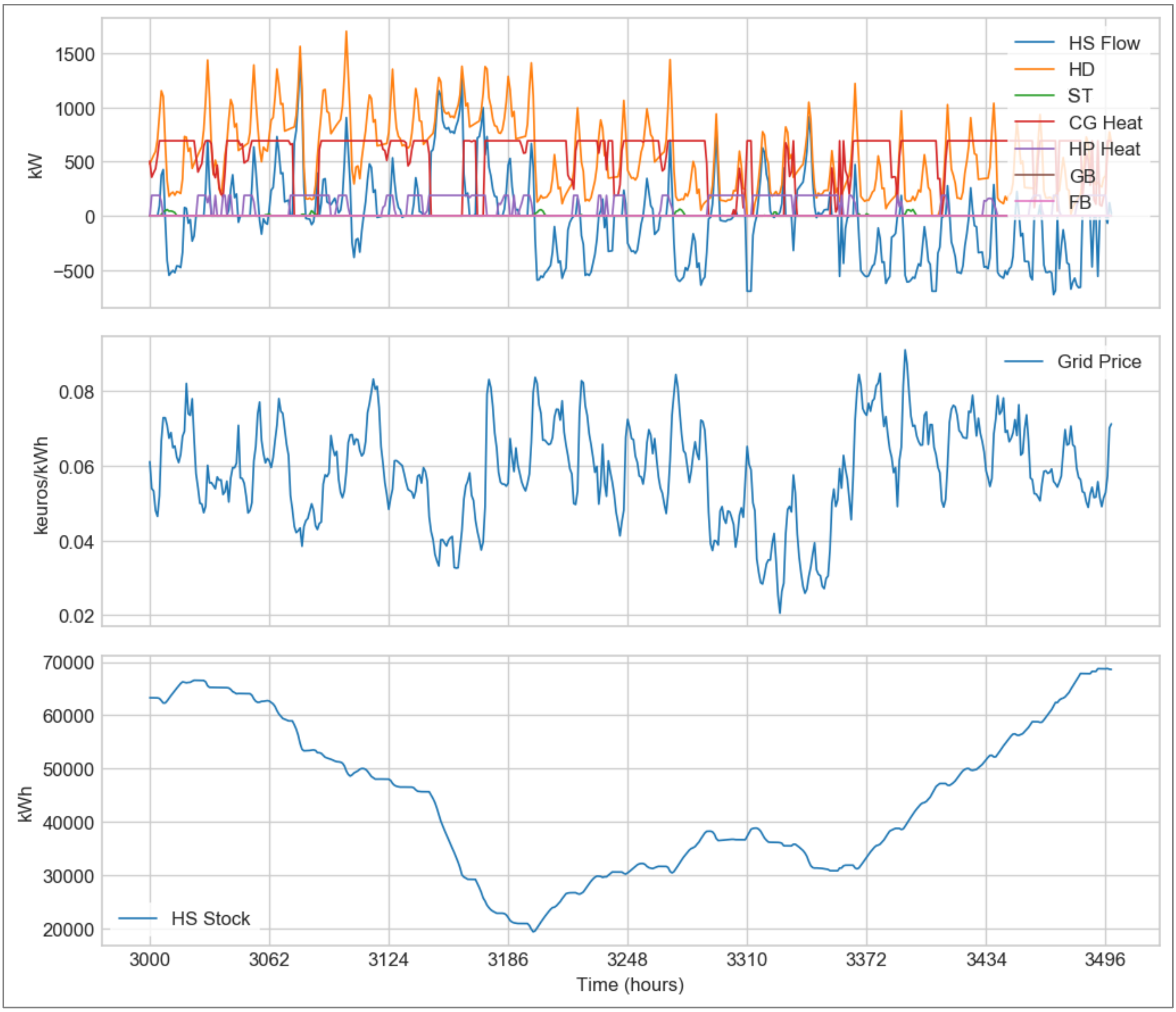



*Figure 63: Zoom on the inter-season period, for the LP-OneShot configuration*

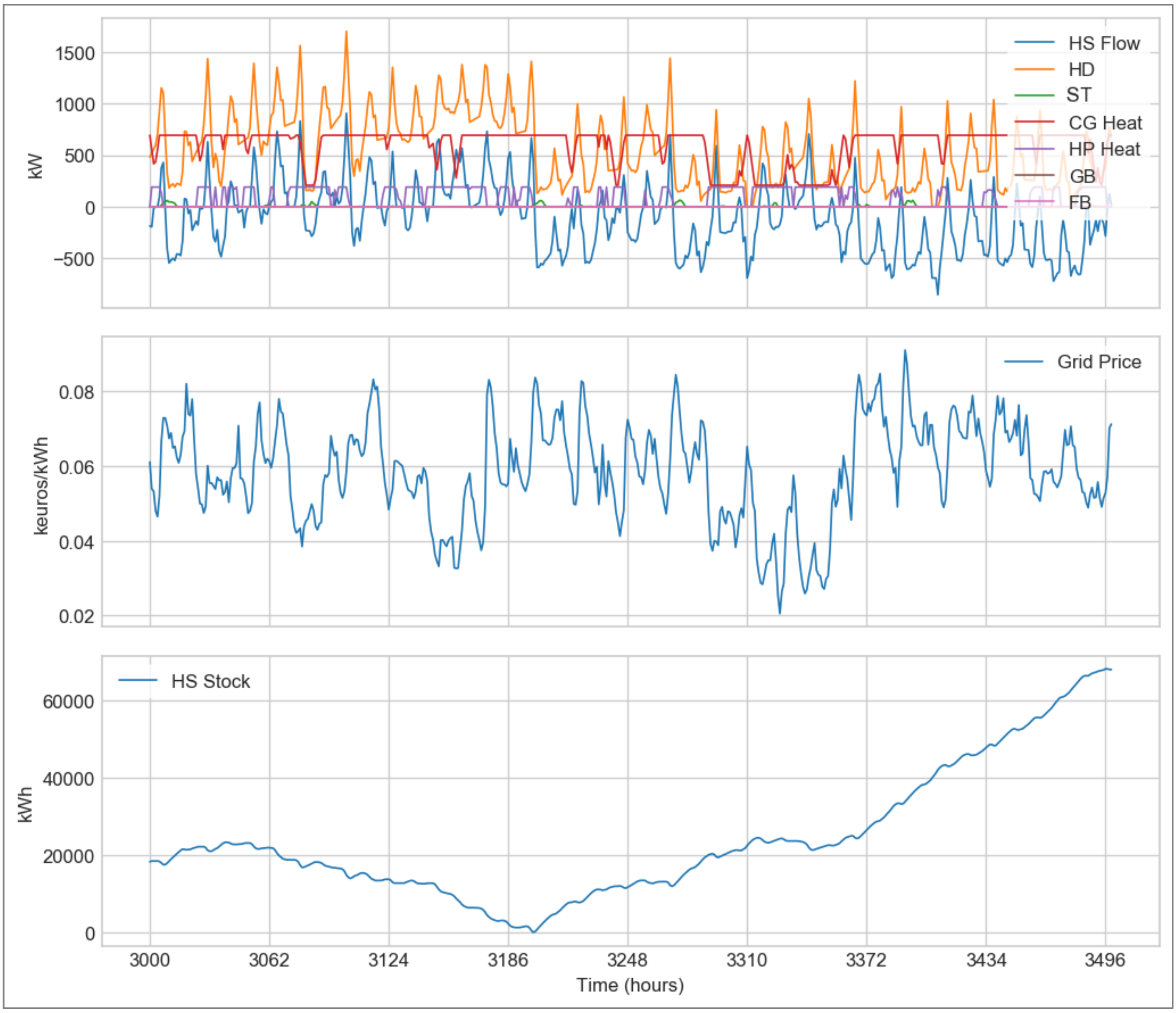



*Figure 64: Zoom on the inter-season period, for the MILP-OneShot configuration*

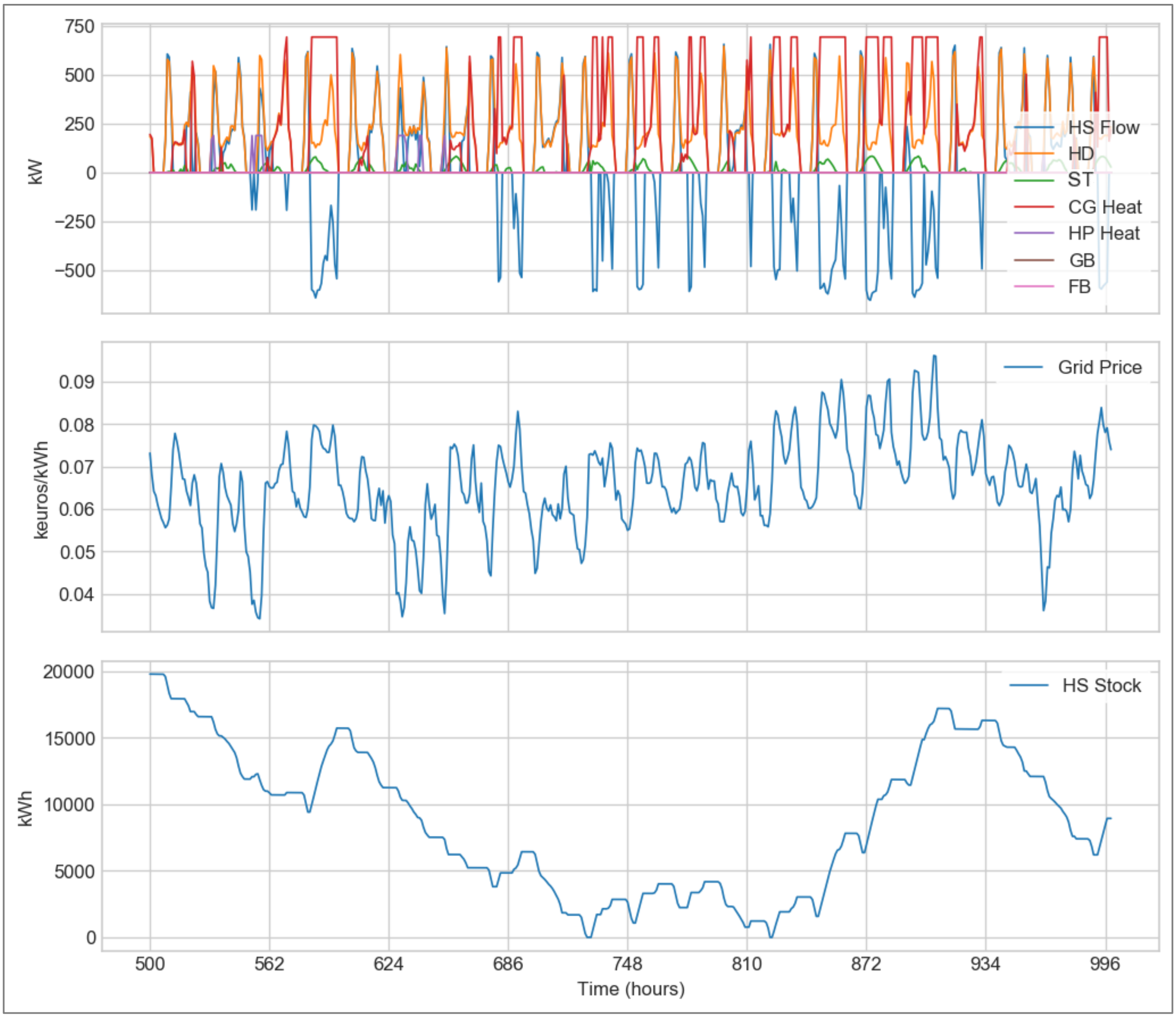



*Figure 65: Zoom on the summer period, for the LP-OneShot configuration*

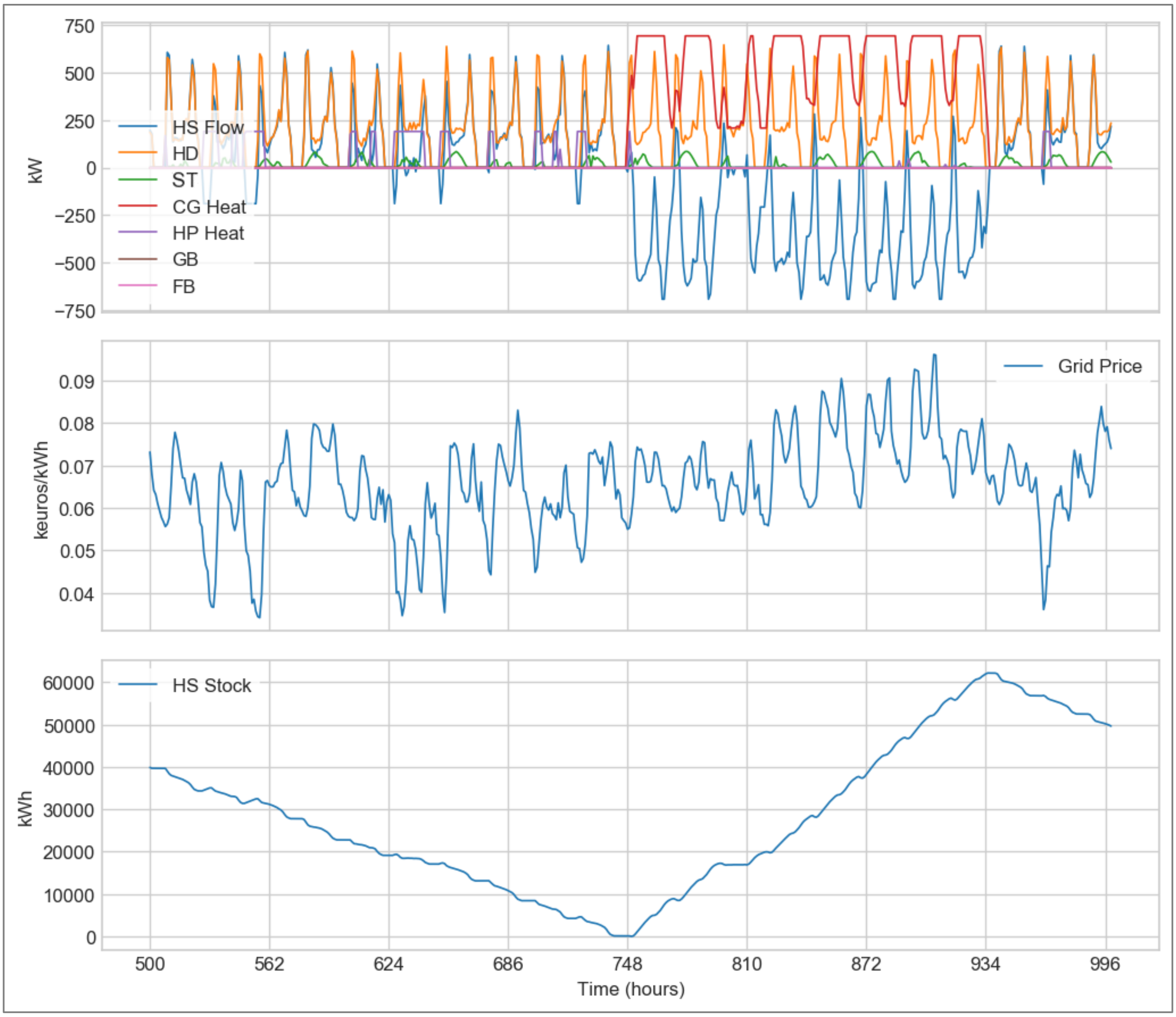


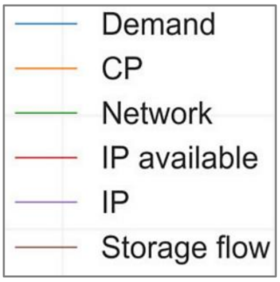

*Figure 66: Zoom on the inter-season period, for the MILP-OneShot configuration*

# Appendix G: Supplementary Material (Chapitre 3)

Figures with full resolution can be downloaded via this link (https://github.com/EtienneCuisinier/Appendix-G).

Legend for upper graphs:

(units/hour)

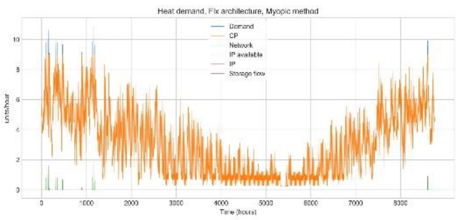


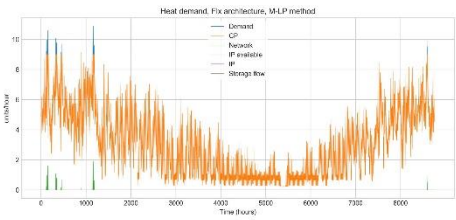

Legend for lower graphs:

(units)


**Heat demand, Flx architecture**

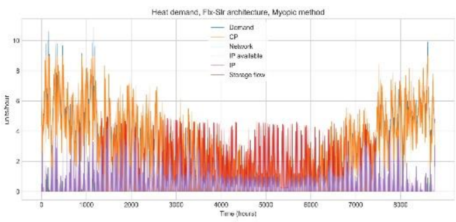
**Cicada method** | **Mean method** | **RpCf method: NA**

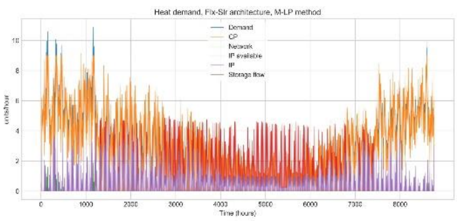



**Heat demand, Flx-Slr architecture**

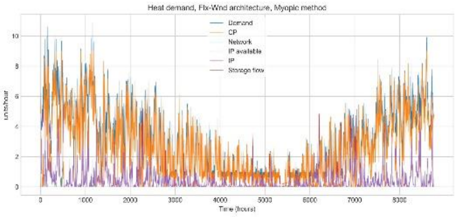
**Cicada method** | **Mean method** | **RpCf method: NA**

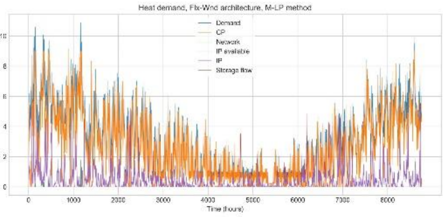


## Heat demand, Flx-Wnd architecture

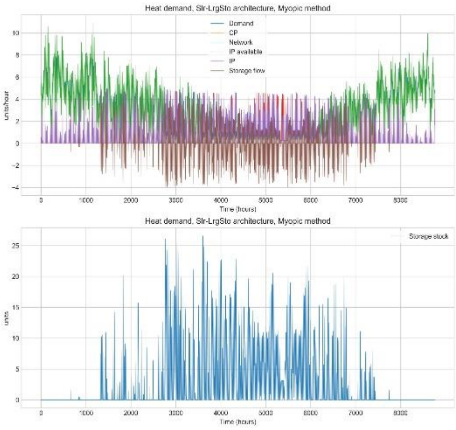
**Cicada method** | **Mean method** | **RpCf method: NA**

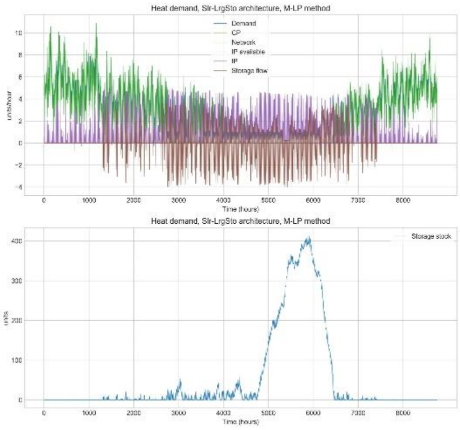


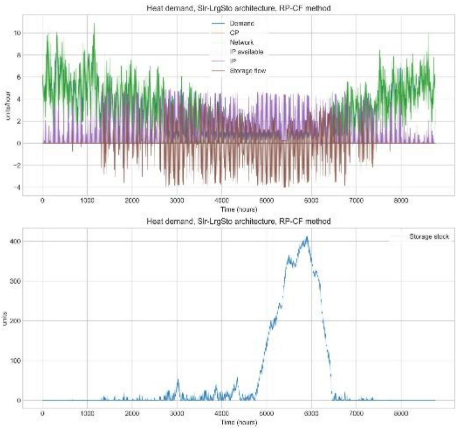




## Heat demand, Slr-LrgSto architecture

**Cicada method** | **Mean method** | **RpCf method**

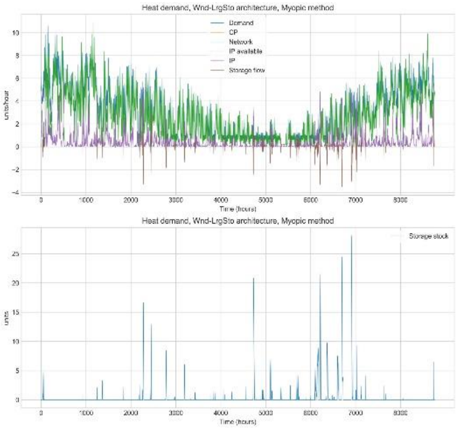


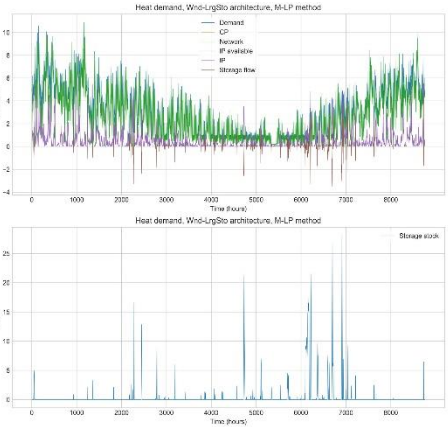



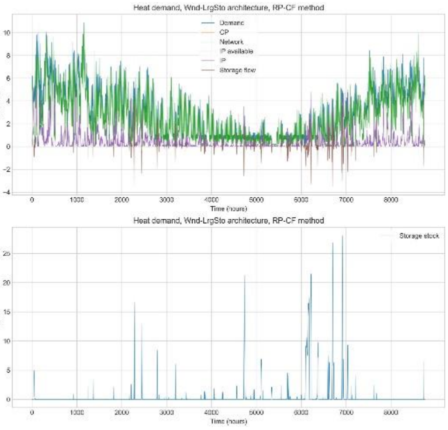




## Heat demand, Wnd-LrgSto architecture

**Cicada method** | **Mean method** | **RpCf method**

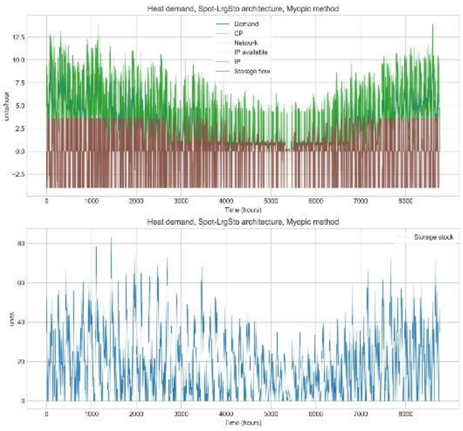


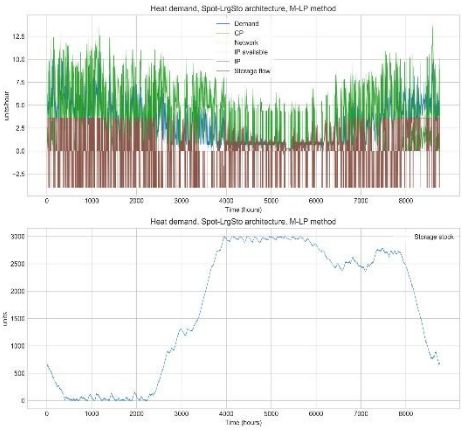



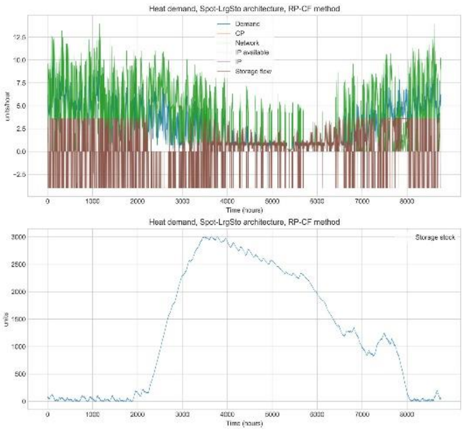



**Heat demand, Spot-LrgSto architecture**

| Cicada method | Mean method | RpCf method |
|---|---|---|

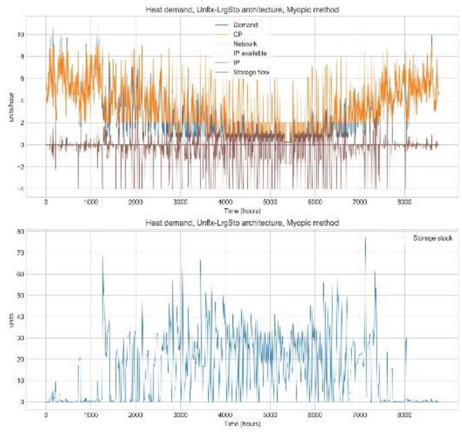


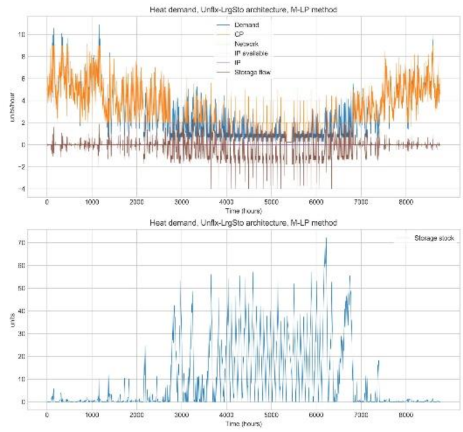


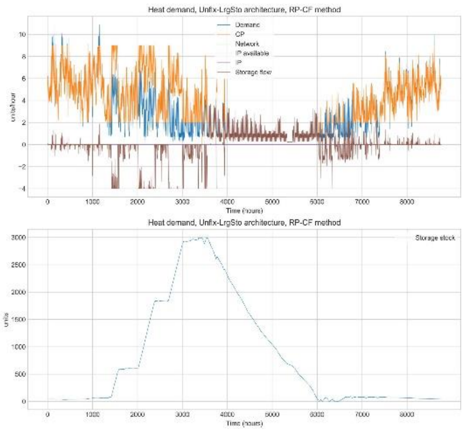



**Heat demand, Unflx-LrgSto architecture**

| Cicada method | Mean method | RpCf method |
|---|---|---|

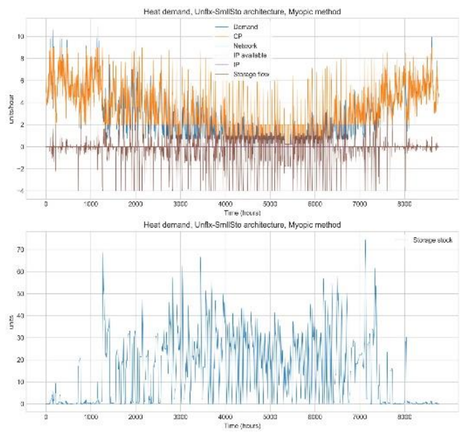


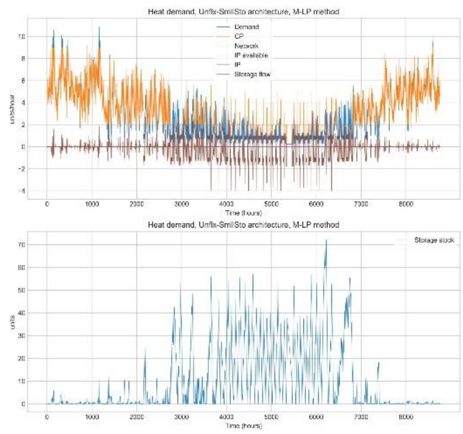


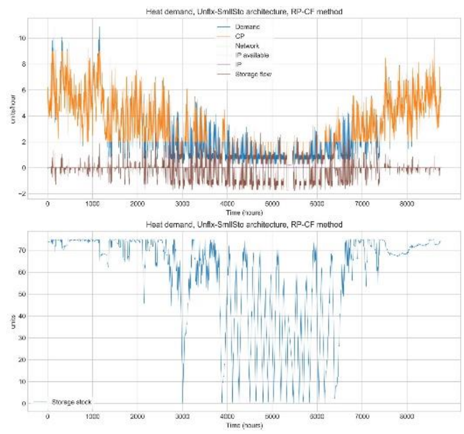



**Heat demand, Unflx-SmllSto architecture**

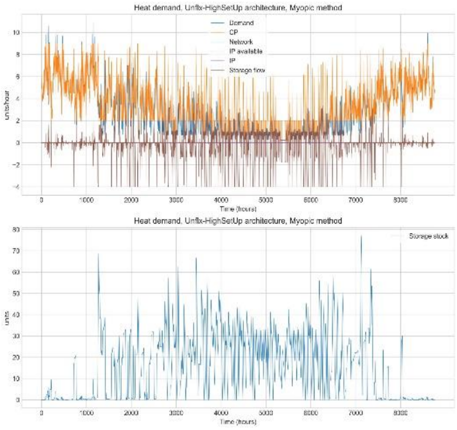
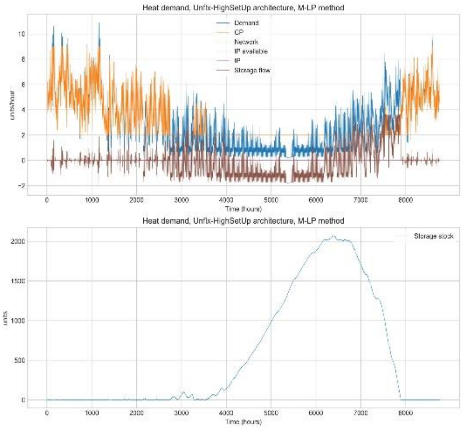
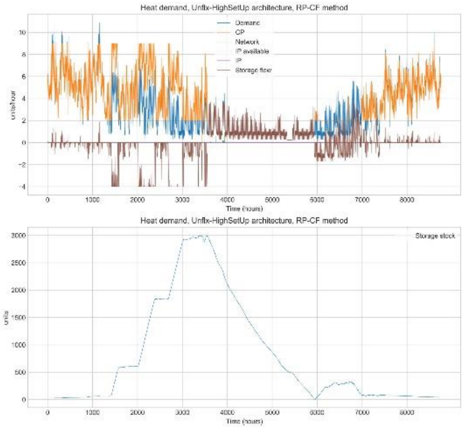
| Cicada method | Mean method | RpCf method |
|---|---|---|



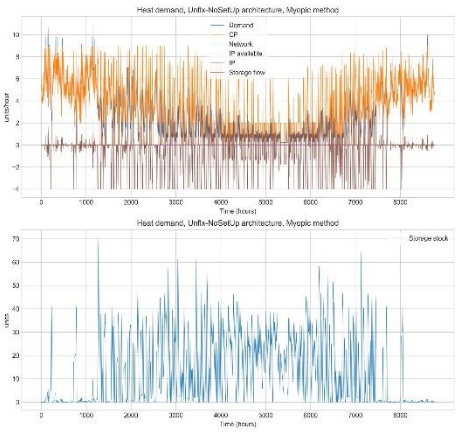
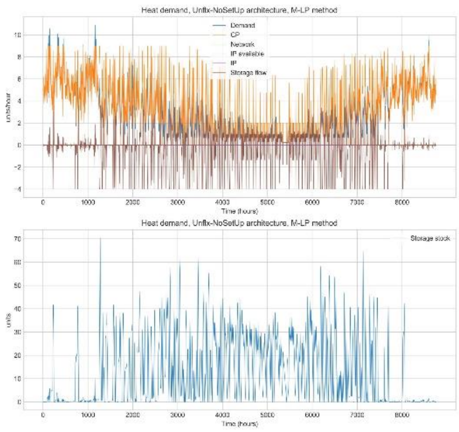
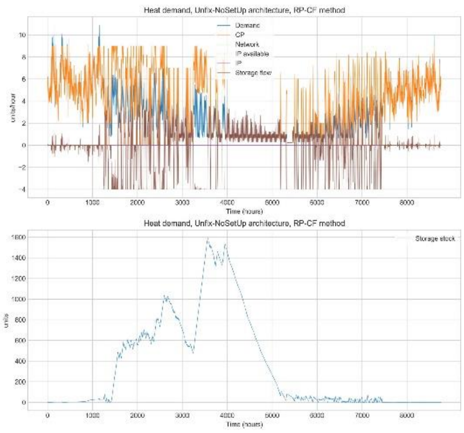




## Heat demand, Unflx-HighSetUp architecture

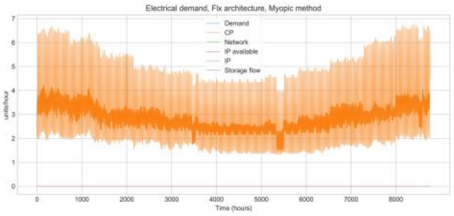
| Cicada method | Mean method | RpCf method |
|---|---|---|
|  |  |  |

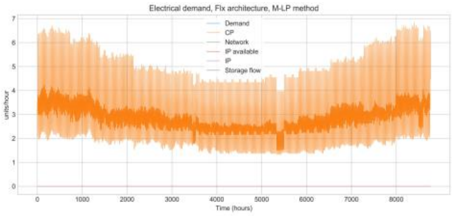
## Heat demand, Unflx-NoSetUp architecture

| Cicada method | Mean method | RpCf method |
|---|---|---|
|  |  |  |

### Electrical demand, Flx architecture

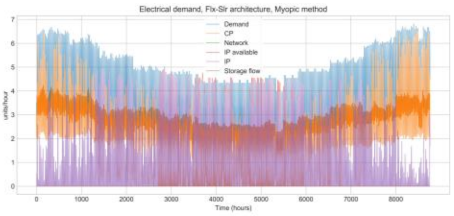
| Cicada method | Mean method | RpCf method: NA |
|---|---|---|

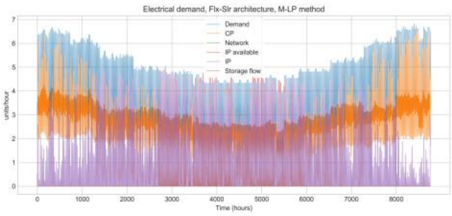



### Electrical demand, Flx-Slr architecture

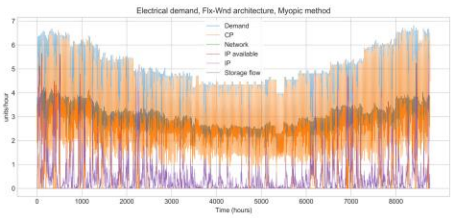
| Cicada method | Mean method | RpCf method: NA |
|---|---|---|

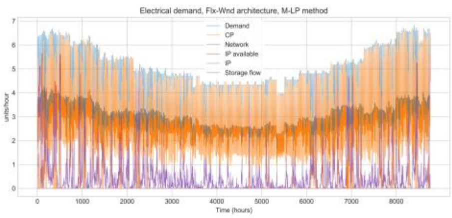



### Electrical demand, Flx-Wnd architecture

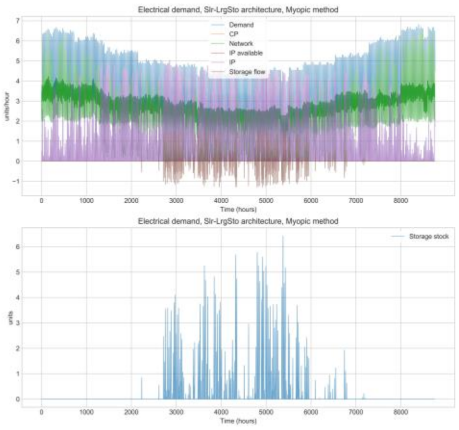
| Cicada method | Mean method | RpCf method: NA |
|---|---|---|

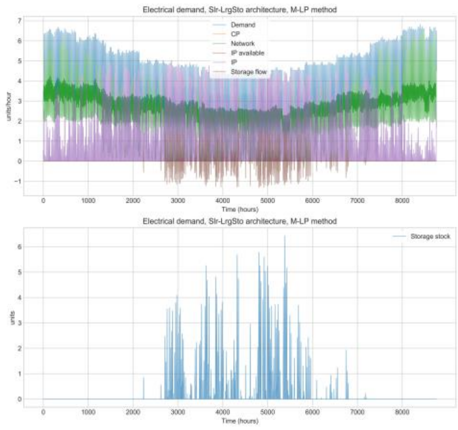


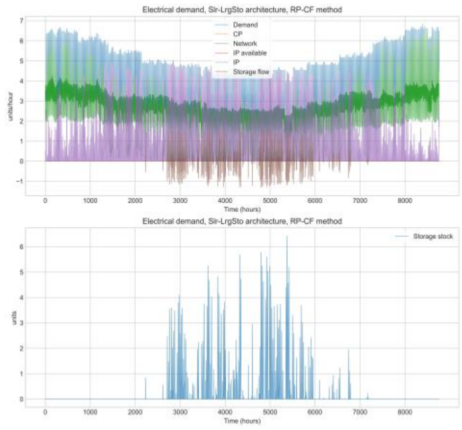



### Electrical demand, Slr-LrgSto architecture

| Cicada method | Mean method | RpCf method |
|---|---|---|

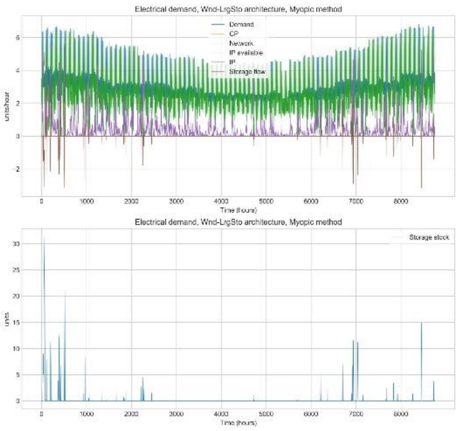


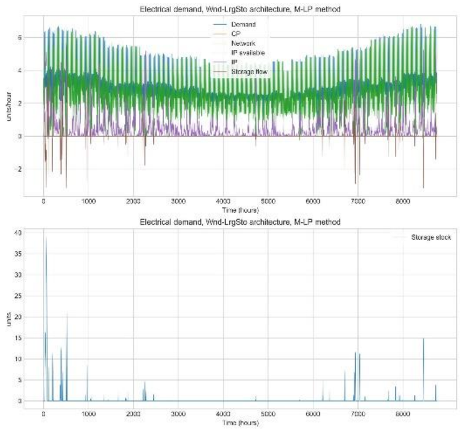


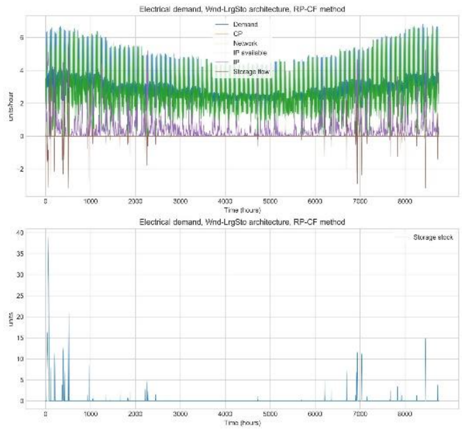



### Electrical demand, Wnd-LrgSto architecture

| Cicada method | Mean method | RpCf method |
|---|---|---|

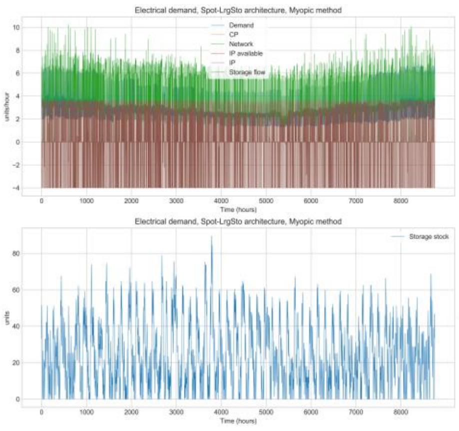


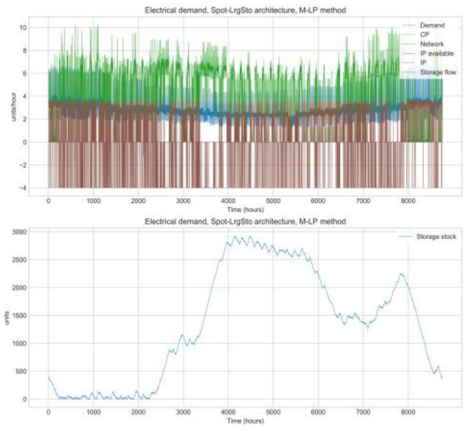


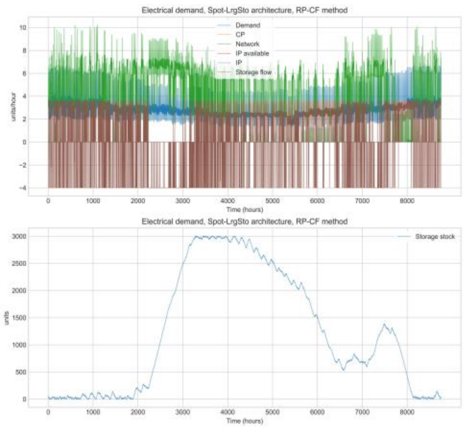



### Electrical demand, Spot-LrgSto architecture

| Cicada method | Mean method | RpCf method |
|---|---|---|

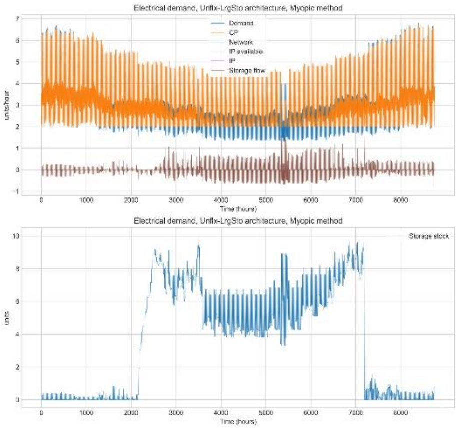


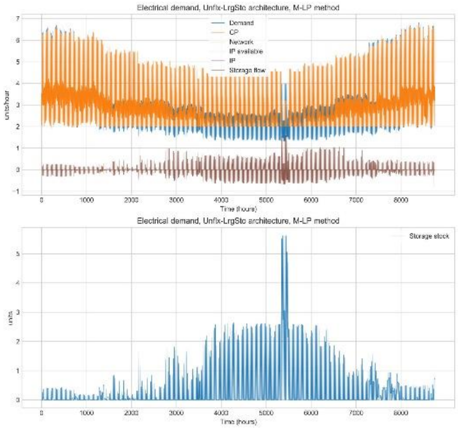


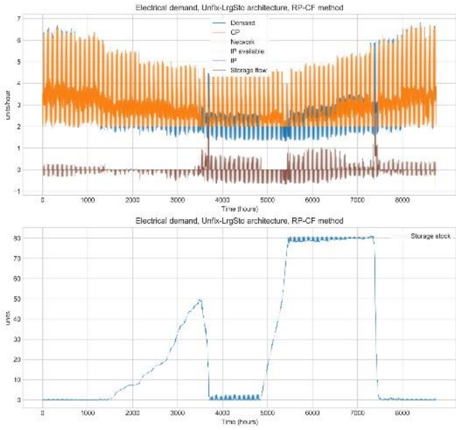


**Electrical demand, Unflx-LrgSto architecture**

| Cicada method | Mean method | RpCf method |
|---|---|---|

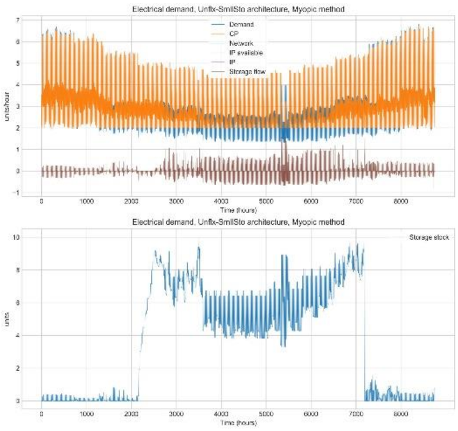


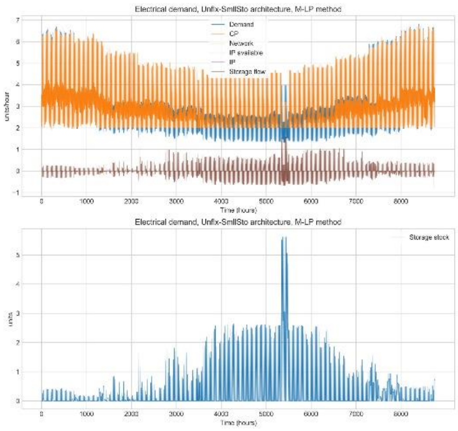



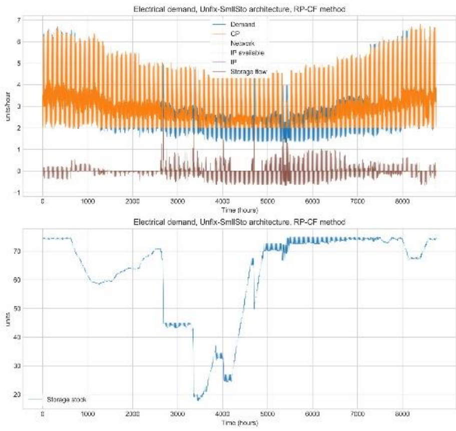




**Electrical demand, Unflx-SmallSto architecture**

| Cicada method | Mean method | RpCf method |
|---|---|---|

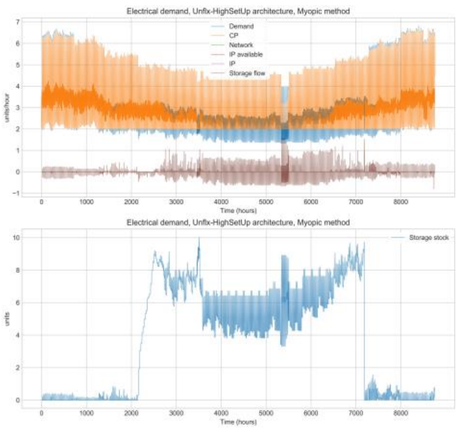


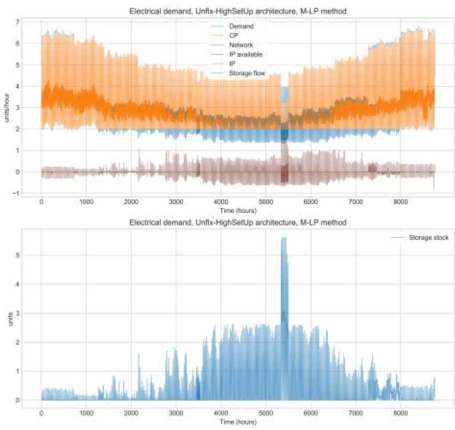



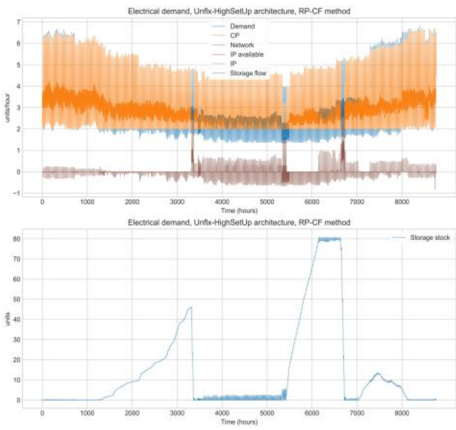




**Electrical demand, Unflx-HighSetUp architecture**

| Cicada method | Mean method | RpCf method |
|---|---|---|

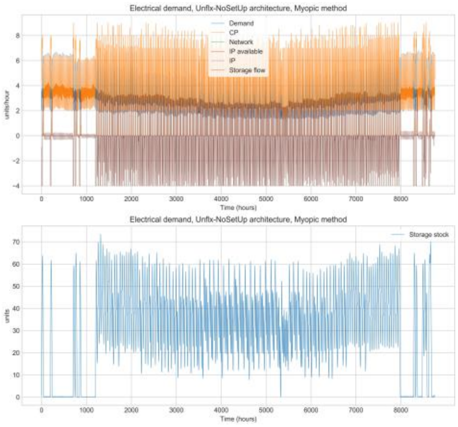


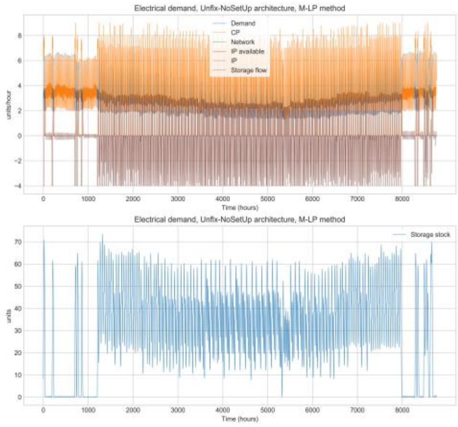



## Electrical demand, Unflx-NoSetUp architecture

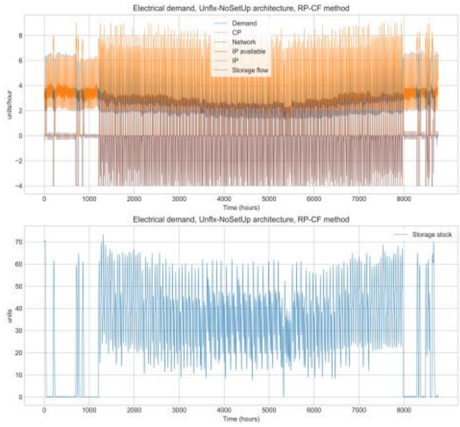
### Cicada method




### Mean method

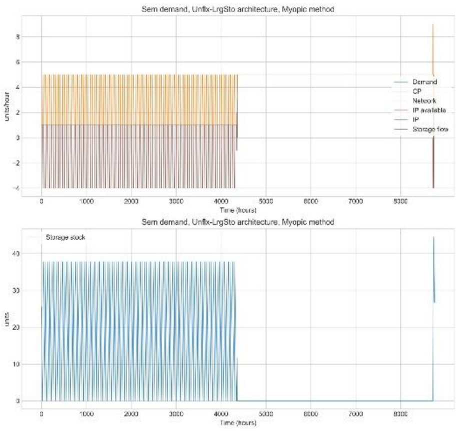



### RpCf method

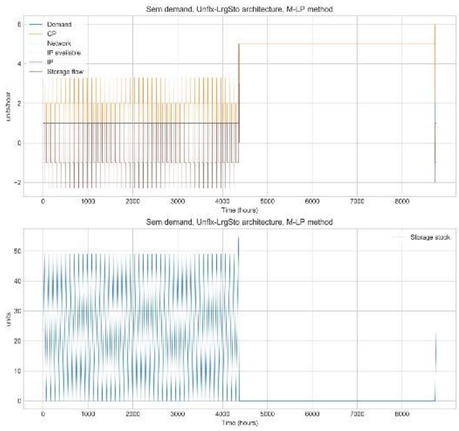



## Semestrial demand, Unflx-LrgSto architecture

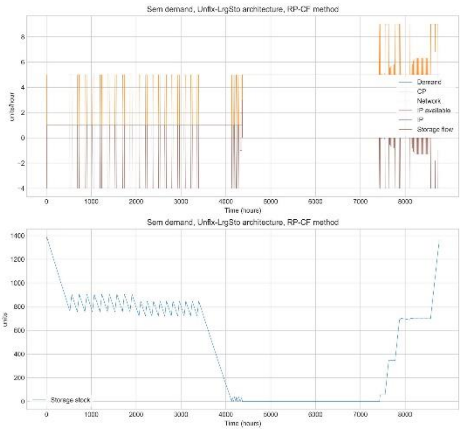
### Cicada method




### Mean method

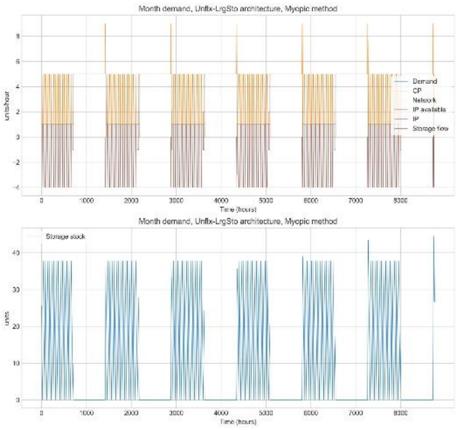



### RpCf method

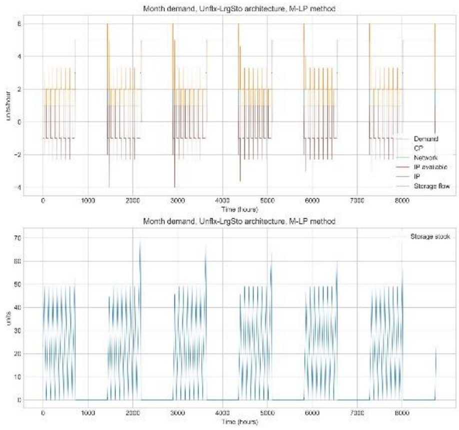



## Monthly demand, Unflx-LrgSto architecture

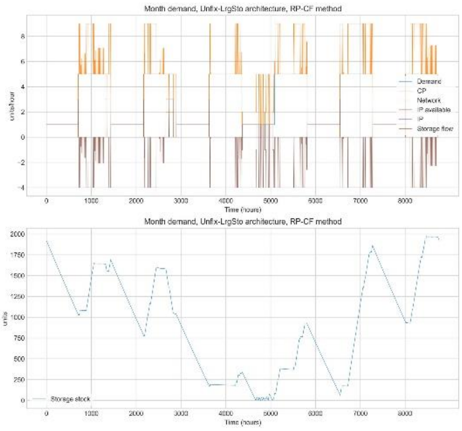
### Cicada method




### Mean method

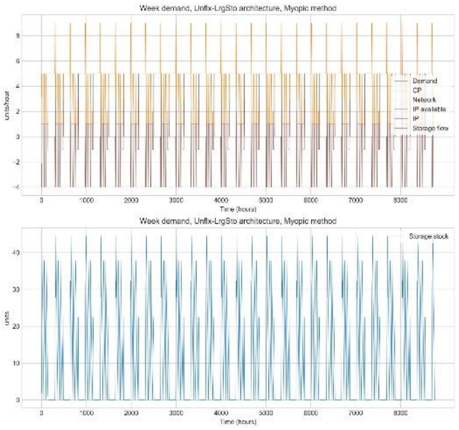


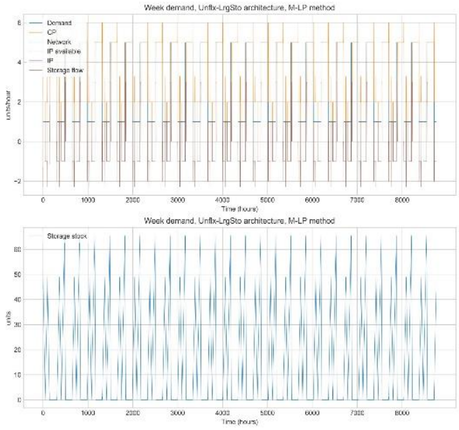

### RpCf method

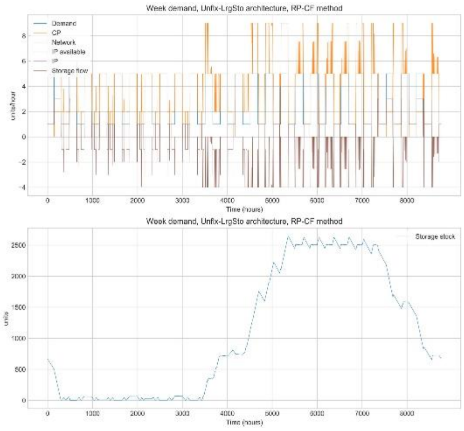


## Weekly demand, Unflx-LrgSto architecture

**Cicada method** **Mean method** **RpCf method**

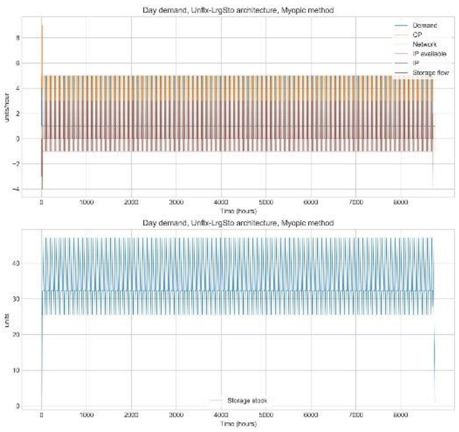


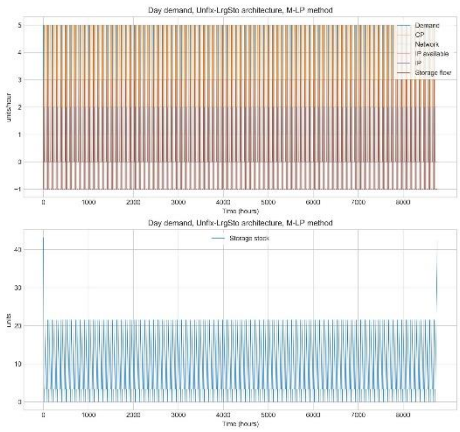



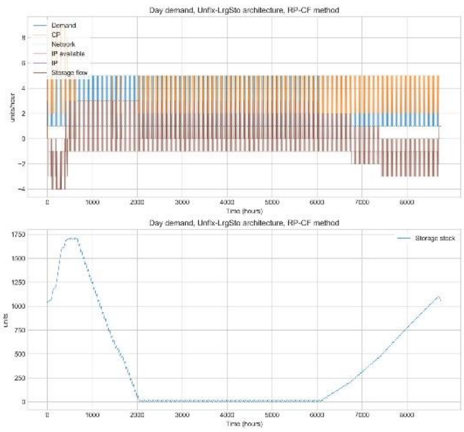




## Daily demand, Unflx-LrgSto architecture

**Cicada method** **Mean method** **RpCf method**

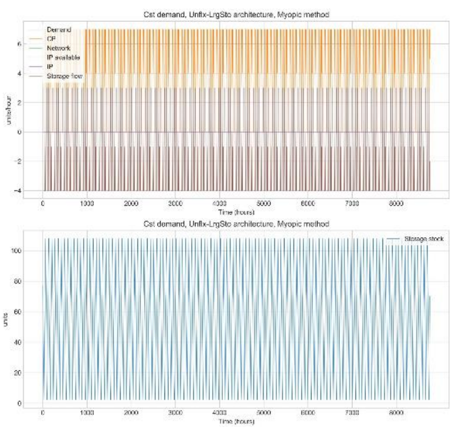


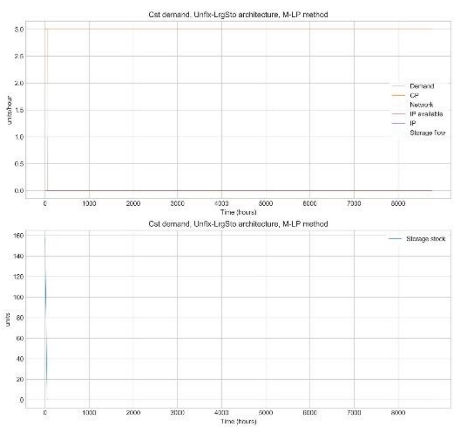



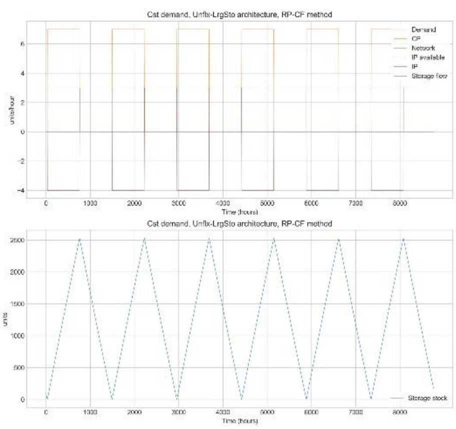




## Constant demand, Unflx-LrgSto architecture

**Cicada method** **Mean method** **RpCf method**



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# Résumé

Les défis environnementaux et plus particulièrement le défi climatique poussent les pouvoirs publics à légiférer en faveur d'une économie moins carbonée. Ces décisions se traduisent à l'échelle locale par la recherche de performance énergétique et le remplacement de sources d'énergies fossiles par des sources intermittentes, renouvelables, fatales ou de récupération. Ces deux actions peuvent être entreprises dans le secteur de l'industrie, de la mobilité, de la production locale d'énergie, des micro-réseaux d'électricité ou des réseaux de chaleur et de froid.

L'utilisation de sources renouvelables, la recherche de synergies entre plusieurs besoins et formes d'énergies complexifient ces systèmes Ils peuvent alors inclurent différentes technologies de production, conversion et stockage d'énergie : parc photovoltaïque ou éolien, cogénérations, chaudières, électrolyseurs, batteries, stockages thermiques *etc*. Concevoir de tels systèmes devient une tâche particulièrement difficile, et leur légitimité économique et écologique en dépend. Une des difficultés est de représenter le futur système sur toute sa durée de vie (plusieurs dizaines d'années), de planifier son évolution, tout en tenant compte de son fonctionnement heure par heure, voire minute par minute. En effet, la demande et la production d'énergie varient au sein d'une journée mais aussi d'une année à l'autre. La modélisation mathématique est alors un outil nécessaire pour simuler, optimiser, comprendre et dimensionner le système.

Cette thèse propose deux nouvelles approches pour concilier décisions opérationnelles sur le court et le long terme. Elles permettent de répondre à des questions pratiques telles que : « Faut-il produire davantage aujourd'hui et stocker pour demain ou le mois prochain ? ». Pour cela, les décisions immédiates sont modélisées de façon détaillée, tandis que les décisions à venir sont agrégées pour maîtriser les temps de calcul et tenir compte de prévisions incertaines. Ce travail s'inscrit dans un cadre méthodologique permettant de simuler finement l'opération d'un système, pour mieux le concevoir.

De nombreuses méthodes de modélisation et d'optimisation pour la planification des systèmes énergétiques existent. Cette thèse propose également une revue bibliographique originale et une réflexion sur l'impact de différents niveaux d'hypothèses de modélisation sur les temps de calcul et la pertinence des résultats obtenus. Ces deux derniers apports pourront guider les modélisateurs vers des méthodes pertinentes pour leur cas d'application ou vers l'élaboration de nouvelles méthodes.

# Summary

Environmental concerns as climate change urge politics to act for decarbonizing our economy. Locally, researchers, companies, municipalities and individuals try to reach more performant energy system and replacement of fossil fuels by renewables or fatal sources. This work can lead to transformations in sectors such as industry, mobility, local energy production, micro-grids, and district heating and cooling networks.

The recourse to intermittent energy sources, and the pursuit of synergies between energy vectors and between needs increase the complexity of current systems, which can include multiple production, conversion and storage technologies. Numerous technologies exist: solar panels, wind turbines, cogenerations, boilers, electrolyser, batteries, thermal storages *etc*. Hence, designing such systems is a difficult task and further conditions their economic and ecological interests. The complexity derives from the need to simulate and plan the system evolution over its lifetime (decades) while accounting for its operation every hour or minute. In fact, demand and energy production vary within days and between years. Mathematical programming is a performant tool to simulate, optimise, understand and design such systems.

The present work proposes two new approaches to optimise short-term and long-term operational decisions jointly. They answer practical questions such as "Should we produce more today and store for long-term needs?". In both methods, immediate decisions are detailed, while long-term decisions are aggregated in order to limit computation times and eventually consider imperfect forecasts. This work is part of a methodological framework that makes it possible to finely simulate the operation of a system and reach better designs.

Numerous modelling and optimisation methods exist for the planning of energy systems. This thesis also contributes to the state of the art with an original survey on these methods. Furthermore, it assesses the impact of several modelling assumptions on computation times and on the relevance of results. This can help future modellers to select appropriate methods or design new ones.