Combined analysis for physical and economical management of energy systems for housing

Timothé Gronier

THÈSE

UNIVERSITÉ DE PAU ET DES PAYS DE L'ADOUR

École doctorale des sciences exactes et leurs applications

présentée et soutenue publiquement le 2021

par **Timothé Gronier**

pour l'obtention du grade de
Docteur de l'Université de Pau de des Pays de l'Adour

(mention Énergétique)

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	Dr. Sylvain Quoilin	Université de Liège
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Résumé

La transition énergétique, c'est-à-dire le passage d'un mix énergétique basé sur les énergies fossiles à un mix basé sur les énergies renouvelables, est largement acceptée comme une nécessité imposée par les objectifs mondiaux de lutte contre le réchauffement climatique. Malheureusement, cette transition ne se fait pas sans heurts. Si l'on se restreint à des considérations purement techniques, les sources d'énergie pressenties comme les piliers des futurs mix énergétiques, le solaire et le vent, sont intermittentes et non contrôlables. De plus, les zones les plus productives ne sont pas nécessairement celles où l'on consomme le plus. Les principales solutions envisagées pour corriger ce double décalage, spatial et temporel, sont respectivement la rénovation du réseau électrique et le développement du stockage. Il s'agit de solutions coûteuses.

Le travail réalisé dans cette thèse se concentre sur une autre approche, complémentaire, le Demand-Side Management (DSM). Ce dernier est un paradigme dans lequel le gestionnaire de réseau d'énergie peut, dans une certaine mesure, adapter la consommation aux contraintes de production. Le principe n'est pas neuf, les tarifs heures pleines/heures creuses faisant pleinement partie du DSM. Plus précisément, notre recherche a porté en premier sur le développement d'un logiciel capable de gérer en temps réel des réseaux d'énergie en s'appuyant sur du Direct-Load Control (DLC), c'est-à-dire en pilotant directement certains équipements domestiques. L'objectif principal est de se servir de la flexibilité offerte par le DLC pour améliorer l'utilisation locale des énergies renouvelables et ainsi de limiter les besoins en stockage ou les appels au réseau. Une telle méthode soulève de nombreuses questions hors du champ physique. En effet, on s'intéresse ici également aux aspect économiques du problème, non seulement via une approche techno-économique classique, mais aussi via une collaboration avec le laboratoire d'Économie de l'Université de Pau et des Pays de l'Adour. Au travers de ces interactions, nous nous sommes basés sur une approche contractuelle, où différents contrats sont proposés aux consommateurs (avec ou sans DLC) et nous avons conçu un ensemble de règles adaptées. On s'intéresse en particulier aux questions suivantes : quelles compensations financières pour les consommateurs ? quel modèle économique pour le gestionnaire du réseau ? L'approche repose sur trois piliers fondamentaux : les appareils, les contrats et les stratégies. Un logiciel associé a été conçu pour qu'il soit facile d'ajouter des éléments pour chaque objet (ajouter une nouvelle technologie de production, par exemple). Dans un second temps, nous avons réalisé des simulations visant à éclaircir les relations entre taux de consommateurs participant au DLC, demande en énergie (quelle quantité ? consommée à quel moment ?), réseaux d'énergie présents (électricité, chaleur, gaz ?), technologies disponibles pour la production, la conversion ou le stockage (quelles technologies ? quelles capacités installées ?) et, enfin, stratégie appliquée pour la gestion des réseaux (quelle priorité ? en appliquant quelle technique ?). Si les résultats obtenus via ces simulations ne permettent pas de répondre définitivement à ces questions, plusieurs observations peuvent être faites. D'abord, l'utilisation du DLC améliore bien l'usage des énergies renouvelables et réduit bien la nécessité de recourir au réseau, que ce soit pour l'achat ou la revente d'énergie. Ensuite, des effets de seuil semblent exister : l'impact du DSM est marginal au-delà de certains taux de participation. Enfin, si le DSM réduit le montant des factures, les taux de coupure sont très (trop ?) élevés avec les stratégies et les contrats utilisées.

Mots-clés: *demand side management*, *demand response*, énergies renouvelables, simulation, *smart grids*

Abstract

Energy transition, *i.e.*the passage from a fossil fuel-based energetic mix to a renewable-based energetic mix, is commonly accepted as a necessity imposed by the fight against climate change. Unfortunately, this transition is not smooth. Regarding only technical issues, energy sources identified as the basis of the futur energetic mix, sun and wind, are intermittent and non-controllable. Moreover, the most productive areas are not necessarily those where consumption occurs. The main solutions considered to resolve this spatial and temporal gap are respectively electric grid renovation and the diffusion of storage. These solutions are expensive.
The work realized in this thesis explores on another approach, complementary, Demand-Side Management (DSM). This one is a paradigm in which the grid manager can adapt partially the consumption to production constraints. This principle is not new, as time of use tariffs are fully part of DSM. More precisely, our research started with the development of a software designed to manage in real-time multi-energy grids and relying on Direct-Load-Control (DLC), *i.e.*by monitoring directly some domestic appliances. The main objective is to use the flexibility offered by DLC to improve the use of local renewable energy and thus to reduce the need of storage or energy exchanges with the grid. This method raises numerous questions outside of the physical field. Here, we integrate economical aspects of the problem, not only via a classical techno-economical approach, but also via a collaboration with the economy laboratory of Université de Pau et des Pays de l'Adour. Through our interactions, we based our work on a contract-based approach, where different contracts are proposed to consumers (with or without DLC) and we designed a set of adapted rules. We are especially concerned with the following questions : Which return for consumers ? Which economical model for the grid manager ? Our approach is based on three main objects : devices, contracts and strategies. A software has been developed with this approach and addition of new elements for each object (add a new production technology, for example). Then, we realized simulations exploring the relations between DLC popularity, energy demand (which quantity ? consumed when ?), kind of energy networks (electricity, heat, gas ?), available technologies for production, conversion or storage (which ones ? With which capacity ?) and applied strategy for grid management (Which objective ?). If results obtained thanks to these simulations do not allow to draw definitive conclusions, several observations can be made. First, using DLC improves renewable energy usage and reduce the need to call the grid, either for buying or selling energy. Second, it seems that thresholds effects exist. Last, if DSM reduces effectively consumers' bills, curtailment rates observed with our current strategies and contracts are very (too much ?) high.

Keywords: demand side management, demand response, renewable energy, simulation, smart grids

Chapitre 1

Introduction générale

1.1 Contexte

Le changement climatique est un défi majeur du XXI$^{\text{ième}}$ siècle. Fort heureusement, son origine est connue et diverses manières de le combattre ont été identifiées. L'utilisation d'énergies fossiles étant l'un des principaux problèmes, la transition énergétique s'impose comme l'une des principales solutions. Cette dernière est le passage d'un mix énergétique basé sur les énergies fossiles à un autre basé sur des énergies renouvelables ou au moins décarbonées ("décarbonées" si l'on considère que le nucléaire est une partie de la solution et non du problème). L'accord de Paris, ratifié par plus de 190 pays dans le monde (dont les États-Unis et la Chine, les plus gros pollueurs), statue que l'augmentation de température moyenne sur terre ne doit pas dépasser 2^oC (et idéalement 1.5^oC) à la fin du siècle, comparé aux niveaux pré-industriels. Cet objectif implique d'accélérer la transition énergétique, *i.e.*le déploiement des énergies renouvelables. De nombreuses politiques ont été mises en place pour fournir une feuille de route et fixer des buts intermédiaires. Par exemple, l'Union Européenne souhaite que les émissions de gaz à effet de serre soient réduites de 40% par rapport aux niveaux de 1990 d'ici 2030 et de 100% d'ici 2050. De telles politiques de soutien sont nécessaires car les énergies renouvelables ont plusieurs inconvénients (voir [1], rapport explorant différents scénarios de mix énergétiques pour 2050).
En effet, si le coût des énergies renouvelables tend à se rapprocher du coût des autres énergies, de nombreux problèmes se posent du point de vue de l'exploitation. L'ancien modèle reposait sur des unités de production de grande capacité, plus ou moins flexibles : si l'on ne peut pas qualifier une centrale nucléaire de flexible, on peut au moins programmer ses périodes d'arrêt. Or, le soleil et le vent sont identifiées comme des sources d'énergie primaire majeures dans un mix énergétique renouvelable. Et ni l'un ni l'autre n'offre un confort d'utilisation équivalent aux énergies fossiles. Le vent, d'abord, est difficile à prévoir et n'est pas une source fiable : à plusieurs semaines ventées peuvent succéder d'autres semaines de calme plat. La production solaire, ensuite, s'avère relativement stable d'une année sur l'autre, mais atteint son pic en été et autour de midi, là où les pics de consommation se situent plutôt en hiver et pendant la soirée. D'autres énergies existent, comme l'énergie hydraulique ou la géothermie, sont plus souples mais assujetties à des contraintes géographiques : les lieux les plus adaptés à la production ne sont pas nécessairement ceux où l'on consomme le plus. Ainsi, de nouvelles difficultés apparaissent du point de vue la gestion de ces réseaux (notamment l'équilibrage du réseau électrique).
Il existe de nombreux axes de recherche visant à résoudre ces problèmes. D'abord, on pense aux travaux sur le stockage d'énergie, qui permet de gérer le décalage temporel [2]. Ces travaux portent sur l'amélioration des technologies existantes ou le développement de nouvelles. Pour le moment, c'est une solution coûteuse, au moins 80 $\$/kWh$ toutes technologies confondues d'après [3] et qui ne règlent pas tous les problèmes environnementaux. On s'interroge aussi sur les meilleures manières de dimensionner et de piloter des systèmes énergétiques complexes. Ces deux questions, proches, sont souvent traitées ensembles, principalement à l'aide de logiciels d'optimisation [4, 5]. De tels recherches en ont entraînés d'autres sur des sujets connexes, notamment sur la modélisation des technologies de production [6, 7, 8] (comment calculer et prévoir la production d'un panneau photovoltaïque ? De quels paramètres dépend-elle ?) et de

la consommation (comment prévoir ou modéliser les comportements des consommateurs ? À quelle échelle de temps ? Avec quelle fiabilité ?) pour plusieurs niveaux de granularité, allant de l'appareil [9] au pays tout entier [1] en passant par le bâtiment [10] ou le quartier [11]. On peut d'ailleurs relever que plusieurs pays, dont la France fait partie, laissent en libre accès de nombreuses données (courbe de consommation agrégée, production/échanges à différentes échelles spatiales, *etc.*) à la fois pour l'électricité et pour le gaz. Enfin, tous ces axes se déclinent sur les autres vecteurs énergétiques, en particulier les réseaux de chaleur et de froid [12]. Certains travaux portent aussi spécifiquement sur des réseaux multi-énergies, notamment à travers le couplage entre plusieurs réseaux d'énergie via la cogénération ou des points de connexion (*energy hubs*) tels que présenté par [13, 14].
Cependant, on trouve d'autres approches qui ne reposent pas uniquement sur des aspects techniques, comme le Demand-Side Management, sur lequel porte cette thèse.

1.2 Demand Side Management

Le Demand-Side Management est le terme le plus général pour décrire le paradigme dans lequel on ne considère plus la demande comme inflexible mais comme partiellement ajustable aux besoins du gestionnaire du réseau. Pris au sens large, le terme recouvre des méthodes très variées [15, 16], incluant les politiques d'efficacité énergétique. Ces techniques sont illustrées sur la Fig.1.1. L'objectif initial du DSM était de lisser au maximum la courbe de demande, afin de réduire les pics de consommations. En effet, dans les mix énergétiques traditionnels, la puissance maximale des unités de production doit être égale (ou supérieure) au pic de consommation. On s'intéresse alors au Peak-to-Average Ratio (PAR), comme dans [17] : le rapport entre le pic de consommation et la consommation moyenne. Plus le PAR est bas, plus la puissance des unités de production est basse et plus le taux de charge de ces dernières est élevé, ce qui amène un coût de l'énergie plus intéressant. De plus, le DSM peut simplifier la vie du gestionnaire du réseau ou des des producteurs d'énergie de plusieurs façons, ainsi que l'explique [18] : amélioration de la stabilisation de la tension, réduction des risques de congestion, facilitation des opérations de maintenance, *etc.*.
Le terme Demand Response (DR) recouvre les techniques permettant d'adapter les comportements des utilisateurs à des contraintes de production ou de gestion du réseau [19]. Les plus anciennes méthodes ne modifient pas la demande en temps réel mais adaptent relativement en amont les habitudes des consommateurs. Par exemple, historiquement, on peut faire démarrer le DR avec les tarifs Time Of Use (TOU, heures pleines/heures creuses en français) : dans ce cas, il s'agit de modifier les habitudes des consommateurs de manière statique. Le nombres de couples plages horaires/prix d'achat n'est d'ailleurs pas limité à 2 : en Espagne, certains contrats définissent 3 plages horaires par jour, chacune étant associée à un prix différent. Au cours du temps, des techniques plus raffinées sont apparues. On peut citer ici les tarifs Tempo anciennement proposés par EDF aux particuliers, dans lesquels, 22 jours par an, de novembre à mars, EDF se réserve le droit de multiplier par 4 le prix de l'électricité. Ce type de tarification est appelé critical peak pricing : le prix est la plupart du temps fixe mais augmente significativement lors des pics. Dans le même ordre d'idée, on trouve également, notamment en France, les tarifs RTP (Real Time Pricing), qui suivent le prix horaire de l'électricité sur le marché national : on espère alors que les consommateurs ajustent leur consommation à l'évolution des prix. En France, ce que l'on peut rattacher au DSM se limite, globalement, à ces différents tarifs pour le marché électrique relevant du *price-based* DR : les consommateurs ne s'adaptant pas d'eux-mêmes sont pénalisés. Au contraire, il existe des programmes de DR dits *incentive-based* dans lesquels les consommateurs participants sont récompensés. Le *capacity market*, l'*emergency program* et le *demand bidding/buyback* de la Fig.1.1 consistent en des versements ponctuels aux consommateurs,à chaque fois qu'il s'effacent ou réduisent leur consommation. Un consommateur souscrivant à un *interruptible program* a accès à un rabais systématique sur le prix de l'énergie en échange de la promesse de s'effacer sur demande de son fournisseur. Le Direct-Load Control (DLC) est une technique de DR dans lequel une entité extérieure au consommateur a directement 'la main' sur certains de ses appareils, sous certaines conditions. Il s'agit également de la seule technique dans laquelle le consommateur est passif et celle qui permet par conséquent la réactivité la plus importante.

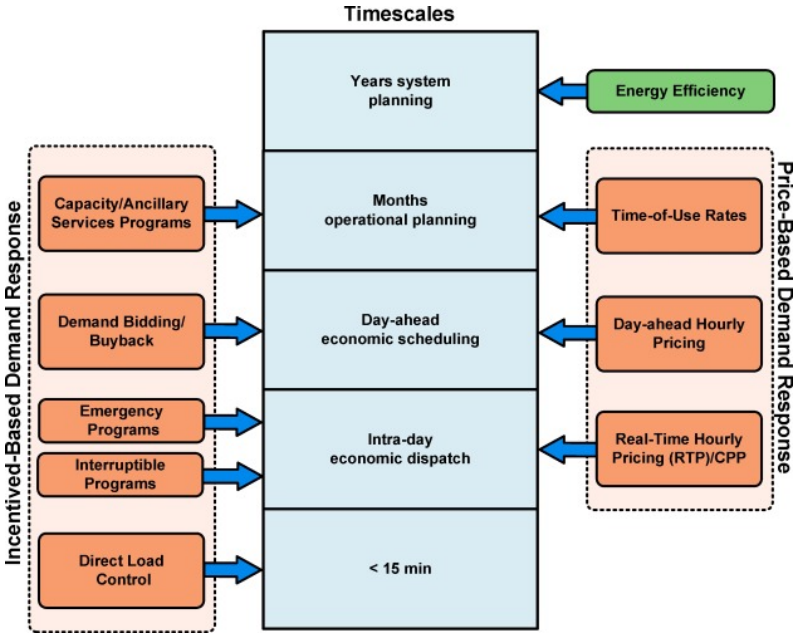

FIGURE 1.1 – Présentation de différentes techniques rattachées au DSM extrait de [19] (qui l'avait adapté de [16])

Il existe une vaste littérature sur le DR en général : scopus propose près de 1500 articles scientifiques publiés en 2021 comprenant le terme 'Demand Response' [1]. De nombreuses études sont d'ailleurs des simulations ou des expériences réalisées dans des cas particuliers, à différentes échelles, de l'habitation (appelé HEMS, Home Energy Management System, comme par exemple dans [20]) au microgrid [21, 22] : ce dernier correspond à un réseau de "petite" taille pouvant aller de quelques bâtiments à une ville. Il s'agit d'une échelle d'étude assez courante dans laquelle on considère souvent des réseaux locaux coupés d'un réseau principal. Un tel modèle décrit bien la situation de communautés isolées de petite ou de moyenne taille, telles que des petites îles (Ouessant dans [23]) ou des zones peu peuplées et/ou difficiles d'accès (l'Himalaya indien dans [24]). Ces simulations ou expériences diffèrent sur de nombreux points. Déjà, on retrouve les différents types de tarification présentés ci-dessus (comme dans [25], où on en teste 3 différentes). On s'interroge également sur les stratégies de gestion à adopter : cherche-t-on à lisser la courbe de consommation [17], augmenter l'auto-suffisance [26] ou à diminuer directement les coûts d'exploitation [27] ? Une fois la stratégie choisie, de nombreux modèles numériques existent, notamment en terme de techniques d'optimisation (même si on trouve plus d'approches heuristiques, *i.e.*basée sur des approches aléatoires,comme dans [28]). Certains articles s'intéressent à l'implémentation concrète de ces techniques, en terme d'électronique, par exemple [29]. Le pilotage du DR couplé à des énergies renouvelables et/ou à des systèmes de stockage fait l'objet de nombreux travaux ([30], par exemple). On étudie aussi le gisement de flexibilité à différents niveaux [19], selon le type de consommateur ([31] pour les bâtiments de bureaux/résidentiels ou [32] pour les industriels) ou en classant les différents appareils [22]. Si on l'associe à des effets positifs, il peut être difficile de quantifier l'impact du DR. En effet, dans la réalité, on a soit la courbe sans DR soit la courbe avec, pas les 2 : mesurer son impact quand il est mis en place demande donc un travail spécifique, comme [33].

Si l'électricité reste la principale énergie associée au DSM et au DR, les réseaux de chaleur (et de froid) ne sont pas oubliés [34], car on y retrouve des bénéfices similaires. Il existe même des expérimentations dans de grands réseaux de chaleur comme celui de Turin [35]. Ils offrent même une souplesse supplémentaire au gestionnaire : on peut plus facilement exploiter le réseau en lui-même. En effet, on peut sur ou sous-chauffer temporairement un réseau de chaleur, ce dernier agissant comme un stock. Les travaux portant sur les réseaux multi-énergies [36] et les réseaux de gaz [37] sont plus rares mais existent : on y

1. consulté en octobre 2021

espère que l'intégration du DR apportera les mêmes avantages qu'ailleurs.

Par ailleurs, le développement de l'électronique et de l'internet des objets permettent d'envisager des réseaux d'énergie traitant une masse importante d'information. De tels réseaux s'inscrivent dans le paradigme des Smart Grids (SG), terme aux nombreuses significations, ainsi que le présente [38]. En effet, il est indifféremment employé pour qualifier des réseaux d'énergie plus instrumentés que les réseaux traditionnels, comme par exemple ceux intégrant des compteurs intelligents tels que Linky ou Gazpar (on parle alors de *smart metering*) ou des réseaux semi-autonomes aux fonctionnalités avancées, telle que le repérage et la correction de certaines avaries techniques. On peut dire que le terme SG recouvre tous les réseaux (avant tout électriques) intégrant des innovations en terme d'acquisition et/ou de traitement des données. Ces réseaux, qui gèrent une masse importante d'informations, rendent accessibles l'utilisation du DLC à une vaste échelle. Une telle technique a comme avantage de pouvoir cibler précisément et pertinemment les consommations à reporter, effacer, ou ajuster : un gestionnaire réseau disposant de telles possibilités pourrait faire coïncider une partie du chauffage de l'Eau Chaude Sanitaire (ECS) avec une production photovoltaïque, sans générer beaucoup d'inconfort pour le consommateur. Néanmoins, un minimum d'inconfort subsistera toujours, car de telles techniques sont intrusives et impliquent donc un désavantage pour le consommateur. Ces questions d'intrusivité et, plus généralement, de transmission et de collecte d'informations liées à la consommation d'énergie domestique génèrent des inquiétudes quant aux problèmes de sécurité de la donnée et de respect de la vie privée. Heureusement, ces thèmes sont aussi abordés par la recherche [39] (et encadrés par la loi RGPD, d'ailleurs).
Il n'existe pas, à notre connaissance, de logiciels centrés ni sur le DSM en général, ni sur le DLC en particulier, la plupart étant des logiciels de pilotage/dimensionnement de systèmes d'énergie renouvelables qui l'intègrent à la marge comme option, ainsi que le décrit [40] (HOMER energy est régulièrement utilisé par exemple). Ils ne permettent en particulier pas de simuler des masses importantes d'objets appelant des prises de décisions individuelles, ce qu'exige le DLC. Les travaux de simulation sur le DR qui n'utilisent pas des logiciels généralistes font appel à des codes "maison" qui n'ont pas vocation à être généralisés.

Pour conclure, on peut dire que, malgré la grande quantité d'articles portant sur le DSM et même sur le DR en particulier, il est très difficile de dégager des principes ou des modèles généraux, en raison du nombre élevé de paramètres dont l'influence, prise isolément ou couplée à d'autres, est méconnue.

Enfin, on ne peut pas réduire limiter la recherche sur le DSM aux sciences exactes. De nombreuses problématiques en relation avec l'attitude des consommateurs relèvent directement des sciences sociales. Cela explique que cette thèse soit incluse dans le projet CAPEESH, qui finance également une thèse en économie : certaines questions ont ainsi pu être abordées de manière pluridisciplinaire.

1.3 Économie

1.3.1 Quelques notions économiques

Il existe plusieurs définitions de l'économie. Ici, on dira qu'il s'agit de la science qui s'intéresse à la production, à la consommation et à l'échange de biens et de services. L'économie est constituée de plusieurs disciplines mais on peut à peu près la découper en deux : la macro et la micro-économie. La première s'intéresse à l'économie à un niveau agrégé et traite de croissance, de chômage, d'inflation, de dette nationale. La seconde traite des comportements des agents dans les différents marchés. Les agents sont les participants au marchés, séparés entre producteurs et consommateurs. Les marchés sont les lieux de rencontre dans lesquels se font les échanges. Ils ne sont pas nécessairement des espaces physiques et ils comportent des règles et/ou des contraintes de fonctionnement.
Les agents, en fonction de l'offre et de la demande, font des choix (consommer ou ne pas consommer par exemple). En règle générale, on considère que les agents vont chercher à maximiser leur surplus, *i.e.*le gain qu'ils peuvent obtenir via une transaction. La valeur de ce gain correspond à la différence entre l'utilité (notée U, mesure du bien-être, de la satisfaction apportée par un produit) associée à ce que l'on reçoit et celle associée à ce que l'on donne. Cette utilité associée découle de la perception des agents et varie donc d'un agent à l'autre. Par exemple, elle est inversée entre un consommateur et un

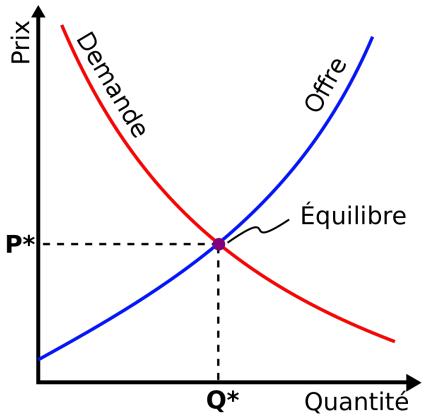

FIGURE 1.2 – Exemple de courbe prix/quantités [2]

producteur : le consommateur trouvera le bien plus utile que l'argent qu'il dépense pour l'acheter, au contraire du producteur. L'utilité varie également d'un consommateur à l'autre : deux consommateurs peuvent préférer des biens différents. Surtout, le prix à partir duquel un consommateur n'achète plus un bien ou un service varie. Cette sensibilité au prix se calcule via l'élasticité définie comme $e = \frac{\partial Q}{\partial P}$, avec P le prix et Q les quantités échangées. Cette grandeur est généralement négative, *i.e.*les consommateurs achètent moins quand le prix augmente. Bien entendu, les prix ne sont pas fixés librement et dépendent des coûts de production.
Les relations entre le surplus, quantités échangées et le prix sont au cœur des travaux de la microéconomie. Elles sont notamment étudiées à l'aide des notions de valeurs "marginales". Par "marginale", on entend la valeur associée à la dernière quantité échangée. Pour les consommateurs, elle correspond à l'utilité qu'on associe à la dernière quantité que l'on consomme. Cette utilité a tendance à diminuer quand les quantités augmentent : par exemple, on associe peu d'utilité à posséder un deuxième lave-vaisselle quand on en a déjà un. Pour les producteurs, elle correspond au coût de production (C) de la dernière unité. Mathématiquement, elles correspondent respectivement à $\frac{\partial U}{\partial Q}(Q_{changes})$ et $\frac{\partial C}{\partial Q}(Q_{changes})$. Ces notions de coût et de surplus marginaux permettent de déterminer les quantités échangées à partir du prix : les consommateurs arrêtent d'acheter quand le prix atteint l'utilité qu'ils associent à l'achat d'une quantité supplémentaire. Pareillement, les producteurs arrêtent de produire lorsque leur coût de production marginale rejoint le prix de vente. Le prix qui maximise les quantités échangées est appelé prix d'équilibre et correspond au point d'intersection des courbes d'offre et de demande, comme l'illustre la Fig.1.2.

Maintenant que ces différentes notions ont été présentées, on peut aborder les principales hypothèses souvent faites en microéconomie. D'abord, la microéconomie étudie principalement les équilibres, *i.e.*les moments ou les quantités et les prix sont stables. Même quand plusieurs temps sont présents dans un modèle, il s'agit la plupart du temps d'une succession d'équilibres. Ensuite, la microéconomie s'inspire de la théorie des jeux et suppose en règle générale que les agents sont rationnels, *i.e.*qu'ils vont chercher à maximiser leur surplus individuel. Enfin, la plupart du temps, on se place dans les conditions de la concurrence pure et parfaite, *i.e.*dans une configuration qui satisfait les conditions suivantes : un grand nombre d'acheteurs et de producteurs afin qu'aucun d'entre eux ne détienne un pouvoir suffisant ; des produits identiques et interchangeables ; aucune barrière n'existe pour produire sur ce marché ; et toutes les informations sont connues de tous. Il est important de remarquer que l'utilisation de "souvent" ou "en règle générale" signifie que certains travaux prennent des hypothèses plus fines (parce que plus adaptées à l'objet étudié) ou évaluent leur validité. On peut penser au marché des vendeurs de voitures d'occasion tel que décrit dans [41], dans lequel la concurrence pure et parfaite ne s'applique pas en raison du déficit d'information du consommateur. En effet, la qualité du produit n'est pas perceptible par le consommateur au moment de l'achat et ce dernier sait que le vendeur peut donc dissimuler des défauts. Dans ce contexte,

2. schéma provenant de Wikipédia et sous license Creative Commons

les consommateurs partent du principe que tous les produits ont des défauts et refusent de les acheter à un prix élevé. Ainsi, une bonne voiture d'occasion sera vendue au prix d'une mauvaise voiture d'occasion, chose impossible dans le cadre de la concurrence pure et parfaite, les informations étant connues de tous.

Il est à noter que le premier objectif de la microéconomie théorique, à laquelle nous avons recours, n'est pas de réaliser des modèles prédictifs. Il est d'étudier ou de proposer les mécanismes régissant différents marchés. Par exemple, on cherche à comprendre comment évoluent les quantités échangées en fonction du prix, à identifier la configuration menant au surplus maximum, producteurs et consommateurs inclus, ou encore à décrire comment se répartissent les consommateurs entre deux producteurs concurrents. Concrètement, cela signifie que dans de nombreux modèles, on n'associe jamais une valeur numérique à une grandeur. L'exercice est d'ailleurs assez compliqué, puisque même des grandeurs comme le coût ou le prix sont à prendre au sens large : l'argent est compris dedans mais on y associe également une notion d'effort à fournir.
On peut retrouver et approfondir les notions présentées ici dans le livre "Introduction à la microéconomie" [42].

1.3.2 Économie, énergie et DSM

Le but de cette partie est de présenter des notions économiques ciblées en lien avec le travail effectué. Pour commencer, l'économie s'est concentrée sur l'étude du réseau électrique et du marché de l'électricité. En France, entre autres, il se déroule à une échelle nationale, bien que des échanges soient possibles avec l'extérieur et, surtout, il ne permet basiquement pas de stock. En réalité, il y a plusieurs marchés selon l'échelle de temps considéré. Déjà, des accords sont conclus en amont entre producteurs et fournisseurs pour les productions/consommations les plus stables. Ensuite, il y a le marché horaire, où sont attribuées toutes les quantités dont on prévoit qu'elles seront consommées. Ce marché horaire fonctionne sur un système d'enchères : les producteurs et les fournisseurs publient des couples quantité/prix. Ces couples sont triés par prix décroissant pour les fournisseurs et par prix croissant pour les producteurs. Si l'on trace les 2 courbes comme illustré sur la figure 1.3, on voit que la quantité échangée est alors égale à la quantité à laquelle se rencontre les 2 courbes, *i.e.*quand $Q_{conso}(P) = Q_{prod}(P)$. Le prix correspondant à cette quantité échangée devient alors le prix unique pour toutes les quantités échangées et c'est lui qu'on appelle le RTP. Enfin, après que tous les consommateurs aient été servis, vient le marché de l'ajustement, où l'on attribue les quantités "orphelines", qui ont bien été produites et consommées mais qui n'ont pas donné lieu à la transaction correspondante. Ces quantités proviennent du fait que tous les marchés situés avant la consommation effective de l'électricité reposent sur des modèles prédictifs pour la consommation et la production et qu'il y a toujours un écart entre le prévu et le réel.

En économie, quand le marché horaire est étudié, le modèle le plus répandu consiste à se baser sur les coûts de production marginaux : les technologies renouvelables ne nécessitant pas de carburant, leur coût de production marginal peut être fixé à 0. Cela permet d'expliquer qu'elles soient produites en priorité (parce qu'elles sont les moins chères) sans avoir besoin de modéliser l'obligation d'achat dont elles jouissent. Les autres technologies sont divisées en 2 catégories : les technologies de base, utilisées en priorité et les technologies d'appoint, utilisées en cas de consommation importante. Dans la même logique, les technologies de base, le nucléaire en France, sont considérées comme vendant moins cher leur énergie pour pouvoir la vendre en priorité.

Le comportement des consommateurs a aussi été analysé. L'un des résultats les plus importants concerne l'élasticité : à court-terme, elle est faible, *i.e.*la grande majorité des consommateurs ne vont pas changer leurs comportement d'une heure sur l'autre ou d'une semaine sur l'autre mais plutôt d'une année sur l'autre. L'explication est simple : on ne constate le prix de l'électricité et du gaz qu'une fois la facture reçue, auquel s'ajoute le lissage de la facture (les fournisseurs tendent à lisser la facture pour éviter des déséquilibres importants entre l'été et l'hiver). On ne s'interroge donc pas sur le prix de l'électricité au moment où on la consomme. Ce résultat est capital car il rend toutes les approches basées sur la réactivité des consommateurs délicates : il faut accompagner le signal prix d'un autre, un SMS prévenant de l'élévation du prix, par exemple.
En ce qui concerne la modélisation du DR en particulier, le modèle le plus courant est contre-intuitif : les quantités effacées ne sont pas des quantités non-consommées mais des quantités rachetées aux consom-

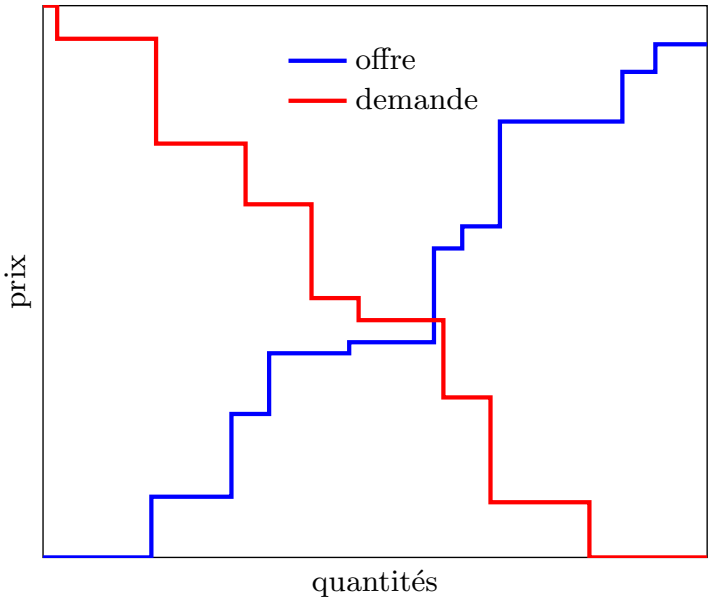

FIGURE 1.3 – Illustration du marché horaire de l'électricité

mateurs. Cela signifie qu'on les considère comme des quantités produites. Ainsi, au lieu de diminuer le volume de quantités échangées, le DR le maintient en créant artificiellement un supplément de production. Ce choix de modélisation a l'avantage de mettre sur un pied d'égalité quantités effacées et quantités réellement produites : on peut donc choisir entre l'une ou l'autre en comparant leurs prix respectifs. On parle ici uniquement de quantités effacées et non de quantités décalées dans le temps, car il n'y a pas à ma connaissance d'étude portant spécifiquement sur elle. Néanmoins, il en existe sur le risque de rebond : les quantités effacées à un instant t peuvent être simplement reportées à $t+1$. C'est ce comportement qui a conduit, par exemple, EDF à passer d'une unique plage horaire heures pleines/heures creuses à une gamme de plages horaires choisies localement par Enedis : avant, tous les chauffe-eaux démarraient à la même heure, ce qui créait un pic au milieu de la nuit.
Maintenant que ces quelques éclaircissements sur l'état de l'art en économie ont été fournis, il est possible de présenter le travail réalisé dans cette thèse.

1.4 Objectifs de la thèse

1.4.1 Conception et développement de PEACEFULNESS

On peut rappeler ici l'absence d'outil numérique dédiés au DR ou au DLC qui permettraient de mener des études plus générales et systématiques sur le sujet. L'objectif à long terme du projet de recherche est ainsi de proposer un logiciel permettant de gérer en temps réel des réseaux multi-énergies s'appuyant sur du DLC. La raison est la suivante : le DLC permet de gérer séparément des appareils offrant différents types de flexibilité et aussi en raison de notre approche contractuelle. En effet, nous avons choisi d'adopter une approche contractuelle, dans laquelle le contrat définit les prix d'achat et de vente d'énergie mais aussi les possibilités offertes au gestionnaire (report, effacement, étalement du besoin). Fatalement, nous avions donc besoin de connaître la demande de chaque consommateur pris isolément, ce qui impose de toute façon une granularité fine. L'idée derrière cette approche contractuelle est la suivante : sachant que les consommateurs s'adaptent pas ou peu à l'équilibre entre offre et demande (et aux évolutions de prix qui en découlent) en temps réel, des contrats de DLC permettent de définir clairement au préalable les modalités du DLC et ensuite de laisser un tiers se charger de la gestion au jour le jour. Ainsi, dans un même temps, les consommateurs et le gestionnaire réseau bénéficient respectivement d'une offre de DLC souple (puisqu'on peut fixer les conditions à l'échelle des appareils) et d'une demande très réactive

(puisque modifiée directement par le gestionnaire lui-même). Une telle approche imposant un volume de données important, il convient de s'assurer qu'elles soient traitées rapidement, le réseau électrique imposant une réactivité de l'ordre de la minute.
Dans notre logiciel, le gestionnaire est ce qu'on appelle un agrégateur : un agent intermédiaire gérant plusieurs consommateurs dialoguant à leur place avec les producteurs et les transporteurs d'énergie. Nos agrégateurs sont en charge d'une zone géographique relativement réduite et continue : il n'est pas question ici d'agrégateurs en charge de consommateurs répartis ici ou là sur l'ensemble du pays. Ils sont également responsables de la gestion de tous les éléments du réseau : infrastructure de transport, unité de production, de conversion et de stockage. Ce parti pris donne à l'agrégateur la possibilité de favoriser l'autoconsommation de l'énergie produite localement, notamment via les énergies renouvelables. Mais attention : si toutes les consommations et productions sont transmises à l'agrégateur pour qu'il puisse équilibrer le réseau, le pouvoir qu'il a sur celles-ci dépend du contrat. Ainsi, l'agrégateur ne pourra pas imposer du DLC aux gens n'ayant pas adopté un contrat l'autorisant explicitement. D'ailleurs, la définition de ces contrats, l'évaluation de leur utilité à l'échelle du réseau (pour les consommateurs, les producteurs et le gestionnaire) et les mécanismes de compensation associés sont au cœur du travail de recherche effectué par nos collaboratrices économistes.
Dans cette thèse, le premier objectif est de développer un logiciel appelé `PEACEFULNESS`, porté uniquement sur la simulation, mais satisfaisant toutes les autres exigences exprimées ci-dessus. Il fallait donc mettre au point une architecture et un algorithme adaptés et intégrer divers modèles pour la consommation et la production, et éventuellement pour la conversion ou le stockage (si les délais le permettaient). D'un point de vue informatique, il s'agit d'un logiciel orienté objet, écrit en Python3, dans lequel il est facile d'ajouter de nouveaux appareils, profils de consommation, vecteurs énergétiques, contrats et stratégies de gestion. En effet, une fois la documentation achevée (via la rédaction d'un wiki et la préparation d'un tutoriel), il est prévu qu'il soit disponible en open-source sur github. Ce dernier est une sorte de réseau social du développement de logiciels open-source, car il permet aux uns de publier leurs projets et aux autres de participer librement à ceux qui les intéressent. La facilité de prise en main et d'ajout d'éléments étaient donc des points de vigilance. Le détail du modèle conçu est présenté dans le premier chapitre.
Le choix de se limiter à de la simulation vient, déjà, d'une contrainte lié à la durée de la thèse. Par ailleurs, comme mentionné dans la partie 1.1, le pilotage réel de réseaux multi-énergie sans DSM est déjà suffisamment délicat pour être l'objet de travaux de recherche. De plus, le fait d'intégrer activement un nombre important de consommateurs à une expérimentation requiert des partenaires politiques et s'accompagne de problématiques juridiques. Par conséquent, le travail réalisé sera de nature prospective et tous les résultats, en particulier ceux tirés des cas d'études, seront tributaires d'une validation expérimentale.

1.4.2 Études de cas

Cette thèse ne se limite pas au développement de `PEACEFULNESS`. Son second objectif est d'utiliser les fonctionnalités qui seront disponibles durant la thèse pour réaliser des cas d'études. Ces cas simuleront des réseaux, mono ou multi-énergie, réalistes mais pas tirés de données de terrain : en effet, nous n'avons trouvé ni études, ni données fournissant des profils de consommation à l'échelle des appareils. D'ailleurs, même en disposant de telles données, nous n'aurions pu que supposer les profils de demande : en effet, la demande, *i.e.*ce que les gens souhaitent diffère de la consommation lorsqu'on applique du DR. Par exemple, "je veux que mon lave-vaisselle ait fait un cycle pendant la nuit" est une demande. Le profil de consommation correspondant est le profil des puissances appelées par le lave-vaisselle pendant la nuit. Ainsi, même si l'on dispose de la consommation d'un appareil, on ne peut pas déterminer avec certitude la demande correspondante.
`PEACEFULNESS`est capable de sortir facilement des bilans économique et énergétique à différents niveaux de granularité (appareils, agents, contrats, agrégateur ou nature de l'énergie). Des indicateurs plus complexes, issus de ces bilans sont disponibles : les minima, maxima et moyennes et aussi des indices normalisés tels que le taux d'autoconsommation de la production locale ou le taux de refus de service aux consommateurs ou les revenus de l'agrégateur. On se sert ensuite de ces différentes métriques pour réaliser des analyses de sensibilités : sur une base similaire, on s'intéresse à l'impact du taux de participation à des programmes de DLC, des stratégies employées par l'agrégateur et de l'environnement technologique. Deux études de ce type sont présentées dans ce document et constituent chacune un chapitre de la thèse. La première porte

sur une comparaison entre un réseau purement électrique et un réseau de chaleur et sur des stratégies aux objectifs similaires mais utilisant des approches physiques ou économiques pour y parvenir. La seconde est le fruit d'une collaboration avec Dr Ramousse et Dr Fitó, tous deux membres du LOCIE. On y propose une méthode permettant d'intégrer la présence de DLC chez les consommateurs dès la phase de conception du système de production d'énergie. Cette méthode est ensuite appliquée sur un exemple. L'évolution du dimensionnement y est donc étudiée en plus des autres métriques. Via une collaboration avec l'université de Saragosse, en Espagne, nous avons eu l'opportunité de nous pencher sur la viabilité économique de petits agrégateurs-producteurs privés. Dans ce travail, mené en majeure partie par Dr Pinto, grâce au code qu'il a développé pendant sa thèse, nous avons étudié deux agrégateurs, l'un en France, l'autre en Espagne. Ayant accès aux mêmes technologies, ces deux agrégateurs diffèrent par le profil de demande à satisfaire et la tarification. Chacun de ces agrégateurs se positionne comme l'unique fournisseur d'énergie d'un lotissement de 50 personnes et optimise via le code de l'université de Saragosse son système de polygénération. On s'intéresse à la viabilité économique de tels mini-agrégateurs en se basant sur la "valeur nette actualisée (NPV pour Net Present Value en anglais), sans toutefois négliger d'autres aspects via l'observation des émissions de CO_2 et des choix technologiques. Il est important de noter que ce dernier travail n'inclut pas de DSM.

1.5 Structure du document

Le corps de ce document est composé d'articles publiés ou soumis. Dans cette section, je précise ma part de travail personnel pour chacun des chapitres.
Le chapitre 2 détaille le modèle développé pour `PEACEFULNESS`. Le modèle a été co-construit tout au long de la thèse avec mes encadrants, mais j'ai développé seul le logiciel. J'ai également largement contribué à la rédaction de l'article. Il est soumis à *Smart Energy*.
Le chapitre 3 porte sur la simulation d'un quartier résidentiel à l'aide `PEACEFULNESS`. J'ai conçu le cas d'étude, réglé les différents paramètres et réalisé les simulations et le post-traitement. J'ai écrit toutes les parties en dehors de l'introduction. Il est aussi soumis à *Smart Energy*.
Ce troisième travail expose les résultats de notre collaboration avec le LOCIE, une articulation entre `PEACEFULNESS`et une méthode de dimensionnement. La démarche générale et le cas d'étude ont été conçus collectivement. Je me suis chargé de toute l'investigation liée à `PEACEFULNESS`, en particulier les simulations. Concernant la rédaction, j'ai décrit les aspects liés au DSM dans la méthodologie et analysé tous les résultats du point de vue du DSM et participé à la conclusion. Ce travail est d'ores et déjà publié dans la revue *Energy* (https://doi.org/10.1016/j.energy.2021.121517).
Le dernier chapitre est celui réalisé avec l'université de Saragosse sur la pertinence économique d'agrégateurs d'énergie indépendants. J'ai participé à la conception du cas et a la rédaction. Je me suis aussi servi de `PEACEFULNESS`pour fournir les profils de consommation. Il est soumis à *Energy*.

Chapitre 2

Modélisation

PEACEFULNESS: A platform for transverse evaluation of control strategies for multi-energy smart grids

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Abstract

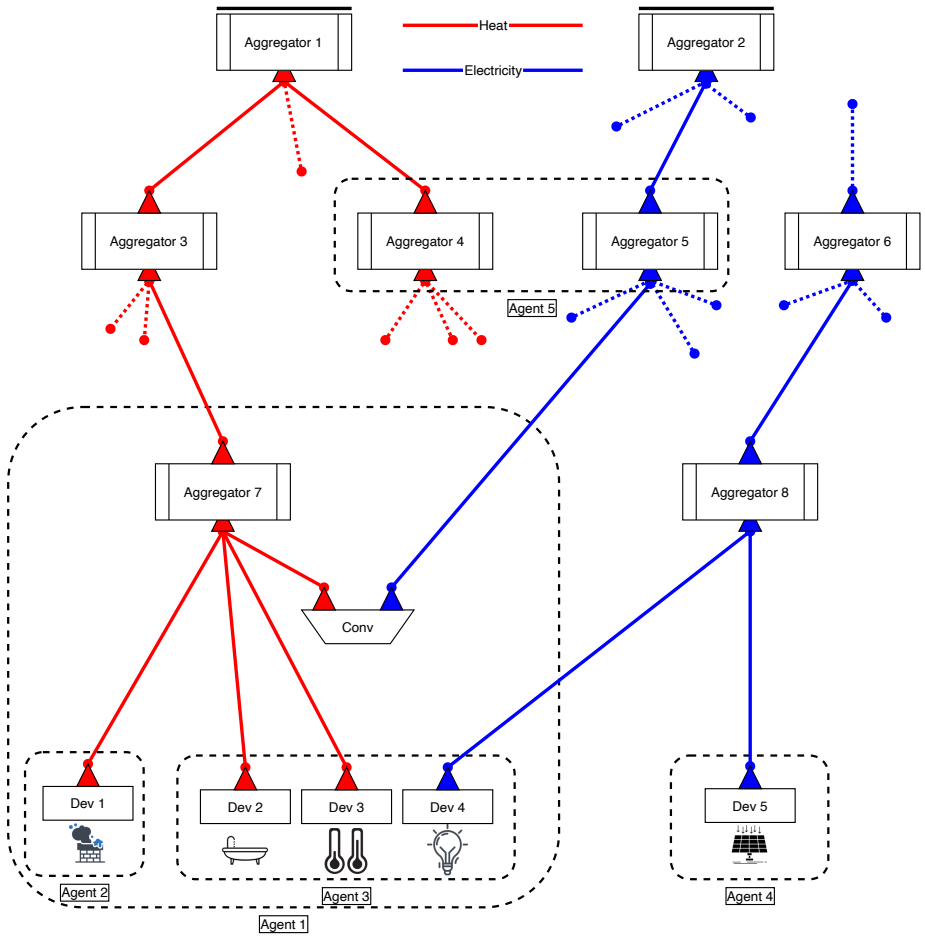
This paper presents the PEACEFULNESS software platform, an open framework dedicated to multi-energy smart-grids, based on a techno-economic modeling integrating economic and legal considerations (contracts). As such, it is mainly oriented towards the evaluation of multi-energy grid supervision strategies, *i.e.* the energy management, and the corresponding policies and legal organization. The main goal is then to highlight the various possible behaviors and strategies to organize the probable future interconnections between the different energy carriers. In particular, it aims at investigating how to maximize the use of renewable energy sources (RES), using Demand Side Management (DSM) techniques and energy storage, in a shared economy context. The open-source tool PEACEFULNESS, written in Python, is described here in details. It combines a top-down description of the energy networks and connections between the various agents (energy providers, distribution system operators, aggregators, consumers, producers, prosumers, *etc.*), together with a techno-economic bottom-up description for all devices. Here, both public databases and users' data (basic heating demands or based on buildings modeling) can be used, as well as generic or more specific models (*e.g.* PV panels with constant or temperature-dependent efficiency). As one of its major specificity compared to other tools, it extends the use of DSM techniques to various energy grids which can also interact altogether. Furthermore, different economic models can be set for both the aggregators and the customers, and even among themselves. As a last competitive advantage, PEACEFULNESS allows to simulate the operation and supervision of tens, and even hundreds, of thousands of agents. It also provides a reporting system giving access to all the data, with a configurable granularity and frequency for the retained indicators. Finally, several validation cases are presented, followed by a series of test cases with increasing size: a smart home, a smart district (2 000 housings) and a smart community (50 000 housings).

Keywords: smart mixed grids; multi-carrier energy flows; DSM; aggregator; energy models; renewable generation; energy storage

Highlights:

- energy management system handling DSM for coupled multi-carrier energy networks
- operation either at the building or regional scales (from single home to thousands of people)
- large simulation width, from single day to years, with minutes to hourly steps
- integration of legal and socio-economic considerations in the market framework
- possibilities to test simultaneously (or not) various configurations of DSM approaches and level of flexibility, as well as different adoption curves of these tools

Graphical highlight:



Contents

Nomenclature

Latin symbols

A	surface area, m^2
A	incidence matrix of a DH, −
$\mathtt{a}_0$	optical efficiency, −
$\mathtt{a}_1$	first heat loss coefficient, $W\,m^{-2}\,K^{-1}$
$\mathtt{a}_2$	second heat loss coefficient, $W\,m^{-2}\,K^{-2}$
B	benefits,
$\mathcal{C}$	consumption, kWh
$\mathtt{C}$	thermal capacitance, $J\,kg^{-1}$
CF	concentration factor, −
$C_{\mathcal{P}}$	power coefficient, −
c	specific heat capacity, $J\,K^{-1}\,kg^{-1}$
CAPEX	capital expenditures,
CF	cash flow,
COP	coefficient of performance, −
D	demand, kWh
DOD	allowable depth of discharge, %
E	total energy, J or kWh
EER	coefficient of performance, −
$\mathtt{G}$	building heat loss coefficient, $W\,K^{-1}\,m^{-3}$
g	gravitational acceleration, $m\,s^{-2}$
Hh	hydraulic height, m
h	specific enthalpy, $J\,kg^{-1}$
$\mathcal{I}$	solar irradiance, $W\,m^{-2}$
IT	income tax,
ItR	interests rate, %
Iv	investments,
$\mathcal{L}$	latent heat, $J\,kg^{-1}$
LF	loss factor, %
LHV	lower heating value, $J\,m^{-3}$ or $J\,kg^{-1}$
m	mass, kg
NOCT	nominal operating cell temperature, °C
OPEX	operational expenditures,
$\mathcal{P}$	power, W
P	price,
PAR	peak-to-average ratio, −
Q	heat, J or kWh
q	flow-rate, $m^3\,s^{-1}$ or $L\,s^{-1}$
$\mathtt{R}$	thermal resistance, $W^{-1}\,K\,m^2$
r	discount rate, %
S	supply, kWh
SD	self-discharge, %/month
SOC	state of charge, %
T	temperature, K or °C
t	time, s or min
$\boldsymbol{U}$	velocity, $m\,s^{-1}$
V	volume, m^3

Greek symbols

γ	ground roughness factor, −
η	efficiency, − or %
κ	open-circuit voltage thermal coefficient, K^{-1}
Ξ	exergy, J or kWh
ρ	density, $kg\,m^{-3}$
τ	time constant, s

Subscripts and superscripts

a	air
amb	ambient
bot	bottom
bui	building
c	cooling
cell	cell
ch	charge
cut	cutoff
beg	beginning of the fusion
dis	discharge
el	electrical
fu	fuel
end	end of the fusion
Q	heat
ht	heating
in	indoor
inv	inverter
l	liquid
liq	liquidus
M	melting
nom	nominal
out	outdoor
pan	panel
pp	pipe
ref	reference
s	solid
sol	solidus
sp	set point
th	thermal
top	top
wt	water

Acronyms

BB	biomass burner
BEES	battery electrical energy storage
BIM	building information modeling
BIPV	building-integrated photovoltaic
CCHP	combined cooling, heating and power
CHP	combined heating and power
CSP	concentrated-solar plant
DBPS	dynamic building performance simulation
DC	district cooling
DH	district heating
DHC	district heating and cooling
DHW	domestic hot water
DLC	direct load control
DR	demand response
DSM	demand side management
DSO	distribution system operator
ECC	electricity control center
ECS	energy consumption scheduler
ED	economic dispatch
EMS	energy management system
EU	European Union
FERC	Federal Energy Regulatory Commission
GA	genetic algorithm
GDP	gross domestic product (PIB)
GHG	green-house gas
GIS	geographic information system
HEMS	home energy management system
HP	heat-pump
IAM	integrated assessment models
ICES	integrated community energy systems
ICT	information and communications technology
IEA	International Energy Agency
IMF	International Monetary Fund
IOA	input-output analysis
IoE	internet of energy
IoT	internet of things
IPBES	Intergovernmental Panel on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
IRR	internal rate of return
LCA	life cycle assessment
LCO	levelized cost
LHTES	latent heat thermal energy storage
LS	load scheduling
LS	load shifting
MCDA	multi-criteria decision analysis
MCES	multi-carrier energy system
MES	multi-energy system
PCM	phase-change material
PV	photo-voltaic
RES	renewable energy sources
RTP	real time pricing
SG	smart grid
SHTES	sensible heat thermal energy storage
ST	solar thermal
TOU	time-of-use
TOUP	time-of-use pricing
TSO	transmission system operator
WT	wind turbine

1 Introduction

1.1 Foreword

Apparently, we will finally know what the future holds for us: in light of the upcoming IPCC report, huge challenges and strong efforts are to be planned, and our way to consume energy should change drastically. Hopefully, researches on such issues have begun for a long time. Therefore, there are already several possibilities to pave the road for a new energy paradigm. To name but a few, the increasing installed capacities of renewable sources (RES) [1–3], such as photovoltaic (PV) and wind turbine (WT), aim at decarbonizing our societies [4]. Meanwhile, there is a global impetus for district heating (DH) and cooling (DHC) [5,6], especially in Europe [6–8], with deeper integration of RES [9,10]. Besides, since a couple of decades, this trend is strengthened by the appearance of multiple energy infrastructures [11–13] and polygeneration networks [14], or in general with the 4$^{\text{th}}$ DH generation [15,16]. Similarly, one can also cite the emergence of integrated community energy systems (ICES) [17], energy hubs [18,19] or coupled operation of DH and electrical networks [20]. Furthermore, the concept of intelligent networks, *a.k.a.* smart grids (SG) nowadays, developed to manage shortcuts and congestion issues, has shown to be particularly relevant for an efficient operation of electric grids [21]. A complete presentation of their principles, advantages and weaknesses, and of the associated methods (demand-side-management (DSM), demand-response (DR), load-scheduling (LS)...), being out of scope of the present paper, it is only recalled that the underlying idea is to influence and modify the consumers consumptions. Interested readers are referred to [22] and [23,24], but also to the excellent reviews provided in [25–27]. Though focused towards the European context, it could be useful to look also at the JRC's compendium [28]. Nevertheless, it is worth mentioning that such techniques are particularly efficient to cope with the variability problems raised by non-predictable intermittent RES [29,30]. Indeed, they are clearly pointed out as serious candidates for energy efficiency and to promote flexibility [31,32], or to secure the future power systems [33]; for instance, for Europe and North Africa, it has been interestingly shown that 15 to 37% reduction of the maximum peaks could be obtained [34]. In the sequel of the numerous studies pertaining to DSM in electrical grids, the natural path is to extend their use to other energy vectors, such as DHC [35,36] and DH [37,38]. Thus, interesting concepts have been proposed, such as dual DSM (or 2DSM) to manage electrical and thermal flows at the city level [39], or Nash equilibrium optimization to manage electrical and gas flows in a pelagic islanded micro-grid [40] and Stackelberg game for residential agents [41]. Afterwards, the underpinning evolution is the promotion of multi-energy SG [16,42,43] and of multi-energy systems (MES) [12].

1.2 Literature review

As far as modeling of multi-energy networks is concerned, there is a distinction to do based on system's size. Thus, integrated assessment models (IAM) concern the regional or country scale, whereas planning and operational tools for ICES apply to city or district levels; let us add that both are equally useful and can be interconnected, in the manner of global and regional climate models. In this respect, several tools are available to model from the building's size to the national one. A listing of these programs, and a list of references describing them is available on the web[1]. In addition, in [44], a very exhaustive review was carried out to identify the most relevant tools to analyse the integration of RES. With a collaboration with the developers, they performed a painstaking analysis of 37 tools over 68 (with dedicated paragraph for all of them), using as main classification criterion the ability to simulate a

[1] such as https://wiki.openmod-initiative.org/wiki/Main_Page or https://www.energyplan.eu/othertools/

100% RES situation (Tables 3 p. 1063 and 4 p. 1064 summarized the main properties). Though restrained to electrical systems, the strategic review proposed by [45] gave important insights of the various market regimes, and a good description of the corresponding tools. For the optimized planning and analysis of ICES, bottom-up descriptions can be found in [46]. Together with a pertinent overview of optimization problems, an interesting section on regulation is given. Software tools for district-level energy systems were very well described in [47], and more specifically three parts concerning MES and low-temperature DH, RES and seasonal storage, and links between demand and urban micro-climate. A very synthetic and didactic summary is available in Table 1 p. 1397 of this reference. More recently, [48] screened meticulously 51 tools for ICES, and retained 13, focusing on RES planning and energy storage and DSM. In addition to the (excellent) initial screening and the final results, summarized in their Tables 1 pp. 676-677 and 2 p. 678, they proposed an engrossing methodology to select between various tools. Then, a comprehensive review of techno-economic analysis methods at building, regional and national scales is available in [49], which compared also 31 computer tools and 20 arithmetical models (gathered in Fig. 4 p. 403). Rural and islanded situations are also treated. Lastly, a very complete review of 75 tools, ranging from small-scale power systems to global long-term ones, is developed by [50]. Here, a compelling analysis is available between bottom-up and optimization problems, as well as computable general equilibrium models. As a final note, the recent analysis of energy-economy-environment models of [51] is also worth considering in the perspective of the future tools development; and IAMs are particularly well synthesized here.

1.3 Contribution and novelty of the study

Regarding that all energies and poly-generation systems should be included in planning and operational tools [14], it is proposed here a method to allow for the simulation of multi-energy SG. The novelty is to couple techno-economic modeling with economy and legal considerations, `PEACEFULNESS` being developed in a multi-disciplinary framework including Physicists, Economists and Jurists. Its main goal is to shed light on the various behaviors and strategies to organize the future possible inter-connections between the different energy vectors. Without jeopardizing both the balance and the operational efficiency of the present grids, the goal is to see how maximizing RES, using DSM techniques and energy storage, in a shared economy context [52]. Besides, `PEACEFULNESS` permits to test a huge variety of scenarii, with thousands of customers, some adopting flexibility contracts. To achieve it, aggregators belong to the agents modeled. In terms of contribution, this paper presents:

- an holistic energy management approach [53, 54] dealing with all types of energy and a whole set of technologies (fossil and renewables, controllable or not, *etc.*);
- various DSM contracts (in variable proportion), obeying heuristics but which can also handle optimization tools [55];
- aggregators, whose number and positioning are configurable, close to multi-agent systems [56], but also from stand-alone home energy management systems (HEMS) [57].
- the possibility to simulate tens of thousands of agents;
- a large list of specific or average indicators, both physical and financial;
- a transparent and open-source approach [58].

Organization of the paper is: Section 2 presents the modeling and assumptions, with illustrations of the DSM by aggregators. Validation cases and detailed examples are provided in section 3. Those latter vary from a single smart home to a complete community involving hundreds of thousands appliances and customers. Finally, conclusions and perspectives are developed in section 4.

2 Model and methods

PEACEFULNESS is deeply guided by legal and policy contexts, in their present form but also on their possible evolution [53,54,59]. Similarly, the type and distribution of aggregators and of flexible contracts among the customers have tried to integrate the conclusions and remarks provided by social sciences [60]; in fact, and in spite of not being developed in the present study (due to a lack of place), it is planned to include nudges and experimental exploitations of PEACEFULNESS.
As depicted in Fig. 1, PEACEFULNESS can handle several agents. These later can be consumers with different types of loads (residential, commercial, hospital, *etc.*); they can also be producers, centralized (*e.g.* an always accessible national grid) or distributed; and finally, there are prosumers, producing one or several types of energy (electricity, heat, gas, *etc.*). Finally, agents include aggregators, either as third-party managing and/or exchanging with several other agents or as HEMS. All grids can work in autonomous mode, or in connection with one or several macro-grids.

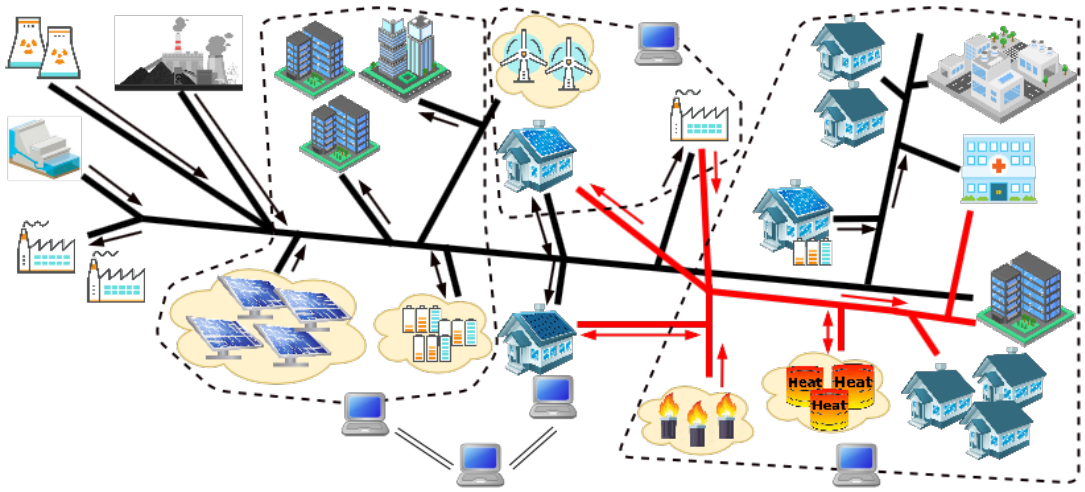


Figure 1 – Schematic example of the type of multi-energy smart-grids simulated by PEACEFULNESS

2.1 General description

As depicted in Fig. 2, management of the interconnections between the agents and the networks is inspired by a bottom-up description. Thus, each device presents a dynamic specific consumption or production profile; *i.e.* at every step, and integrating their current internal state, all of them report the amount of energy they need or produce according to endogenous parameters (previous state of charge and discharged power for instance) and exogenous ones (*e.g.* weather conditions). All devices are connected and under the supervision of one (and only one) aggregator, apart from storages and conversion

units. Aggregators are in charge of the energy balance of both their customers and the networks. Their supervision can lead them to authorize or not some devices to produce or consume. Several different strategies are available to ensure this balance (*e.g.* business as usual or autarky mode).
The rules of the game between aggregators and devices are technically handled by a contract. It sets the prices at which energy is bought or sold by the devices, and defines the level of "authority" (possibility of reducing or adjusting the energy levels) that the aggregator has over the devices. In compensation to this flexibility, customers achieve to different pricing (lower prices, extended off-peak prices...). To allow a more flexible modeling, a top-down approach is also set and aggregators behave like devices for higher-level aggregators to which they are connected. Consequently, the whole hierarchical structure and the positioning of aggregators can be easily modified. In addition, it permits a bidding selection where child aggregators can choose their parent aggregators after a competition based either on energy quantity, prices or any other parameters.
Communication between the entities is done through the exchange of messages containingrelevant information: energy supply or demand, price signals, or any other key indicator defined by the user (*e.g.* CO_2 footprint). The role of these messages, which can be bottom-up or top-down, is to guide the decision-making process, and to transmit these decisions (once arbitrated) to all entities.

2.2 Supervision process

Supervision is handled with two consecutive phases, one ascending and the other descending, divided into five steps. Chronologically, the ascending phase involves two steps:

1. Each device sets its needs (consumers) or supply capacity (producers), and communicates them to its aggregator through its contract. The latter can modify the message sent to apply contractual constraints (*e.g.* limited power call) and add missing information.

2. The aggregator performs a local balance and transmits, using the same procedure, its demand/supply to the higher-level aggregator, again through the contract filter.
   This process continues until the root aggregator is reached, which ends the bottom-up phase.

The descending phase concerns the decision-making process, and consists of three steps:

1. The root aggregators check their capacity to satisfy the demand, and can choose to satisfy it entirely (BAU) or partially (autarky) according to its capacities and available flexibility contracts. Once the choices arbitrated, the decision is transmitted to the entities under, through the contract that completes the level of supply/demand granted and the associated tariffs.

2. Each lower-level aggregator receives its energy repartition scheme, and must try to reconcile with the needs expressed before. In case of deficits, she must prioritize between the managed devices and apply a strategy, considering the different contracts.
   At the end of this stage, a similar transmission process to the sub-level is performed.

3. Finally, each device receives its possibility of consumption/production and updates its status accordingly.
   This marks the end of the whole supervision.

From an algorithmic point of view, as strategies rely on this two-phase process and not on a general optimization, the complexity of resolution in each aggregator is about $n \log(n)$, with n being the number of devices managed by the aggregator.

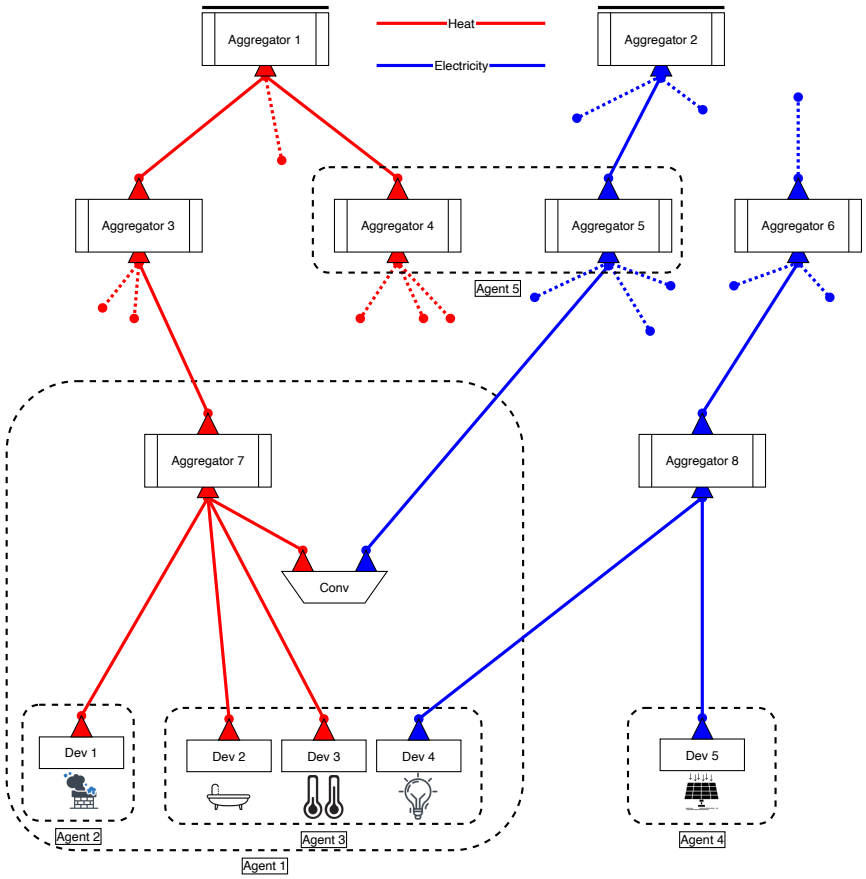


Figure 2 – Schematic example of the possible interactions between each agents, their perimeter of influence and the energy exchanges for each flows

2.3 Meteorological data

Weather conditions can be required for RES such as PV and WT, or for heating/cooling needs. Here, wind speed, total and normal irradiation, outdoor temperature and the position of the sun are taken from `PVGIS` [61]. It would also have been feasible (as planned in a near future) to rely instead on the `SWERA` database[2], on a global climate model such as `HadCM3` [62] or on a mesoscale numerical weather prediction tool such as `WRF`[3]. For the specific case of radiation, one can also refer to [63, 64] or on recognized expert websites: IEA PVPS[4], Solar Bankability Consortium[5] or the European Photovoltaic Technology Platform[6].

2.4 Devices

Generally, black box models are largely ignored to prefer mainly white-box models, *i.e.* physical-based models. Here, both are available. A non-exhaustive list of devices is presented thereinafter. These latter correspond either to various type of energy (electricity or heat for example) or to specific features (low-voltage and high-voltage); the currently available natures are: low voltage electricity, high voltage electricity, low-temperature heat, medium-temperature heat, high-temperature heat, low-temperature cold, high-temperature cold, low-pressure gas, high-pressure gas.
For both supply and demand profiles, a by-default technical profile is always available. It contains basic and essential physical characteristics, and pre-defined parameters (*e.g.* a given user profile for DHW).

2.4.1 Production units

The first are the most famous intermittent ones, namely PV and WT providing low voltage electricity, and solar thermal collectors (ST) producing low-temperature heat.
For WT, the produced power reads [65]:

$$\mathcal{P}_{\mathrm{WT}} = \begin{cases} 0 & \text{if} \quad U \leq U_{cut,\mathrm{bot}} \text{ or } U \geq U_{cut,\mathrm{top}} \\ \frac{1}{2}\rho_{\mathrm{a}}\, C_{\mathcal{P}} U^3 \frac{U^3 - {U_{cut,\mathrm{bot}}}^3}{{U_{\mathrm{nom}}}^3 - {U_{cut,\mathrm{bot}}}^3} \times A \times \eta_{\mathrm{WT}} & \text{if} \quad U_{cut,\mathrm{bot}} < U \leq U_{\mathrm{nom}} \\ \frac{1}{2}\rho_{\mathrm{a}}\, C_{\mathcal{P}} U^3 \times A \times \eta_{\mathrm{WT}} & \text{if} \quad U_{\mathrm{nom}} < U \leq U_{cut,\mathrm{top}} \end{cases} \tag{2.1a}$$

$$U = U_{\mathrm{ref}} \left(\frac{z}{z_{\mathrm{ref}}} \right)^{\gamma} \tag{2.1b}$$

where the efficiency, the power coefficient, the wind velocity thresholds and reference velocity, and height are dependent on the technology, while the ground roughness factor is a soil parameter linked to the surface state [65–67].

[2] https://openei.org/wiki/Solar_and_Wind_Energy_Resource_Assessment_(SWERA)
[3] https://www.mmm.ucar.edu/weather-research-and-forecasting-model
[4] https://iea-pvps.org/
[5] http://www.solarbankability.org/results.html
[6] www.eupvplatform.org

PV panel production is well-known [68, 69]:

$$\mathcal{P}_{\text{PV}} = \mathcal{I} \times A \times \eta_{\text{PV}} \times \eta_{\text{inv}} \tag{2.2a}$$

$$\eta_{\text{PV}}(T) = \eta_{\text{pan}} \left(1 - \kappa\left(T_{\text{cell}} - T_{\text{cell}}^{\text{ref}}\right) + \aleph \log_{10} \mathcal{I}\right) \approx \eta_{\text{pan}} \left(1 - \kappa\left(T_{\text{cell}} - T_{\text{cell}}^{\text{ref}}\right)\right) \tag{2.2b}$$

$$T_{\text{cell}} = T_{\text{amb}} + \left(\text{NOCT} - T_{\text{cell}}^{\text{ref}}\right) \frac{\mathcal{I}}{\mathcal{I}^{\text{ref}}} \tag{2.2c}$$

though other relations are also available for the efficiency or the cell temperature [70, 71].
Lastly, the ST production is (following the ISO standard EN 9806 [72][7]):

$$\mathcal{P}_{\text{ST}} = \mathcal{I} \times A \times \eta_{\text{ST}} \tag{2.3a}$$

$$\eta_{\text{ST}}(T) = \mathtt{a}_0 - \frac{\mathtt{a}_1}{\mathcal{I}}\left(T - T_{\text{amb}}\right) - \frac{\mathtt{a}_2}{\mathcal{I}}\left(T - T_{\text{amb}}\right)^2 \tag{2.3b}$$

with the optical efficiency, the first and second heat loss coefficients being collector-dependent.
For the non-intermittent RES, one can rely on hydraulic dam for electricity [73–76]:

$$\mathcal{P}_{\mathsf{h}} = \rho_{wt} \mathsf{g} \Delta H h \times \mathsf{q}_{wt} \times \eta_{\mathsf{h}} \tag{2.4}$$

with the efficiency, the volumetric flow-rate and the hydraulic height varying between the different apparatus but also between Kaplan, Pelton and Francis turbines;
and on biomass burners for heat (and electricity in case of cogeneration plants) [77–80]:

$$\mathcal{P}_{\text{BB}} = \mathsf{q}_{\text{fu}} \times LHV \times \eta_{\text{BB}} \tag{2.5}$$

Finally, heat and cool production from reversible HP are:

$$\mathcal{P}_{\text{HP}} = \begin{pmatrix} \text{COP} \\ \text{EER} \end{pmatrix} \times \mathcal{P}_{\text{el}} \tag{2.6}$$

The last elements to be defined are DH and DHC, which could still involve fossil fuels. However, whatever the generation systems, it is governed either by the above or equivalent relations [5, 81–84]. The important parameters are the supply temperatures [35] and the heat losses [8, 85, 86]. For a more complete description, it is also possible to include an hydraulic and a thermal model: the first one mainly concern the pressure in the pipes and the associated mass flow-rates, and the second one the temperatures and the associated exchange heat powers [8, 9, 19, 35, 37, 87–89].
A similar approach can be used for the electrical grid [90, 91], where voltages (magnitudes and angles) and impedance evolutions can be simulated for both the real and reactive power [19, 20, 92].

In spite of being alternatively source or sink of energy, storage technologies are included in this section. For the sake of clarity, only the main technologies will be described, namely electrical energy storage through batteries (BEES) and thermal energy storage (TES).
In the first case, the available energy is governed by [26, 66, 93–97]:

$$E_{\text{BEES}} = (1 - \text{SD}) E_{\text{BEES}}^{t-1} + \left(\eta_{\text{BEES,ch}} \mathcal{P}_{\text{ch}} - \frac{\mathcal{P}_{\text{dis}}}{\eta_{\text{BEES,dis}}}\right) \Delta t \tag{2.7a}$$

$$(1 - \text{DOD})\, \text{SOC}_{\max} \leq \text{SOC} \leq \text{SOC}_{\max} \tag{2.7b}$$

[7] which superseds the former EN 9806

In the same way, for TES, only sensible (SHTES) and latent (LHTES) storages are described (thermo-chemical storages being still at a lower TRL) [98]. Nonetheless, contrary to many studies, the modeling does account for the temperature variation and heat losses [48]. Thus, the energy evolution is:

$$E_{\text{SHTES}} = (1 - LF)E_{\text{SHTES}}^{t-1} - \rho_{wt} c_{wt} \Big(T_{\text{SHTES}} - T_{\text{pp}} \Big) \times \mathfrak{q} \Delta t + \mathcal{P}_{\text{th}} \Delta t \tag{2.8}$$

New storage temperature is in the sensible case:

$$T_{\text{SHTES}} = T_{\text{SHTES}}^{t-1} + \frac{E_{\text{SHTES}} - E_{\text{SHTES}}^{t-1}}{\rho_{wt} c_{wt}} \tag{2.9}$$

and for a latent storage:

$$T_{\text{LHTES}} = \begin{cases} T_{\text{ref}} + \dfrac{\dfrac{E_{\text{SHTES}}}{m_{\text{SHTES}}} - h_{\text{ref}}}{c_{\text{PCM},s}} & \text{if} \quad E_{\text{SHTES}} < h_{\text{beg}} \\ T_M & \text{if} \quad h_{\text{beg}} \leq E_{\text{SHTES}} \leq h_{\text{end}} \quad \text{for first-order transition} \\ T_M + \dfrac{\dfrac{E_{\text{SHTES}}}{m_{\text{SHTES}}} - h_{\text{end}}}{c_{\text{PCM},l}} & \text{if} \quad E_{\text{SHTES}} > h_{\text{end}} \end{cases} \tag{2.10a}$$

$$T_{\text{LHTES}} = \begin{cases} T_{\text{ref}} + \dfrac{\dfrac{E_{\text{SHTES}}}{m_{\text{SHTES}}} - h_{\text{ref}}}{c_{\text{PCM},s}} & \text{if} \quad E_{\text{SHTES}} < h_{\text{sol}} \\ T_{\text{sol}} + \dfrac{E_{\text{SHTES}} - h_{\text{sol}}}{h_{\text{liq}} - h_{\text{sol}}} \Big(T_{\text{liq}} - T_{\text{sol}} \Big) & \text{if} \quad h_{\text{sol}} \leq E_{\text{SHTES}} \leq h_{\text{liq}} \quad \text{otherwise} \\ T_{\text{liq}} + \dfrac{\dfrac{E_{\text{SHTES}}}{m_{\text{SHTES}}} - h_{\text{end}}}{c_{\text{PCM},l}} & \text{if} \quad E_{\text{SHTES}} > h_{\text{liq}} \end{cases} \tag{2.10b}$$

2.4.2 Loads

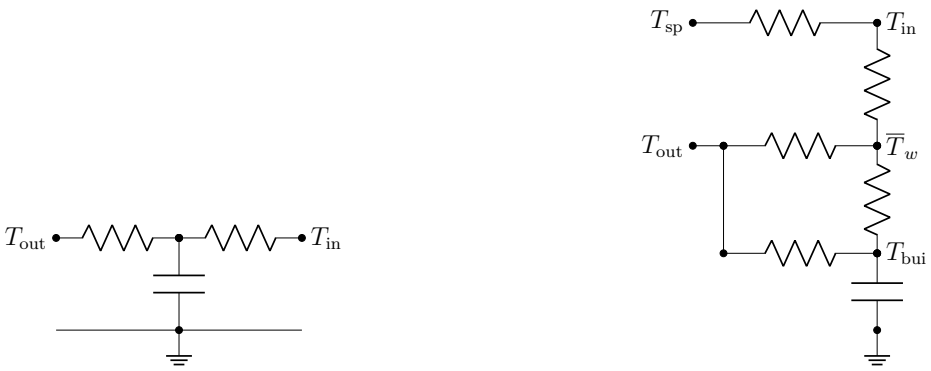
In general, most consumption devices do not need a physical modeling, with two notable exceptions being space heating (or cooling) and DHW. In the first case, there exist several bottom-up building stock models [99, 100], among which CREEM, BREHOMES, Johnston's, UKDCM, DECarb and CDEM models [101, sec. 3 pp. 1686-1689]. As a matter of fact, many models often rely on thermal resistance-capacitance ($\mathtt{R}-\mathtt{C}$) models [102, 103][8]. Moreover, gray or black box models could also be used, as for example using statistical survey data and historical measurements [105] or combination of these latter with building simulations [106] or linear models [88].
Thus, heating demand can be expressed:

$$\mathcal{P}_{ht,c} = \mathtt{G} \cdot V \cdot (T_{\text{sp}} - T_{\text{out}}) \tag{2.11a}$$

$$\mathcal{P}_{ht,c} = \frac{\mathtt{C}}{\Delta t} \cdot \left(T_{\text{sp}} - T_{\text{out}} - (T_{\text{in}} - T_{\text{out}})\, e^{-\frac{\Delta t}{\tau}} \right) \quad . \tag{2.11b}$$

or with one of the classic $\mathtt{R}-\mathtt{C}$ model (see Fig. 3).
For the DHW demand, a simple first law calculation is taken. The inlet temperature of cold water drawn from the pipes network as well as the temporal required flow-rates vary along the year and hours; they

[8] successor of ISO 13790:2008 [104]



(a) Wall (b) Building

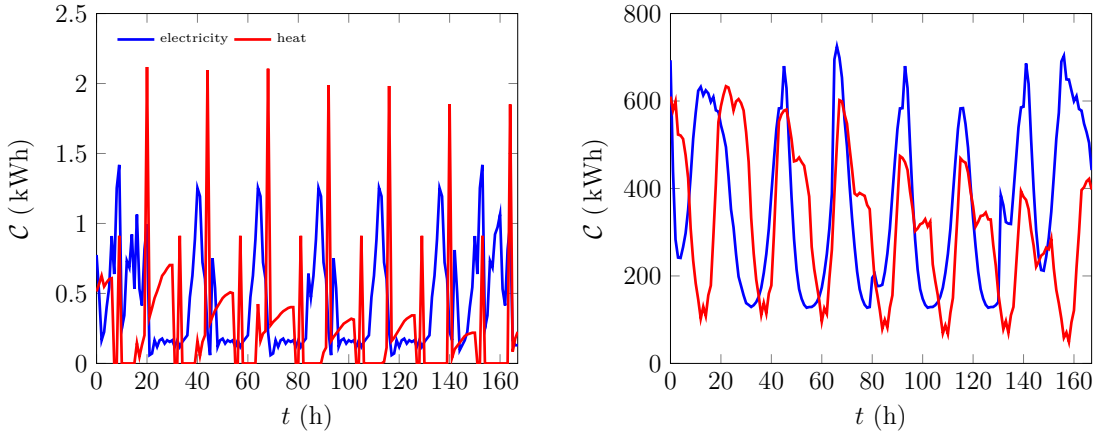
Figure 3 – Examples of R − C models

are provided in the current study by the French environment agency [107] and the related ministry [108]. Other possibilities could rely on mathematical modeling [106, 109–111] or profiles from dedicated IEA's report [112, 113] or on statistical analysis and measurements [114].

Finally, the last load profiles required come from the electrical appliances. In the present approach, it was decided to model individually only those appliances that can handle DSM orders. Indeed, the other devices usually do not represent an important part of the domestic consumptions, or they are not widely spread in households (and not expected to be in a near future). Consequently, a "background" profile aggregating all their profiles was created, using a specialized tool [115, 116]. Here again, other possibilities are offered as for instance with bottom-up models [117, 118], stochastic approaches [119, 120], or from measures [121].

2.5 Haphazardness

As clearly highlighted in [36, Fig. 5 p. 710], the existence of a common peak between various consumers do not mean that it occurs exactly at the same time. One cornerstone of PEACEFULNESS being to simulate large amount of agents, a generation tool permits to create easily large sets. Furthermore, since individual agents consumptions are quite discontinuous, as most devices have only a switch on/off, and unlike the aggregated load, some devices parameters can be randomized to represent such a behavior. As an example, the level of consumption (peak and mean), the length or the beginning of the usage, *etc.* can be tuned to allow for randomization. The corresponding process is based on a Gaussian law where the mean is the standard value and the standard deviation is set by the user. Thus, Fig. 4 illustrates the efficiency of this method: the individual profile is discontinuous, especially concerning heat, but the aggregated load of a set of 1 000 agents generated with this method and using the same pattern is clearly smoothed and representative of the usual behavior observed by DSO. Finally, by combining several of these randomized profiles generations, it is possible to obtain (quasi)-haphazardous profiles very close to real ones.



(a) Individual profile (b) Overall aggregate profile (after randomization)

Figure 4 – Examples of consumption profiles over one week

2.6 Flexibility operation

2.6.1 DSM

Among all the available techniques, and given the most prominent and interesting [27, 34], the retained ones in `PEACEFULNESS` are load shedding to constrain an agent for several minutes or hours, curtailment to temporarily limit the demand/supply, and load shifting at earlier times with direct load control (DLC) and at later times (LS).

The overall methodology is inspired by a hierarchical control [122] yet it is implemented in a pragmatic way, using an hybridation method combining both a centralized and a decentralized coordination [39, 111]. In practice, when faced with DSM needs, the various aggregators can propose to activate one of the above techniques for some of the voluntary agents having subscribed such contracts. Obviously, the utility of these contracts being of a lower quality (for the demand can be restrained), an incentive is proposed to the customer. She can therefore benefit from another pricing policy, based either on different off-/on-peak prices (or any equivalent time-of-use pricing -TOUP-) or on a real-time pricing (RTP). Once again, other possibilities could be tested, as for example with reward mechanisms for the consent effort, managed as a cooperative game program [123].

From a technical viewpoint, thermostatically controlled loads (TCLs) offer a great possibility in terms of DSM [122], and similarly, the setting temperature of TES [39]. The indoor temperature is also an easily accessible parameter which can vary between two thresholds, defining lower and upper comfort range, without important noticeable effects for the customer. This option is also used, especially since it is under-exploited in spite of a huge potential [99]. Eventually, some appliances are partially or totally deferrable [30] and this option is available for dishwasher, washing machine and equivalent devices.

Finally, all these elements permit to define a set of aggregators with some DSM capacities, which can be engaged depending on a list of pre-defined fixed orders managing their activation and dispatching [48]. Here, everything is tunable and modifiable, and various rules can apply to different agents (consumers, prosumers, aggregators...).

2.6.2 Contracts and aggregators' strategies

As said above, contracts have two goals: assigning a price signal to transactions, and modifying the message sent by the device in regard of non-physical conditions. Different pricing policies are proposed and the price can be either static, with a given schedule (TOUP), or dynamic. For these latter, there are several approaches available: it is possible to choose a RTP, at a national or regional scale, but also equilibrium prices calculated at the scale of the aggregator, directly from local considerations. Eventually, these dynamic prices can also be linked to consumer's contracts: the more the curtailed period, the more costly it is to curtail the customer, for example. Concerning the messages sent by the devices, they originally consider only physical constraints, such as the possibility (or not) to interrupt the device without any harmful effects or the urgency of an usage, *etc.* Secondly, contractual constraints unsurprisingly apply and can redefine the former message given the needs of the grid or aggregator from one hand, and the DSM options available in the contract from the other hand. Five different contracts have been tested, yet without any lack of generality since it would not be difficult to envisage and implement other ones. Concretely, these are 'business as usual' (BAU) contract, which does not allow any modification; and contracts proposing one of the above DSM techniques. Lastly, as contracts are attached to devices, it is possible to have a contract, from the legal acceptation, which proposes a DLC contract for the space heating but a BAU contract for the dishwasher... Moreover, more complex contracts, specific to storage or conversion devices, are responsible for their activation: for storage, the contract defines the conditions to buy or to sell energy, or even to stay passive during a round of exchange... In fact, such possibilities will allow energy providers, aggregators and/or any equivalent department from a DSO, to test the various mix of options that could be proposed to the customers, and the consequences, boons and drawbacks for all of the agents.

The contracts between the costumers (consumers, producers, prosumers) being defined, it is now time to present the various strategies accessible to the aggregators. Their main role is to ensure that energy grids are balanced and to efficiently manage both the supply and demand. To do so, each aggregator arbitrates between all the options allowed by the contracts with the agent under its perimeter and by communicating and exchanging with other aggregators. Here are some decisions they can take: to buy / sell energy to another aggregator, to charge / discharge a storage, to start / shutdown production or conversion units, to apply DSM techniques (curtailement, DLC, LS, *etc.*)... Based on the local balance of energies, differentiating mandatory ones (PV panels or non-DSM consumers for example) from adjustable ones (gas plant, BEES or DHW for example), the strategy orients the decisional choices of the aggregator to exchange (or not) with other aggregators and, then, to distribute both production and consumption offers among the different devices. Naturally, mandatory demands or proposals of energy supply by non-controllable devices must be satisfied, otherwise it is considered that the SG fails.
Thus, it is possible to consider many combinations between the exchange policy and the energies dispatching. Once again, without any lack of generality but for the sake of simplicity, four strategies are presented. First, the 'always satisfied' always try to satisfy all the devices requirements. Second, the 'profitability' strategy satisfy urgent needs only when the aggregator can earn money. Then, the ' light autarky' strategy, close to a "connected island mode" [124], aims at promoting self-sustainability but without decreasing the users comfort: exchanges are made only to satisfy urgent needs, and the dispatching orders are based on a ranking of all the non-urgent needs. Practically, a customizable function is defined to allow to serve equivalently all devices, or to organize the classification using a single parameter (such as the price, the degree of emergency, the quantity, *etc.*) or a combination of them (*e.g.* a weighted sum of the product of energy quantity with price, *etc.*). Finally, the 'autarky' strategy represents a stand-alone mode where the aggregator is islanded from the other external agents: no exchanges

are allowed and the demand can be satisfied only with the local supply (from both available production and storage units).

3 Results and discussion

3.1 Validation cases

Due to the numerous elements possibly in interaction in `PEACEFULNESS`, a series of simulations dedicated to the validation of the different characteristics was set up, based on analytical solutions. Each simulation of this series tests one feature and checks that numerical values calculated during the run correspond to the reference values. Most of them are a replication of a simple situation, where the feature tested is the only element changing. As a side effect, such configuration highlights the impact of each feature on the code.

In total, these tests are divided in 8 different families to check the validity for the agents hierarchy, contracts flexibility, contracts tariffs, converters, devices, distribution strategies, exchange strategies, natures, aggregators hierarchy and user profiles. Three of them, having been identified as cornerstones, are detailed hereafter, namely contract flexibility, distribution strategy and exchange strategy. In fact, these choices are governed by the important impacts of the DSM on the devices profiles, which can be easily visualized.

Besides, following [49], a comprehensive set of indicators is proposed to render for all involved scales, *i.e.* from building's size [125] to communities... Furthermore, all outputs, like energy or money balances at different levels (device, agent, aggregator, nature of energy or contract), can be exported. Several refined values are also proposed. At an aggregator scale, its benefits, the PAR, the mismatch, self-consumption, coverage rate and curtailment rates can be calculated for all agents. Finally, these values can be exported at the chosen frequency and it is possible to compute automatically the minimum, the maximum, the mean and the sum for any output. An option to generate automatically the corresponding graphs is also available.

3.1.1 Contract flexibility

Contracts first put a price on every exchange of energy. Second, they define the level of flexibility, *i.e.* the possibilities for the aggregator to modify demand/supply. Here, three different contracts corresponding to different levels of flexibility are created: a BAU contract, a cooperative contract where devices can be shifted or modulated in power, and a curtailment contract. Then, three different dishwashers are created, one for all of these contracts. All are managed by an aggregator without any production or storage units, but authorize to exchange with the national electrical grid, supposed to be able to buy or sell an infinite amount of energy. Finally a 'light autarky' strategy is adopted for each aggregator. This implies that non-urgent needs are not satisfied if no energy is available locally. No local production being available, only urgent needs will be served. Consequently, it imposes that:

- with a BAU contract, all the needs are urgent, *i.e.* dishwasher is served as soon as it asks;
- with a cooperative contract, the emergency level is left untouched. The dishwasher is served at the last moment allowing to be on-time;
- with a curtailment contract, no needs are urgent, *i.e.* dishwasher is never served.

Corresponding results are provided in Fig. 5. The agreement is excellent between the simulated scenarios and the theoretical solutions, whatever the type of contracts.

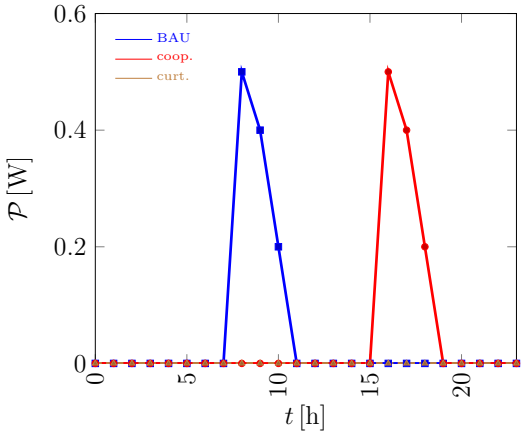


Figure 5 – Energy consumptions as a function of the contract flexibilities: comparisons between the numerical results (symbols) and analytical solutions (lines)

3.1.2 Distribution strategy

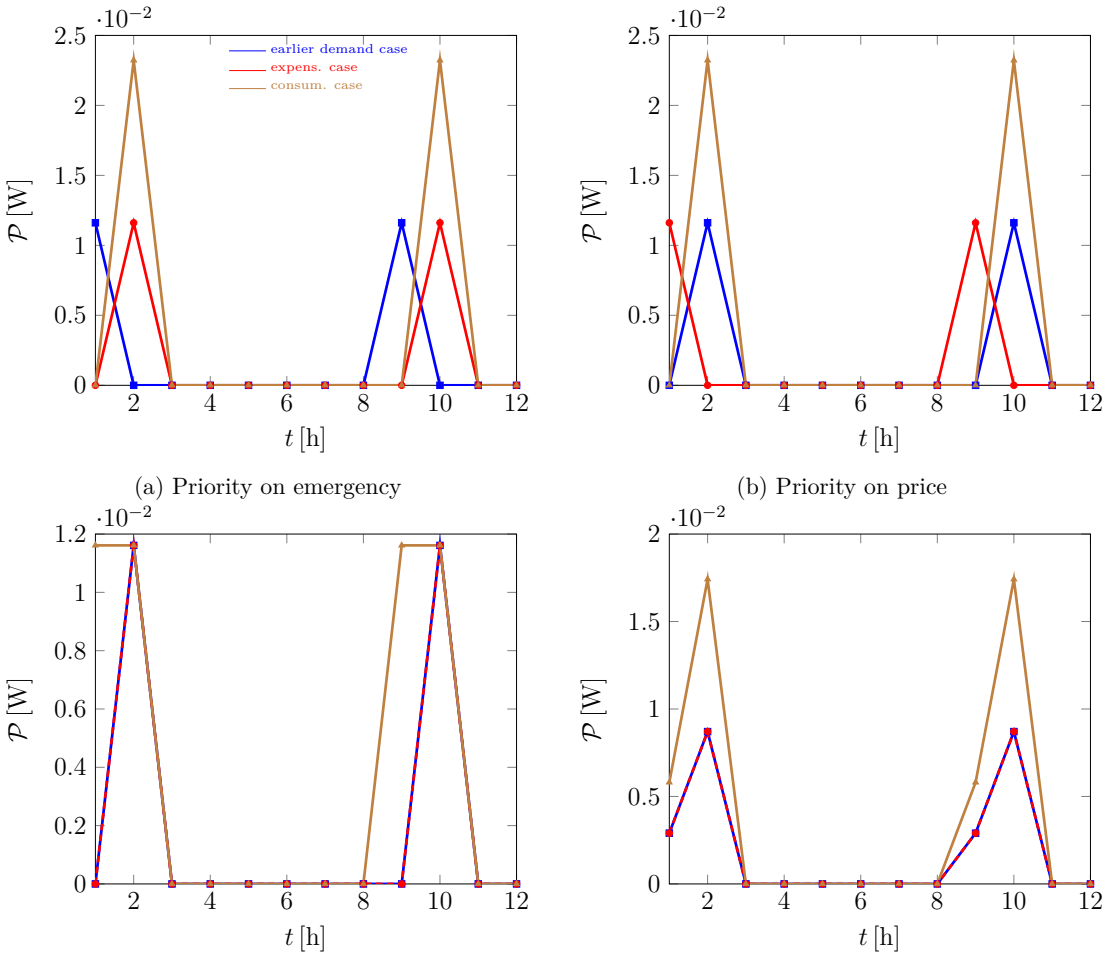
This example tests the different priorities available for the strategy set-up during the distribution phase. Four aggregators are created, with a different strategy regarding with the various distribution paths. One of them serve partially all the devices, *i.e.* all receive the same proportion. For the other ones, only a part of the devices are fully satisfied, based on a selection by decreasing emergency, price or quantity of energy asked/proposed. In each of these aggregators are created three water heaters each: the first asks for an earlier demand, the second pays a higher price and the third asks for an higher amount of energy. Generation is present, but it is not enough powerful to satisfy the demand of these three water heaters. Concretely, the observed behaviors should be, for the aggregator based on:

- Emergency: the first device, having a higher value of emergency, is served in priority;
- Price: the second device, paying a higher price, is served in priority;
- Quantity: the third device, asking for more energy, is served in priority;
- Partial satisfaction: all the devices are served partially at the same time.

Corresponding results are shown in Fig. 6. Here again, an excellent agreement is observed.

3.1.3 Exchange strategy

In the last case, we consider three aggregators, with different strategies regarding the exchanges with the outside world. The first aggregator applies a 'light autarky' strategy, in which exchanges are made only when urgent demands cannot be satisfied. The second aggregator applies an 'autarky' strategy, and so it never exchanges with the exterior of its SG. The last aggregator applies an 'always satisfied' strategy, to satisfy all demand. Here again, three identical water heaters belong to each aggregators: the first has a BAU contract, the second a cooperative contract, the third a curtailment contract. No local production is installed and consequently, aggregators rely completely on the outside to satisfy the consumptions. Therefore, it means that in the SG with an aggregator applying a :



(a) Priority on emergency

(b) Priority on price

(c) Priority on quantity

(d) Proportionnal distribution

Figure 6 – Energy consumptions as a function of the distribution strategies: comparisons between the numerical results (symbols) and analytical solutions (lines)

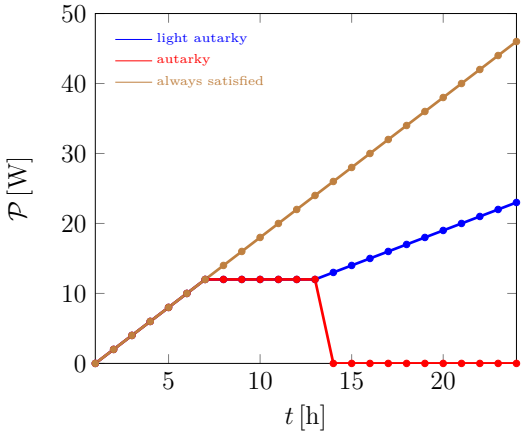


Figure 7 – Energy consumptions as a function of the exchange strategies: comparisons between the numerical results (symbols) and analytical solutions (lines)

- 'light autarky' strategy, the water heater with a BAU contract is served when calling, the one with a cooperative contract at the last moment, and the last with a curtailment contract is never served.
- 'autarky' strategy, no DHW is served.
- 'always satisfied' strategy, the three water heaters are served as soon as they ask.

The Fig. 7 shows that simulated calculations and analytical solutions match perfectly.

3.2 Test cases

Now, three examples are presented to illustrate the different studies realizable with `PEACEFULNESS`, involving different scales, energy systems and returned ouputs.

3.2.1 smart home

This first case deals with the energy bill and the individual consumption of a single housing; the aggregator playing here the role of an HEMS. The test is realized over four weeks, at the end of March, June, September and December. For managing the house, the aggregator applies a light autarky strategy and it is connected to the national electrical grid.
The housing is equipped with the following electrical devices: a 5 kW heater, a 2 kW DHW, a dishwasher, a washing machine, a dryer and lastly a background unit accounting for several small appliances (kettle, hair dryer, *etc.*). Added to this, 10 m^2 of PV are installed on the roof. The location is situated in Pau, south-west of France. Finally, the inhabitants have a cooperative contract for their consumptions, where buying energy costs 0.15 €/kWh. PV is associated with a BAU contract where selling energy brings in 0.10 €/kWh. Eventually, this case is compared with a BAU scenario without any supervision. As depicted in Fig. 8, the heating needs vary (logically) significantly from one season to another; it vanishes in summer and is the most important demand in winter and spring. Only the PV panels and the water heater are affected by season: the former producing more in summer while the latter consumes

a bit less. For these three devices, seasonal variations are also observed, caused by meteorological conditions (external temperature and irradiation here). The other devices have stable patterns among days and seasons. When comparing the boons of the DSM by the aggregator (see Table 1), two important effects can be noticed. First, the maximum peak is singularly reduced since the called power decreases from 5.13% in winter, where the demand is the highest, to 18.75% in summer. Moreover, these peaks are shifted, with up to 4 h offset. Such a gap can also greatly help in the operation of the production units, and to avoid the start-up of technologies with higher marginal costs, lower efficiency, more CO_2 emissions. The second very important conclusion is the evolution of the peak-to-average ratio (PAR), and the overall consumption. The former is decreased between 11.76% to 47.62%, and the latter from 15.64% to 51.26%; such reductions clearly offer a greater flexibility and huge energy and economy savings. From the system's viewpoint, this indeed permits to plan a more stable and constant operation of the generation capacities, and the capacity design is diminished. For a more day-to-day application, where existing capacities are already installed and running, this allows for a limitation of the installation of new capacity to absorb the increasing demand.

Table 1 – Smart home: comparison between DSM case and a BAU case

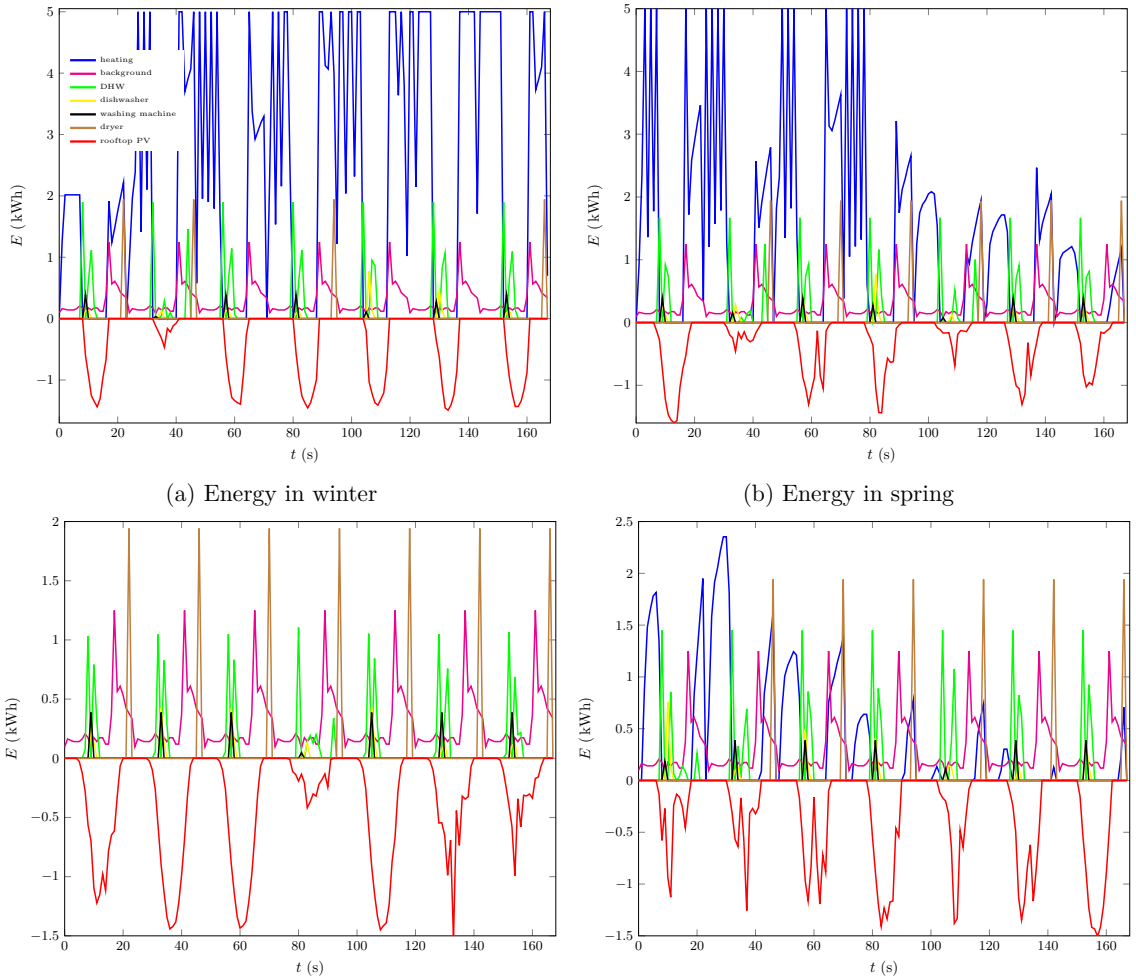
case		maximum power (kW)	time	PAR (−)	quantity (kWh)
winter	present DSM	7.4	23h	0.45	561
	BAU	7.8	19h	0.51	665
spring	present DSM	7.4	23h	0.31	387
	BAU	7.5	19h	0.46	573
summer	present DSM	2.6	22h	0.22	96
	BAU	3.2	22h	0.32	174
autumn	present DSM	5.1	3h	0.22	193
	BAU	5.7	6h	0.42	396

3.2.2 smart district

Table 2 – Dwellings composition in smart districts

Type	Number of persons	Amount	Devices
Apartment	1	500	Background, heating, DHW, washing machine
Apartment	2	1000	Background, heating, DHW, washing machine, dishwasher, dryer
House	5	500	Background, heating, DHW, washing machine, dishwasher, dryer

This case is oriented towards district-scale situations, with higher amounts of customers and numerous appliances. It involves 2 000 housings, connected to the regional electrical grid and possibly to a local DH fed by a 0.7 MW wood-fired plant and with a 2 MW HP as back-up. Local RES are 4000 m^2 of PV and a 1.5 MW WT. These later being intermittent, only the thermal power is controllable. For the housings, they are divided into 500 and 1 000 apartments inhabited by a single person and a couple respectively, and in 500 5-persons houses, equipped as presented in Table 2. For each categories, the proportion of contracts is: 50% BAU, 30% cooperative and 20% curtailment. In an upcoming paper, preliminary studies [126,127] will be resumed to see the influence of the proportions of each contract due to its relative importance [36] but also to help in the understanding of the needed thresholds for such



(a) Energy in winter

(b) Energy in spring

(c) Energy in summer

(d) Energy in autumn

Figure 8 – Demand and supply profiles for the single housing

contracts. Two aggregators are in charge of the energy management of this district, one for electricity and the other for heat. Both apply a light autarky strategy. Aggregators try to maximize self-sufficiency. A regional electrical grid is available. HP has a static efficiency of 3.5. The simulation is performed for a whole year for a district in Pau, France. The outputs scrutinized in this test are mainly the self-sufficiency of the local electrical grid, and the energy balances for electricity and heat and between the local producers.

Results are gathered in Fig. 9. In compliance with the previous observations, and the randomization process, the overall electricity consumption is stable over the year. However, it is not the case for electricity production: PV produce more in summer and the WT generation is unstable, with huge variations. Interestingly, one can remark however good levels of electrical coverage rate and self-consumption. On average, less than 20% of the electricity production is injected into the regional grid, thus avoiding balance issues for the DSO. Furthermore, the coverage part is commonly above 50%, which thus limits the dependency on the external grid and the need for new capacity. When looking at the heat demand and supply, it is logically more strongly affected by seasonality. However, a very good correlation is obtained between the production and consumption curves, due to the real-time adaptation of the thermal production, if needed, by the HP. With DSM, the number of periods where the remedy to the HP is required is relatively low. As a consequence, the biomass can run regularly at its full capacity, and on average at more than 60%. This is highlighted by the very high level of heat coverage rate, limiting electricity purchases to fulfill part of the HP needs. Finally, it is important to quantitatively pinpoint the advantages of the present configuration and of DSM by the two aggregators. As can be seen in Table 3, the maximum peak is really reduced since it achieves 16.67% and 50% for electricity and heat respectively. It is accompanied by a decrease of 24.1% and 22.85% of the corresponding demand, which is significant at these amounts of consumption (several thousands of kWh). As a last remark, it is worth mentioning that such calculations are not expensive and can be performed in 1.7 hours with an "Intel® Core™ i5-7300HQ 2.5 GHz x 4", 8 Go RAM, Debian 10. Brought back in term of time periods and persons, this corresponds to 0.7 s per simulated day or to 1.2 s per person and per year.

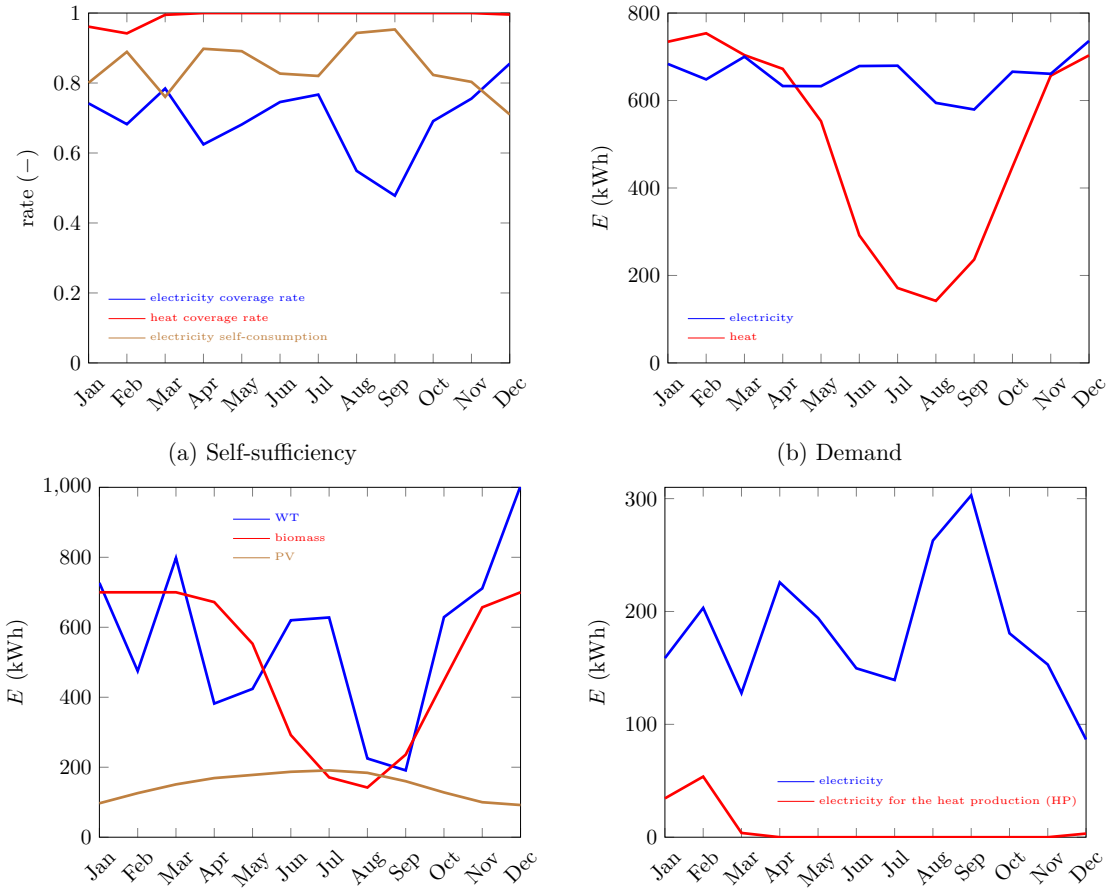
Table 3 – Smart district: comparison between DSM case and a BAU case in the format elec/heat

case	maximum power (MW)	month	PAR (−)	quantity (MWh)
present DSM	1.5/1.0	Dec/Feb	0.44/0.41	5765/4415
BAU	1.8/2.0	Feb/Feb	0.58/0.14	7595/5723

3.2.3 smart community

Table 4 – Dwellings composition of the smart community

Aggregator	Type	Number of persons	Amount	Devices
eco-district	House	2	5000	Background, heating, DHW, washing machine, dishwasher, dryer, PV
with PV	House	5	5000	Background, heating, DHW, washing machine, dishwasher, dryer, PV
eco-district	House	2	5000	Background, heating, DHW, washing machine, dishwasher, dryer, ST
with ST	House	5	5000	Background, heating, DHW, washing machine, dishwasher, dryer, ST
condomium	Apartment	1	12000	Background, heating, DHW, washing machine
district	Apartment	2	9000	Background, heating, DHW, washing machine, dishwasher, dryer
	House	5	9000	Background, heating, DHW, washing machine, dishwasher, dryer



(a) Self-sufficiency

(b) Demand

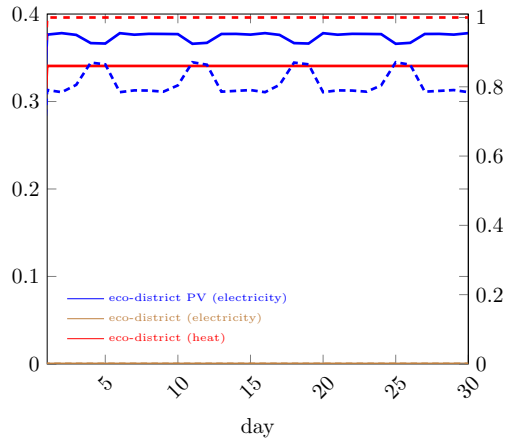
(c) Local production

(d) Energy exchanges (bought to the regional grid)

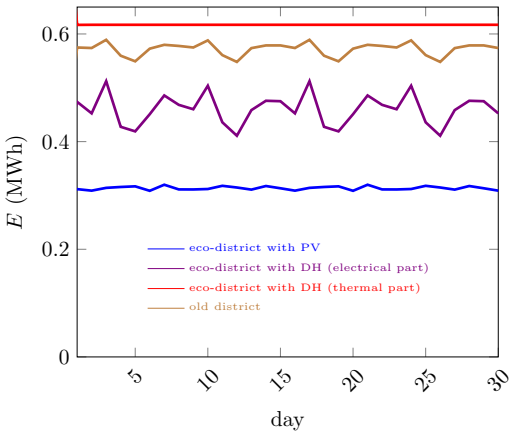
Figure 9 – Smart district operation over the year

This last case concerns a community involving three districts in Marseille, a city in the south-east of France with a mediterranean climate. This example involves a very large number of customers, since it comprises 50 000 housings and a total of 145 000 people, distributed and equipped as detailed in Table 4. The first two districts are eco-districts, with a different production system, *ceteris paribus*. Each of them is composed of 5 000 houses inhabited by 2 people and of 5 000 others occupied by a family of 5 people. In one of them, all houses do have building-integrated PV while the other eco-district is connected to a solar DH (containing also a HP). The third and last district is classical, composed of condomiums without any production system. It contains 12 000 apartments inhabited by 1 people, 9 000 with a couple and another 9 000 with 5-people families. Among all these customers, proportion to participate to DSM are: 50% BAU, 30% cooperative and 20% curtailment. For all the aggregators, a light autarky strategy is applied. Cost of electricity is at 0.10 /kWh while its resale is set at 0.15 /kWh.

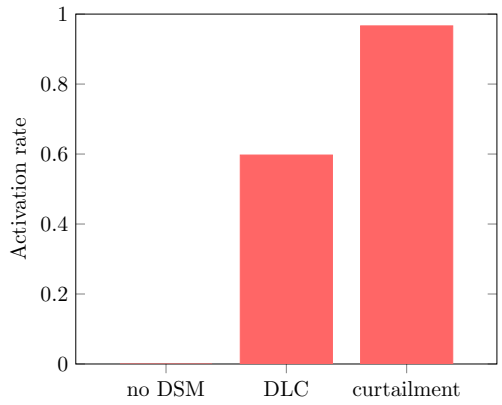
The simulation is run for the month of March. In this test, the investigated parameters will be curtailment rate of consumers for each different contract, the level of energy consumption and the profits realized by the aggregators.
When looking at Fig. 10, the first interesting result in Fig. 10a concerns the coverage rate and self-sufficiency of the two eco-districts. Apart for the electrical needs of the second district, only equipped with thermal generation, self-sufficiency shows very high levels with, respectively, 70% and 100% for the eco-district with PV and the eco-district with a solar DH. Consequently, the corresponding coverage rate for the electrical and thermal needs are 27% and 54%. Both districts having the same type of population and demand, this highlights first the interest of local thermal production (and not only electrical one) and second the pressure release that can be achieved when combining these RES with DSM. Lastly, the associated energy balances for each district are provided in Table 5. In a second step, it is worth noticing that when such possibilities are offered, the aggregators can heavily rely on DSM for the energy balances (see Fig. 10c). Nevertheless, it is also shown in Table 6 that the associated rates are different from one district to the other, though all of them have the same levels of participation for each contract. Such a difference is primarily explained by their various consumption profiles, and is also due to their different generation sources. This leads to two main remarks. First, curtailment rates can be tuned to be less a burden for both consumers and producers. This can be achieved either by combining more RES, and/or by increasing the number of such contracts to share this effort (both solutions are to be studied in an upcoming work). Second, the curtailment rate is not really higher even if no production units are available, as in the third district. This implies that, instead of a headlong rush for installation of new capacity to fulfill the ever increasing demand, DSM contracts could clearly play a more significant role. Naturally, this must be further investigated, and associated to a rigorous financial approach to see what would be at the end the most economically efficient solution. Eventually, it is important to remark that aggregators can earn money, as shown in Fig. 10d. Even in the unfavorable present situation, where the aggregator do not own neither production units nor any energy storage facilities to help her to manage supply and demand, the aggregation effect combined with the DSM approach permit to bring out a leeway and, consequently, to generate some profits. This underlines, if needed, the boons for the entrance of such participants in the energy market [128, Chapter III, Articles 17.1 and 19.1 and 32.1].
As above, the final remark will concern CPU time. Indeed, even in this example involving 276 000 devices for the 50 000 housings and 145 000 people, the needed time is only 4.5 hours. In terms of ratio, this corresponds to 0.1 s per people, or to 0.05 s per devices, which is more than acceptable.



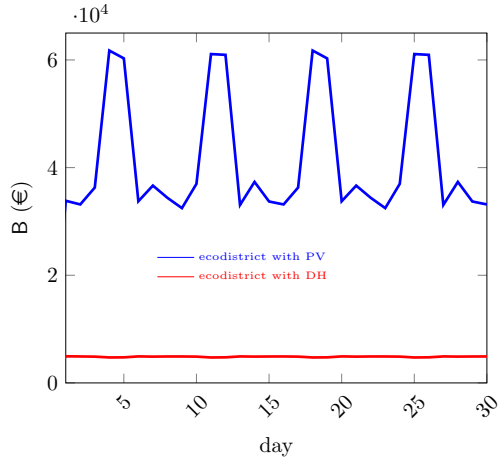
(a) Coverage (solid lines) and self-sufficiency (dashed)



(b) Consumptions



(c) Curtailment rate for each specific contract



(d) Aggregator's profits

Figure 10 – Smart community operation in March

Table 5 – Averaged monthly energy balances in MWh

aggregator	total consumption	local production	energy bought (external exchange)
eco-district with PV	463	182	336
eco-district with DH (in the format elec/heat)	113/74	0/40	122/9.7 †
old condomiums	576	0	576

† value corresponding to the heat demand (74-40=34) divided by the COP of the HP (34/3.5)

Table 6 – Overall curtailment rates

Aggregator's type	Consumers	Producers
eco-district with PV	0.31	0
eco-district with DH (in the format elec/heat)	0.46/0.62	N.A./0.52
old condomiums	0.57	N.A.

4 Conclusion

This paper extended the concept of smart grid to various grids (electrical, gas, heat, *etc.*) in mutual interactions. Combining a bottom-up description with a top-down management approach, `PEACEFULNESS` allows an holistic description of energy networks. Both centralized and distributed generation, as well as historical and RES technologies are available and can be managed; controllable or intermittent. Several DSM techniques are eligible for each nature of energy. Moreover, they can apply to productions (such as WT or hydraulic dams) or consumptions (*e.g.* space heating or elastic appliances), or to storage (for instance, BEES or SHTES). Strengths of `PEACEFULNESS` were demonstrated through several validation cases, highlighting the possibilities in terms of contract flexibility, distribution strategy and energy exchanges strategy with the external grids. In addition, an analysis has been conducted on three examples ranging from a single smart home to a large smart community. Each time, the interests of both the aggregator and DSM possibilities have been clearly shown. Results also present the wide range analysis opportunities offered, specifically concerning the earnings affordable.
Besides, it should be noted that present examples were primarily focused on the demonstration capacities of `PEACEFULNESS`. Several upcoming papers will further demonstrate these possibilities, and more interestingly, they will develop one of the aforementioned points. For example, the inclusion of storage, as well as other combinations of both RES and DSM contracts proportions will be scrutinized. In parallel, the possible profits for the aggregator will be further investigated. Such an analysis is planned both from a pure economic way but also using techno-economic analysis. Meanwhile, an increasing cost of the curtailment and shifting techniques will be tested to avoid high rates, especially for single customers [123]. Moreover, the elasticity-price on demand will also be handled. Finally, a deeper inclusion of behavioral schemes will be analyzed [129–133], as well as inclusion of rebound effects [134–138] or use of nudges [139]. Concerning the political considerations, an ongoing study aims at targeting the possible existence of minimal (and maximal) thresholds required to fulfill the future increase in energy demand [140]. Furthermore, the use of a second-best approach will be looked as [141]. In this respect, `PEACEFULNESS` will permit to see if the market could lead to the adoption of such levels or if regulation will be needed [142].

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Chapitre 3

Études de cas

Highlights

- DSM is tested for increase use of renewable energy in smart-mixed-grids
- Impacts of the level of DSM adoption by customers are investigated
- Tens of simulations are performed, each involving several thousands of agents with tens of appliances

Graphical highlight

Techno-economical analysis of demand response adoption and management strategies in smart-mixed-grids

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Abstract

Demand Response (DR) is an efficient and complementary approach to energy storage so as to cope with the management difficulties of renewable energy sources (RES). Specifically, Direct Load Control (DLC) has great potential as it allows managing both production and consumption.

Here, 2 districts of 11,000 inhabitants relying on DLC, partially fueled by renewable energy, are simulated. One of this district is fully electrical while the other has access to a District Heating Network. Some consumers participate to DLC and receive lower tariffs but some prefer traditional energy contracts. Different levels of participation to DLC and different grid management strategies are tested. Especially, 2 strategies with the same objective are tested, but the first one is based on physical criteria when the second is based on economical ones.

At the end, DLC has a positive impact on grid at the cost of a degradation of service for consumers participating (but their bills decrease). For several metrics, threshold are observed regarding levels of DLC participation. Last, the physical and the economical-based approaches give similar results.

Keywords: Smart grid; Renewable energy integration; Demand side management; Simulation

Contents

Nomenclature

Latin symbols

A	surface area, m^2
C	thermal capacitance, $J\,kg^{-1}$
$C_{\mathcal{P}}$	power coefficient, $-$
c	specific heat capacity, $J\,K^{-1}\,kg^{-1}$
COP	coefficient of performance, $-$
D	demand, kWh
E	total energy, J or kWh
E^{ff}	total energy, J or kWh
EER	energy efficiency ratio, $-$
G	building heat loss coefficient, $W\,K^{-1}\,m^{-3}$
g	gravitational acceleration, $m\,s^{-2}$
Hh	hydraulic height, m
$\mathcal{I}$	solar irradiance, $W\,m^{-2}$
LHV	lower heating value, $J\,m^{-3}$ or $J\,kg^{-1}$
MCC	marginal cost of curtailment, $/\,kWh$
NOCT	nominal operating cell temperature, °C
$\mathcal{P}$	power, W
P	price,
q	flow-rate, $m^3\,s^{-1}$ or $L\,s^{-1}$
R	residual effort, %
T	temperature, K or °C
t	time, s or min
$\boldsymbol{U}$	velocity, $m\,s^{-1}$
V	volume, m^3
z	height, m

Greek symbols

η	efficiency, $-$ or %
κ	open-circuit voltage thermal coefficient, K^{-1}
ρ	density, $kg\,m^{-3}$
τ	erosion velocity in curtailment contracts, s

Subscripts and superscripts

a	air
amb	ambient
bot	bottom
c	cooling
cell	cell
cut	cutoff
el	electrical
fu	fuel
gd	grid
h	hydraulic
ht	heating
in	indoor
inv	inverter
nom	nominal
out	outdoor
pan	panel
pp	pipe
ref	reference
sp	set point
top	top
wt	water

Acronyms

BAU	business as usual
BB	biomass burner
BEES	battery electrical energy storage
CCHP	combined cooling, heating and power
CHP	combined heating and power
DH	district heating
DHC	district heating and cooling
DHW	domestic hot water
DLC	direct load control
DR	demand response
DSM	demand side management
HEMS	home energy management system
HP	heat-pump
LS	load shifting
PV	photo-voltaic
RES	renewable energy sources
RTP	real time pricing
TES	thermal energy storage
TOU	time-of-use
TOUP	time-of-use pricing
WT	wind turbine

1 Introduction

1.1 Foreword

Though faced with probably the most paramount challenges it has ever encountered, Humanity is still engaged in a dangerous headlong rush towards more energy demand while relying too much on fossil fuels [1]. Moreover, the actual deployment of more decarbonized technologies, despite real and important (and to be pursued), is not replacing former generation plants but is instead added to a global portfolio; this latter stacking more and more sources of energy rather really replacing them. Besides, this trend should not change drastically in the coming years since the political uncertainties tend to favor a balanced solution including fossil plants [2]. However, very good reviews on possible decarbonization scenarios have shown that even the less agressive scenario implied efficiency efforts never seen before [3, 4]. As a consequence, it is clear that renewable sources (RES) will not be sufficient to address the issues raised by the limiting of the global warming. To tackle such a problem, increase of flexibility in the energy paradigm seems indispensable [5–7]. Furthermore, among the relevant technical solutions to achieve such a goal, demand side management (DSM) and similarly demand response (DR) appear as serious candidates [7,8]. In fact, the underlying principles and methods behind smart-grid are particularly pertinent due to the appearance of the concept of 4^{th} district heating generation [9, 10], or to manage intelligently multi-energy infrastructures [11, 12] as well as networks with multi-generation systems [13, 14].

1.2 Literature review

For the specific case of Europe (and North Africa), a decrease of the peak values around 15 and 37% has been estimated [15]. For more general and global advantages of DSM, as well as a rather exhaustive definition, the interested readers are referred to excellent reviews on the topic as in [6, sec. 3, pp. 787-791] or in [16] for coordination mechanisms. A complete analysis on the literature on smart-grids and DR being out of scope of the present work, the following examples will focus either on multi-energy cases or on load management (*e.g.* curtailment, direct load control, *etc.*). Thus, micro-grids relying on combined-heat-and-power (CHP) were tested without and with batteries (BEES) and DR programs in [17]. With a 25% curtailment limit, both solutions lead to a 15.77% decrease of the peak (from 558 kW to 470 kW). In the same idea, by testing three scheduling algorithms on electrical clusters, and also new cost metrics, large modifications of the loads were obtained in [5] for non-flexible power on-demand loads and deferrable loads (mainly electric vehicles and thermostatically controlled appliances and electrical storage). In another vein, a reduction of 39% of the energy costs can be easily obtained by defining intelligently a user-expected price, used in a simple DR algorithm comparing this later with a real time pricing (RTP) to make decisions [18]. Still with a dynamic pricing methodology, appliances were scheduled as a function of market prices and price penalties to find the best time horizon in [19]. It was thus shown that important reduction of the peak demand and increase of the load factor could be achieved, associated with a 68% reduction of the energy payments. Then, using interestingly an intermittent heating, which imposed bounds on temperature only at some hours, the procurement and consumers costs were reduced from 15 and 13% for heat needs in Belgian buildings [20]. Meanwhile, energy shifted was more than double and 14% of flexibility was attained with the same thermal comfort. By means of a new pricing policy, a for-profit aggregator-based residential DR approach achieved a 12.5% peak reduction of 5555 customers by rescheduling their loads [21]. Thermal inertia can also be used to maintain the stability of the electrical grid [22]: flexibility options offered by thermal storage (TES) permitted to reshape significantly the load durations and, correspondingly, the times of high

power consumption. In the same way, a hierarchical energy management system using three temporal decomposition (for heat, gas and electricity) was able to reduce the operating costs of a poly-generation micro-grid [23]. Later, in [24], a 6.37 MW curtailed power was attained (over 16.04 MW) to limit congestions failures only by rendering all non essential loads curtailable. When PV and BEES are both available on a grid, an interesting 'reputation-based' load management demonstrated the possibilities of 68% of cost savings [25]. Similarly, load shifting in district heating (DH) can alleviate the peak power between 685 kW and 900 kW on a distribution loop [26]. Such results were obtained simply by small positive anticipative changes of the thermal request of buildings. Still in the framework of coordination method for appliance scheduling, a very promising method was developed in [27]. There, the day-ahead management of a very large amount of devices and smart homes was tested with two models (group-based and turn-based) and led to significant peak (14%) and cost (20%) reductions. In the same way, yet only for electrical grids, an incentive program was proposed to customers allowing to be curtailed in a micro-grid including RES (PV, wind, CHP) and TES; it was able to reduce the operational costs up to 6% [28]. Another example of optimization of consumption/production of energy hub (electrical and thermal) after determination of the marginal price on each branch was presented in [29]. The DR program involved a RTP, and costs and peak reductions were obtained for both the hubs and the the grid (-10% and -14%, -29% and -14% respectively). In an extension of the above work, schedules of start-up and shut-down of heating systems could reduce thermal peak from 5% to 10% in one of the distribution networks of the Torino DH [30]. In a completely different context, since it concerns pelagic islands, a day-ahead distributed algorithm was set up in [31] to find the Nash equilibrium between minimization of the operational costs for the providers and maximization of the revenues for the aggregator and of the payoffs for the users. Finally, control scheme of the elastic demand by means of dynamic price signal broadcasting was successfully tested in [32], to tackle RES fluctuations.

1.3 Contribution and novelty of the study

In light of the above discussion, it appears that DR programs need still to be investigated in the case of multi-energy infrastructures, be it for the analysis of RES integration but also to further improve energy efficiency. Added to this, there is still a room for debate concerning the business model of the aggregator [33, 34], or any equivalent third-party in charge of the energy balance and responsible for both networks equilibrium and customers satisfaction. These are the two first cornerstones of the present paper:

1. studying the boons (or not) and drawbacks of implementing DR in smart mixed grids, in terms of energy efficiency, and of increase deployment and use of RES;

2. testing various strategies, and associated tariffs policies, to see if any value is added by such an organization, and where it is captured.
   Since most business models are more guided by regulatory constraints than by physical factors [33], we will start from classic schemes, using various pricing used in DR programs like market mechanisms for the adoption by the customers [5]. Here, the idea is to start with light evolution of the contractual interactions, and to pave the way towards more share economy [35].

Furthermore, once such rules have been defined, there is still a huge question to answer: how many people with such contracts are needed to really see some benefits ? And, are there any thresholds (minimum and maximum) ? In fact, more than flexibility, it queries the level of flexibility needed (or not) for DR to have significant impacts, and really justify its use. This research question was already addressed for electrical storages in order to limit excessive curtailment [36], or to target preferentially

buildings representing the main electrical consumption (*i.e.* more than 90%) [37]. In the same way, an enlightening study focused on the welfare impacts of DR depending on the noncooperative and cooperative behaviors of the agents [38]. More recently, the influence of the number of flexible users in a DH was investigated in [26, 30]. To the best of the authors knowledge, such an analysis has never been performed for multi-energy grids and it is therefore the last contribution proposed in the present work. To summarize, the main novelty of this paper is:

- to investigate the efficiency of DR for better use of RES in smart mixed grids;
- to investigate the influence of the type of contracts and their proportion among customers on the physical and socio-economical parameters;
- to explore the guidance of some political and economical decisions on the evolution of the energy market, in terms of need for enforced (or not) deployment of flexible contracts among customers.

2 Methodology

2.1 DSM

`PEACEFULNESS` (platform for transverse evaluation of control strategies for multi-energy smart grids) is a python open-source tool developed to model day-to-day management of multi-energy grids incorporating DSM [39]. It is able to handle hundreds of thousands of agents (consumers, producers, prosumers, *etc.*), with possibly tens of thousands appliances, combining various supply and/or demand profiles for electricity, heat, cold, gas... Energy management and balance of the different grids, locally or regionally, are under the responsibility of aggregators, which can also rely on DSM (and especially on DLC) to fulfill their role. Depending on the terms defined in the contracts with the agents, aggregators can serve, delay or reject an offer of consumption or production. Indeed, through a collaboration with Economists and Jurists, a set of possible contracts and system's organization have been defined: The underlying idea is that any effort consent by the customers is rewarded by another pricing policy (lower prices, extended off-peak pricing, *etc.*), or with other types of incentives. `PEACEFULNESS` is designed to be used as well as building's scale than at urban or regional levels. To ensure relatively low and acceptable calculation time (especially for electrical grids), the decision-process favor rule-based nheuristics on optimization methods, yet these latter could also be used. The basic overall principle for the whole energy management is depicted in Fig. 1. For the moment, `PEACEFULNESS` is only available for modeling but it should be extended for real-time operational controls. Simulations can be performed on an hourly or minute basis, for several months or years.

2.2 Devices

They are one of the key elements and represent the appliances consuming, producing, converting or storing energy. At the beginning of each turn, devices compute how much energy they want to consume or produce. Computing of this quantity varies from one appliance to another (see below), but it can be based on technical characteristics, user's habits (for domestic appliances) and databases (*e.g.* meteorological data for RES and temperature-related devices...). Then, a message is built composed of their minimum and maximum energy requirements, and an index of emergency. At this step, only users' habits, such as temperature setpoint for space heating or the last moment to start a cycle for a dishwasher, and technical constraints, as the irradiation for PV production or the maximum power of

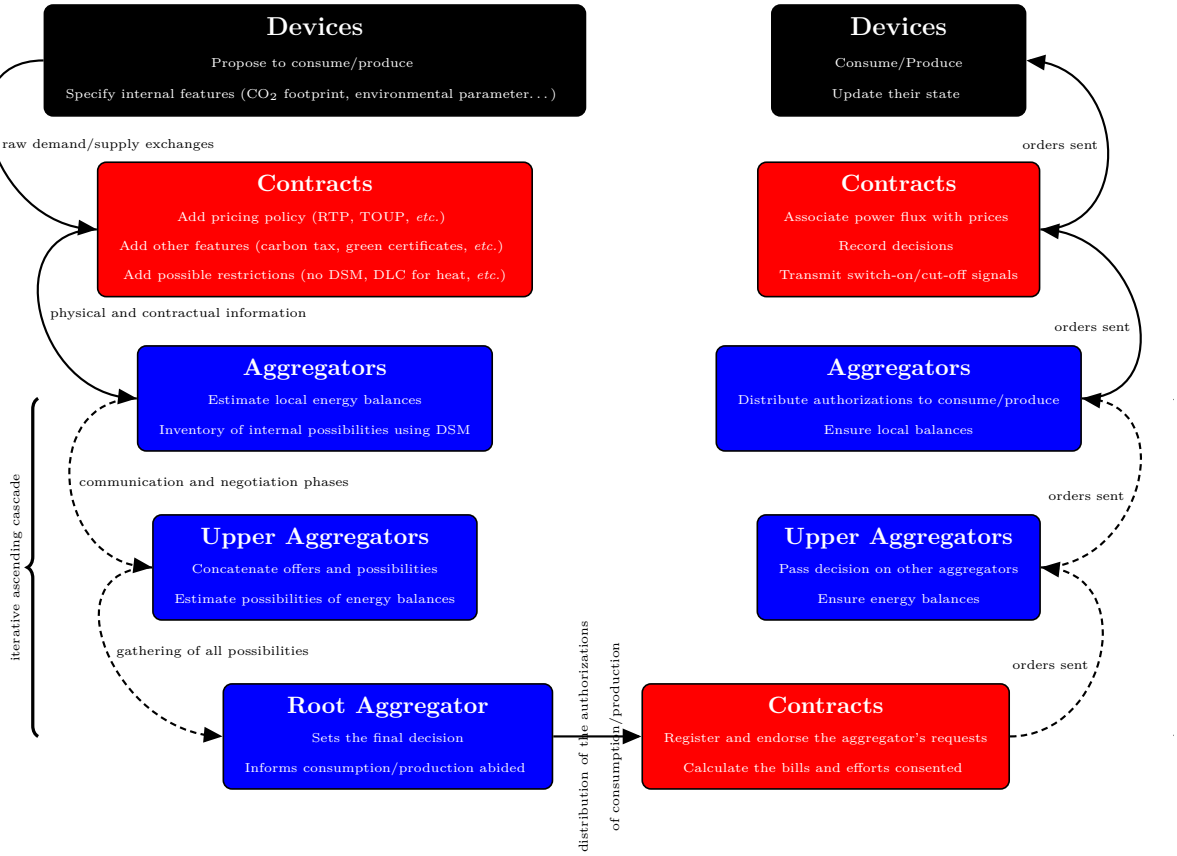


Figure 1 – Round decision process of the DSM tool

a water heater, are taken into account. Neither DSM nor pricing policies are involved, since they are managed by the contracts (see further).
Once this message will have been treated by the contract and, later, by the aggregators, the devices will know at the end of the round what quantity of energy they can consume or produce. Based on their initial request, they will update their internal state accordingly. Consequently, it allows them to know, for example, if a scheduled cycle has started or if they will have to ask for it once more during the following round.

2.2.1 Demand

First of all, it is important to notice that in a DLC paradigm, demand and consumption are different things. The former corresponds to the quantity of energy asked when the latter is the energy effectively consumed. Here, demand construction, independent from the enforcement of a DLC maneuver, is detailed, whereas consumption patterns are analyzed in section 4, as an outcome of DSM supervision.
In `PEACEFULNESS`, the demand is logically the sum of all the energy demand from each devices; each of them thus expressing its own needs in function of its features. In this study, six devices are involved (though many others are available): dishwashers, dryers, washing machines, space heating, water heaters (for DHW) and "background consumption". This latter represents all the non-shiftable devices with low levels of consumption: as their individual treatment has no interest for the grid manager, they are grouped together. Practically, background profiles were established by [40].
Shiftable devices, *i.e.* dryers, washing machines and dishwashers, are modeled with a cycle of consumption and a usage profile. The first indicates how many times the device will need energy and the corresponding needs; for instance, a dishwasher may have a program with corresponding needs: 1 kW the first hour, 3 kW the second hour, 0.5 the third and finally 2 kW for the last hour. The second indicates the usage done of this cycle, that is to say a time width englobing the hour ranges during which a cycle has to be launched and fully executed; as an example, the previous 4h program has to be done before the return of the user at 6.00 pm and can therefore be launched between 8.00 am and 2.00 pm.
Space heating is modeled classically with respect of a temperature setpoint, possibly varying during time. The corresponding quantity of energy is then calculated with a $\mathtt{R}-\mathtt{C}$ model [41], or any equivalent model [18, 42–45]:

$$E_{ht,c} = \Delta t \cdot \mathtt{G} \cdot V \cdot \left(T_{\text{sp}} - T_{\text{out}} - (T_{\text{in}} - T_{\text{out}})\, e^{-\frac{\Delta t}{\tau}}\right) \tag{2.1a}$$

$$E_{ht,c} = \mathtt{C} \cdot \left(T_{\text{sp}} - T_{\text{out}} - (T_{\text{in}} - T_{\text{out}})\, e^{-\frac{\Delta t}{\tau}}\right) \quad . \tag{2.1b}$$

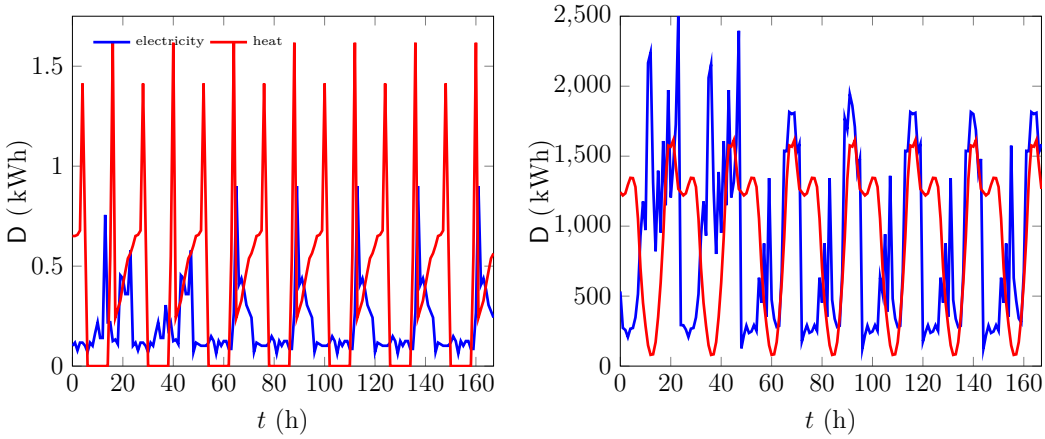
Likewise, models decomposing consumption between a basis and temperature-related demande could be used [46, 47], or even energy efficiency resource standards [48].
DHW profiles is composed of ranges of hours available to heat the water and the volume to be heated. All the usage data are extracted from [49]. Calculation of the amount of energy is made in two steps: first, the volume of water to be heated is calculated[1], secondly, the energy needed is deduced using the first law:

$$V_{\text{h}} = V^{\text{m}}_{\text{DHW}} \frac{40 - T_{\text{pp}}}{60 - T_{\text{pp}}} \quad . \tag{2.2a}$$

$$E_{\text{DHW}} = \rho_{wt} V_{\text{h}} \cdot c_{wt} \cdot (60 - T_{\text{pp}}) \tag{2.2b}$$

[1] It is different from the volume of hot water consumed. In France, DHW is heated at 55-60°C and consumed around 40°C.

That being said, the hundreds of thousands devices are not generated one after one. Instead, a random generator has been developed, using a customizable finite number of different profiles. Concretely, during the creation of each dwelling, a haphazard draw on the main characteristics of the device (level of consumption, start time of usage, *etc.*) is made: the mean is the value in the profile and the standard deviation is chosen by the user. With this method, we can, on the one hand, keep realistic individual profiles, with discontinuities and asynchronous behaviors between different agents. On the other hand, we can obtain smoother aggregated curbs, coherent with the real ones. An example of the differences between an individual profile and the corresponding aggregated demand of 1 000 people (once again, without any form of DSM) is viewable on Fig. 2.



(a) Individual profiles

(b) Aggregated profiles

Figure 2 – Examples of demand over one week

2.2.2 Production

Among the various generation sources available, five different production devices are used in this study: PV panel, WT, hydraulic dam, biomass burner (BB) and HP. PV and WT are not considered as flexible here, therefore their production must always be evacuated, one way or the other. However, the supervision can modulate the production of dams, HP and biomass burners. For the sake of clarity, yet without any loss of generality, no inertia is considered when running these technologies. They can consequently produce any amount of their maximal capacity.

PV production depends on the irradiation and the cell temperature, and it is given by [50, 51]:

$$\mathcal{P}_{\text{PV}} = \mathcal{I} \times A \times \eta_{\text{PV}} \times \eta_{\text{inv}} \tag{2.3a}$$

$$\eta_{\text{PV}}(T) = \eta_{\text{pan}} \left(1 - \kappa\left(T_{\text{cell}} - T_{\text{cell}}^{\text{ref}}\right) + \aleph \log_{10} \mathcal{I}\right) \approx \eta_{\text{pan}} \left(1 - \kappa\left(T_{\text{cell}} - T_{\text{cell}}^{\text{ref}}\right)\right) \tag{2.3b}$$

$$T_{\text{cell}} = T_{\text{amb}} + \left(\text{NOCT} - T_{\text{cell}}^{\text{ref}}\right) \frac{\mathcal{I}}{\mathcal{I}^{\text{ref}}} \tag{2.3c}$$

For WT production, one gets [28, 52]:

$$\mathcal{P}_{\text{WT}} = \begin{cases} 0 & \text{if} \quad U \leq U_{cut,\text{bot}} \text{ or } U \geq U_{cut,\text{top}} \\ \frac{1}{2}\rho_{\text{a}}\, C_{\mathcal{P}} U^3 \dfrac{U^3 - {U_{cut,\text{bot}}}^3}{{U_{\text{nom}}}^3 - {U_{cut,\text{bot}}}^3} \times A \times \eta_{\text{WT}} & \text{if} \quad U_{cut,\text{bot}} < U \leq U_{\text{nom}} \\ \frac{1}{2}\rho_{\text{a}}\, C_{\mathcal{P}} U^3 \times A \times \eta_{\text{WT}} & \text{if} \quad U_{\text{nom}} < U \leq U_{cut,\text{top}} \end{cases} \tag{2.4a}$$

$$U = U_{\text{ref}} \left(\frac{z}{z_{\text{ref}}} \right)^{\gamma} \tag{2.4b}$$

For the electrical production of a dam, one can use the following expression [53–56]:

$$\mathcal{P}_{\mathsf{h}} = \rho_{wt} \mathsf{g} \Delta H h \times \mathsf{q}_{wt} \times \eta_{\mathsf{h}} \tag{2.5}$$

The heat production of a biomass burner is [57–60]:

$$\mathcal{P}_{\text{BB}} = \mathsf{q}_{\text{fu}} \times LHV \times \eta_{\text{BB}} \tag{2.6}$$

Finally, heat and cool production from reversible HP rread:

$$\mathcal{P}_{\text{HP}} = \begin{pmatrix} \text{COP} \\ \text{EER} \end{pmatrix} \times \mathcal{P}_{\text{el}} \tag{2.7}$$

2.3 Contracts

As told above, contracts are first in charge of the pricing policy for the contemplated transactions. Secondly, given the allowed DSM rules for each device, they can modify (or not) the request sent by these latter before transmitting it to the aggregator. As an example, if no DSM is authorized, the emergency is set to maximum and the entire requested power is asked. In contrast, a curtailment contract will always indicate that a demand can be cut or delayed if necessary. In addition, other information than the ones related to the energy features can be provided, such as the carbon footprint, *etc.* To reward customers choosing DSM contracts, it was mentioned that several possibilities could be endorsed: an incentive for the amount curtailed, an equivalent amount available later (without modification of the price, especially during peak hours), a favorable TOUP ...

In the present study, a modified TOUP is enabled and three types of contrats are tested. The first, Business As Usual (BAU), is the contract for customers refusing DSM. It corresponds to the present paradigm where no efforts are asked and it is possible to consume or produce whatever and whenever they want. The second, "Cooperative" is a contract authorizing DLC but with little losses of comfort: it activates the shiftable devices, manages water heating and has a ± 1°C margin for space heating. Practically, given the thermal inertia of the building, it is for instance possible to slightly overheat to maximise usage of solar energy and then to reduce the evening consumption, or on the contrary, to let the temperature falls (within the above margin) to wait for the last moment to consume when thermal response is fast. People with this contract has a 10% discount on energy for both the off-peak and on-peak tariffs. The third contract, "Curtailment", gives the power to the aggregator to outright reject any demand or supply. Obviously, such a constraint is pretty tough and, as a consequence, people accepting such contracts are rewarded in two ways. First, they also have the aforementioned 10% discount. Second, and more interestingly, an approach directly inspired from Economics works [33, 34, 61] is tested: the aggregator has to repay them the energy it refuses to them: refusing a demand, is, for the aggregator, like buying energy from a producer. Practically, the price of the energy repaid by the aggregator increases

with the effort made by a consumer: curtailing a second time someone is more expensive than curtailing someone for the first time and the aggregator is encouraged to distribute the effort among the consumers (having such contracts). This price is a product of the effort E^{ff} and a coefficient defined by the user:

$$\mathsf{P}_{\mathsf{refund}} = E^{\text{ff}} \cdot \mathsf{MCC} \tag{2.8}$$

This effort is incremented each time the customer is curtailed, proportionally to the amount of energy rejected:

$$E^{\text{ff}} = E^{\text{ff}} + \frac{E_{\text{refused}}}{E_{\text{served}}} \tag{2.9}$$

Meanwhile, the effort is also decremented at each round, following an exponential decrease, whose velocity is governed by two parameters: a residual and the time necessary to reach it. For example, a residual of 50% after 1 week would mean that, after 1 week without curtailment, the value of effort is divided by 2:

$$E^{\text{ff}} = E^{\text{ff}} \cdot \exp\left(\frac{t \cdot \ln(1-R)}{\tau}\right) \tag{2.10}$$

2.4 Aggregators and strategies

Aggregators are the agents in charge of clusters of customers and of their devices [62]. Concretely, they have to make sure consumption and production are equal at each time step. Several options are available to them: modulate the production, use storage, exchange energies with other energy networks but also adapt the consumption curb through DLC. In order to arbitrate between these different options, aggregators are relying on a strategy. In `PEACEFULNESS`, aggregators have a spatial identity: they are in charge of all the buildings of this village or of this district.

When they receive the messages sent by contracts, they make local energy balances and decide how much they want to exchange, taken into account all the previous parameters and the options really feasible inside their own perimeter of influence (*e.g.* access to a storage, or not, *etc.*) [5]. Three exchanges strategies are presented in this work: "Always Satisfied", "Light Autarky" and "Profitable". "Always Satisfied" is the no-DSM strategy, where every demand or supply of energy is always accepte. It serves as a reference when comparing with grids incorporating DSM. "Light Autarky" is a strategy aiming to maximize self-sufficiency while guaranteeing a minimum service: it does not exchange energy if it is not to satisfy urgent needs. "Profitable" is a strategy where the aggregator, once a solution is found for urgent needs, exchanges only if it can make benefits on the transaction.

As it was shown in Fig. 1, once aggregators know how much they have exchanged with the outside (because other aggregators have the choice to accept or refuse the exchange), they have to distribute energy internally. To do so, two approaches are demonstrated in this article: "Full Service" and "Partial Service". In the full service approach, all the demands and proposals of energy are sorted according to an user-defined criterion. Once it is made, aggregator satisfies completely the first devices in the sorted list. In this study, emergency is the chosen criterion. In the partial service approach, every non-urgent demand or proposal is served, but not completely: they all receive the same proportion of energy demand.

2.5 Dedicated example

In Fig. 3, an illustration is presented for the implementation of DSM for one of the strategy employed in this study. There, at the beginning of a supervision round, the example of a dryer asking to start

a non-urgent cycle is shown. This demand is thus transmitted to its contract. The latter adapts the message, since DLC constraints are accepted by this device and, consequently, non-urgent tasks can be curtailed. A price signal is also tagged with this demand, and sent to the aggregator. Then, this one, considering all the demand to fulfill and for the dryer's needs are non-urgent, decides to refuse this start-up in accordance with its "Light Autarky" strategy. This decision is sent to the contract. As this specific kind of contract has nothing to do here, it just transmits the information to the dryer. The dryer learns it won't be able to start the cycle: it will ask for it once again next time. The round ends here.

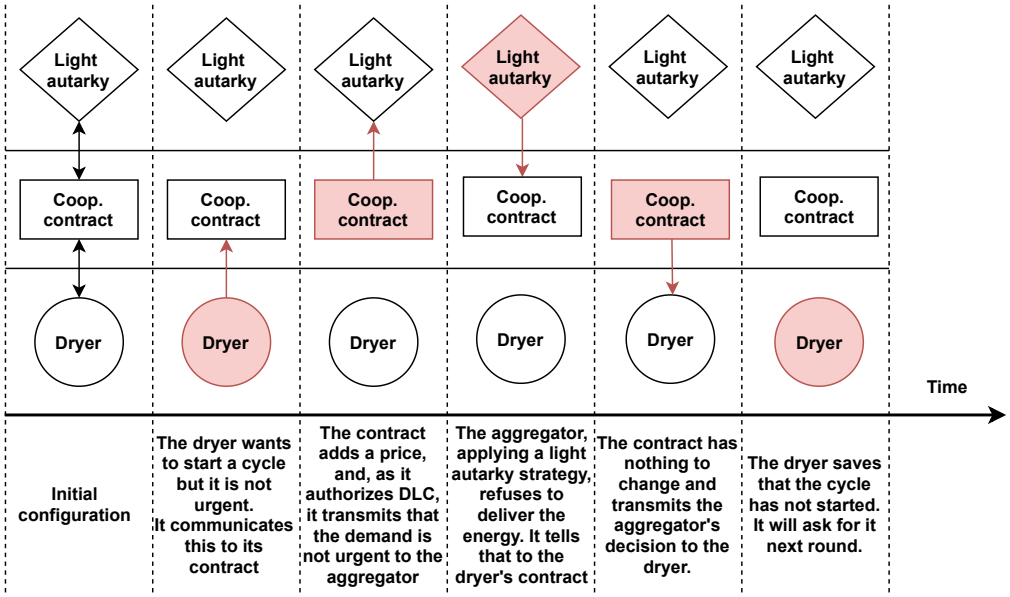


Figure 3 – An illustration of DSM process

3 Cases investigated

3.1 Description

Two different smart-districts will be presented to study the influence of the DSM strategies on the fulfillment of the customers needs, the equilibrium of the network, and the corresponding costs. In both cases, 5 000 dwellings, distributed as presented in Table 1, are involved. For the DSM strategies to be tested, a physical and an economical approaches are used; they have in common the objective to test if such a choice is neutral or not. Concerning the level of engagement of the customers to DSM contracts, five values will be tested, from 0 to 80%. Indeed, DSM having potentially non-linear effects, it is fundamental to investigate the influence of its widespread (and maybe its needs) among the population. The first case investigated is represented on Fig. 4a. It deals with a single energy network, namely an electrical grid. Non-flexible RES are available through 12 500 m of PV panels and 5 WT of 6 MW each, as well as a controllable 3 MW hydraulic dam associated with a flexible contract allowing the aggregator of the grid to manage its production (start-up or shut-down, full power or not, *etc.*).

The second case is illustrated by Fig. 4b and considers multi-energy networks, since the previous electrical grid now co-exists with a DH network. For the generation, only the above non-flexible RES are installed for electricity, while heat (for space heating and DHW) are provided by the DH by means of a flexible 2 MW BB and a 2 MW HP.
For the sake of simplicity, basic loads are the same in the two cases. Furthermore, the sizing is insufficient to cover all the needs and therefore, the backup solution lies in the connection with the regional electrical grid. Besides, non-flexible RES will generate important production peaks (especially the WT) that will have to be handled by the aggregators. All meteorological data correspond to the city of Pau, in France.

Table 1 – Description of the dwellings

Type	Number of persons	Amount	Devices
Apartment	1	2000	Background, heating, DHW, washing machine
Apartment	2	2000	Background, heating, DHW, washing machine, dishwasher, dryer
House	5	1000	Background, heating, DHW, washing machine, dishwasher, dryer

n.b.: Background is an aggregated profile, combining TVs, computers, lights, kettles, *etc.*

The different prices practiced are detailed in Table 2. They were set up with the "Profitable" strategy in mind. On the electrical side, the aggregator looses money when it uses national grid energy to satisfy DSM customers needs and when it sells renewable energy to the national grid. On the DH side, using the local producer to fuel the DSM customers is also unprofitable. Thus, an aggregator using a "Profitable" approach is encouraged to maximise the local consumption of RES, especially the non-flexible ones, *i.e.* PV and WT. Being set like this, it is expected to behave similarly to light autarky strategies. The price of the HP comes from the cost of electricity: HP is seen like a cooperative consumer for the local electrical grid and thus pays electricity 15.3 c / kWh. Divided by its efficiency of 2.5, it gives a price of 6.12 c / kWh for the DH.

Table 2 – Financial parameters

	Electricity					Heat			
	National grid		Producers	Consumers		HP	Producer	Consumers	
	buying	selling		BAU	DSM			BAU	DSM
Price	17	5	14	17	15.3	6.12	10	10	9

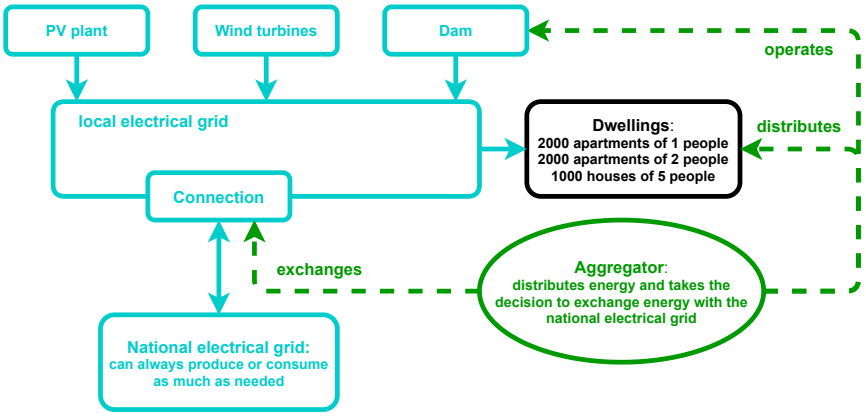
Concerning the curtailment contract, we chose that the effort had to reach 1% of its initial value after 1 month. We also imposed that the refund for the consumer had to reach the price of electricity from the national grid after three demands entirely rejected per day, *i.e.* 90 hours per month. We used the following formula to find the corresponding refund:

$$\mathsf{P}_{\mathsf{refund}} = \frac{\mathsf{P}_{\mathrm{gd}} - \mathsf{P}_{\mathrm{DSM}}}{N_{\mathrm{h/month}}} \tag{3.11}$$

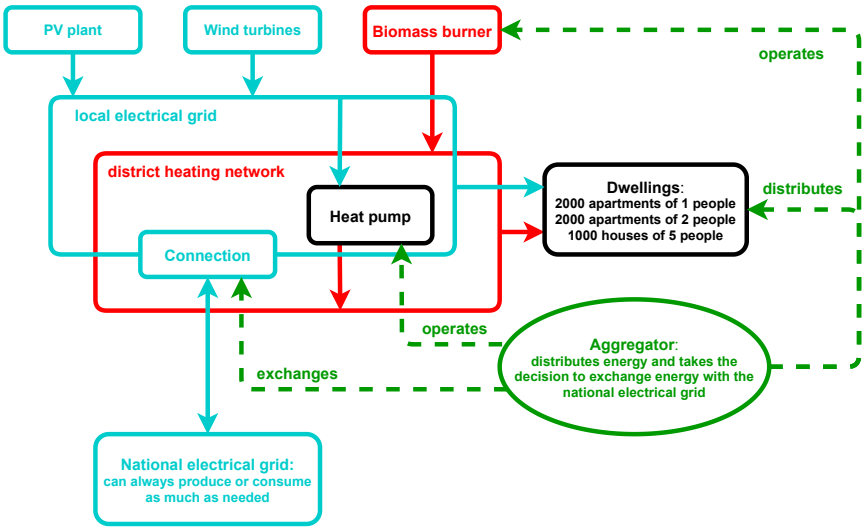
At the end, we get a refund per demand refused of 0.019 c for electricity and 0.011 c for heat.

3.2 Simulation plan

As mentioned before, the main goal is to explore the impact of DSM in two different smart-grids, scrutinizing different grid management approaches and DSM penetration levels. Concretely, three parameters are varied all along this work:



(a) Smart electrical grid



(b) Smart electrical and thermal grid

Figure 4 – Schematic representation of the two smart-districts investigated

- DSM proportion: the percentage of people having subscribed to a DSM program. Four different levels are investigated, from 20 to 80%, the case with 0% being also treated and taken as a reference. It was hypothesized that cooperative contracts are more popular than curtailment contracts, as they are less constraining, in a 40/60% proportion.
- Exchange strategy: two situations were considered regarding exchanges with the national electrical grid, namely "Light Autarky" and "Profitable" (see subsection 2.4).
- Distribution strategy: two candidates are investigated here, "Full Service", where even some non-urgent needs are fully covered, and "Partial Service", where all non-urgent needs are partially covered (see *ibidem*).

Finally, this leads to 32 combinations, plus 2 references cases with no DSM at all, which are all presented in Table 3. The simulation lasts for a whole year, at an hourly time step.

Table 3 – Simulation plan

Name of the run	smart grid	Contracts proportion (%)			Exchange strategy	Distribution strategy
		BAU	Cooperative	Curtailment		
RE	electricity	100	0	0	classic	N/A
AFE20	electricity	80	12	8	autarky	full
APE20	electricity	80	12	8	autarky	partial
PFE20	electricity	80	12	8	profitable	full
PPE20	electricity	80	12	8	profitable	partial
AFE40	electricity	60	24	16	autarky	full
APE40	electricity	60	24	16	autarky	partial
PFE40	electricity	60	24	16	profitable	full
PPE40	electricity	60	24	16	profitable	partial
AFE60	electricity	40	36	24	autarky	full
APE60	electricity	40	36	24	autarky	partial
PFE60	electricity	40	36	24	profitable	full
PPE60	electricity	40	36	24	profitable	partial
AFE80	electricity	20	48	32	autarky	full
APE80	electricity	20	48	32	autarky	partial
PFE80	electricity	20	48	32	profitable	full
PPE80	electricity	20	48	32	profitable	partial
RM	multi-energy	100	0	0	classic	N/A
AFM20	multi-energy	80	12	8	autarky	full
APM20	multi-energy	80	12	8	autarky	partial
PFM20	multi-energy	80	12	8	profitable	full
PPM20	multi-energy	80	12	8	profitable	partial
AFM40	multi-energy	60	24	16	autarky	full
APM40	multi-energy	60	24	16	autarky	partial
PFM40	multi-energy	60	24	16	profitable	full
PPM40	multi-energy	60	24	16	profitable	partial
AFM60	multi-energy	40	36	24	autarky	full
APM60	multi-energy	40	36	24	autarky	partial
PFM60	multi-energy	40	36	24	profitable	full
PPM60	multi-energy	40	36	24	profitable	partial
AFM80	multi-energy	20	48	32	autarky	full
APM80	multi-energy	20	48	32	autarky	partial
PFM80	multi-energy	20	48	32	profitable	full
PPM80	multi-energy	20	48	32	profitable	partial

3.3 Outputs analysed

In this work, physical, social and economic aspects of grid management and DSM are analysed. If peaks and self-sufficiency are essential in an energetical approach, curtailment rates and bills of consumers are the key performance indicators for social desirability. Last, producers revenues and aggregator profits are needed to assess the economical sustainability of the system. Therefore, we analyse the following outputs:

- Raw peaks: consumption and production peaks during the whole year.
- Mismatch peak: most important differences between local consumption and local production during the year: consumption corresponds to the largest excess of consumption and production to the largest excess of production.
- Self-consumption: proportion of local production being consumed locally.
- Coverage rate: proportion of energy consumed being produced locally.
- Curtailment and delaying: proportion of needs expressed by devices being refused by the aggregator.
  Here, it is worth mentioning that it does not necessarily imply comfort losses, since it corresponds also to LS (for example DHW or dishwashers) where the demand is just postponed. It is calculated for consumers and producers separately.
- Consumers bills: money spent monthly by consumers.
- Producers revenues: quantity of money received by the producers along the year.
  Note that no production costs are integrated in this study.
- Aggregator profits: profits realized by the aggregator along the year by trading energy and managing production and consumption appliances.

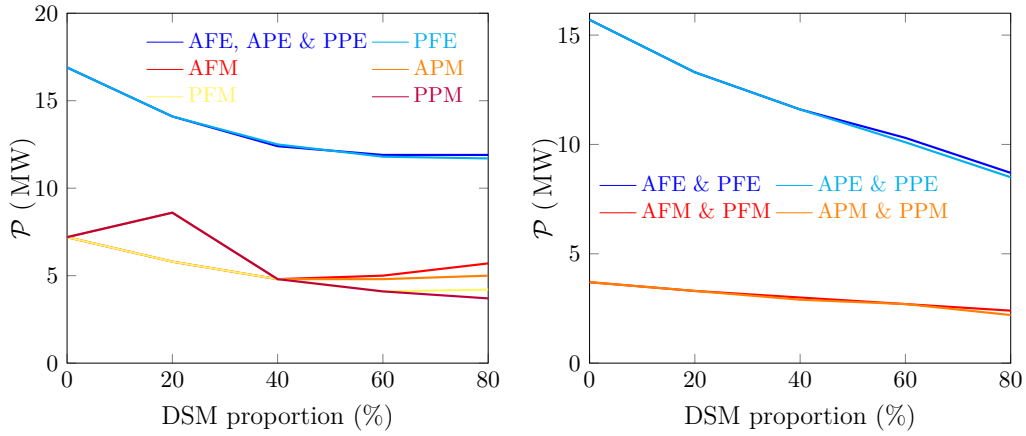
4 Results and discussion

To have a synthetic view of the two test cases, physical powers have been gathered in Fig. 5 while the operational and economic parameters are visible in Fig. 6.

4.1 Smart electrical grid

The specific results for the electricity-only network are detailed in Table 4. As a reminder, in this case, the aggregator has to manage a PV plant, six WT and an electric dam to satisfy 5 000 dwellings. It has also access to the national electrical grid. Examples of the obtained production profiles, and the corresponding total production and consumptions are shown in Fig. 7 for the AFE20 and AFE80 cases.

First, it is important to note in Fig. 5a that consumption peaks are decreased up to 30% with DSM penetration of 60%. Second, it is worth noticing that no more gains are achieved by increasing this proportion to 80%. This clearly demonstrates the interest of DSM, but also that it is not necessary for all the customers to shift towards such contracts. Besides, there are few differences observed here between the tested distribution and exchange strategies. At best, the "Profitable" and "Full Service"



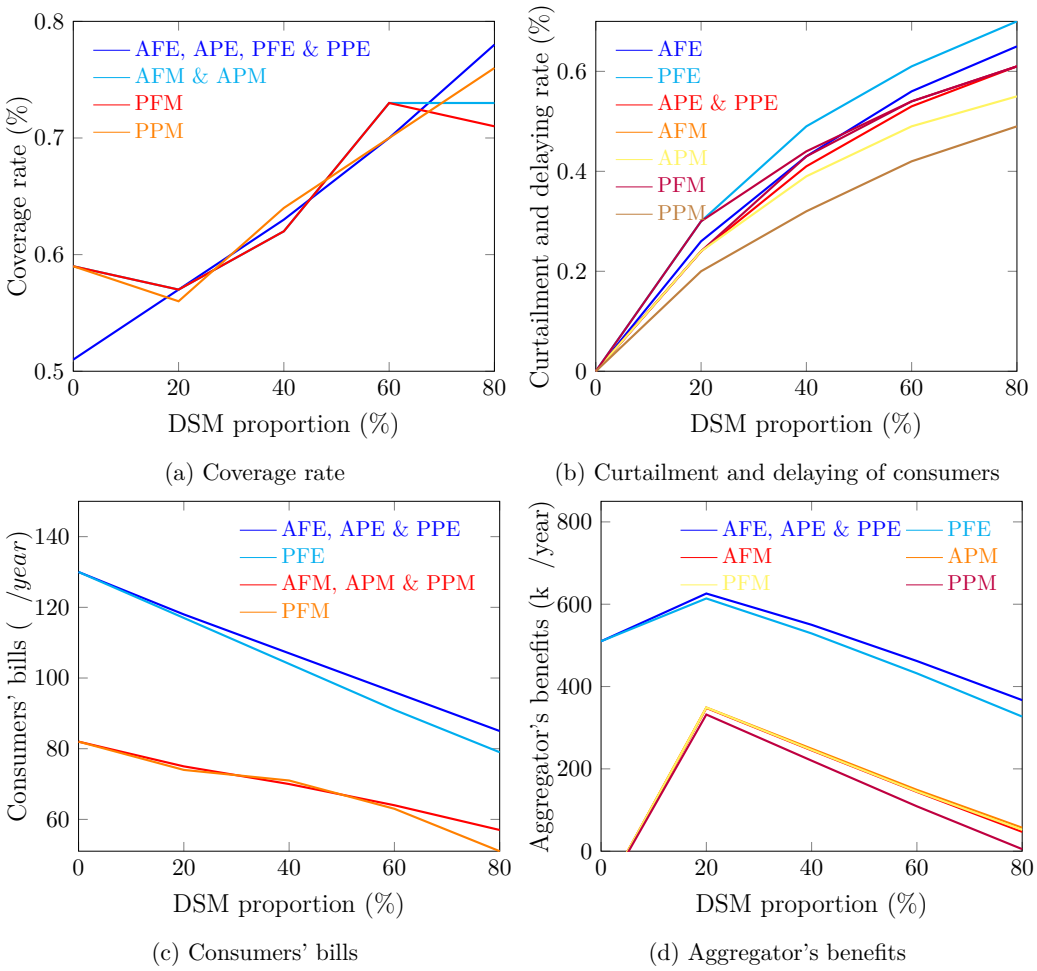
(a) Electrical consumption peaks

(b) Electrical mismatch peaks

(c) Heat consumption peaks

(d) Heat mismatch peaks

Figure 5 – Evolution of supply and demand as a function of strategy and DSM adoption



(a) Coverage rate

(b) Curtailment and delaying of consumers

(c) Consumers' bills

(d) Aggregator's benefits

Figure 6 – Metrics evolution in function of strategy and DSM, part 2

configuration leads to a reduction of 4% by comparison with the other schemes (corresponding to an absolute 1.2% decrease from the reference case). Concretely, it implies that a very high level of demand would be necessary, *i.e.* a very large energy community, for this 1.2% supplementary reduction to be meaningful. In any case, it is of second order when compared with the use of DSM. Lastly, the mismatch is also singularly decreased since it is 46% lower when participation to DSM is of 80%. Similarly, strategies employed are not very different, those preferring "Partial Service" being 3% better than the others. Concerning production, we can see on Table 4 that the different levels of DSM and strategies have no importance: the peak is always at 22.4 MW when it is of 24.5 MW for the reference case. This is due to the impossibility here to cut-off PV or WT production, and only dam generation is controllable, which is the least powerful source. Nonetheless, as observed in Fig. 7, the final profiles can be very different and the DSM can really decrease the mismatch between supply and demand. Unfortunately, a precise analysis demonstrated that no flexible consumption was available during the peak with the present configuration, *i.e.* for such a district and its RES: the rise of wind production being progressive, they were all used by the aggregator in the hours preceding the peak. This means that, in an approach aiming specifically at reducing production excess, meteorological forecast would have been mandatory to get reductions scaling with DSM participation yet it would have been feasible.

Simulations show that DSM is able to improve the self-sufficiency of the district. For self-consumption, *i.e.* RES production absorbed locally, the situation is the same as for production and production excess peaks: a gap is observed between reference configuration and DSM ones (from 75% to 90%), with close values for the latter. The explanation is also the same: the non-controllable nature of PV and WT production limit DSM possibilities. However, this is already a real improvement, which could be further exploited with forecasts and use of storage (but with extra costs). For coverage rate (proportion of consumption satisfied by local production), it increases proportionally with the participation to DSM, as shown by Fig. 6a: it goes from 51% to 78%, which is excellent, whatever the strategy implemented. Reference has, by definition, no curtailment but DSM solicited both consumers and producers. On the consumers side, illustrated by Fig. 6b, curtailment and delaying increase with DSM participation, up to 70%. More important, the strategy adopted by the aggregator has here a significant impact: the best strategies are those applying Partial Service, followed by the Autarky Full Service (+5-10% compared to the bests) and the Profitable Full Service is the worst (+15-20%). The relative efficiency of the Partial Service comes from the fact that, as it tries to serve everyone, it tends to start earlier the different devices and this reduces the delaying (accounted in this metric). Moreover, Profitable strategies do not necessarily use the dam to satisfy non-urgent needs and it is thus not so efficient. For producers, the Profitable Full service strategy tends to curtail more than the others strategies (between 23% and 100% more), and more with an increasing DSM levels (from 16% to 20%). The three other strategies, however, are almost insensible to this level, and give identical results with less curtailment when DSM increases (from 13% to 11%). This upturn comes from DSM: passing from 20 to at least 40% of participation creates more flexible demand and allows to improve the use of the dam. The difference between strategies arises from the previous difference on consumer's curtailment and delaying. In summary, there is indeed a (natural) increase or curtailment yet this latter can be limited, and it achieves high values only for a small part of the consumers (the maximum having such contract being 32%). In contrast, production is rarely limited.

Eventually, on the financial side (see Fig. 6c), consumers' bills decrease significantly from 130 to 79 per month. And here, people curtailed are finally not losing so much: the curtailed energy is not consumed, and consequently not bought, while the rest of the consumption is obtained at a cheaper price. Besides, no differences beyond 10% are observed among strategies and they are a consequence of consumers curtailment. Similarly, producers' revenues are inversely proportional to producers curtailment: for all

strategies except Profitable full service, it decreases from 4.4 to 3.6 M per year when 20% of people participate to DSM and then rises to 3.9. For the Profitable full service strategy, it decreases continuously with DSM, to 3.5 M per year. Concerning the aggregator's profits, presented on Fig. 6d, Profitable Full Service strategy, once again, differs from the others, earning less and less than the others as DSM increases (up to 11% less). The effect of DSM is interesting here: an important increase is seen between the reference scenario (510k) and the 20% DSM cases (614 and 626k). This comes from the better usage of local RES allowed by DSM. As renewable energy is cheaper, it improves aggregator's benefits. Meanwhile, as observed earlier, going beyond 20% does not increase significantly this usage. Thus, when DSM is adopted by 40 to 80% of the population, the reduction of consumption, combined with the lower tariffs offered by DSM, lead to a reduction of the benefits. However, there is still place for a profitable business for an aggregator, showing thus the feasibility of such modifications of the market.

4.2 smart electrical and thermal grids

The results for the multi-energy network are detailed in Table 5 (electricity/heat). Here, the aggregator has access to a PV plant, WT and a connection with the national grid to satisfy electrical needs of the 5 000 dwellings. Space heating and DHW are covered by a DH having access to a BB and a HP. As previously, various profiles over the year are presented in Fig. 8 for the AFM20 and AFM80 cases.

Beginning by the analysis of the peaks, it is noticeable that increasing DSM always allows to decrease largely consumption peaks, for both electricity (from 7.2 to 3.7 MW) and heat (from 11.3 to 5 MW) (Figs. 5a and 5c). Profitable strategies are better for high levels of DSM participation (up to -25/45% compared to autarky, and the same behaviour is observed for partial service compared to full service (around -10% for both energies). Meanwhile, when 20% of people have DSM contracts, the peak is not better than the reference for heat and even worse for electricity (from 7.2 to 8.6 MW). This is a matter of timing: generally, partial service strategies tend to serve earlier than full service. Nonetheless, increasing DSM allows to reduce mismatch peaks for consumption for all strategies. Production peaks, however, never change on both networks for different reasons. On the electrical grid, the two RES, PV an WT, are not controllable, with no reduction possibility. Meanwhile, the mismatch peak for production tells us that DSM is unable to improve the usage of this production peak: it comes form the fact that electrical loads are far less flexible than thermal ones. On the DH side, production peak measures the BB production; 2 MW being the max capacity. It means that it is used at full capacity at least once in the year. There is no mismatch on production on the DHN because, as the production is fully controllable, the plant is activated only when consumption is available.

One of the consequence of this is that, contrary to electricity, all the DH production is consumed. As said before, the lack of flexibility for both production and consumption forbids DSM to improve self-consumption: in all cases, reference scenario included, it goes from 60 to 65%. However, the coverage rate is really improved by DSM for both electricity (+73%) and heat (+45%). Fig. 6a shows the averaged coverage rate, both energies included. The chosen strategy has little influence for electricity but not for the DH: Profitable strategies are a bit more efficient (up to +10% more).
Curtailment on the consumer side increases with DSM. Highest values are observed for heat (up to 87%) than for electricity (up to 57%), for an average of 71-76% for both energies, as shown on Fig. 6b. The chosen strategy has a significant impact, but differently for electricity and heat. Profitable strategies practice less curtailment than autarky ones (from -25 to -43% for full service and from -30 to -63% for the other) on the electricity grid. It has opposite effects on the DH: it goes up to 87% for Profitable full service, 69% for Profitable partial service, 66% for autarky full service and 62% for autarky partial ser-

Table 4 – Results for the full electricity configuration

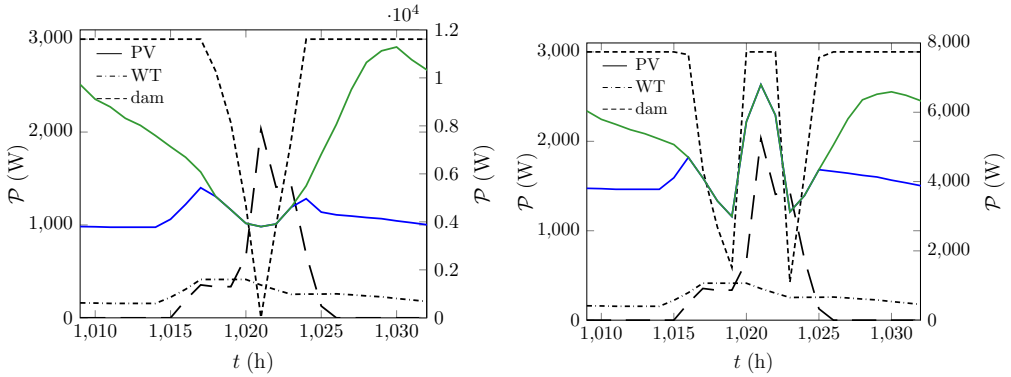
Name of the run	Raw peaks		Mismatch peaks		Self-sufficiency		Curtailment and delaying		Money balances		
	Cons.	Prod.	Cons.	Prod.	Self-consumption	Coverage rate	Consumers	Producers	Consumers	Producers	Aggregator
	MW	MW	MW	MW	%	%	%	%	*/month*	*M /year*	*k /year*
RE	16.9	24.5	15.7	21.7	75	51	0	0	130	4.4	510
AFE20	14.1	22.4	13.3	19.3	88	57	26	13	119	3.8	626
APE20	14.1	22.4	13.3	18.9	88	57	24	13	118	3.8	626
PFE20	14.1	22.4	13.3	18.9	89	56	30	16	117	3.5	614
PPE20	14.1	22.4	13.3	18.9	88	57	24	13	118	3.6	626
AFE40	12.4	22.4	11.6	18.9	89	63	43	11	108	3.9	550
APE40	12.4	22.4	11.6	18.6	89	63	41	12	107	3.9	550
PFE40	12.5	22.4	11.6	18.6	90	62	49	17	104	3.5	529
PPE40	12.4	22.4	11.6	18.6	89	63	41	12	107	3.7	550
AFE60	11.9	22.4	10.3	18.6	90	70	56	11	97	3.9	462
APE60	11.9	22.4	10.1	18.6	90	71	53	11	95	3.9	462
PFE60	11.8	22.4	10.3	18.6	90	68	61	18	91	3.4	432
PPE60	11.9	22.4	10.1	18.6	90	71	53	11	95	3.9	462
AFE80	11.9	22.4	8.7	18.6	91	78	65	10	86	4.0	367
APE80	11.9	22.4	8.5	18.6	90	78	61	11	85	3.9	367
PFE80	11.7	22.4	8.7	18.6	90	76	70	20	79	3.5	327
PPE80	11.9	22.4	8.5	18.6	90	78	61	11	85	3.9	367

vice. For producers, there is no curtailment for the electrical grid (PV and WT being non-controllable). In the DH, it works as observed in the previous section: the maximum curtailment is reached at 20% of DSM participation and then reduces to 90% when DSM increases, just like in the electricity-only grid: DSM offers new opportunities to use the local plant. All strategies are equal (between 27 and 31%) except Profitable full service, which curtails 50% more.

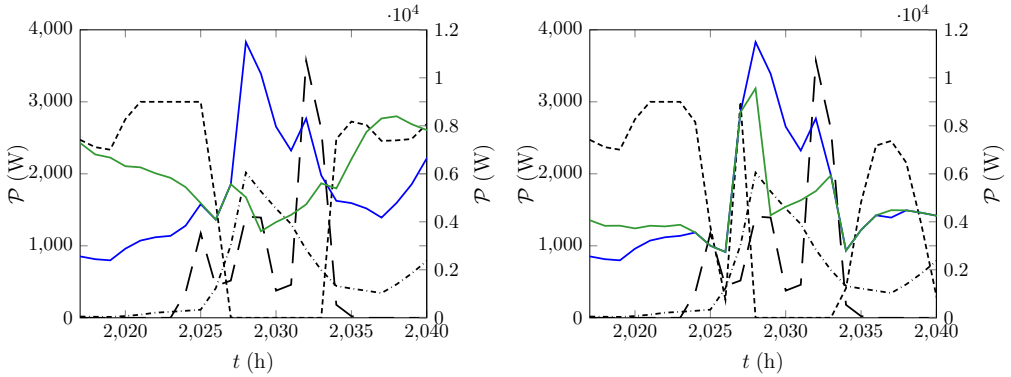
As observed in the previous example, producers' revenues are inversely proportional to producers' curtailment. Consequently, they are always equal to 1.9 M per year for electricity and evolve a bit for heat. They are around 1.0 M per year for Profitable full service and 1.3 M per year for the others. Concerning consumers' bills, depicted on Fig. 6c, they decrease with DSM, in the same proportions for electricity and heat (-30%), for almost all strategies. The only exception is the Profitable full service strategy for heat: as it curtails more, bills are lower, with a maximum reduction of 50% when compared to the reference scenario. Lastly, aggregator's benefits, presented on Fig. 6d, are always positive overall but, in configurations with 80% DSM, it looses money on the DH alone. Generally, increasing DSM tends to reduce the benefits, because of curtailment and lower tariffs (from 178 /170 k per year to 72 /-69). Among the different strategies, close results are obtained for electricity. For heat, however, Profitable partial service strategy is noticeably worse: it earns between 12 (with 20% DSM participation) and 36 k (with 80% DSM participation) less than the other strategies.

Table 5 – Results for the electricity and heat configuration

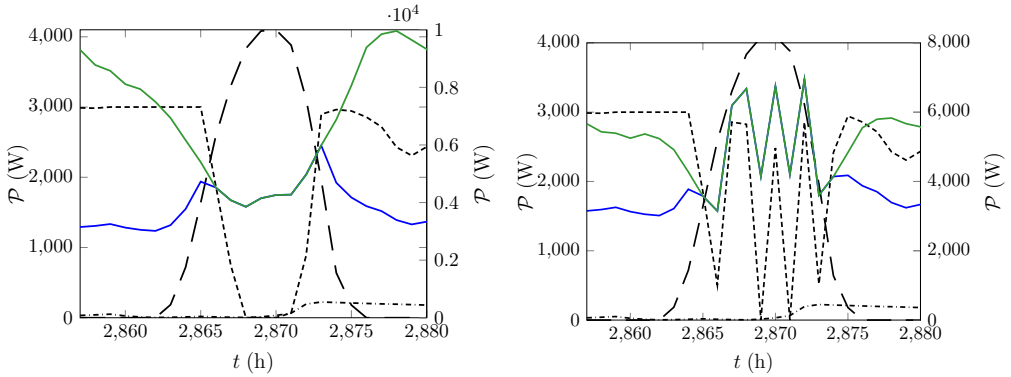
Name of the run	Peaks		Mismatch peaks		Self-sufficiency		Curtailment and delaying		Money balances		
	Cons. MW	Prod. MW	Cons. MW	Prod. MW	Self-consumption %	Coverage rate %	Consumers %	Producers %	Consumers /*month*	Producers *M* /*year*	Aggregator *k* /*year*
RM	7.2 /11.3	22.4 /2.0	3.7 /11.3	21.0 /0	61 /100	40 /65	0 /0	0 /0	52 /30	1.9 /1.8	207 /-325
AFM20	5.8 /9.0	22.4 /2.0	3.3 /7.0	21.0 /0	62 /100	45 /71	23 /30	0 /31	48 /28	1.9 /1.2	178 /170
APM20	8.6 /11.3	22.4 /2.0	3.3 /11.3	21.0 /0	62 /100	45 /70	19 /30	0 /31	47 /28	1.9 /1.2	178 /171
PFM20	5.8 /9.0	22.4/2.0	3.3 /7.0	21.0 /0	61 /100	44 /70	13 /50	0 /36	48 /26	1.9/1.1	175 /174
PPM20	8.6 /11.3	22.4 /2.0	3.3 /11.3	21.0 /0	61 /100	44 /72	7 /33	0 /30	47 /28	1.9 /1.2	176 /158
AFM40	4.8 /7.5	22.4 /2.0	3.0 /5.5	21.0 /0	64 /100	50 /77	39 /48	0 /29	44 /26	1.9 /1.2	150 /95
APM40	4.8 /7.1	22.4 /2.0	2.9 /5.1	21.0 /0	63 /100	50 /76	33 /46	0 /30	44 /26	1.9 /1.2	151 /98
PFM40	4.8 /7.0	22.4 /2.0	3.0 /5.0	21.0 /0	62 /100	48 /76	24 /70	0 /40	48 /23	1.9 /1.0	145 /101
PPM40	4.8 /6.9	22.4 /2.0	2.9 /4.9	21.0 /0	61 /100	49 /80	15 /52	0 /29	44 /25	1.9 /1.3	147 /73
AFM60	5.0 /9.0	22.4 /2.0	2.7 /7.0	21.0 /0	65 /100	55 /82	49 /59	0 /28	41 /24	1.9 /1.3	117 /27
APM60	4.8 /7.5	22.4 /2.0	2.7 /5.5	21.0 /0	63 /100	55 /81	42 /56	0 /29	39 /24	1.9 /1.2	117 /32
PFM60	4.1 /6.1	22.4 /2.0	2.7 /4.1	21.0 /0	62 /100	53 /83	35 /81	0 /45	41 /19	1.9 /1.0	110 /35
PPM60	4.1 /6.0	22.4 /2.0	2.7 /4.0	21.0 /0	60 /100	54 /88	22 /63	0 /28	40 /23	1.9 /1.3	112 /-3
AFM80	5.7 /9.0	22.4 /2.0	2.4 /7.0	21.0 /0	66 /100	60 /86	57 /66	0 /28	37 /23	1.9 /1.3	80 /-33
APM80	5.0 /8.3	22.4 /2.0	2.2 /6.2	21.0 /0	64 /100	61 /85	48 /62	0 /28	36 /23	1.9 /1.3	81 /-24
PFM80	4.2 /5.1	22.4 /2.0	2.4 /3.1	21.0 /0	63 /100	59 /90	43 /87	0 /52	37 /15	1.9 /0.85	72 /-20
PPM80	3.7 /5.0	22.4 /2.0	2.2 /3.0	21.0 /0	60 /100	59 /94	30 /69	0 /27	36 /21	1.9 /1.3	74 /-69



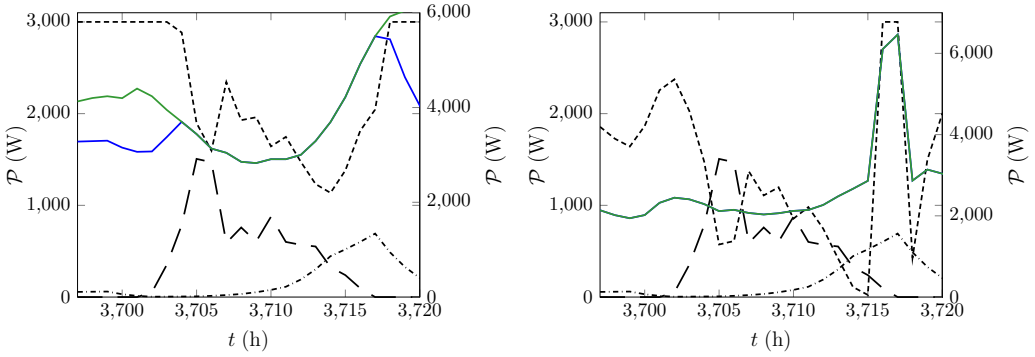
(a) week 6



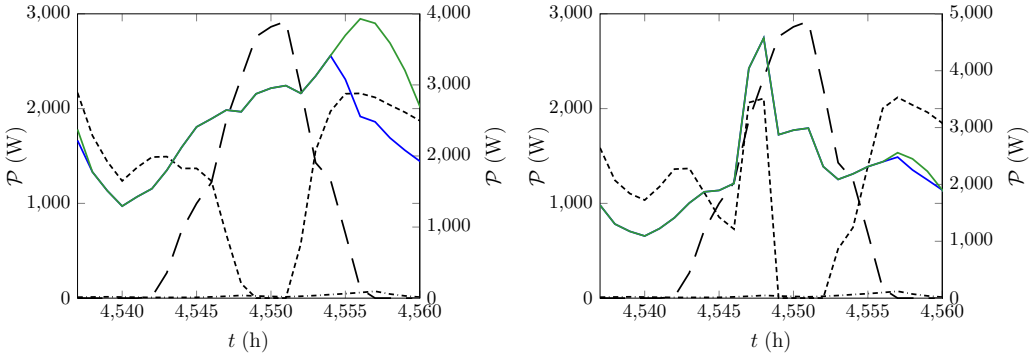
(b) week 12



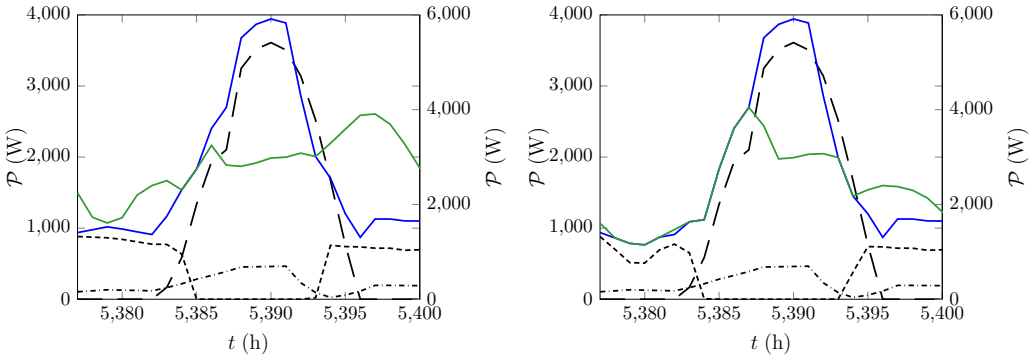
(c) week 17



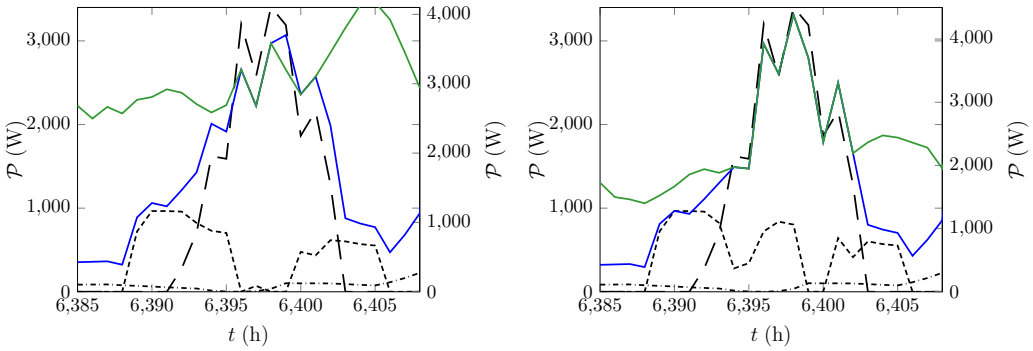
(d) week 22



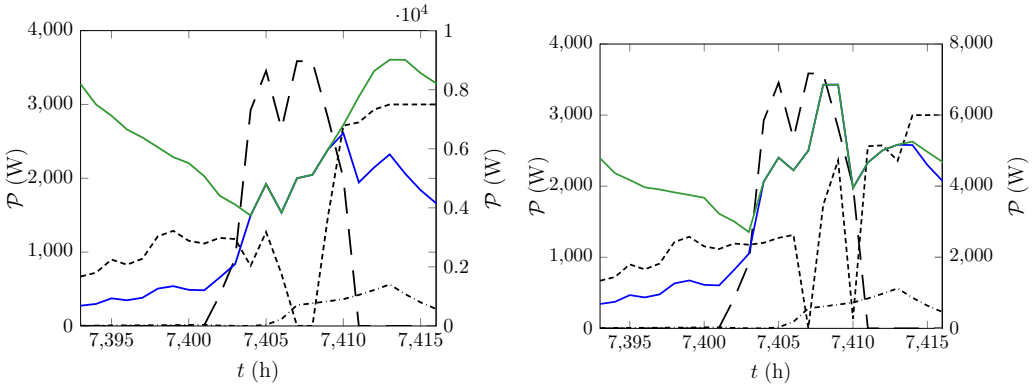
(e) week 27



(f) week 32

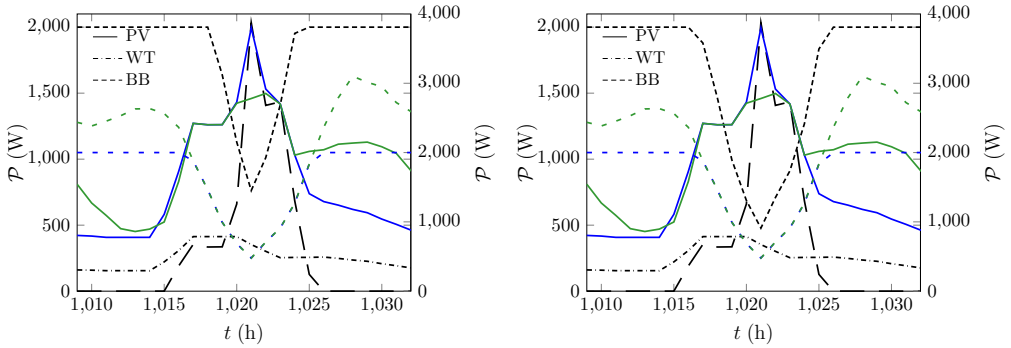


(g) week 38

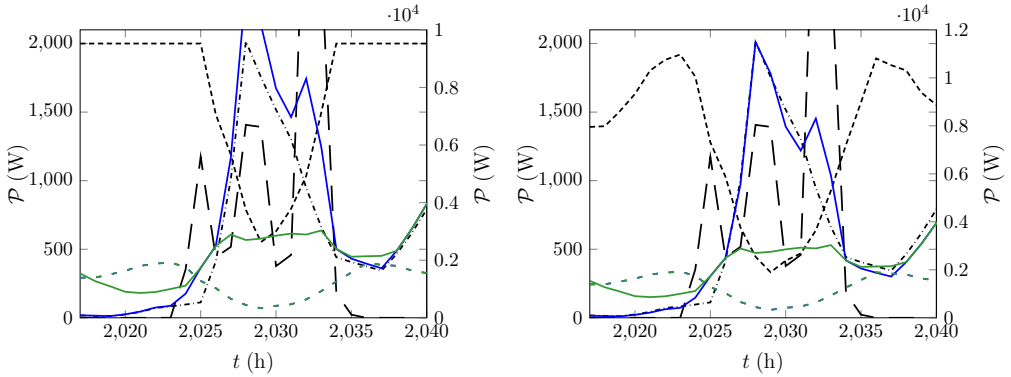


(h) week 44

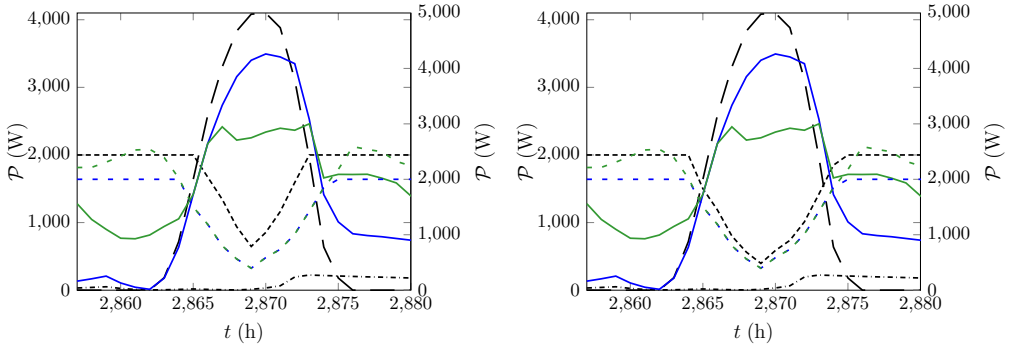
Figure 7 – Examples of local production (black, left axis) with the total production and consumption (blue and green, right axis) for the AFE20 and AFE80 cases (left and right respectively)



(a) week 6



(b) week 12



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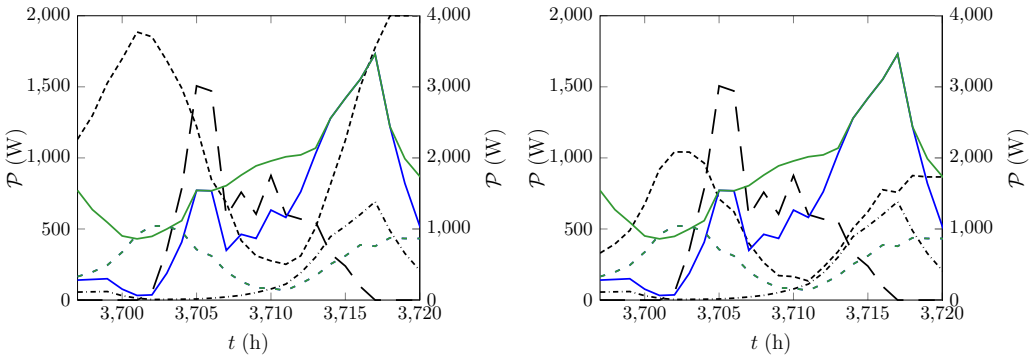

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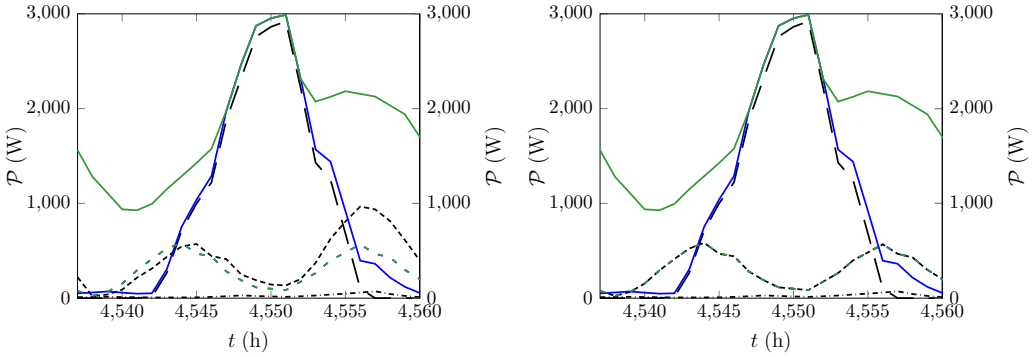

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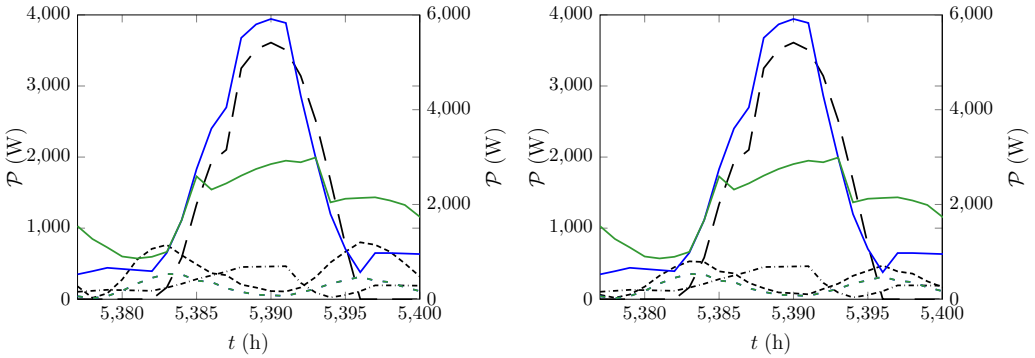

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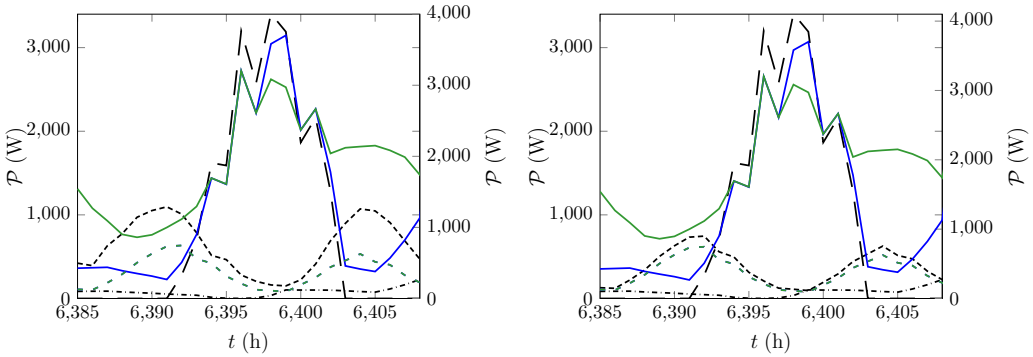
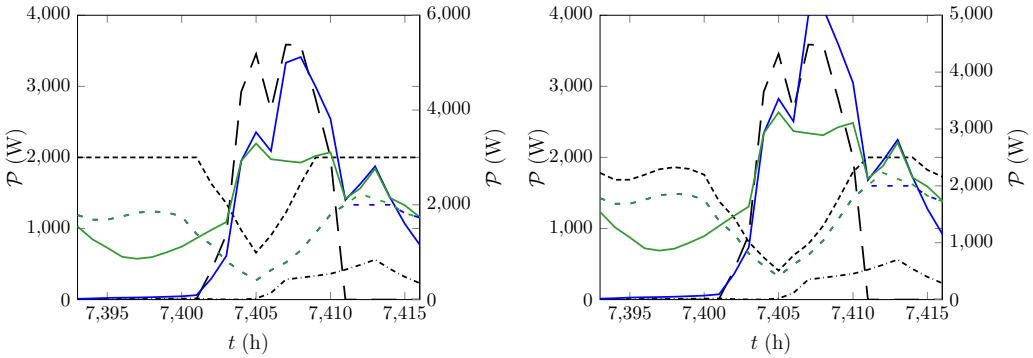


(g) week 38



(h) week 44

Figure 8 – Examples of local production (black, left axis) with the total production and consumption (blue and green, right axis) for the AFM20 and AFM80 cases (left and right respectively)

5 Conclusion

In this study, `PEACEFULNESS` platform was used to explore the advantages and drawbacks of DSM techniques on multi-energy smart-grids, but also the equivalence between physical and economical approaches. In the same time, the influence of the number of participants on the flexibility was addressed. Two situations were considered, a smart electrical grid and a smart electrical and thermal grid, with presence of RES each time. These networks involved several thousands of customers, with tens of thousands controllable and non-controllable devices offering thus different levels of elasticity. Finally, several tens of simulations were performed, varying the proportion and type of contracts among customers, as well as the strategy of the aggregators. In both examples, as expected, limited impacts are observed on production since it was set as rigid. Therefore, low curtailments and limited decrease of the profits are obtained. In contrast, a more pronounced effet is seen for consumers, more subject to curtailment. Consequently, there is possibly a strong decrease of the consumption peaks, yet accompanied by a decrease of the bills. In addition, the mismatch between supply and demand can be singularly reduced, and both self-sufficiency and coverage-rate are increased. Nevertheless, their improvement could be further facilitated by other type of organisation. All in all, little differences are observed between strategies, regarding both exchange and distribution policies: there is always less than 15% of divergence between them. This means that the economical approach did as well as the physical one, which highlights the boons of testing new market configurations. Finally, thresholds effects are observed especially for producer's curtailment (and thus, revenues), consumption peaks and self-consumption. The main conclusions are the interests of DSM for increase the local use of RES, yet it has been demonstrated that further benefits could be obtained with forecasts and storages. The two options are under investigation, using a kernels approach [63] in the first case, and considering both electrical and thermal storages in the second.

As perspectives, it is planned to extend the analysis by considering also behavioral schemes [64–69], and especially rebound effects [70–74]. Meanwhile, a more thorough analysis of the position of aggregators and of the interactions between the agents will be conducted to see if they must really play on vertical differentiation [75] or if sharing economy concepts could be developded [35] .

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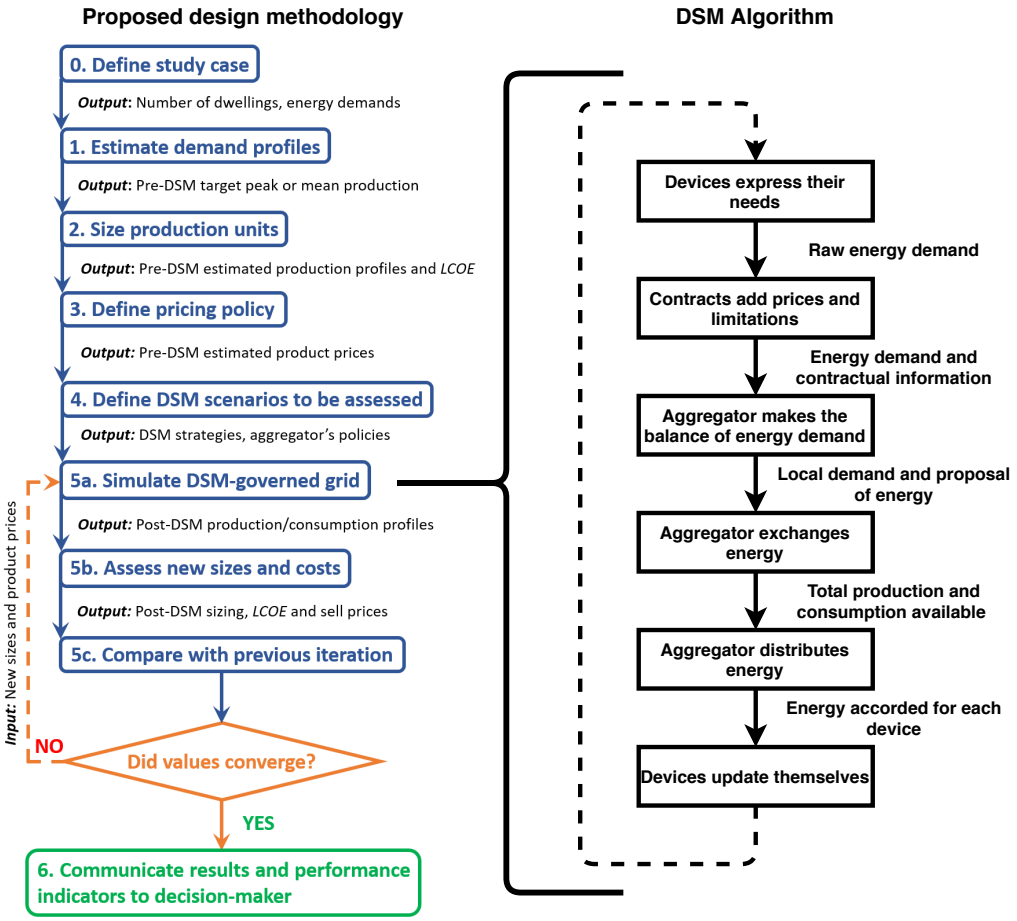
Chapitre 4

Intégration du DSM à la phase de dimensionnement d'un réseau multi-énergie

Highlights

- Iterative sizing method to account for the load control strategy in the design stage
- Method is illustrated through an example case with both electric and thermal loads.
- 10 scenarios evaluated, different load control strategies and types of contracts.
- Method proved to reduce equipment size and improve several other indicators.
- Method proved iteration-stable: all scenarios converged after 2 iterations.

Graphical highlight



Iterative sizing of solar-assisted mixed district heating network and local electrical grid integrating demand-side management

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Abstract

Demand-side management and load-shifting strategies can reduce peak loads as well as temporal production/consumption mismatch, two classic issues in district energy networks that integrate solar sources. Nevertheless, the classic current sizing methods for such networks only consider the total demand, and not the possible loads after use of such techniques. The present paper aim is so to ascertain the connection between the possible demand reductions and the capacity design of generation sources. The study proposes an iterative sizing method with demand-side management as the central pillar. It retro-fits production units by assessing the network's overall performance through several criteria, both energetic and economical and with operational considerations. Exergy, which accounts for the quality of energy and is especially useful for multi-energy networks, is also considered. The method is illustrated on a mixed grid coupling a standalone heating network with a local electrical grid. Thousands of residential dwellings, with haphazard demands covered by solar-assisted technologies and a heat-pump are used in a series of ten scenarios with various management strategies, pricing policies and types of end-user contracts. In summary, the iterative method reduced the number of installed solar thermal collectors and photovoltaic panels by 13-38% and 8-30%, respectively. Furthermore, the method is stable: results converged after 2 iterations, in all scenarios. We also discuss the influence of low or high demand-side management penetration rate, and the final sizing selection by the decision-maker.

Keywords: Sizing; Demand-Side Management (DSM); District Energy Networks (DEN); Solar energy; Mixed-energy grids; Exergy.

Contents

Nomenclature

Latin symbols

A	surface area, m^2
a_0	optical efficiency, $-$
a_1	first heat loss coefficient, $W\,m^{-2}\,K^{-1}$
B	benefits,
$\mathcal{C}$	consumption, kWh
C	cost,
CAPEX	capital expenditures,
CF	cash flow,
COP	coefficient of performance, $-$
CRF	capital recovery factor, $-$
d	duration, s
E	total energy, J or kWh
$\mathcal{I}$	solar irradiance, $W\,m^{-2}$
LCOE	levelized cost of energy, /(kWh)
LT	life time, year
O&M	operation and maintenance costs,
$\mathcal{P}$	power, W
P	price,
Q	heat, J
r	discount rate, %
T	temperature, K or °C
t	time, s or h

Greek symbols

ϵ	exergy efficiency, $-$ or %
η	efficiency, $-$ or %

Subscripts and superscripts

amb	ambient
avg	average
avl	available
cons	consumed
d	day
elec	electrical
ht	heating
Ht	heat needs
pp	piping
req	required

Acronyms

CHP	combined heating and power
DHW	domestic hot water
DLC	direct load control
DR	demand response
DSM	demand side management
EDF	Électricité de France
HP	heat-pump
IEA	International Energy Agency
PV	photo-voltaic
RTP	real-time pricing
ST	solar thermal
TOU	time-of-use

1 Introduction

1.1 Foreword

According to the 2018 version of "world energy outlook" from the IEA [1], the total primary energy demand should increase between 26.8% and 37.7% in 2040 depending on the scenario implemented (new or current policies respectively), while the heating and cooling energy requirements should increase respectively by 70% by 2050 [2]. Furthermore, in both of the IEA cases, and even for the last scenario (called sustainable development[1]), it is planned a strong increase of the renewables capacity of 98%, 125% or 211% respectively for the same period, since almost all countries in the world are trying to tackle the issue of decarbonization. On this point, the reader is referred to Loftus *et al.* [3] for an interesting analysis on the relative feasibility of seventeen global decarbonization scenarios. Meanwhile, many energy policies or roadmaps tend to aim to better energy efficiency in all sectors (transport, buildings, *etc.*) or to better address the corresponding issues [4]. As an example, the European Directive 2012/27 [5] thus clearly stated quantitative targets for the year 2030 and beyond in its Chapter I Article 1. Nonetheless, increased efficiency can sometimes be followed by rebound effects, either globally [6] or at the household's scale [7]. As far as renewable generation is concerned, the projections concerning the retained technologies clearly show that solar and wind energy should pave the way, though hydropower will still be deployed when feasible and bio-energy (especially the developing hydrogen sector) should also play a significant role. However, the former solutions are clearly known to face foreseeability and intermittence issues [8], as for instance with large PV deployment [9], not to mention possible negative prices as it has been observed in Germany [10] or in the US [11]. Despite no noticeable harmful effects are noticed for the moment, these difficulties are already appearing due to the present shift towards more decentralized and distributed energy resources (generation and/or storage) and the increase of the number of prosumers.

As a matter of fact, it is generally admitted that the promotion of flexibility is one of the main solutions to solve the above difficulties. As there are different methods and approaches to define and implement flexibility measures (which are well presented in Lund *et al.* [12]), there is not one unique solution to handle such a problem. Firstly, the flexibility can arise from intrinsic features of some devices relying for instance on their operational flexibility potential, for electric systems [13], heating systems for housings [14] and inter-connection between technologies [15], or even by re-orienting their use as with thermal plants operated as combined heat-power (CHP) plants [16], and also simply with these latter ones [17,18]. Another possibility is to rely on the demand side, as for instance by playing with the thermal inertia of buildings [19], of buildings cluster [20], of district heating networks [21] or even both [22]. Secondly, the energy storage, for instance, can give fast or long flexibility depending obviously on their size but above all on their type: electrical [23] and battery-types [24], short and/or long term thermal storage [25], separated or combined [26]. Added to this, they can be used alone or combined [27], or even in a combination of various technologies and types [28]. Thirdly, the flexibility can be the result of a better integration and synchronization between various energy networks *inter alia* the electrical grid and the gas grid but also with the more and more common district heating (and/or cooling) networks [29]. The concept of the 4$^{\text{th}}$ Generation of District Heating and smart energy systems [30] is completely in phase with this approach, as well as the development of integrated community energy systems [31], energy hubs [32] or coupled district heating and electrical distribution networks [33]. Last but not least, the flexibility can come from the use of intelligent systems or smart-grids, originally designed

[1] in which the total energy demand is decreased by -1.84%, yet which is also pointed out as requesting a "complete reversal of the historic relationship between economic growth, energy demand and emissions"

for electricity networks [34], but showing high potential, as demonstrated for Europe and the US or Brazil and India [35], and which can ease the coordination between renewable generations and energy storages for example [36]. Furthermore, such concept is applicable to thermal grids and mixed/combined grids [37, 38]. Finally, these approaches are also often relying on adaptation of the load/demand side with the use of demand side management (DSM) or demand response (DR) techniques. Indeed, the corresponding potential and leeway appear to be high in Europe [39], be it in district heating [40] or to manage slow or fast power requirements [40].
In the present study, the retained approach will combine four of the five above possibilities, letting aside energy storage.

1.2 Literature review

A rich and ever-growing literature is devoted to smart grids and DR and DSM, and studies pertaining to multi-energy grids and their design and capacity sizing are ubiquitous. A stringent analysis should require a painstaking review that is clearly beyond the present scope. However, the corresponding papers demonstrate two important characteristics [36,40–42]: i) adapting the demand leads to a decrease of the peak consumptions and a strong modification of the load profiles, ii) capacity sizing (and corresponding single- or multi-objective optimization) usually use both features as set-points. Considering these two points, it is clear that a possible quandary is undoubtedly entailed by the fact that these two effects are not considered altogether.
Thus Stötzer *et al.* [43] have interestingly studied the theoretical potential of DSM. Considering a German city of 500,000 inhabitants, they pointed out that an optimization process based on genetic algorithms can lead to a reduction of the peak consumption from 120 MW to 80 MW, and to integration of 8 GW of renewable generation. However, these possible reductions are not used to question the sizing and capacity needs of the whole system, which are let as future perspectives. In Pan *et al.* [44], the differences in time-response of an electrical grid and a district heating network, where CHP units dominate, are used to correct several types of disturbances. In conjunction with the topic of the present study, it is proven that both electricity and heating systems can be affected by any effects modifying the normal strategy of operation. Besides, it is stated that this work is only an elementary step and that future studies should consider (among others) more strategies and operational conditions.
In [45], Amrollahi and Bathaee propose an interesting techno-economical study of an electrical microgrid involving both PV and wind turbines as well as battery storage handled without or with DR. The minimization of the total net present costs with `HOMER` has demonstrated that the sizing is influenced since a 36.8% peak reduction is obtained together with a 57.9% increase in the load factor. So, it highlights the link between DR programs and sizing optimization. Nevertheless, the test case concerns only a forestry camp, that is to say an autonomous microgrid of a relatively low size. Besides, it is conducted only for electricity, and added to this, only for the nondispatchable renewable sources. Even closer to the present study, Bahl *et al.* argue in [38] that DSM should be considered when optimizing an energy network for industrial applications. For the trigeneration system they are considering, with three absorption chillers, three compression chillers, two boilers and three CHP units, very interesting results are obtained. For instance, they show that the most promising steps to perform DSM are not only those with demand peaks, and consequently that heuristics focused on these latter are not sufficient. Here again, the influence of DR strategies on the consumption and associated sizing is so identified. However, the industrial situation is still limited, and perspectives call for an application to general energy systems.
More recently, Khawaja *et al.* have performed in [46] an enlightening study for the city of Newcastle UK. An evaluation method is proposed to compare the initial sizing of an electrical standalone hybrid grid (with PV, battery storage, diesel combustion engine and a fuel-cell) with the implementation of

a similar system obtained using finite automata. Considering only PV capacity, it leads to more than 50% of decrease, from 140 kW to 60 kW. Therefore, the benefit of a retro-active sizing is shown, yet it is done for a standalone electricity-only grid and should be enlarged. Meanwhile, the tested energy management strategies do not focus on the classic and well-known DR methods.

1.3 Contribution and novelty of the study

With regard with the previous analysis, there is an impetus for a crossover study focusing on the interconnections between loads modifications due to DR programs and the capacity sizing of generation sources in multi-carrier energy grids. The main role of the present paper is thus to pinpoint these possible impacts of DSM on the sizing of the generation units. The modification of the sizing for the underpinning systems is so analyzed from both an energetic and an economical point of view, for the consumers, but also for the aggregators when present. As far as "smart" devices and energy management strategies are concerned, since they are prone to be more and more integrated (specifically with the rise of the 5G), another research question is the assessment of their impact on the sizing and if integrating DSM is worthy or not.
In terms of contribution, this paper describes a mixed grid coupling a standalone heating network with a local electrical grid, connected with the national grid, in which aggregators can set DSM for customers eager to adopt it. Renewable generation is ensured by PV panels and solar thermal collectors, which are intermittent. A heat-pump (HP) is also available in case of insufficient heat supply. As the primary objective is to assess the effect of DSM on sizing, a simplified case is chosen where neither energy storages nor forecasting are considered. Then, two types of sizing are considered: i) a first one based on the consumption peak (*i.e.* the classic and usual method); ii) a second one based on the mean consumption. Furthermore, two types of DSM techniques are tested, direct load control and curtailment, together with two levels of penetration of the associated contracts (*i.e.* two various proportions of agents embracing them). Last but not least, three strategies are scrutinized concerning the business-model for the aggregator and so the energy exchanges. All these steps are performed with `PEACEFULNESS` [47,48], a platform for transverse evaluation of control strategies for multi-energy smart grids, developed in `Python` and whose aim is to simulate or manage such networks.
The novelty of the present work is threefold.

- The network investigated, the most extended so far in this DSM-integrated sizing approach, involves thousands of customers and two types of energy (electricity and heat). In addition, from the demand side, stringent test cases are also considered with these thousands of inhabitants, since they are clustered in three main load profiles corresponding to different types of families yet with randomized variations among them to present their own needs in electricity and heat.

- Secondly, the district heating network is considered in the economic analysis. Moreover, the levelized costs of energy are computed for both the electrical and heat grids.

- Thirdly, a painstaking analysis is conducted for several performance indicators involving specifically the self-consumption and coverage rates but also the exergy efficiency and the bills and profits (if any) are calculated for respectively the customers and the aggregators.

The rest of this paper is organized as follows. Section 2 describes the methodology for the sizing procedure and its iterative retrofitting, and the modeling framework. Section 3 presents the case study and experimental plan. Finally, the results and discussions are developed in Section 4, and conclusions and perspectives are drawn in Section 5.

2 Methodology

As shown in Fig. 1, the approach is based on a 7-steps procedure integrating DSM techniques:

0. **Case definition**. The number and types of dwellings are given, together with their demands for each energy types, which permit to size the capacities of the various technologies (ST, PV, HP). Here, two sizing rules are used, based on the peak or average consumptions. Then, the DSM strategy is set and the sizing adapted iteratively until convergence is reached. Meanwhile, the relevant assessment criteria to identify the best DSM strategy are detailed.

1. **Demand profiles**. They differ from the consumption profiles since the former are static, and correspond to the 'ideal' energy needs, while the latter represent the real consumption, depending on the DSM arbitration. The basic profiles come either from real operational data or are calculated with surrogate models.

2. **First sizing**. Knowing the demands and the above sizing rule, capacities are computed, as well as the LCOE. Note that at this step, the optimal size of the production units can be determined by a mono-objective optimization assisted by any numerical tool.

3. **Pricing policy**. Tariffs are attributed for all agents (consumers, producers, aggregators), depending on the basic structure (TOU, real-time pricing, *etc.*) and on the associated adaptations when DSM is involved.

4. **DSM configuration**. Two techniques can be used here in the iterative process, namely DLC and curtailment, with various ratios of consumers adopting them.

5. **Iterative sizing**. The following steps are repeated until convergence (associated parameters were defined in 1). Note that the method is not dependent on the chosen DSM tool:

   (a) Simulation of the DSM-governed grid.

   (b) Calculation of the new sizings, LCOE and prices based on these results.

   (c) Comparison between the new sizing and the previous one.

6. **Final suggestion for decision-maker(s)**. The list of the possible sizings is presented, accompanied by their performance criteria (production and consumption peaks, self-sufficiency, exergy efficiency, *etc.*), to help stakeholders in the choice for the most suitable operation-mode.

For the real-time management of the multi-energy grids, as done in the step 5.a), the `PEACEFULNESS`[2] model is used [47, 48]. It is a multi-disciplinary tool, involving physicists, economists and jurists, which allows to handle a multi-agent-based system where a partial or complete control of either the supply or the demand can be done. The digital platform based on this structure can simulate micro-grids, at the housing's scale or for districts or cities, which are able to operate in standalone modes or in connection with one or several macro-grids (such as the national or regional electrical grid). These grids can describe various types of centralized and distributed multi-generation, both fossil and renewable, such as hydraulic dam, biomass burner, PV, wind turbines... On the other hand, a lot of different loads can be set and customized in function of their size or other features or number of associated people as for example with $\mathtt{R}-\mathtt{C}$ models and set indoor temperature, consumptions profiles for domestic hot

[2] platform for transverse evaluation of control strategies for multi-energy smart grids

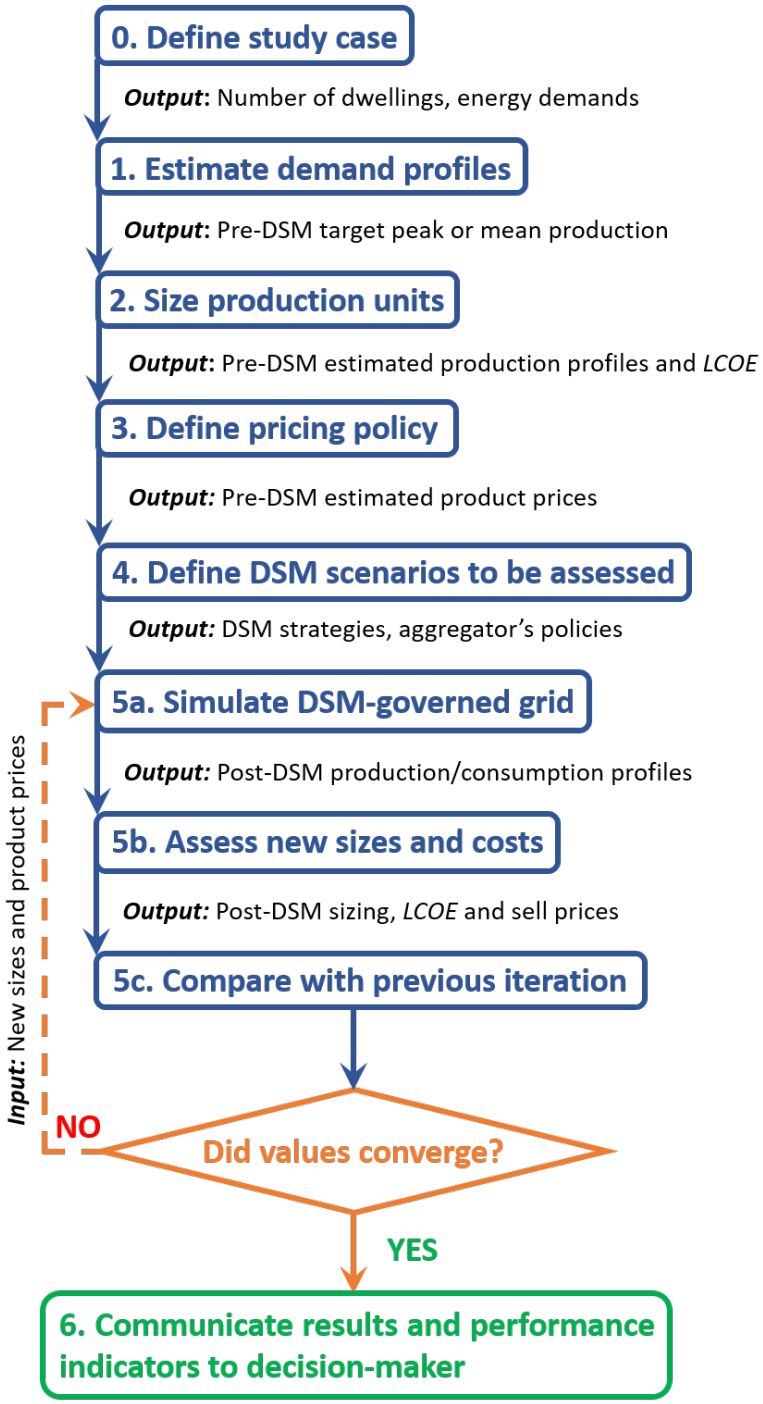


Figure 1 – Schematic representation of the algorithm

water... The cornerstone between demand and supply relies on aggregators. These are special agents which can be either independent and act as third-parties, or be associated with an other agent such as a customer or group of customers, or even a distribution system operator. Their main role is to authorize or forbid some devices to produce or consume energy. To supervise these choices, they have access to various features of the demand/supply (quantity involved, emergency, associated price, *etc.*) relative to the ongoing round. For the sake of clarity, all values represent the real-time loads, and no forecasting nor uncertainties are considered in the present case. In practice, the aggregators also have to fulfill the rules defined in the contract (*e.g.* acceptation or not of curtailment or shifts) between a consumer and the energy providers. Obviously, customers participating to DSM have access to a lower price of energy: the higher level of constraint accepted, the lower price of energy. Last but not least, the local balances are governed by a given strategy (such as autarky for instance), which vary among the tested scenarios. Contracts and strategies are detailed in section 3.1.3.
In brief, the algorithm used is composed of 6 steps, as described in Fig. 2:

1. Devices express their needs by sending a message to their contracts.
   At this stage, only physical considerations are taken into account.

2. Contracts complete this message, adding a price and specifying if the device request can be reported, canceled, half-served... Then, this completed message is sent to the aggregator.

3. The aggregator makes a balance of production and consumption. Notably, it distinguishes between the urgent demands, that must be served, and the non-urgent demands, presenting more flexibility.

4. The aggregator exchanges energy between district heating network and local electric grid.

5. The aggregator decides which quantity of energy is bought from or sold to the national electric grid.

6. The aggregator distributes the energy 'permits' or orders among devices.

7. Devices update themselves according to the decisions made by the aggregator.

3 Description of the tests

3.1 Configuration

The energy system consists in a small district, schematized in Fig. 3. It involves both a district heating network and a local electric grid, which is also connected to the national grid. The loads correspond to various buildings, occupied by different types of families, with their own electrical and heat needs. Renewable generation is provided by PV panels and ST collectors, and a HP is also available to compensate any default in heat. The external grid is supposed to accept infinite injections or demands without any limitations. Fig. 4 illustrates all these elements, and provides a line diagram showing the configuration of the integrated heat and electricity system.

Concerning the two aforementioned sizing rules, the peak-approach does not raise issues on the demands, yet contingencies are plausible and the corresponding costs are clearly maximized (and resources not optimally used). In contrast, for the mean-approach, far cheaper, a possible risk of lack of energy could arise. In both cases, an aggregator is responsible for ensuring the balances of the grids, by means of two actions: distributing energy among the various carrier energy systems, or exchanging with the

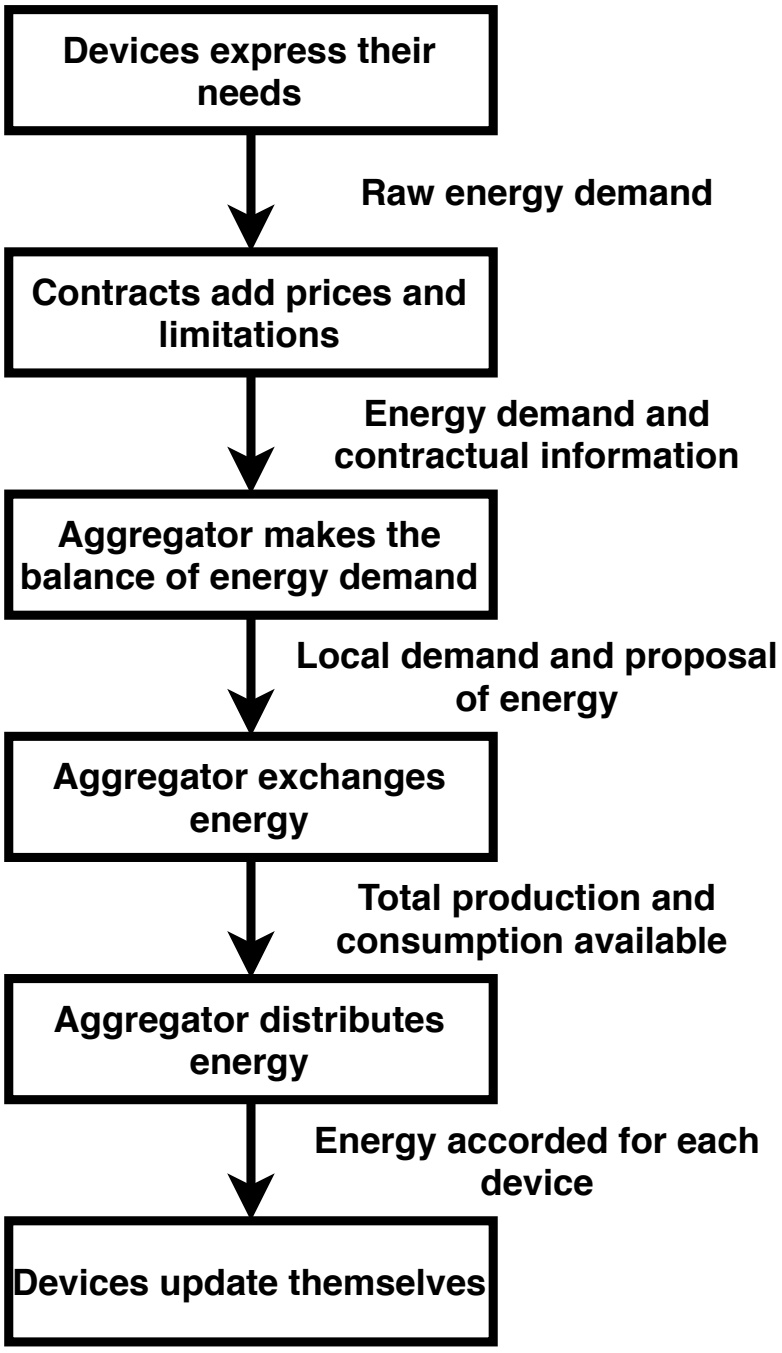


Figure 2 – Process of one round of the DSM tool

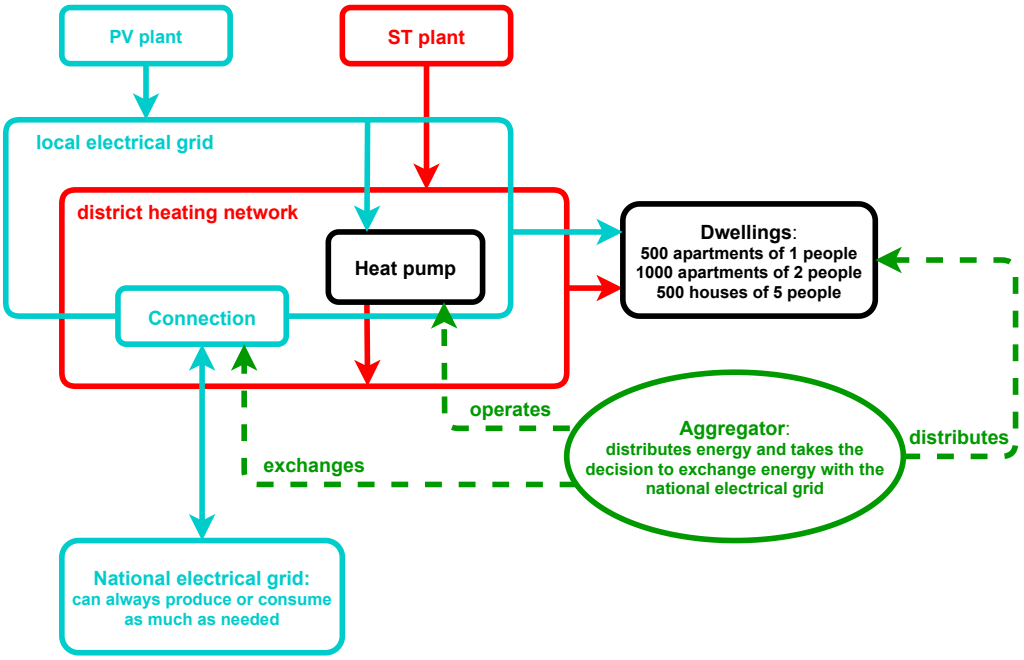


Figure 3 – Representation of the case in the initial configuration

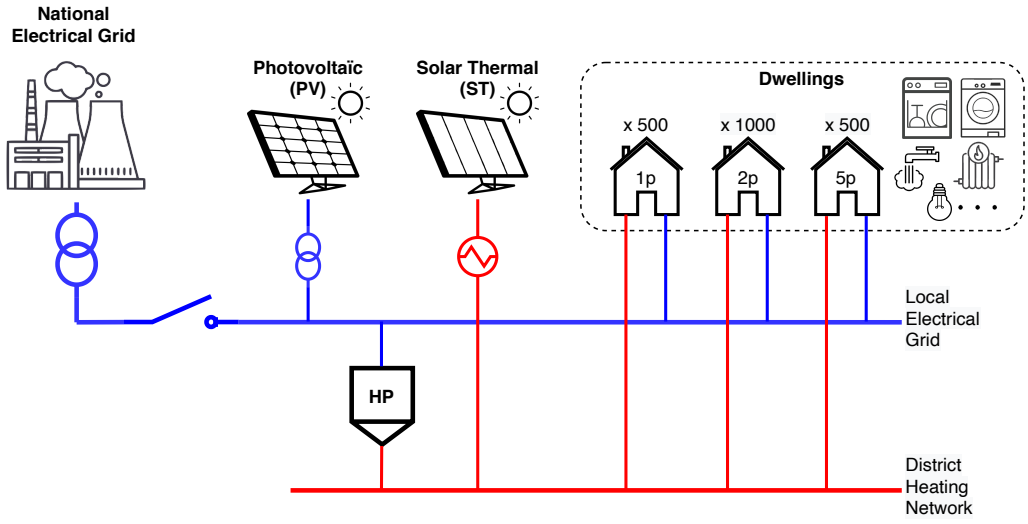


Figure 4 – Configuration of the mixed grid with local electrical grid and district heating network

national electrical grid. There are two key parameters here: the strategy applied by the aggregator (favorizing self-sufficiency or profitability), and the proportion of DSM contracts among the consumers (from 0% to 67% participation to DSM). For each run, the overall performances are evaluated through various indicators: energetic indicators (self-consumption, peaks of consumption and production, overall exergy efficiency, *etc.*) but also economic ones, like the aggregators revenue or the bill paid by consumers. This hybrid energy grid is located in Pau, France whose corresponding meteorological data (solar irradiation and ambient temperatures) are extracted from `PVGIS` [49]. It is simulated over 1 year with a time step of 1 hour.

3.1.1 Construction of the demand profiles

Demands from the 2,000 dwellings come from various apparatus (see Table 1), which are all modeled individually. The behavior of each device is defined first by its type, indicating if shifts and power adjustments are authorized, and then by its technical features. For instance, it can be its efficiency, maximal power (if any), full description of a complete cycle (*e.g.* washing machines, dishwashers and dryers), *etc.*. Lastly, a user profile is giving the pattern of utilisation (*e.g.* every evening, once a week). Practically, the duration of cycles and consumptions of dishwashers, washing machines and dryers were extracted from [50], whereas the background profile (see Table 1) is generated by the activity tool developed by Richardson *et al.* [51–53]. Space heating is modeled through a classic physical bottom-up lumped capacitance model, using a RC model for the building [54]. We considered here that the two apartments had the same surface and thus the same heating demand. For the user's behaviors, we distinguish between evening and night. In the evening, the set temperature is $20°C \pm 1°C$, which means that the comfort is ensured while the temperature stays between 19°C and 21°C. During the night, it is $18°C \pm 3°C$. For the DHW, a monthly variation is considered, in compliance with a French standardized method [55], but a variable inlet temperature is taken all along the year (varying from 9 to 21°C). Some examples are provided in Fig. 5.

Table 1 – Description of the dwellings

Type	Number of persons	Amount	Devices
Apartment	1	500	Background, heating, DHW, washing machine
Apartment	2	1000	Background, heating, DHW, washing machine, dishwasher, dryer
House	5	500	Background, heating, DHW, washing machine, dishwasher, dryer

n.b.: Background is an aggregated profile, combining TVs, computers, lights, kettles, *etc.*

Finally, all the temperature-dependent consumptions present monthly variations, as depicted in Figs. 5a and 5b, and the background electric consumptions are based on weekly variations, as illustrated in Fig. 5c. Background profiles vary also with the size and the number of inhabitants. Shiftable loads have, by definition, no predefined working periods but their consumption cycle is described in Tab. 2. Besides, a randomization step has been added to obtain more haphazard profiles for the total needs. It uses a Gaussian function to modify the peak and pattern consumption. In practice, the following initial pertinent parameters, characteristic of the load, have been considered: the consumption level, the duration of the usage, and the start hour. Each of them is modified through the following process: the initial value of the parameter is taken as a mean value, and new profiles are built using a standard deviation of this input. Then, a random draw is made and the randomized value is the one used in the profile of the device. Consequently, the final real end-users present different patterns of consumptions, which lead to aggregated profiles that are not a simple homothetic multiplication of a single profile.

Here again, an illustration of the difference between the consumption profile of the apartment inhabited by 1 person and the aggregated total consumption is visible in Fig. 6.

Table 2 – Example cycles for shiftable electric loads

Device	Consumption (kWh)	Duration (min)
Dishwasher	0.5 then 0.4	48 then 30
Dryer	0.67	40
Washing machine	0.4	1

3.1.2 Initial sizing

The priority is given on solar PV for producing the electricity, but it is also possible to retrieve unmatched demand by means of the national grid since the district is not islanded. Similarly, this grid can be used in case of excess of production.
Concerning the installed technologies, a constant efficiency of 15 % is taken for the PV panels. In a same manner, ST collectors represent the main heat generation sources. However, the excess heat produced by ST is dissipated. The ST efficiency is calculated dynamically [56]:

$$\eta_{\mathrm{ST}} = a_0 - \frac{a_1}{\mathcal{I}}\Big(T_{\mathrm{fluid}} - T_{\mathrm{amb}}\Big) \quad , \tag{3.1}$$

with $a_0 = 0.833$, $a_1 = 2.7095\,\mathrm{W\,m^{-2}\,K^{-1}}$ and $T_{\mathrm{fluid}} = 45°\mathrm{C}$.
In case of heat mismatch between production and consumption, the HP is used. It is a single unit, directly connected to the district heating network, and it consumes preferentially PV-electricity to promote self-consumption. The COP is supposed static and its value set at 3.6.

Given the hourly power consumptions over the entire year, associated with the above load profiles, it is easy to determine both the peak and average energy needs $\mathcal{P}_{\mathrm{max}}$ and $\mathcal{P}_{\mathrm{avg}}$. Then, the computation of the corresponding surface areas is straightforward. Next, the sizing of the HP is based on the night needs in heat. However, since these ones represent either space heating or DHW, a specific method is adopted because the former is always supposed urgent (and must therefore be fulfilled) while the DHW needs can often be shifted. Therefore, the heat peak due to space heating is first identified alone and, then, the (possible) remaining available energy for DHW is computed:

$$E_{\mathrm{avl}} = d_{\mathrm{night}}\left(\mathcal{P}^{ht}_{\mathrm{max}} - \mathcal{P}^{ht}_{\mathrm{avg}}\right) \quad , \tag{3.2}$$

where d_{night} is the night duration, taken constant to 8h.
The sizing of the HP imposes thus that:

if $E_{avl} \geq E^{DHW}_{req}$ **then**

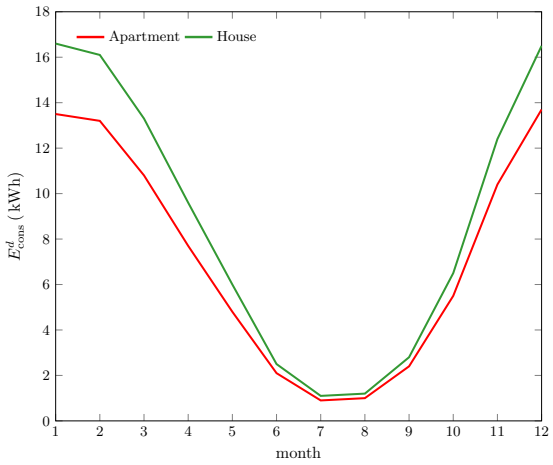
$$\mathcal{P}_{\mathrm{HP}} = \mathcal{P}^{ht}_{\mathrm{max}} \quad , \tag{3.3}$$

else

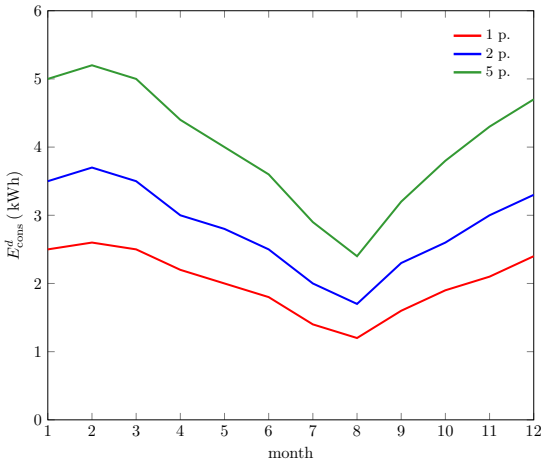
$$\mathcal{P}_{\mathrm{HP}} = \mathcal{P}^{ht}_{\mathrm{max}} + \frac{E^{\mathrm{DHW}}_{\mathrm{req}} - E_{\mathrm{avl}}}{d_{\mathrm{night}}} \quad . \tag{3.4}$$

n.b.: in the second case, the extra-need in energy for DHW is assumed to be delivered all along the night in order to minimize the size of the HP.

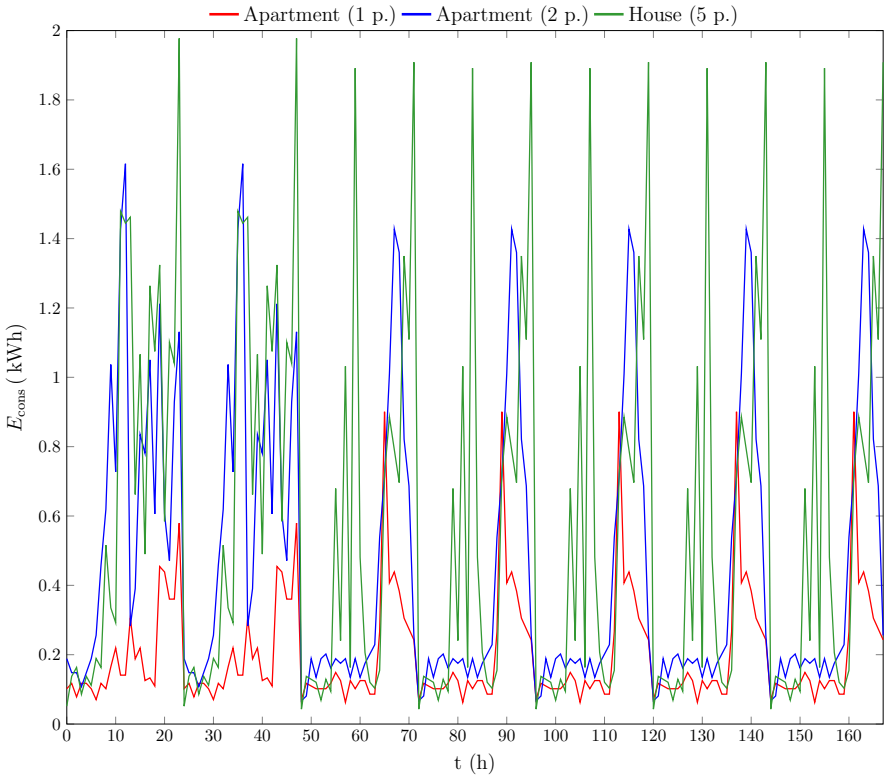
Eventually, the sizing of the HP, and of both the total PV and ST areas, are obtained.



(a) Monthly variation of the heating

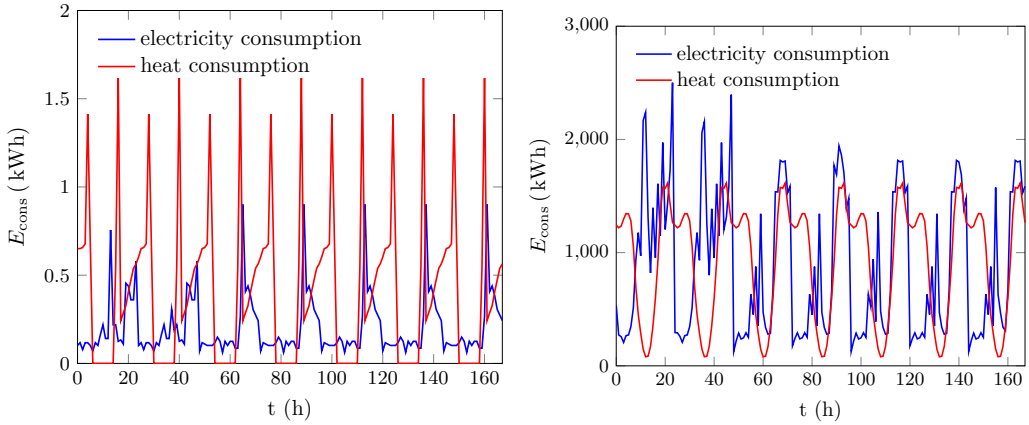


(b) Monthly variation of the DHW consumption



(c) Weekly variation of the electric consumption of background devices

Figure 5 – Variation of consumption for the different devices



(a) Individual profiles

(b) Aggregated profiles

Figure 6 – Consumption profiles over one week

3.1.3 LCOE, contracts and energy tariffs, and management strategies

Among the various existing economic methods to assess the profitability of an investment, such as value or rate methods, the LCOE [57] is often used since it permits to compare the effectiveness to produce energy for a given amount of money. This is the retained parameter in the present study, and so its annuitized value is calculated for each unit:

$$\text{LCOE}_k = \frac{\mathsf{CRF}\left(\text{CAPEX}_k + \mathsf{C}_{\text{pp}} + \text{O\&M}_k\right)}{E_k} \quad , \tag{3.5a}$$

$$\mathsf{CRF} = \frac{\mathsf{r}\,(1+\mathsf{r})^{\text{LT}}}{(1+\mathsf{r})^{\text{LT}} - 1} \quad . \tag{3.5b}$$

Then the LCOE is computed for both electricity and heat. In the first case, electricity is sold at 10 c /kWh and bought at 20 c /kWh from the external grid. In the second case, the mean value is a weighted average between the values of the ST and HP, depending on their respective energy contribution to the final heat:

$$\text{LCOE}_{Ht} = \frac{\sum_{i=1}^{\text{LT}} Q_i^{\text{ST}}\,\text{LCOE}_{\text{ST}} + \sum_{i=1}^{\text{LT}} Q_i^{\text{HP}}\,\text{LCOE}_{\text{HP}}}{\sum_{i=1}^{\text{LT}} \left(Q_i^{\text{ST}} + Q_i^{\text{HP}}\right)} \quad . \tag{3.6}$$

All the needed values for the above parameters are provided in Table 3.

In the present study, the role of the contracts is twofold. First, they define the prices at which energy is bought or sold. Second, they define the type of control allowed for the aggregator, for each device. Three contracts are considered here:

- Business As Usual (BAU);
- Direct Load Control (DLC);
- Curtailment.

Table 3 – Parameters values for the economic analysis [57–59]

Parameters	Value or expression		
	PV	ST	HP
CAPEX(k)	3.50 $/\mathrm{W_{pk}}$	0.94 k $/\mathrm{m^2}$	1.47 /W
O&M(k)	N/A	$0.02\%_{\mathrm{CAPEX}}$	$\mathrm{CAPEX_{HP}} \times Q_i^{\mathrm{HP}}$
C_{pp}(k)		$0.10\%_{\mathrm{CAPEX}}$	
LT		25	
r		3%	

BAU contracts force the aggregator to respect all the requirements of any device, which corresponds to the case without any DSM. On the contrary, DLC and curtailment contracts allow the aggregator to modify the profile curves. In the first case, this control of the load can be operated by i) modifying the starting time (for dishwashers or dryers for instance), ii) slightly overheating or letting the temperature decrease for space heating, as long as the temperature remains in the above operational comfort temperature limits, iii) heating the DHW if the tank is not fully charged. In the second case, it simply consists in a cancelling of the consumption. Obviously, in exchange of these constraints, the consumers benefit from specific tariffs. Thus, the prices associated with the DLC and curtailment contracts are respectively 10% and 20% lower than the current price (BAU). The lowest price for both heat and electricity, is the rounded up value of their respective LCOE.

Lastly, three different strategies are considered for the aggregator, to decide the way to set the various contributions of each agent, depending on the produced and needed quantities of each type of energy and on the level and type of contracts in the set of consumers. For the sake of simplicity, no prosumers are considered and all production units are assumed to belong to the aggregator. These strategies are:

- Always satisfied;
- Light autarky;
- Profitable.

Here again, the first one corresponds to no DSM and is the reference case. The Light autarky strategy is designed to favor self-consumption: calls to the external grid are limited only to urgent demands. The profitable strategy aims to maximise the profits of the aggregator, which ensures that urgent demands are satisfied but will serve consumers only if it is less rentable than selling to the grid.

3.2 Simulation plan

Given the previous methods for the sizing, and the above types of contracts and strategies, an experimental plan involving 10 cases is built; it is summarized in Table 4. The different proportion of people participating or not to DSM are assumptions of the tests: we just assume that curtailment contracts are less popular than DLC ones, as they are more constraining. Moreover, different prices are taken for heat and electricity: flat prices (*i.e.* constant) and TOU prices (on and off-peak) are respectively chosen, calculated. The corresponding values are given in Table 5; for the on-peak tariff, it is 40% higher than off-peak, following the scheme of EDF (the French historic national electricity provider). As explained in the previous section, they are derived from the calculation of the LCOE.

Table 4 – Simulation plan

Name of the run	Sizing	ID	Contracts proportion	Strategy
Reference scenario mean	Mean	RM	100% BAU	Always Satisfied
Light Autarky low DSM contracts mean	Mean	ALM	67% BAU, 20% DLC, 13% curtailment	Light Autarky
When profitable low DSM contracts mean	Mean	PLM	67% BAU, 20% DLC, 13% curtailment	When profitable
Light Autarky high DSM contracts mean	Mean	AHM	33% BAU, 40% DLC, 27% curtailment	Light Autarky
When profitable high DSM contracts mean	Mean	PHM	33% BAU, 40% DLC, 27% curtailment	When profitable
Reference scenario peak	Peak	RP	100% BAU	Always Satisfied
Light Autarky low DSM contracts peak	Peak	ALP	67% BAU, 20% DLC, 13% curtailment	Light Autarky
When profitable low DSM contracts peak	Peak	PLP	67% BAU, 20% DLC, 13% curtailment	When profitable
Light Autarky high DSM contracts peak	Peak	AHP	33% BAU, 40% DLC, 27% curtailment	Light Autarky
When profitable high DSM	Peak	PHP	33% BAU, 40% DLC, 27% curtailment	When profitable

Table 5 – Energy prices (in c / kWh)

Sizing	Contract	Electricity on-peak/off-peak	Heat
Mean	BAU	0.19/0.14	0.21
	DLC	0.17/0.12	0.19
	Curtailment	0.15/0.11	0.17
Peak	BAU	0.39/0.28	0.31
	DLC	0.35/0.25	0.28
	Curtailment	0.25/0.28	0.25

3.3 Performance assessment of the DSM-governed grids

3.3.1 Convergence criterion

The proposed iterative process leads to a new sizing, depending on the loads modifications due to the DSM. In order to control the convergence rate of the corresponding loop, the following criterion is adopted:

$$\xi = \frac{\left|\frac{A_{PV}^{n} - A_{PV}^{n-1}}{A_{PV}^{n-1}}\right| + \left|\frac{A_{ST}^{n} - A_{ST}^{n-1}}{A_{ST}^{n-1}}\right| + \left|\frac{\mathcal{P}_{HP}^{n} - \mathcal{P}_{HP}^{n-1}}{\mathcal{P}_{HP}^{n-1}}\right|}{3} \tag{3.7}$$

It corresponds to the average normalized sizing difference, between 2 iterations, in terms of installed capacity, for the different production units (PV, ST and HP). Then, we set 2% as the value below which convergence is reached.

3.3.2 Performance indicators

Once the final converged sizing is obtained, each solution is analyzed by 10 different metrics, so as to develop a broader analysis. All those metrics are expected to be DSM-sensible, as they derive from energy management:

- the self-consumption rate and the coverage rate;
- the exergy efficiency;
- the curtailment rates for consumers and producers;
- the peaks of consumption and production, and the maximum energy mismatch;
- the benefits of the aggregator and the bill paid by consumers.

The self-consumption and coverage rates are, respectively, the proportion of the production consumed locally and the proportion of local needs satisfied by the local production. They evaluate the level of dependency on the national electric grid or, in other words, the level of autonomy and associated resiliency.
The grid's yearly exergy efficiency ϵ_{grid} (*i.e.* upstream of the end-users) is the ratio of all useful exergy outputs to the exergy inputs:

$$\epsilon_{\text{grid}} = \frac{\sum_{i=1}^{\text{LT}} Q_{Ht}^{\text{end users}} \left(1 - \frac{T_0}{T_{\text{grid}}}\right) + E_{\text{elec}}^{\text{end users}}}{\sum_{i=1}^{\text{LT}} \mathcal{I} \left(1 - \frac{T_0}{T_{\text{sun}}}\right) (A_{\text{ST}} + A_{\text{PV}}) + E_{\text{elec}}^{\text{EDF}}} \tag{3.8}$$

The useful exergy outputs correspond to the electricity $E_{\text{elec}}^{\text{end users}}$ (kWh) and the heat $Q_{Ht}^{\text{end users}}$ (kWh) sold to the residential end-users. In the case of electricity, energy equals exergy. The exergy content of the heat delivered to residential users is calculated for $T_{\text{grid}} = 363$K, which is an acceptable hypothesis for the service temperature of a 4$^{\text{th}}$ Generation District Heating Network dedicated to a residential application [60]. The reference temperature was $T_0 = 293$K. As exergy inputs, the solar irradiance $\mathcal{I}$ coming from the Sun is currently associated with a black body at $T_{\text{sun}} = 5778$K. This irradiance varies over time, and its yearly profile was obtained for the city of Pau (France) from the meteorological

database `PVGIS` [49]. Its annual sum was multiplied by the panels' total surface in order to determine the total solar input. The remaining input is the electricity provided by the national grid.
The curtailment rates represent the proportion of energy demand not covered, over the total energy demand. They play a major role in the satisfaction of producers and consumers.
The consumption and production peaks are, respectively, the highest instantaneous consumption and production throughout the year. The mismatch is the difference between local production and local consumption. For electricity, the mismatch peak represents the peak of energy exchanged with the national electrical grid. For heat, it represents the peak of usage of the heat pump. Negative and positive values correspond respectively to the sale and to the purchase of energy from outside.
The aggregator benefits are the profits made by the aggregator over the observation period, and conversely, the energy bills represent the average money spent by a consumer each month.

The case studied is summed up below:

- consumption: 2000 dwellings, key devices modeled individually, basic profiles randomized
- production units: HP, PV panels and ST collectors
- 2 sizings, one based on the mean consumption and one on the peak consumption
- tariffs based on the calculation of the LCOE
- 3 different contracts: BAU, DLC and curtailment
- 3 different strategies: always satisfied, light autarky and profitable
- 10 simulations with different sizing, DSM participation and strategies
- convergence criterion based on the sizing of the 3 technologies
- technical and economic performance indicators. Among them, exergy is calculated.

4 Results and discussion

4.1 Analysis of the iterative process with the final sizes

Firstly, the initial results for the pre-sizing obtained with each method are presented in Table 6. Then, in Table 7, the entire set of physical and economic results are given altogether, as well as the convergence rate, after the iterative sizing. First, for all the scenarios, iterations converged in two steps below 2%. Our interpretation of this fast convergence is that the case studied is quite simple in terms of DSM possibilities. More precisely, the new sizings for the PV panels and ST collectors obtained after the first round of DSM-governed simulations do not change significantly the situation for the aggregators during the second round: they are constrained by the mismatch between the production period (around midday) and the main consumption period (the evening). This is also the reason why the Heat Pump's nominal power remains at 3.8 MW, independently of the DSM approach (see Table 6). Would we have included storage, more manageable renewable plants (such as dams) or demand and production forecast, we would have more interaction between sizing and DSM. In this case, more iterations would have been expected.

For the sake of clarity, the LCOE is presented for electricity and for heat, and, for the latter, a distinction is made between ST and HP. Last but not least, it is worth mentioning that the HP power is the same for every case, that is 3.8 MW; such a result is, *ceteris paribus*, very logical since the maximum output is needed during night where all cases behave similarly in the present study.

Foremost, all surfaces and LCOE are higher when the sizing is based on the peak consumption. This indicates a clear oversizing, and so such a method is not economically optimal. To further highlight this point, one can note the values for the surface area, which are 2 to 4 times greater that with the mean-approach. It can also be observed that the ST heat LCOE is between 2-fold and 7-fold higher than for the HP. There are three factors leading to this result: 1) Investment cost of ST is higher than that of the HP, especially when sized with respect to peak demand; 2) All heat produced by the HP is sold to the users, while much of the heat produced by ST is dissipated; 3) Despite consuming electricity, the HP is an energy-efficient unit due to its COP of 3.6. Furthermore, the influence of solar temporal mismatch is an interesting point for analysis. Note how the LCOEs for electricity are 4 to 5 times lower than those of heat produced by solar thermal collectors. Efficiency is certainly not the cause of this discrepancy, since that of ST (60 to 80%) is higher than that of PV panels (15%). And although PV has lower investment costs than ST, this only explains partially the differences in LCOE. Thus, the most influential factor is the temporal mismatch. As it is later presented hereinafter, much of the heat produced by solar collectors is dissipated (see red values in Table 8, at column "curtailment ratios", sub-column "producers").

Table 6 – Initial sizings

Approach	Sizing			LCOE (/kWh)			
	ST $A(\mathrm{m}^2)/\mathcal{P}(\mathrm{MW})$	PV $A(\mathrm{m}^2)/\mathcal{P}(\mathrm{MW})$	HP $\mathcal{P}(\mathrm{MW})$	Heat (ST)	Heat (HP)	Heat (overall)	Electricity (PV)
pre-sizing mean	8431/1.2	18165/0.93	3.8	0.483	0.104	0.165	0.109
pre-sizing peak	20985/3.80	48712/2.50	3.8	0.993	0.107	0.249	0.223

Table 7 – Final sizes

Run	Sizing		LCOE (/kWh)				Iterations
	ST $A(\mathrm{m}^2)/\mathcal{P}(\mathrm{MW})$	PV $A(\mathrm{m}^2)/\mathcal{P}(\mathrm{MW})$	Heat (ST)	Heat (HP)	Heat (overall)	Electricity (PV)	
RM	8031/1.46	17233/0.89	0.535	0.106	0.174	0.108	2
ALM	6711/1.22	15222/0.78	0.398	0.125	0.182	0.105	2
PLM	6711/1.22	15222/0.78	0.372	0.157	0.218	0.105	2
AHM	5260/0.96	12792/0.66	0.297	0.159	0.198	0.102	2
PHM	5260/0.96	12792/0.66	0.317	0.152	0.218	0.102	2
RP	18340/3.33	48712/2.50	1.056	0.150	0.315	0.232	2
ALP	18347/3.33	44722/2.30	0.930	0.168	0.355	0.221	2
PLP	18347/3.33	49450/2.54	0.852	0.213	0.430	0.234	2
AHP	18340/3.33	44790/2.30	0.851	0.213	0.430	0.232	2
PHP	18340/3.33	48765/2.50	0.851	0.213	0.430	0.233	2

4.2 Results for the different scenarios

4.2.1 Mean trends

The main results of the simulation of DSM-governed grids are presented in Table 8, differentiating the electricity and heat values in blue and red respectively. First, it is worth mentioning that some parameters are invariant: self-consumption of the district heating is equal to 100%, curtailment rate of PV panels to 0%, and the consumption and mismatch peak for heat is 3.8 MW. These results are completely in phase with the hypothesis or operational choices considered in this approach. Thus, the district heating does not have any possibility to sell its energy so it imposes to consume it locally. Next, it is not possible to cut-off the PV panels, and any excess in production is injected in the national grid. For the mismatch, it corresponds to the HP power, whose sizing is imposed by the night needs, which cannot be met by solar generations (without the help of energy storages).
Second, the self-consumption and coverage rates globally increase with active supervision and with the 'popularity' of DSM (*i.e.* their acceptance rate and increase of dedicated contracts). In the most favorable case, it is possible to go from 75% to 88% in the mean sizing configuration, and from 51% to 53% in the peak sizing configuration, in terms of self-consumption of energy produced by the PV panels. For the district heating, the equivalent parameter is the curtailment rate of ST (*i.e.* the percentage of heat dissipated), which is quite constant, whatever the scenario: it goes from 87% to 98%. Concerning the coverage rates, DSM is more effective for heat than for electricity. It is due to the proportion of demand shiftable from the night to day, which is higher for heat (DHW production) than for electricity (dishwashers, dryers and washing machines, not necessarily used daily). Generally, and unsurprisingly, scenarios combining autarky with a high share of DSM contracts are the most efficient in terms of independence from the grid. Another predictable tendency is the better self-consumption of PV electricity (20-30% more) with mean sizing, and similarly, a better coverage rate (around 15% more) with peak sizing. However, this increase in autonomy comes at the cost of curtailment of consumers: if reference scenarios never cut them, it is not always the case for the others. Like before, it is in autarky scenarios combined with high DSM share that this effect is the most important: in the mean sizing, curtailment can achieve 40% for electricity and 78% for heat and, in the peak sizing, 34% and 80%. It is interesting to note that the type of sizing (mean or peak) has only a little impact. This underlines that, if DSM allows some financial savings, it could be at the cost of quality of service for consumers, especially for curtailment contracts.
Lastly, an interesting point to raise is the behavior of the profitable strategy. Buying energy from the national grid always costs 0.20 €/kWh, but the off-peak price of electricity for customers accepting curtailment is around 0.10 €/kWh in mean sizing and around 0.23 €/kWh for peak sizing. Therefore, this leads incontrovertibly to a cut-off in the first case (mean sizing) but not in the second (peak sizing). When looking at the peaks, it appears that behavior differs for each energy. It is most sensible for heat, as it is impacted by both the degree of adoption of DSM contracts and the strategy since they tend to increase the peak from 1.5 MW to 3.4 MW (+127%). In contrast, the sizing does not show any significant impact, and the only noticeable effect is for autarky and high DSM with an increase from 2.6 to 3.4 MW (+31%). As consumption peaks occur, unsurprisingly, during night, only curtailment can reduce them. Thus consumption peaks for electricity vary with DSM participation. Concerning heat, it seems that, even with curtailment, the minimum amount of non-curtailable demand is equal to the maximum power of the HP. This can explain why DSM, in our configuration, failed to reduce significantly these peaks. On the electrical grid, the peaks of production and mismatch vary almost only with the sizing approach. The mismatch peak even goes from a positive value, around 2 MW (a purchase of energy) to a negative value of -2.8 MW (a sale of energy), that is to say a change in behavior

and an amplitude in variation of 140% due to DSM.

Let us consider now the economic analysis. In peak-sizing approaches, the reference scenario is the sole to loose money when selling electricity (-297 k). In general, the mean-sizing approaches loose revenue when peak sizing earn money. It comes from the evolution of the LCOE (on which prices are indexed) between the mean and the peak sizing, which is slightly greater than 0.10 / kWh and around 0.20 / kWh respectively: as buying electricity from the national electrical grid is always equal to 0.20 / kWh, it is rentable in peak sizing but not in mean sizing. However, though selling electricity to the grid brings 0.10 / kWh, it is always disadvantageous for the aggregator, whatever the case. Furthermore, the preponderant low values of coverage rates in all the scenarios (<34%) indicate an important quantity of electricity taken from the national grid, which explains this difference. Another interesting point to raise is that selling electricity to the heat pump is always a financial loss for the national grid: as a matter of fact, the price on the electricity side is divided by 3.6 due to the efficiency of the HP. Nevertheless, in the same time, selling heat from the HP is always a benefit for the district heating. This explains why, in all scenarios, the aggregator earns money in the district heating (from 636 to 1890 k), as its two sources are lucrative. Lastly, the benefits tend to decrease with the increase of DSM, because this increase is accompanied with an increase in curtailment, as said above. From a consumer point of view, autarky combined with DSM reduces the bill up to 32% in mean-sizing, but it has to be linked with the curtailment rates. The savings are less effective in peak-sizing: the maximal reduction obtained is 22%, in the scenario combining autarky with high DSM. Moreover, the profitable strategy has a different impact depending on the sizing: in mean-sizing, it leads to similar bills than the autarky scenarios, yet, in peak-sizing, the bills are the highest of all the scenarios. Here, it has to be reminded that the participation of the agent to a DSM program reduces the price of energy: this explains why scenarios implying high DSM are systematically cheaper than their counterparts with low DSM. Lastly, as said before, the peak sizing multiplies the price of energy, for both electricity and heat: it explains the increase of bills between the mean and the peak sizings (from 84-125 /month to 164-280 /month, *i.e.* +95% and +124%).

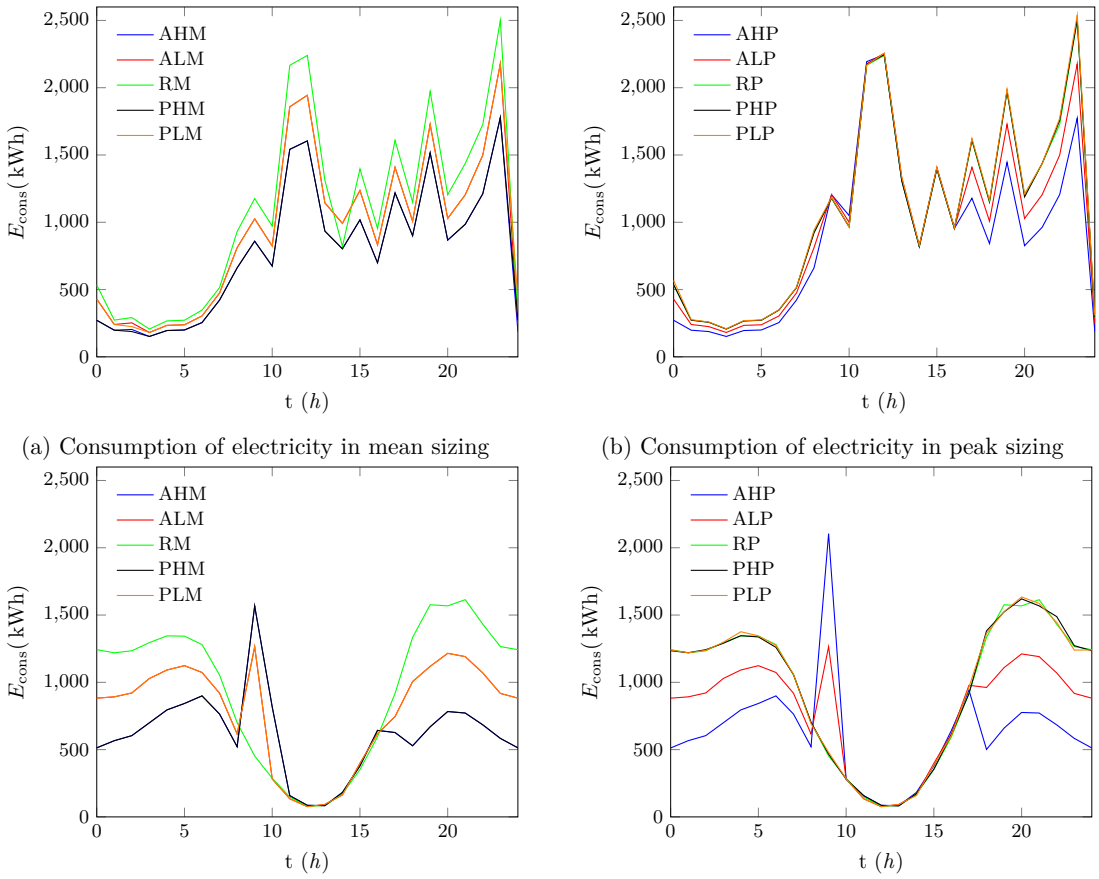
Finally, the overall exergy efficiency is notably higher with mean-sizing than for peak-sizing (20% against 8%), especially due to temporal mismatch. The main explanation comes from the fact that, with peak-sizing, large surfaces of solar panels are installed. However, without storage units, this does not increase at all the matching between productions and consumptions. It is also important to remark that thermal self-consumption, coverage rate and curtailment ratios are approximately the same, no matter the sizing approach. In the same time, electric self-consumption drops notably when switching from mean-sizing to peak-sizing, going from 75-88% to 52%. Consequently, one can conclude that deterioration of the exergy efficiency mainly steams from the drop in electric matching indices. Lastly, the relatively low values of exergy efficiency in all scenarios are somewhat typical of solar-driven systems. Solar irradiation is a high-quality source with an exergy factor around 0.95. On one hand, heat delivered by ST collectors has a much lower exergy factor (around 0.2), and this outweighs their high efficiency (around 80%). On the other hand, PV panels deliver electricity with a low efficiency (15%) but their exergy efficiency is 1.

4.2.2 Impact on consumption and production profiles

The Fig. 7 permits to identify that autarky has a significant impact. Consumption is globally lower, due to the presence of curtailment contracts, which are not served at all. In contrast, the peak of consumption for heat is higher than for electricity. This comes from the need of DHW during the morning: in the reference scenario, these needs are satisfied early, during the night, while for the others, this need is served at the last moment. This allows to employ the ST and to improve the use of renewable

Table 8 – Results of the final iteration, in the format electricity/heat

Run	Self-consumption	Coverage rate	Peaks			Exergy efficiency	curtailment rates		aggregator profits	bill
			consumption	production	mismatch		consumers	producers		
	kWh.kWh^{-1}	kWh.kWh^{-1}	MW	MW	MW	kWh.kWh^{-1}	kWh.kWh^{-1}	kWh.kWh^{-1}	k year^{-1}	month^{-1}
RM	0.75/1	0.15/0.09	2.5/3.8	1.4/1.5	2.5/3.8	0.22	0/0	0/0.94	-170/1218	125
ALM	0.81/1	0.16/0.15	2.2/3.8	1.1/2.1	2.2/3.8	0.20	0.22/0.57	0/0.91	-167/935	106
PLM	0.81/1	0.16/0.15	2.2/3.8	1.1/2.1	2.2/3.8	0.20	0.22/0.57	0/0.91	-118/1118	117
AHM	0.88/1	0.17/0.19	1.8/3.8	0.9/2.6	1.8/3.8	0.20	0.40/0.78	0/0.87	-149/636	85
PHM	0.88/1	0.17/0.19	1.8/3.8	0.9/2.6	1.8/3.8	0.20	0.40/0.78	0/0.87	-156/628	84
RP	0.51/1	0.30/0.11	2.5/3.8	3.1/1.5	-2.8/3.8	0.08	0/0	0/0.98	-297/1058	245
ALP	0.52/1	0.28/0.17	2.3/3.8	3.1/2.2	-2.8/3.8	0.08	0.18/0.56	0/0.97	780/1890	216
PLP	0.51/1	0.24/0.11	2.5/3.8	3.1/1.6	-2.8/3.8	0.08	0/0	0/0.98	1051/2891	280
AHP	0.53/1	0.33/0.27	2.3/3.8	3.1/3.4	-2.8/3.8	0.07	0.34/0.80	0/0.96	617/1442	191
PHP	0.51/1	0.24/0.11	2.5/3.8	3.1/1.5	-2.8/3.8	0.08	0/0	0/0.98	891/2693	264



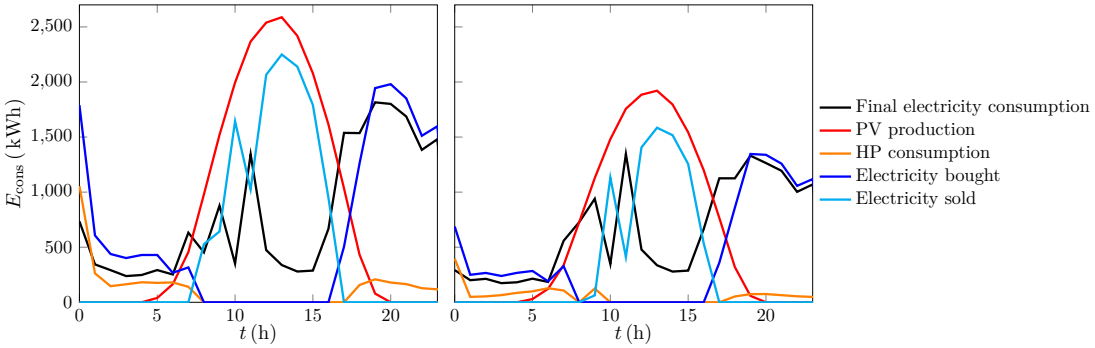
(a) Consumption of electricity in mean sizing

(b) Consumption of electricity in peak sizing

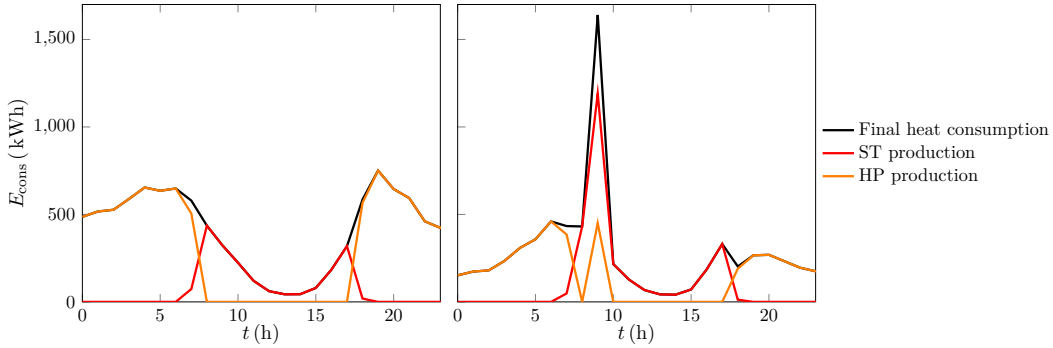
(c) Consumption of heat in mean sizing

(d) Consumption of heat in peak sizing

Figure 7 – One day of consumption in all runs



(a) Division of electricity over one day in: RM on the left and AHM on the right

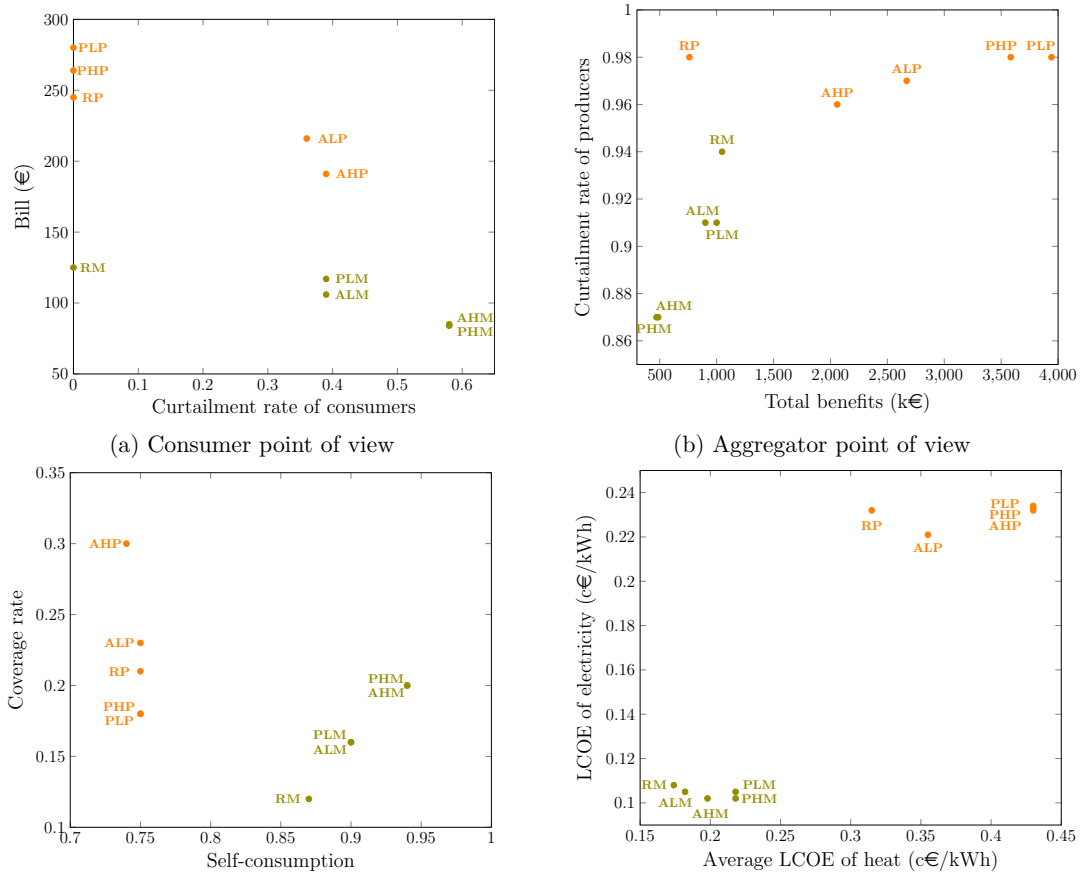


(b) Division of heat over one day in: RM on the left and AHM on the right

Figure 8 – Repartition of production and consumption over one day

energy. On the contrary, on a year basis, the peak of consumption for heat is higher in the reference case (it is reached during a night in winter). Added to this, the profitable strategies behave like autarky in mean-sizing and like BAU in peak-sizing, for the reasons explained in the previous section. Thus, we did not represent them in the figures 8, which compare the repartition of consumption and production between the BAU and the autarky high DSM scenarios, in mean-sizing for a specific day in June. One can note that both the PV and ST are able to satisfy the demand around midday and could even produce more, though solar thermal collectors are switch-off and the major part of the PV production is sold to the national grid.

4.3 Discussion on the choice of a final sizing



(a) Consumer point of view

(b) Aggregator point of view

(c) Dependency on the national grid

(d) LCOEs

Figure 9 – Crossed analysis using clustering method as a function of the sizing rule (mean in olive/peak in orange)

It is now proposed to rise up to have a look on the practical consequences of the present results, and how they can affect or help in a future decision-making process by stakeholders or policy makers.

In fact, several methods have been proposed and tested, yet no selection has been done. Indeed, such a choice is also a political or societal decision. As such, the final selection can be driven by different objectives. After the presentation of the various results, depending on the DSM approach used and on the adopted strategy for the business model, it is therefore impossible to define an universal objective rule to incontrovertibly pilot these decisions. However, it is possible to build a clustering analysis in order to confront some indicators so as to help in pinpointing the best political decision (in its primary definition). Such an analysis is provided in Fig. 9.
For instance, the decrease in energy bills can be related to the rate of curtailment in Fig. 9a. Beyond the logical higher bill due to higher costs when designing the entire system on the peak, it is also clear that it will still lead to higher bills, even with high levels of curtailment (see 'ALP' and 'AHP'). In addition, when adopting the profitable strategy ('PLP' and 'PHP'), the advantage for the customer is absent, whatever the level of DSM since the bill is greater than the reference case. In contrast, with the mean sizing, the bill is mainly governed by the level of DSM, and not by the business model (profitable or light autarky). Put in perspective, this means that a peak sizing would undeniably create high bills, even for more "virtuous" customers, who would agree to reduce their consumptions and accept some curtailments. Besides, for a mean sizing, the choice of the customer to accept or not DSM is the paramount factor, and is clearly more important than the strategy. This gives a high power to the customer, on both its curtailment and bill.
From the aggregator viewpoint, see Fig. 9b, it can obtain higher benefits, but this can sometimes lead to the disuse of some production units. This has to be related with the well-known marginal (production/cost) analysis, that could help here. Furthermore, whatever the sizing approach (mean or peak), it seems that Pareto(-like) frontiers appear, which reveal that each method can present some advantages. In conclusion, the aggregator can have some earnings and in the meantime increase the use of the generation sources. In the same idea, it is shown in Fig. 9c how which scenario can help to choose between favorizing the coverage rate or the self-consumption, and thus achieving more standalone behaviors. And here again, the advantages of the DSM, and its mandatory or optional presence, is singularly different for the mean and peak sizing.
Last but not least, the comparisons of the LCOEs in Fig. 9d clearly entail how the combination of a sizing with a strategy can privilege one nature of energy over the other, and also how efficient can be the level of DSM in each case. When thinking of the incentives that are often used to foster the deployment of some technologies, such observation could give an interesting leeway.

To continue apace the analysis of the practical consequences of the present study, two major questions are undeniably raised: how to handle the fact that the level of penetration of DSM and the corresponding retained techniques may be unknown when designing the capacity ? Even if they are known, what if they evolve with time ? The second question can be answered first since the modification of the sizing due to the use of DSM could be studied more precisely. Moreover, other parameters, such as environmental criteria could also be considered. Added to this, the resiliency of the results and analyses could be further improved by bounding their variations, which could then help to quantify this possible risk. When pushing further the reasoning, a practical answer can be proposed for the first question. If one accepts that such uncertainties exist, or if the previous uncertainty quantification shows that large deviations could occur, a very concrete conclusion could be to modify the sizing to take into account this uncertainty. For instance, one could plan to install a device responsible for a small part of the needs (*e.g.* 10 or 20%) and, contrary to the common sense, to choose a cheaper device with a lower life time. And then, when this one will have to be replaced, it should be possible to see if it is still needed or not. In other words, the possible adjustment could be integrated in the initial costs, and the money savings will first come from the avoidance of the replacement costs. Furthermore, to alleviate the risks

and stress on the energy providers, it is not inconceivable to imagine that an incentive policy could lead to some regulations that will oblige the actors of the energy market to ensure certain levels of DSM, even if DSM has a social cost. In the same manner that laws were voted to force the development of renewable generation, similar objectives could be defined for DSM. The consumer could still be free to choose or not such contracts, as they are constraining and can be seen as intrusive, to change her mind, to change from provider to another, *etc.*. However the actors of the market would have to propose some new contracts, incentives or any other actions (regulations letting the free market operating its own choices) to guarantee these levels of DSM.

5 Conclusion and perspectives

The aim of this article was to propose a novel procedure for the sizing of multi-carrier energy networks, combining several mixed grids, and to assess it through a simple case study. In brief, the main research question is to investigate how the future modifications of the loads due to DSM implementation will modify the design of the capacity. The main characteristic of the approach relies on the use of an iterative procedure, which takes into account these modifications of the demand and supply profiles due to the use of DSM and which consequently adapt the types and power of generation units needed to fulfill them. In the present case, the technologies are focused on solar energy, yet without any lack of generality. Thus, the method can be regarded as an "anticipatory retrofitting" of the design of the generation units. It has been illustrated on a basis test case involving thousands of residential dwellings, with various uncorrelated needs in both electricity and heat. The energy vectors are composed of a district heating network, combined with a local electrical grid, which is also connected to the national grid. The distributed multi-generation systems consist in PV panels and ST collectors, completed by a HP. Two types of DSM are considered, namely direct load control and curtailment, and also two different strategies for the aggregator enforcing these techniques. A series of ten simulations is conducted to highlight the various interactions, as a function of these parameters. Meanwhile, several performance criteria are scrutinized such as the exergy efficiency, economical value, self-consumption and coverage rates, bills and revenues for the customers and aggregators respectively... The most important conclusions drawn from this study are:

- DSM can reduce the size of equipments, the aggregator's profits and the users' final energy bills. In the present case, the number of PV panels and ST collectors calculated by the sizing is reduced by 13-38 % and 8-30 % respectively.
- The method is proven to be iteration-stable: results converge after 2 iterations, in all scenarios. However, it is worth mentioning that this facility could be tempered if energy storages, manageable renewable plants and/or forecasting would be present. Such remarks hold also for technologies like CHP and wind turbines.
- Each DSM strategy improves some performance indicators at the expense of others, especially the curtailment of consumers, which goes from 0% in BAU cases to 80% in the worst case. Since comparison between the different strategies is complicated, a multi-criteria decision-aiding method was developed and recommended after the procedure. Then, some guidance can be provided to help stakeholders in the choices governing the energy policy.

Finally, as the method developed in this paper seems promising, future works will be realized, focusing firstly on other types of technologies, especially combined heat and power and wind turbines, but also on the addition of both energy storages and forecasting (as mentioned just above). Then, the

forecasts of the weather, and consequently of productions, the forecast of demand and the forecasts of prices evolution can be combined altogether to develop other types of strategies. It also permits to be more closed to the real case. Simultaneously, other types of DSM techniques will be implemented, specifically with the possibilities offered by the forecasts. In addition, it is also planned to scrutinize the role and impacts of the possible initial uncertainties, as for example on the DSM adaptability and reactivity, level of penetration, *etc.*. Lastly, the case study will be extended to consider more agents and not only residential loads. This will allow first to test the scalability and also the convergence of the method. Moreover, this will also lead to a diversification of the types of exchanges between all the agents (consumers, producers, prosumers, aggregators) altogether.

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Annex

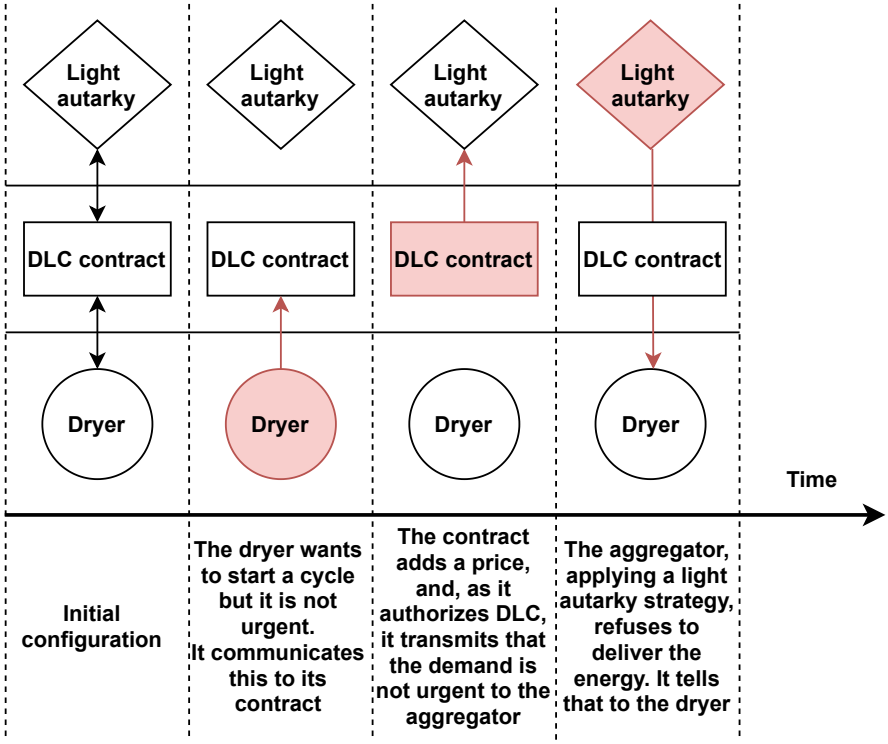

Figure 10 – An illustration of DSM process

Chapitre 5

Étude sur la viabilité économique des agrégateurs locaux

Opportunities and economic assessment for a third-party delivering electricity, heat and cold to residential buildings

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Abstract

Residential sector plays an important role to combat climate change since it represents about 40% of the global final energy consumption and 30% of direct CO_2 emissions in the European Union. Moreover, it is expected that renewable energy development will create grid management issues. Then, polygeneration systems, specifically designed to satisfy the needs of a residential district, have some interest.

This study is focused on the techno-economical assessment of such polygeneration systems. These systems are designed by an optimization tool to meet the demands of 50 dwellings. We tested the financial viability in term of Net Present Value, in 2 locations: Zaragoza, in Spain and Marseille, in France. While consumption levels are similar in these places, regulations are not. Three different financial configurations are investigated. The composition of the system and its CO_2 emissions are also compared to a reference case relying on classical technologies (a gas boiler and a mechanical chiller).

In the end, chosen technologies are similar, with different capacities: mainly PV, reversible heat pump, gas boiler and thermal energy storage. In all situations, the business model turns out profitable while reducing consumers' bills and the CO_2 emissions compared to the reference.

Keywords: Polygeneration Systems; Aggregator; Net Present Value; Optimization; Renewable Energy; Residential Sector

Contents

Nomenclature

Latin symbols

A	surface area, m^2
a_0	optical efficiency, –
a_1	first heat loss coefficient, $W\,m^{-2}\,K^{-1}$
a_2	second heat loss coefficient, $W\,m^{-2}\,K^{-2}$
C	cost,
C	thermal Capacitance, $J\,kg^{-1}$
CAP	installed capacity, kWh or MWh
$C_{\mathcal{P}}$	power coefficient, –
c	specific heat capacity, $J\,K^{-1}\,kg^{-1}$
CAPEX	capital expenditures,
CF	cash flow,
COP	coefficient of performance, –
D	demand, kWh
DD	degree day –
DCF	discounted cash flow,
Dep	depreciation,
DOD	allowable depth of discharge, %
E	total energy, J or kWh
EER	coefficient of performance, –
G	irradiation, $W\,m^{-2}$
Fm	installation costs,
G	building heat loss coefficient, $W\,K^{-1}\,m^{-3}$
$\mathcal{I}$	solar irradiance, $W\,m^{-2}$
IT	income tax,
ItR	interests rate, %
LCC	life cycle cost,
LCOE	levelized cost of energy, /(kWh)
LF	loss factor, %
LHV	lower heating value, $J\,m^{-3}$ or $J\,kg^{-1}$
LT	life time, year
M	Very large number (*i.e.* 1e6), –
MCR	major components replacement,
N	integer number, -
NOCT	nominal operating cell temperature, °C
NPV	net present value,
O&M	operation and maintenance costs,
OPEX	operational expenditures,
$\mathcal{P}$	power, W
P	price,
PP	payback period, year
Q	heat, J or kWh
q	flow-rate, $m^3\,s^{-1}$ or $L\,s^{-1}$
R	revenue,
R	thermal resistance, $W^{-1}\,K\,m^2$
RV	residual value,
r	discount rate, %
SD	self-discharge, %/month
SOC	state of charge, %
T	temperature, K or °C
TI	taxable income,
Tr	tax rates, %
t	time, s or min
$\boldsymbol{U}$	velocity, $m\,s^{-1}$
V	volume, m^3
VAT	value added tax, %
z	position, m

Greek symbols

η	efficiency, – or %
κ	open-circuit voltage thermal coefficient, K^{-1}
ρ	density, $kg\,m^{-3}$
ω	weight of a representative day, –

Subscripts and superscripts

a	air
amb	ambient
c	cooling
$\not{c}$	cycle
cd	cold
cell	cell
ch	charge
cut	cutoff
d	day
dw	dw
dis	discharge
el	electrical
fu	fuel
g	gas
gd	grid
ht	heating
h	hour
in	indoor
inv	inverter
m	month
nom	nominal

out	outdoor
pan	panel
pp	pipe
pur	purchased
ref	reference
sld	sold
sp	set point
stor	storage
th	thermal
wt	water

Acronyms

AbCh	absorption chiller
BEES	battery electrical energy storage
CCHP	combined cooling, heating and power
CHP	combined heating and power
CM	cogeneration module
DH	district heating
DHW	domestic hot water
EU	European Union
FC	fuel cell
FiT	feed-in tariffs
GA	genetic algorithm
GB	gas boiler
GHG	green-house gas
GIS	geographic information system
HP	heat-pump
ICE	internal combustion engine
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IRR	internal rate of return
LCA	life cycle assessment
MILP	mixed integer linear programming
MINLP	mixed integer non-linear programming
MT	micro-turbine
PV	photo-voltaic
RES	renewable energy system
ST	solar thermal
TES	thermal energy storage
TSR	thermal storage for heating
TSQ	thermal storage for cooling
WT	wind turbine

1 Introduction

1.1 Foreword

In the ongoing race for a decarbonized world, challenges are numerous. Indeed, current statistics and future projections clearly show an increase of the demand [1]. Unfortunately, this latter is still mainly based on fossil fuels, which endangers obviously the climate but also abiotic ressources. When analyzing more finely this demand, building sector represents 40% of the total final consumption in the EU, 75% of which being supplied by fossil fuels [2]. The increase by 2050 should be of 79% and 84% for the heating and cooling demand respectively [3]. Therefore, the residential buildings is identified by the IPCC as a paramount objective in the pathway to limit global warming [4].

To tackle such a problem, the usual approach mainly relies on renewable energy sources (RES) and energy efficiency [5, 6]. In the former case, the preferred solutions involve increased deployment of photovoltaic (PV) and wind (WT) energy as well as solar thermal (ST) energy [7–10]. In the latter case, several options are envisaged to increase. It is first planned to further develop district heating and cooling networks [5, 11, 12], and to integrate more smartness [13, 14] and more cross-sectoral interactions [15, 16]. There is consequently a strong impetus for multi-energy systems [17, 18] which flexibilise the energy management, or more appropriately, to energies management since multi-energy flows are involved. Among the available technologies, heat-pumps (HP) and combined-heat-and-power (CHP) are serious candidates [6, 19, 20], especially in a context of renewable electricity or to pave the way for biogas or power-to-gas [2, 18, 21]. Secondly, the smart-grid concept could be further extended, especially to other energy networks, as well as the flexibility of the whole network. To achieve such a goal, it has been pointed out that the advent of aggregators should be promoted [22] to either access all types of market or to increase energy sharing (see for instance Chapter III, Article 16.3 of the previous reference). In the same idea, it appears that innovation in the development of new business models should be encouraged [23, 24]. Finally, it is worth highlighting that all these solutions should benefit or will probably require a more important use of energy storage [2, 10, 23, 25].

1.2 Literature review

With regard to the above discussion, it is clear that a broad portfolio of technologies is to be considered, together with polygeneration systems, when planning the features of the future energy network. Unsurprisingly, many papers have been devoted to such a topic: the interested reader is referred to [14], and [26] for a recent review of future infrastructures involving them, but also to [27] for an overview of models and assessment techniques and to [28] for investment models assessment. To name but a few examples of their advantages, they are particularly well fitted in real-time demand response programmes [29] and help to gain in flexibility [30]; they permit to reduce CO_2 emissions and capital costs [28, 31]; they can increase self-sufficiency [32, 33], *etc.*

Besides, it is common to use optimization when designing energy systems [34, 35]. A complete literature review on this topic is out of scope of the present study, but it is just recalled that such optimization could be done either for a single type of energy or for multiple energy vectors. As an example, a techno-economic optimization of a stand-alone power-only grid, combining PV and WT and a diesel engine (ICE) with batteries (BEES), is conducted in [36] for ten houses located in Ghardaïa, Algeria. In the same manner, an autonomous isolated microgrid based on PV and WT and BEES is designed for Agios Efstratios (a Greek island) by means of a techno-economic analysis in [37]. Similarly, cost minimization is performed in [30] to optimally design a system involving PV and a CHP, as well as BEES and thermal

storage (TES), so as to supply an isolated tourist resort in Northern Italy. Finally, integration inside a district heating of ST field and seasonal storages (with gas boiler as backup) is investigated for a 20 000 inhabitants municipality in Latvia in [38].

Afterwards, and closer to this study are works devoted to poly-generation technologies in multi-carrier energy systems. Let us mention here that the used taxonomy defines polygeneration technologies as appliances able to provide more than one type of energy and multi-carrier energy systems as networks involving several types of energy flows (produced either by single- or poly-generation systems). Thus, Weber & Shah used a MILP optimization to decrease emissions and increase self-sufficiency of a 6 500 inhabitants eco-town in England by combining CHP plants with HP, together with PV, WT and ST [39]. They showed that such a system can be cheaper than a business-as-usual situation. Then, two important conclusions are drawn: firstly, external (historical) grid appeared essential if storages are not involved, and secondly, ST is essential at the building level even if their role is minimal compared to the HP. In [40], Destro *et al.* considered the Italian resort mentioned above, yet for designing here a combined-cold-heat-and-power (CCHP) system composed of PV, CHP and reversible HP. Moreover, cold and hot TES, BEES and pumped hydro storage were also available. Their results highlighted that a system with the reversible HP was the most efficient, though it imposed a cold TES. Interestingly, Das & Al-Abdeli studied in [41] the influence of the electrical and thermal loads on the optimization of a stand-alone grid involving PV and BEES, and ICE or MT used as a CHP plant. The LCOE was not really impacted by the power management strategy, namely following the electric load or the thermal load or both. Besides, this latter possibility resulted in better performance. Next, Jiménez Navarro *et al.* proposed to optimize a CCHP grid for a park located in Málaga, Spain [42]. When minimizing the total annual cost of a CHP, with boiler as backup, combined with mechanical and absorption chillers and cold TES, they showed the importance of a base load demand to guarantee the performance in case of large daily variations. In addition, the demand uncertainties were clearly able to jeopardize the investment. Next, in the context of a high latitude community in Finland, Hirvonen *et al.* performed the techno-economic optimization of a system containing PV, ST and a geothermal HP, and TES [43]. A scaling effect was observed, leading to lower costs for the same performance, when considering 200 buildings instead of 50. Then, in [44], Li *et al.* optimized a multi-energy system combining PV and FC with CHP and electric and gas boilers. Hydrogen storage was also considered, together with the associated electrolyzer. It is worth mentioning that the location of the PV panels, *ceteris paribus*, influenced greatly the sizing of the other components. Moreover, a decrease of the investment costs of the FC and the electrolyzer increased the PV capacity. More recently, Bartolini *et al.* [21] were interested in power-to-gas potential in a multi-energy small district involving a large set of technologies: PV and FC, two types of CHP and air-source HP, sensible TES and Lithium-ion BEES, electrolyzer and hydrogen storage, electric air-conditioning-unit... For real user demands and renewable electricity production data in Austin, Texas, US, they conducted a MILP optimization to minimize the total cost which clearly showed the boons of multi-energy architectures and storages and their interests to achieve RES communities. Using also a MILP approach, Zhu *et al.* maximized the NPV or IRR of five different buildings in Shanghai, China [45]. The involved technologies were PV and WT, together with CHP and electric boiler and TES, as well as an absorption chiller and an electric chiller. Better results were obtained when the optimization criterion was NPV maximisation. Moreover, there was still a need for imported electricity and the impacts of both FiT and electrical and thermal mismatch were important.

Finally, in parallel of these studies pertaining to optimized design, a huge work was also devoted to aggregators, specifically in the field of smart-grids. Indeed, these ones are more and more scrutinized and should be more and more encountered in real applications. Therein, the main role of an aggregator is to group distinct agents [46]. Though interesting, and aimed in a forthcoming study, the organization of

the smartness will not be discussed here. Instead, the focus is set on the business model of aggregators, particularly well presented in [46, 47]. The important underlying question is to asses their economic value [48]. It is indeed particularly tricky due to the current change of both the markets and the role of each actors, accompanied by some uncertainties or too strict legal rules [42] or, in the contrary, by a lack in regulation [49].

1.3 Contribution and novelty of the study

The main goal of this study is to investigate the economic viability of an energy supplier company delivering various types of energy to a set of several tens of customers. This intermediate company is delivering electricity, heat and cold with its own production and storage units, and it has access to the regional electrical and gas grids. Secondly, it plays the role of an aggregator, and as such, can singularly decrease the corresponding demand to these latter grids, and corresponding peaks. Furthermore, by investing directly in these equipments, it relieves such a burden from the basic customers who will not have to assume the initial investment costs and future operating costs. Therefore, the underlying idea is to look if there is an added-value for both this supplier and the customers.
Several technologies are tested, in a polygeneration framework. Various business models will be analyzed. Lastly, this methodology is applied to two different locations (Spain and France) in order to scrutinize the effects of demand and regulations on the final sizing. This latter is done by optimizing a superstructure involving flexible appliances, RES and storage (both electrical and thermal). The objective is to maximize the NPV [45, 50] through a MILP model, while paying attention to the $CO_{2\,\mathrm{eq}}$ emissions.
In terms of contribution, the novelty of this study are manyfold:

1. The range of the test cases is in the mid-term, that is to say between the current historical paradigm and an (hypothetical) completely decarbonized one.
2. Evolutions of the energy prices are considered.
3. Three business models are tested:
   (a) case A: constant price of energy and no resale authorized.
   (b) case B: variable price of energy and no resale authorized.
   (c) case C: variable price of energy and resale authorized.
4. 12 representative days are identified considering hourly energy demand profiles, RES and CO_2 emissions from the grid, for both Zaragoza, Spain and Marseille, France.
5. Optimization is conducted at a small district scale, for 50 dwellings.

The paper is organized as follows. The methodology is presented in section 2 and the test cases in section 3. Section 4 is devoted to the analysis and discussion of the results, and section 6 concerns the conclusions and perspectives.

2 Methodology

The objective is to attend the demand (electricity $E_{\mathrm{dw,el}}$, heating $E_{\mathrm{dw,th}}$ and cooling $E_{\mathrm{dw,c}}$) for a residential building compound of 50 dwellings. Usually, the dwellings owners (customers) enter directly into

individual electricity and gas contracts to fulfill their demands. As mentioned previously, this study aims to evaluate the feasibility of modifying this organization by the introduction of an intermediate company: a third-party, illustrated in Fig. 1, between the customers and the historical grids. This third-party aggregates the demands of the consumers, and also owns different multi-carrier energy systems. By means of polygeneration and storage, it can offer interesting prices on the long term, due to lower losses and operational and maintenance costs. It can also sell energy surplus or rely on the outter grids. On the other hand, the customers do not have to pay the capital expenditures but can still access to cheaper (possibly decarbonized) energy. Added to this, they will keep the possibility to change their energy provider and they are not stuck to binding contracts.
The analysis is performed for Zaragoza, Spain and Marseille, France, considering thus different physical conditions. Likewise, the environmental impact is estimated for both locations through the calculation of $CO_{2\,\mathrm{eq}}$ emissions.

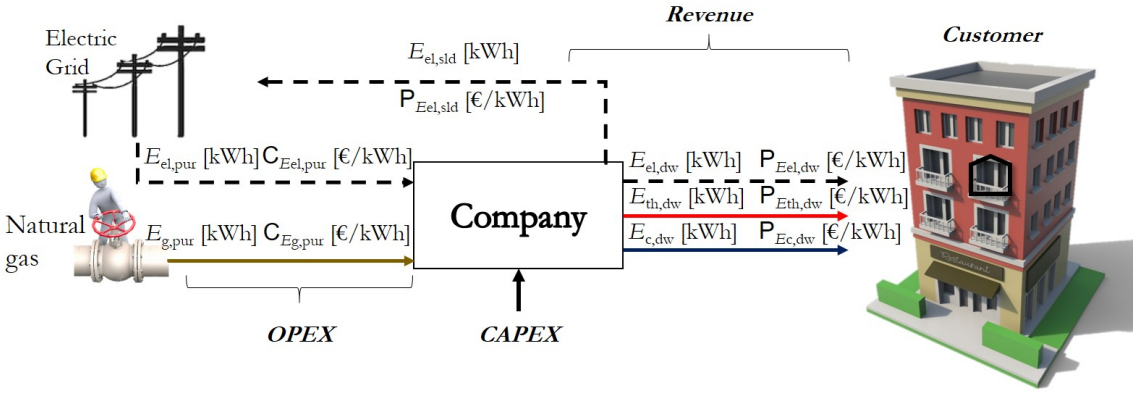


Figure 1 – Illustration of the role of a third-party acting as an aggregator and an energy provider

2.1 Superstructure

The superstructure depicted in Fig. 2 shows the technologies available to cover the demand. The efficiency of every technology is assumed constant. These candidate technologies can be divided according to the kind of energy that they provide. PV panels and wind turbines (WT) produce electricity; gas boiler (GB) and solar thermal collectors (ST), heat; and single-effect absorption chiller (AbCh), cooling. Some technologies supply two services, such as the cogeneration modules (CM), producing both electricity and heat, or the reversible heat pump (HP) providing heating or cooling. Lastly, thermal energy storage is available for heating (TSQ) and cooling (TSR), while batteries (BEES) are considered for electricity. Obviously, the required appliances, such as inverters and inverter chargers, are involved to take into account the need to convert direct current into alternating current and conversely.

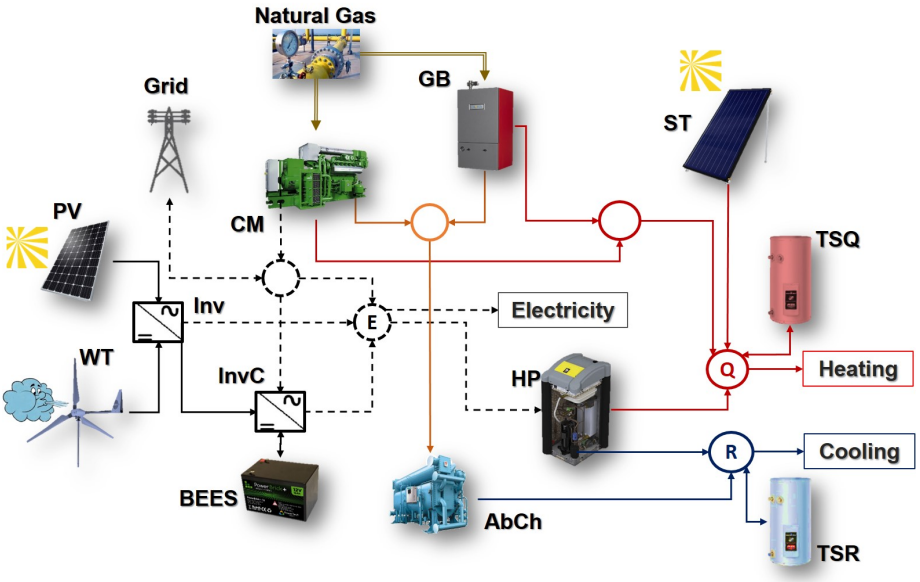


Figure 2 – Basic components of the superstructure involved in the optimization design

Since GHG emissions are to be considered, the corresponding features of the electricity mix in each country is considered. As shown in Fig. 3, the emissions are thus greater in Zaragoza than in Marseille, due to the availability of nuclear energy in France. Similarly, the legal coefficient for natural gas combustion are 0.203 $\mathrm{kg}_{CO_{2\,\mathrm{eq}}}/\,\mathrm{kWh}$ and 0.227 $\mathrm{kg}_{CO_{2\,\mathrm{eq}}}/\,\mathrm{kWh}$ in Spain [51] and in France [52] respectively.

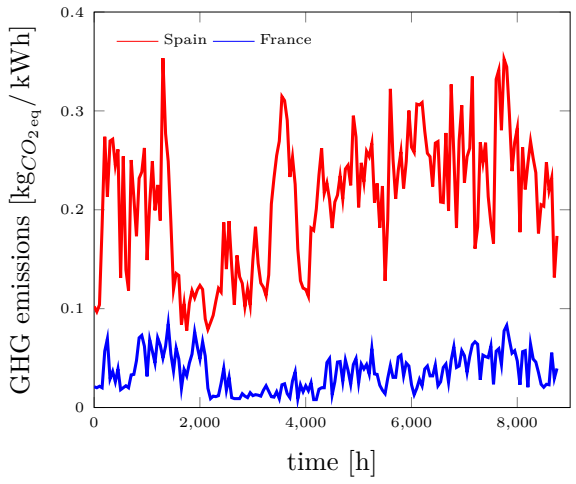


Figure 3 – Hourly $CO_{2\,\mathrm{eq}}$ emissions from the electric grid for Spain [53] and France [54] in 2018

2.2 Supply and demand

2.2.1 Poly-generation production

As mentioned above, there are many types of technologies considered in this study (see Fig. 2) which are further detailed here. The first ones concern the RES producing electricity, namely PV and WT, whose hourly power is for PV [55–57]:

$$\mathcal{P}_{\text{el,PV}} = \mathcal{I}\,A \cdot \eta_{\text{PV}} \cdot \eta_{\text{inv}} \tag{2.1a}$$

$$\eta_{\text{PV}}(T) = \eta_{\text{pan}}\left(1 - \kappa\left(T_{\text{cell}} - T_{\text{cell}}^{\text{ref}}\right)\right) \tag{2.1b}$$

$$T_{\text{cell}} = T_{\text{amb}} + \left(\text{NOCT} - T_{\text{cell}}^{\text{ref}}\right)\frac{\mathcal{I}}{\mathcal{I}^{\text{ref}}} \quad , \tag{2.1c}$$

while WT production is calculated using manufacturers' curves [58].
In the case of heat production by ST, it is proportional to the mean difference temperature between the collector temperature at 60 °C and the ambient temperature [38, 59, 60]:

$$\mathcal{P}_{\text{th,ST}} = \mathcal{I}\,A \cdot \eta_{\text{ST}} \tag{2.2a}$$

$$\eta_{\text{ST}}(T) = \mathtt{a}_0 - \frac{\mathtt{a}_1}{\mathcal{I}}\left(T - T_{\text{amb}}\right) - \frac{\mathtt{a}_2}{\mathcal{I}}\left(T - T_{\text{amb}}\right)^2 \quad . \tag{2.2b}$$

All the other production or conversion energy devices are completely controllable.
Among devices delivering a single type of energy, only the GB and the AbCh are missing. The corresponding description is, for the boiler:

$$\mathcal{P}_{\text{th,GB}} = \eta_{\text{GB}} \cdot \mathtt{q}_{\text{fu}} \cdot LHV \quad , \tag{2.3}$$

and for the chiller:

$$\mathcal{P}_{c,\text{AbCh}} = \text{COP} \cdot \mathcal{P}_{\text{th}} \quad . \tag{2.4}$$

Finally, for cogeneration devices:

$$\mathcal{P}_{\text{th,CHP}} = \eta_{\text{th,GB}} \cdot \mathtt{q}_{\text{fu}} \cdot LHV \tag{2.5a}$$

$$\mathcal{P}_{\text{el,CHP}} = \eta_{\text{el,GB}} \cdot \mathtt{q}_{\text{fu}} \cdot LHV \quad , \tag{2.5b}$$

and the reversible HP:

$$\mathcal{P}_{\text{th,HP}} = \text{COP} \cdot \mathcal{P}_{\text{el}} \tag{2.6a}$$

$$\mathcal{P}_{c,\text{HP}} = \text{EER} \cdot \mathcal{P}_{\text{el}} \quad . \tag{2.6b}$$

n.b.: all these appliances provoke GHG emissions, whose values will be provided further (see Table 3).

2.2.2 Energy storage

For storage, the energy balance is done on an hourly basis, taking into account an energy loss factor. Whatever the type of energy stored (heat or electricity), the evolution of the available energy is:

$$E_{\text{stor}}^{h+1} = LF \cdot E_{\text{stor}}^{h} + \left(\mathcal{P}_{\text{el}}^{\text{ch}} - \mathcal{P}_{\text{el}}^{\text{dis}}\right)\Delta t \quad . \tag{2.7}$$

In the case of BEES, the loss coefficient corresponds to the self-discharge value [61]. Besides the hourly energy losses, the round trip efficiency η_{rt} is also considered. Lastly, the number of cycles must be lower or equal to the cycle life of the battery:

$$N_{\ell} \leq N_{\ell,\text{failure}} \quad . \tag{2.8}$$

On the other hand, for both TSQ and TSR, sensible water tanks are considered since their heat losses are often lower [62, 63] and, more important, because their technology readiness level is higher.

2.2.3 Energies demand

As explained before, consumption profiles are divided between heat (space heating and DHW – $E_{\text{th,dw}} = E_{ht} + E_{\text{DHW}}$ –), cooling and electricity. In the first case, heating and cooling needs are calculated with a classic $\mathtt{R}-\mathtt{C}$ model, or an average volumetric or total heat loss coefficient model [64–68]:

$$\mathcal{P}_{ht,c} = \mathtt{G} \cdot V \cdot (T_{\text{sp}} - T_{\text{out}}) \tag{2.9a}$$

$$\mathcal{P}_{ht,c} = \frac{\mathtt{C}}{\Delta t} \cdot \left(T_{\text{sp}} - T_{\text{out}} - (T_{\text{in}} - T_{\text{out}})\, e^{-\frac{\Delta t}{\tau}}\right) \quad . \tag{2.9b}$$

Outdoor temperatures are taken from [69] and are thus different for Marseille and Zaragoza. $\mathtt{C}$ is set to 0.3 kWhK^{-1}.
For the DHW demand, it is based on a wanted volume of hot water at 40 °C, varying monthly over the year. Initial temperature of the water supplied to the tank is variable and taken from [70]. For an average temperature in the tank of 60 °C, the DHW demand reads:

$$E_{\text{DHW}} = \rho_{wt} V_{\text{h}} \cdot c_{wt} \cdot (60 - T_{\text{pp}}) \tag{2.10a}$$

$$V_{\text{h}} = V_{\text{DHW}}^{\text{m}} \frac{40 - T_{\text{pp}}}{60 - T_{\text{pp}}} \quad . \tag{2.10b}$$

Finally, the electrical consumption is composed of a typical consumption week, with important variations between weekdays and week-ends, and also with differences between Marseille and Zaragoza. Fig. 4 presents the consumption of the day where the peak consumption occurs for heating, cooling and electricity. These peaks are reached in December for heating and July for cooling. As electricity consumption consists in a typical consumption week, the consumption peak occurs the week-end. Lastly, the annual corresponding aggregated consumptions are gathered in Table 1.

Table 1 – Annual energy demands in kWh/year

Location	Dwellings	Heating	Cooling	Electricity
Zaragoza	50	335 412	26 132	206 804
Marseille		234 300	11 014	206 755

2.2.4 Representative days

Usually, when several time series and binary variables are involved, optimization is computationally expensive. Therefore, representative days have been widely used to tackle this issue [71, 72]. Since this work considers up to seven time series, some having high variability such as WT production and hourly

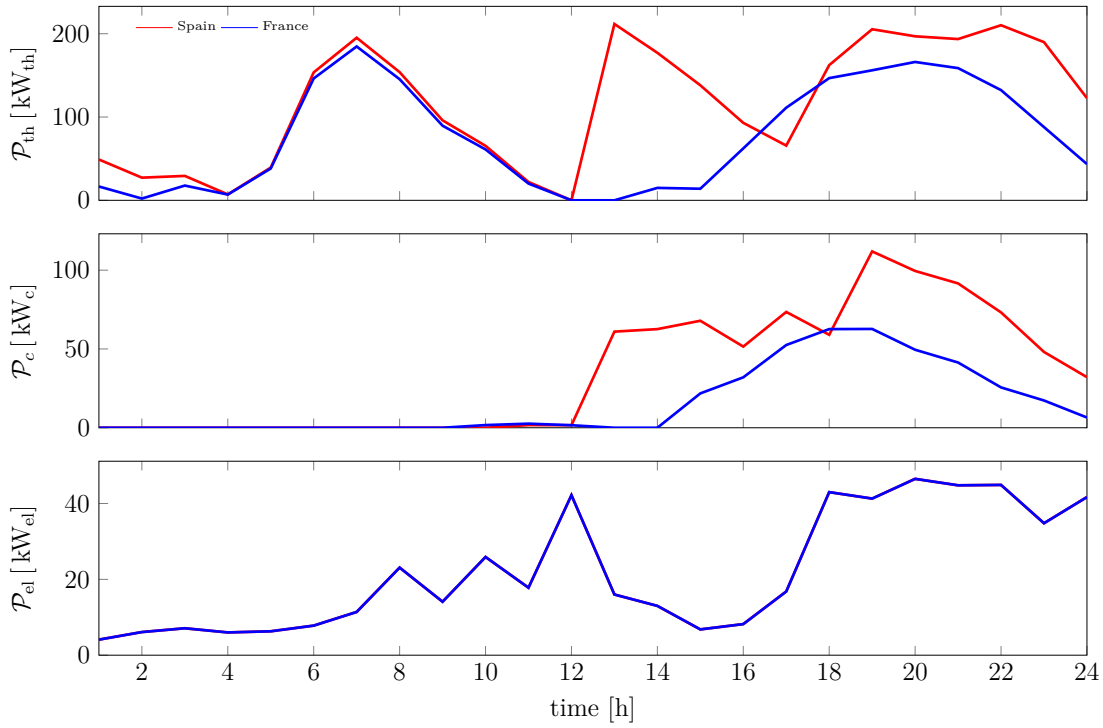


Figure 4 – Daily energy demand profiles at peak, for each energy type

$CO_{2\,eq}$ emissions from the grid (especially in Spain), the kM-OPT method [73] was applied. This method merged two methods, the k-Medoids method developed by Domínguez-Muñoz *et al.* [74] which aims to group the days of the year into clusters; and the OPT method developed by Poncelet *et al.* [75] which fits the data duration curve obtained from representative periods to the duration curve of the original time series.

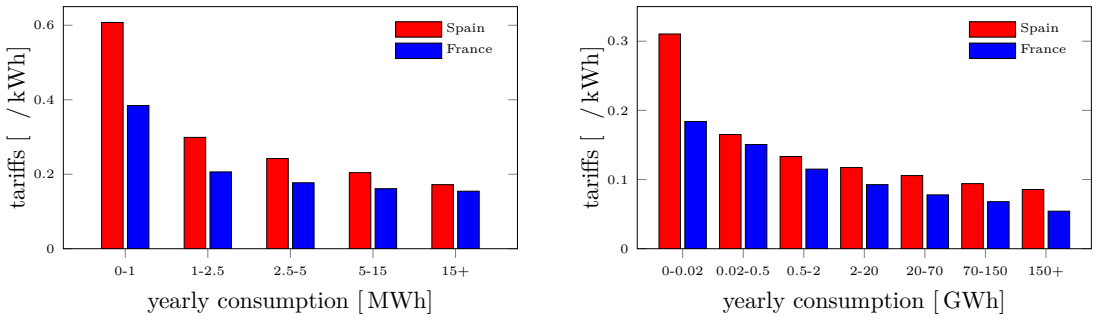
Thus, a set of 12 representative days D_{rep} can be built, where each representative day consists of a set H of 24 time periods h of 1 hour, with a daily respective weight ω for each location. The corresponding values are available in Table 6 and are discusses in section 3.2.

2.3 Economic model

2.3.1 Gross and retail energy prices

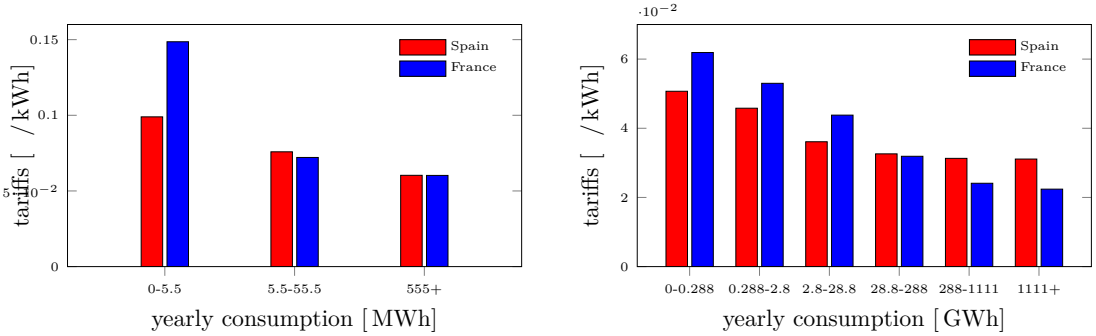
The electricity and fuel prices depend on the total annual consumption: the higher the consumption, the lower the price. Consequently, it is logical to set different available prices for the customers and for the aggregator. Figs. 5a and 5b present the average price for the last 2 years for electricity tariffs for households and non-households respectively. Figs. 6a and 6b present the same average prices for the last 2 years for natural gas. In this sense, for the customers, the reference system is based on household tariffs, whereas the aggregator can buy at non-household prices. For electricity, in the 20-500 MWh/year range, the tariff is 0.1477 €/kWh for France and 0.1582 €/kWh for Spain. For natural

gas, consumption below 288 MWh/year is expected in France, corresponding so to a tariff of 0.0622 /kWh, whereas, for Spain, the expected consumption is about 0.28-2.8 GWh/year, for a tariff of 0.045 /kWh. These are the average values for 2018 [76].



(a) Households (b) Non-households

Figure 5 – Electricity prices [76]

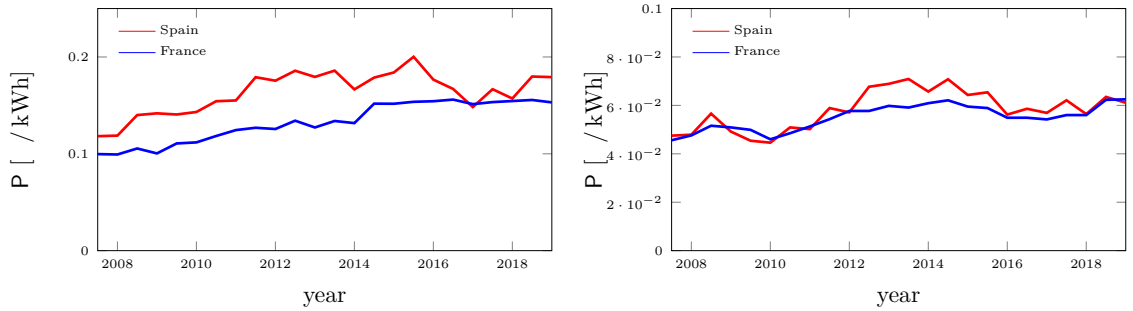


(a) Households (b) Non-households

Figure 6 – Natural gas prices [76]

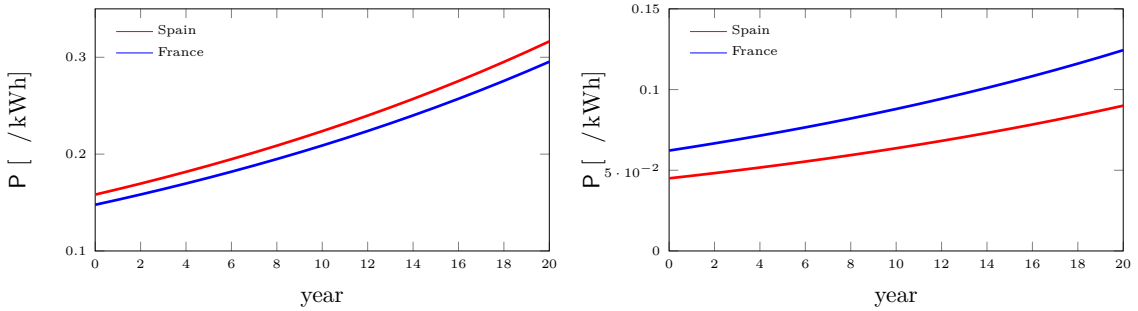
2.3.2 Energy prices evolution

Electricity and natural gas prices have a high variability and tend to increase. From 2007 to 2019 (12 years), electricity and natural gas prices in France and Spain have increased about 50% and 40% respectively (see Figs. 7a and 7b) according to the Eurostat survey tool from the European Commission [76]. Therefore, in a horizon of 20 years (2038), it is expected that electricity and natural gas prices can double or even triple, and hence, also the price of final energy (electricity, heating and cooling).
As a consequence, in an horizon of 20 years, the hypothesis is that electricity and natural gas prices double following an exponential function $\mathsf{P}^i = \mathsf{P}_0(2^{1/20})^i$ (roughly +3.5% per year), where P^i is the unit price of each energy vector at year i. The final prices applied during the present simulations are represented on Fig. 8.



(a) Electricity (b) Natural gas

Figure 7 – Energy prices from 2007 to 2019 for households [76]



(a) Electricity (b) Natural gas

Figure 8 – Retained projections for the energy prices evolution

2.3.3 Net present value

NPV is a commonly used indicator to evaluate the economic viability of an investment, which applies a discount to cash flows. The discount, r, is proportional to the year corresponding to the net cash flows, after balancing the input and output flows. Such method allows to estimate if a quantity of money earned immediately has more value than 10 years later.
In practice, one gets:

$$\mathsf{NPV} = -\mathsf{CAPEX} + \sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{CF}_i}{(1+\mathsf{r})^i} \tag{2.11a}$$

$$\mathsf{CAPEX} = \sum_{\text{set of technologies } j \in J} \Big(\mathsf{C}_j\ (1+Fm_j)\Big) \cdot \mathrm{CAP}_j \cdot (1+\mathsf{VAT}) \tag{2.11b}$$

$$\mathsf{CF}_i = \mathsf{R}_i - \mathsf{OPEX}_i - \mathsf{IT}_i \quad . \tag{2.11c}$$

Revenue comes from the sales of the various types of energy (heat, electricity, cool) to the customer and, for case B and C, to the electricity fed to the grid:

$$\mathsf{R}_i = \sum_{\text{consumers}} \mathsf{P}_{E_{\text{el,dw},i}} E_{\text{el,dw},i} + \mathsf{P}_{E_{\text{th,dw},i}} E_{\text{th,dw},i} + \mathsf{P}_{E_{\text{c,dw},i}} E_{\text{c,dw},i} \ + \left(\mathsf{P}_{E_{\text{el,sld},i}} E_{\text{el,sld},i}\right) \quad . \tag{2.12}$$

Usually, the operational expenditures express as:

$$\mathsf{OPEX}_i = \mathsf{MCR}_i + \sum_{\text{set of technologies } j \in J} \mathsf{O\&M}_{j,i} \quad , \tag{2.13}$$

but in the present case, the second term only contains the operational costs consisting in the purchase of electricity ($E_{\text{el,pur}}$, at unit price $\mathsf{C}_{E_{\text{el,pur}}}$) and of natural gas ($E_{g,\text{pur}}$, at unit price $\mathsf{C}_{E_{g,\text{pur}}}$), since the maintenance costs are considered within the installation factor Fm in Eq. 2.11b.
Accordingly, Eq. 2.13 can be re-written:

$$\mathsf{MCR}_i = \begin{cases} \sum_{j \in J} \dfrac{\mathsf{CAPEX}_j}{(1+\mathsf{r})^i} & \text{if } i < \mathsf{LT}_j \\ 0 & \text{otherwise} \end{cases} \tag{2.14a}$$

$$\sum_{j \in J} \mathsf{O\&M}_{j,i} = \mathsf{C}_{E_{\text{el,pur},i}} E_{\text{el,pur},i} + \mathsf{C}_{E_{g,\text{pur},i}} E_{g,\text{pur},i} \quad . \tag{2.14b}$$

Finally, the income tax is:

$$\mathsf{IT}_i = \mathsf{TI}_i \times \mathsf{Tr} \tag{2.15a}$$

$$\mathsf{TI}_i = \mathsf{R}_i - \mathsf{OPEX}_i - \mathsf{Dep}_i \tag{2.15b}$$

$$\mathsf{Dep}_i = \frac{\mathsf{CAPEX} - \mathsf{RV}}{\mathsf{LT}} \quad . \tag{2.15c}$$

For the sake of clarity, the sum of the discounted cash flow appearing in Eq. 2.11a can be divided into three parts: revenues, operational expenditures an income taxes. Thus, the first term will express for the three cases considered here:

$$\text{case A:} \quad \sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{R}_i}{(1+\mathsf{r})^i} = \aleph \sum_{i=1}^{\mathsf{LT}} \frac{1}{(1+\mathsf{r})^i} \tag{2.16a}$$

$$\text{case B:} \quad \sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{R}_i}{(1+\mathsf{r})^i} = \aleph \sum_{i=1}^{\mathsf{LT}} \frac{(2^{1/20})^i}{(1+\mathsf{r})^i} \tag{2.16b}$$

$$\text{case C:} \quad \sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{R}_i}{(1+\mathsf{r})^i} = \left(\mathsf{P}_{E_{\text{el,sld},0}} E_{\text{el,sld},0} + \aleph\right) \sum_{i=1}^{\mathsf{LT}} \frac{(2^{1/20})^i}{(1+\mathsf{r})^i} \tag{2.16c}$$

$$\text{with} \quad \aleph = \sum_{\text{consumers}} \mathsf{P}_{E_{\text{el,dw},0}} E_{\text{el,dw},0} + \mathsf{P}_{E_{\text{th,dw},0}} E_{\text{th,dw},0} + \mathsf{P}_{E_{c,\text{dw},0}} E_{c,\text{dw},0} \tag{2.16d}$$

Similarly, the second term reads (for all cases):

$$\sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{OPEX}_i}{(1+\mathsf{r})^i} = \sum_{i=1}^{\mathsf{LT}} \frac{\mathsf{MCR}_i}{(1+\mathsf{r})^i} + \left(\mathsf{C}_{E_{\text{el,pur},0}} E_{\text{el,pur},0} + \mathsf{C}_{E_{g,\text{pur},0}} E_{g,\text{pur},0}\right) \sum_{i=1}^{\mathsf{LT}} \frac{(2^{1/20})^i}{(1+\mathsf{r})^i} \tag{2.17}$$

And, eventually, the term associated with the income tax is straightforward, giving Eq. 2.15 and Eqs. 2.16 and 2.17.
Concretely, a 20 years lifetime is considered. A 5% value for the nominal discount rate is common [25,77] and so adopted here; this leads to real discount rate of 3.4%. Finally, the tax rates Tr for the incomes of the aggregator is set to 25%, while the VAT is 21% for Spain and 20% for France. Lastly, the residual value is assumed null at the end of the project.

2.4 Optimization model

As mentioned earlier, the objective function is to maximize the NPV as in [45, 50]:

$$\max \ \mathsf{NPV} = \max \left(-\mathsf{CAPEX} + \sum_{i=1}^{\mathsf{LT}} \mathsf{DCF}_i \right) \quad , \tag{2.18}$$

where the capital expenditures are given by Eq. 2.11b and the discounted cash flows by Eqs. 2.16 and 2.17.
The associated choice variables and constraint conditions are:

- Installation of technologies: The installation of the components is determined by the binary variable Y_{ins} considering the maximum capacity of each component:

$$\mathrm{CAP}(j) \leq Y_{ins}(j) \cdot \max \ \mathrm{CAP}(j) \qquad \forall j \in J \tag{2.19}$$

- Energy balance: It is carried out in each node of the superstructure for every day d and hour h. For the generic variable E, representing any type of energy (electricity E_{el}, heating E_{th} or cooling E_c), one gets for each time step between the inputs and outputs:

$$\sum E^{in}(d,h) = \sum E^{out}(d,h) \qquad \forall \ E_{\in}\{E_{\mathrm{el}}, E_{\mathrm{th}}, E_c\}, \ d \in D_{rep}, \ h \in H \tag{2.20}$$

- Energy storage: The stored energy at the beginning of the day ($h = 1$) must be equal at the end of the day ($h = 24$) due to the use of representative days:

$$E_{\mathrm{stor}}(d,1) = E_{\mathrm{stor}}(d,24) \tag{2.21}$$

- Installed capacity limitations: The total energy production is mandatory equal or lower than the installed nominal capacity:

$$E(d,h) \leq \mathrm{CAP}(j) \qquad \forall \ E_{\in}\{E_{\mathrm{el}}, E_{\mathrm{th}}, E_c\}, \ j \in J, d \in D_{rep}, \ h \in H \tag{2.22}$$

  In the case of the electric grid, the contracted power $\mathcal{P}ct$ is set according to the purchased or sale electricity:

$$\mathcal{P}ct \geq E_{\mathrm{el,pur}}(d,h) + E_{\mathrm{el,sld}}(d,h) \qquad \forall \ d \in D_{rep} \ h \in H \tag{2.23}$$

- Operational restrictions: Partial load PL of the cogeneration module is considered by applying a binary variable Y_{ON} along with the M number. This last one is used to model, for instance, specific piecewise-defined functions; its value being dependent on the type of problem [78].
  Thus, the engine can be operated such that it works with linear performance only above the minimum PL, and below the engine is off. In this way, the engine can modulate according to:

$$\mathcal{P}_{\mathrm{CHP}} - PL \cdot \mathrm{CAP}_{\mathrm{CHP}} \geq -M \cdot (1 - Y_{ON}) \tag{2.24a}$$

$$\mathcal{P}_{\mathrm{CHP}} \leq M \cdot Y_{ON} \tag{2.24b}$$

  Here, a value of 10^6 has been set for M.

- RES: For the renewable production, the aim is to find the surface areas of the PV modules A_{PV} and ST collectors A_{ST}, and the number N_{WT} of WT.

Finally, the optimization of the polygeneration system is carried out by solving a MILP model developed in the optimizer software `Lingo` [79]. During the calculations, the GHG emissions are also computed. They correspond to emissions of burnt fuel and of the electricity mix of the grid:

$$CO_{2\,\mathrm{eq}} = \sum_{d=1}^{12} \omega(d) \left(\sum_{h=1}^{24} CO_{2,\,\mathrm{fu}}(d,h) + CO_{2,\,\mathrm{gd}}(d,h) \right) \tag{2.25a}$$

$$CO_{2,\,\mathrm{fu}}(d,h) = \sum_{j \in J} CO_2(j) \cdot \mathsf{q}_{\mathrm{fu}}(j,d,h) \qquad \forall\, d \in D_{rep},\ h \in H \tag{2.25b}$$

$$CO_{2,\,\mathrm{gd}}(d,h) = CO_{2\,\mathrm{gd}}(d,h) \cdot (E_{\mathrm{pur}}(d,h) - E_{\mathrm{sld}}(d,h)) \qquad \forall\, d \in D_{rep},\ h \in H \tag{2.25c}$$

Therefore, the outputs of the optimization are the presence (or absence) of each component together with its sizing (or installed capacity), the primary energy consumption, the GHG emissions and obviously the value of the maximized NPV.

3 Case studied

3.1 Reference case

In order to establish unambiguously the boons of the present configuration, where customers contract with an aggregator, which owns poly-generation systems and storage, a reference system has been defined (see Fig. 9). Considering the current situations in Spain and France, in this reference system, each dwelling has a GB with an efficiency of 96% to cover the heating demand and a mechanical chiller (Mch) with a EER of 4.0 for the cooling demand. In turn, each dwelling has an individual contract with the electricity and natural gas companies (at household tariffs). The annual electricity and natural gas consumption per dwelling for Zaragoza and Marseille are presented in Table 2.

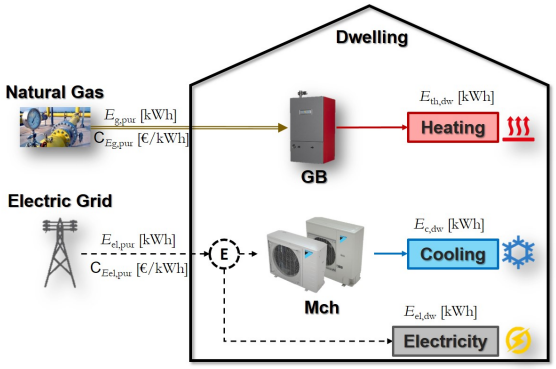


Figure 9 – Conventional reference energy system for a dwelling.

The operational unit price of each energy service can be calculated with the efficiency of the GB and the EER of the Mch, based on the 2018 tariffs. For Zaragoza, electricity consumption is below 5 000 kWh/year and natural gas consumption is below 50 000 kWh/year. For Marseille, electricity and natural gas consumption are both below 5 000 kWh/year.

Table 2 – Annual electricity and natural gas consumption in kWh/year per dwelling-Reference system.

Location	Electricity	Natural gas
Zaragoza	4 268	6 988
Marseille	4 192	4 881

For each case was considered a fixed cost proportional to $\mathcal{P}ct$, around 10 and 30 /kW for France and Spain respectively. In the reference case, based on the energy demand profiles depicted in Fig. 4, the expected contracted power $\mathcal{P}ct$ from the electric grid, for a residential building composed of 50 dwellings, is of 93 kW in Zaragoza and 80 kW in Marseille. For a dwelling in Zaragoza, it is around 1.85 kW and for Marseille around 1.6 kW; as a reminder, large consumption, such as heating, do not rely on electrical appliances, which explains these rather low values.
For both countries, additional fees for electricity and natural gas costs must also be applied as subscription fees. For natural gas, it is about 110 /year, added to the heating bill. For electricity, it is about 120 /year, added to the electricity and cooling bills, proportional to their annual consumption. The individual bills per dwelling are so multiplied by 50 in order to have a reference value. To this end, only operational costs have been considered.

3.2 Simulation plan

First, in Table 3 are presented all the technical, economic and environmental data of the different technologies. The investment costs are calculated based on the unit cost, and considering the installation costs, by applying a factor Fm for each technology (see above). The maintenance costs are within the offset of the average installation costs considered since, for most of the equipments (PV, WT, *etc.*), they are only about 1% of the installation costs [80]. Replacements costs are also integrated.
Secondly, the characteristics of the three cases evaluated, summarized in Table 4, are:

- Case A: Selling the energy services to the customer at 95% of the reference price, remaining constant for 20 years. Electricity sale to the grid is not allowed.
- Case B: Selling the energy services to the customer at 70% of the reference price at the starting point (2018), and increasing these prices in the same way of the electricity and natural gas (exponentially at $a_0(2^{1/20})^i$). Electricity sale to the grid is not allowed.
- Case C: Selling the energy service to the customer at 70% of the reference price at the starting point (2018), and increasing these prices in the same way of the electricity and natural gas (exponentially at $a_0(2^{1/20})^i$). Electricity sale to the grid is allowed at 0.05 /kWh.

Table 5 shows the unit cost of electricity and natural gas for households, as well as the unit price for electricity, heating and cooling.
Finally, the set of 12 representative days D_{rep} is shown in Table 6. Two additional days corresponding to cooling and heating peak demands are considered with weight zero, having influence in the sizing equipment but not on the operational cost.

Table 3 – Technical, economic and environmental data

Component	Technical data (Tech)	Economic data (Econ)			Environmental data (Env)	References		
		C	Fm	N_{comp}	GHG emissions [$kg_{CO_2eq}/\star$]	Tech	Econ	Env
CM	$\eta_{el} = 28\%$; $\eta_{th} = 56\%$; $PL = 15\%$	1 150 /kW_{el}	0.7	10	65 kg_{CO_2eq}/kW_{el}	[81]	[82]	[83]
PV (polycrystalline)	255 W_{pk}; $\eta_{pan} = 15.66\%$; $\kappa = 0.0032\,K^{-1}$	113.4 /m^2	0.9	20	161 kg_{CO_2eq}/m^2	[84]	[85]	[86, 87]
WT	30 kW	2 330 /kW	0.9	20	720 kg_{CO_2eq}/kW	[58]	[88]	[89, 90]
ST	$a_0 = 81\%$; $a_1 = 3.188\,W\,m^{-2}\,K^{-1}$; $a_2 = 0.011\,W\,m^{-2}\,K^{-2}$	257 /m^2	1.5	20	95 kg_{CO_2eq}/m^2	[91, 92]		[93]
GB	$\eta_{GB} = 96\%$	80 /kW_{th}	0.5	20	10 kg_{CO_2eq}/kW_{th}	[94]		
HP	COP = 3.0; EER = 4.0	400 /kW_{th}	0.5	20	160 kg_{CO_2eq}/kW_{th}	[95, 96]		[83]
AbCh	COP = 0.7	485 /kW_{th}	1.5	20	165 kg_{CO_2eq}/kW_{th}	[97]		
TSQ	$LF = 0.2\%h^{-1}$	212 /kWh_{th}	0.1	15	31 kg_{CO_2eq}/kWh_{th}	[94, 95]		[98–100]
TSR	$LF = 0.5\%h^{-1}$	257 /kWh_{th}			62 kg_{CO_2eq}/kWh_{th}			
BEES(lithium-ion)	$\eta = 95\%$; DOD = 90%; $N_{\text{f,failure}} = 2000$; $LF = 0.0042\%h^{-1}$	370 /kWh	0.25	12	160 kg_{CO_2eq}/kWh_{el}	[101, 102]		[103]
Inv	$\eta = 98\%$	400 /kW	0	15	191 kg_{CO_2eq}/kW	[104, 105]		[86, 87]
InvC	$\eta = 94\%$	774 /kW	0.25					

Table 4 – Summary of the three different test cases

Case	Pricing	Selling electricity
A	95% of initial reference price, without increase	No
B	70% of reference price, increase throughout the years	No
C	70% of reference price, increase throughout the years	Yes

Table 5 – Tariffs and unit price services for 1 dwelling reference system 2018.

Location	Customers		
	$\mathsf{P}_{E_{\mathrm{el,dw},0}}$ [/kWh]	$\mathsf{P}_{E_{\mathrm{th,dw},0}}$ [/kWh$_{\mathrm{th}}$]	$\mathsf{P}_{E_{\mathrm{c,dw},0}}$ [/kWh$_{\mathrm{c}}$]
Zaragoza	0.2430	0.0802	0.0608
Marseille	0.1774	0.1558	0.0443

Table 6 – Set of representative days

Location	Month	day (d)	weight (ω)	Month	day (d)	weight (ω)	Month	day (d)	weight (ω)
Zaragoza	February	37	34	May	132	37	August	228	39
	February	50	23	May	136	23	September	245	28
	April	112	19	May	146	27	September	256	38
	April	115	35	July	208	18	December	339	44
Marseille	January	24	22	June	165	44	September	256	33
	January	29	28	June	168	29	November	310	44
	February	44	13	July	193	37	November	319	50
	May	143	24	August	220	22	December	352	19

4 Results

The optimization model has 56 456 constraints and 45 394 variables of which 2 689 are integers. The runtime varies from 1 minute up to 3 hours, case C being the longest. All runs were performed on an Intel Core i5-6200 CPU @ 2.3 GHz, with a memory of 8 GB and 64-bit system.

Table 7 shows the results of the optimization for the installed capacity for each appliances and cases; Tables 8 and 9 gather the corresponding investment costs and electricity and natural gas consumption. Moreover, the final bills for the customers, for the reference case as well as the three test cases, are provided in Table 10. The summarized values of the economic indicators are presented in Table 11. Eventually, Table 12 presents the annual $CO_{2\,\mathrm{eq}}$ emissions per dwelling.

Table 7 – Results in terms of capacity (kW) of the optimization of the polygeneration system

Technology	**Case A**		**Case B**		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
$\mathcal{P}ct$	48.8	67.2	48.8	67.2	49.7	67.7
CM	22	4.5	22	4.5	20.2	4.1
PV	29	20.8	29	20.8	49.4	43.1
Inv	35	25	35	25	59.2	51.7
HP	111	69.7	111	69.7	110.6	69.7
GB	82	96.6	82	96.6	87.4	98.8
TSQ	24	9.5	24	9.5	23.7	8.1
TSR	13	0	13	0	12.5	0

Table 8 – Results in terms of investment ( ) of the optimization of the polygeneration system

Technology	**Case A**		**Case B**		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
$\mathcal{P}ct$	1 463	672	1 463	672	1 491	677
CM	51 502	10 527	51 502	10 527	47 806	9 514
PV	48 497	34 550	48 497	34 550	82 476	71 467
Inv	16 854	12 007	16 584	12 007	28 663	24 837
HP	80 271	50 151	80 271	50 151	80 271	50 151
GB	11 907	13 906	11 907	13 906	12 689	14 231
TSQ	6 846	2 661	6 846	2 661	6 695	2 270
TSR	4 265	0	4 265	0	4 265	0

Table 9 – Annual energy flows in MWh/year

Commodity	**Reference**		**Case A**		**Case B**		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
Electricity Purchased	213	210	94	193	94	193	83	178
Electricity Sold	N/A	N/A	N/A	N/A	N/A	N/A	16	21
Natural gas	349	244	418	143	418	143	396	132

Table 10 – Total individual customer bills in k

Source	**Reference**		**Case A**		**Case B**		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
Electricity	34.0	25.9	20.1	14.6	21.4	15.6	21.4	15.6
Heating	19.7	25.5.	10.7	14.6	11.4	15.5	11.4	15.5
Cooling	1.1	0.3	0.6	0.2	0.7	0.2	0.7	0.2
Total	54.8	51.7	31.4	29.4	33.5	31.3	33.5	31.3

Table 11 – Economic results

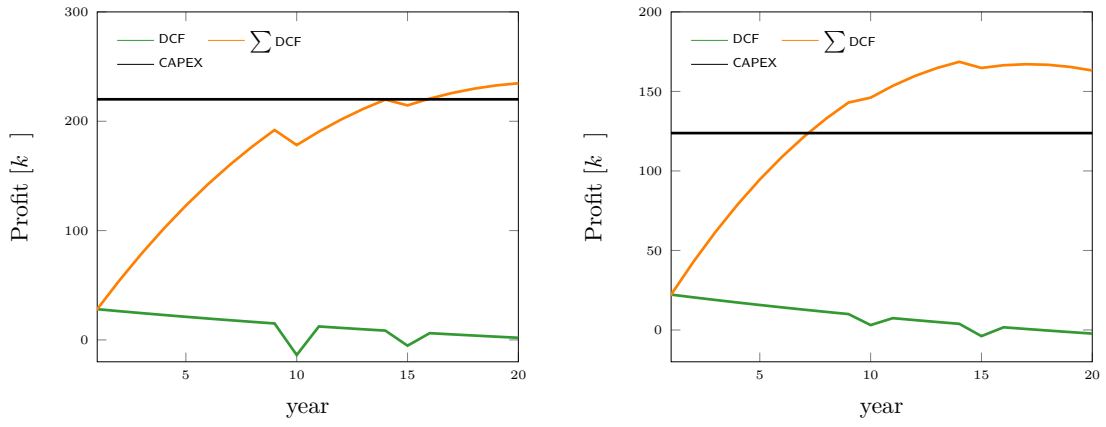
Indicator (k)	**Case A**		**Case B**		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
NPV	14.7	39.4	46.6	69.5	55.0	75.9
CAPEX	220.1	123.8	220.1	123.8	262.9	172.5
$\sum$DCF	234.7	163.2	266.7	193.3	317.9	248.3
R	1 068.3	999.2	1 110.9	1039.5	1 127.2	1 060.3
OPEX	760.0	784.0	760.0	784.4	708.7	732.3
IT	73.6	52.1	84.2	62.1	100.6	79.6

Table 12 – Annual operational $CO_{2\,\mathrm{eq}}$ emissions in $k_{CO2}/year$

Source	**Reference**		**Case A**		Case B		**Case C**	
	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille	Zaragoza	Marseille
Electric grid	44 350	7 550	19 683	7 446	19 689	7 446	14 140	6 267
Natural gas	70 950	55 400	84 919	32 566	84 916	32 566	80 419	29 903
Equipment	0	0	3 382	2 218	3 382	2 218	4 888	3 872
Total	115 300	62 950	107 983	42 229	107 987	42 229	99 446	40 042

4.1 Case A

The optimal configuration is made of HP+GB, some PV, a CM and TSQ. TSR is selected only for Zaragoza Table 7 shows the capacity, Table 8 the investment costs, and Table 9 the consumptions.
In both locations, the contracted power decreases by 48% and 16% in Zaragoza and Marseille respectively, with respect to the reference energy system. This is due to the support of technologies such as PV and the CM. Nonetheless, for Marseille, there is more dependency on the electric grid, the contracted power ($\mathcal{P}ct$) being higher (+37%). As a result, the capacity of technologies such as CHP and PV are lower in Marseille (-80% and -28%): this is because electricity is cheaper in France. The reversible HP capacity in Zaragoza is almost the double of Marseille (111 and 69.7 kW). This explains also the absence of TSR in Marseille.
Concerning energy bought to the electric grid, it decreases by 56% by comparison with the reference system in Zaragoza. In contrast, gas consumption increases there by 20%. For Marseille, electricity and natural gas consumption decrease by 8% and 41% respectively. These results are in accordance with the higher heating demand, along with the lower natural gas price in Zaragoza with respect to Marseille, and also to the difference in installed capacity of CM.
According to the economic results in Table 11, the aggregator business model is clearly more profitable in Marseille than in Zaragoza, yet for average similar savings for the customer around 41% and 42% (see Table 10). This entails first that a real win-win relation is achievable, *i.e.* that both parts can benefit from this configuration. Secondly, in terms of investment effectiveness, the economic projection of the profitability depicted in Fig. 10 underlines that payback period is drastically different: it is of 16 and 7 years for Zaragoza and Marseille respectively. This logically coincides with the important differences in the NPV visible in Table 11.
As a last remark, it is worth mentioning that a positive NPV is obtained, in spite of a progressive decrease of the yearly discounted cash flow. In other words, case A can be beneficial however the aggregator will have to accept that its revenue will be less attractive in the future (due to the constant prices guaranteed to the customers, while its energy costs are increasing when relying on the external grids).



(a) Zaragoza (b) Marseille

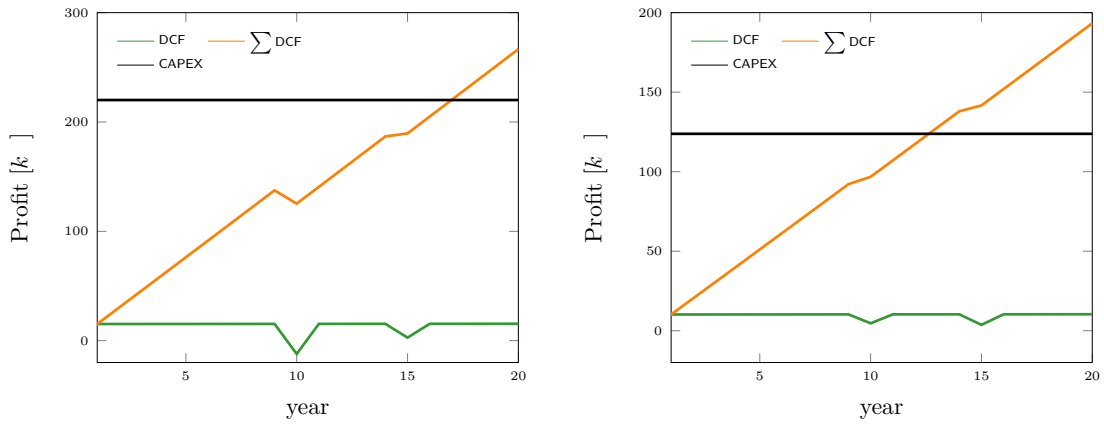
Figure 10 – Economic projection of the profitability in case A

Regarding the environmental impact, Table 12 shows the $CO_{2\,\mathrm{eq}}$ emissions per year due to the investment and operation of the energy system. According to the results, 77% is due to combustion, 18% to the

electric grid and only 5% is coming from the $CO_{2\,\mathrm{eq}}$ emissions embodied in the equipment in France. In turn, for Spain, 79% is due to the combustion, 18% to the electric grid and only 3% arises from the $CO_{2\,\mathrm{eq}}$ emissions of the equipment. Although both locations have similar values in terms of percentage, there is a remarkable difference in absolute terms (+157% for Zaragoza). On the other hand, when the total $CO_{2\,\mathrm{eq}}$ emissions are compared to the reference system, they decrease about 6% and 33% for Zaragoza and Marseille. Therefore, the polygeneration system in this case has a higher impact in Marseille, in spite of the availability of nuclear energy which is already largely decarbonized.

4.2 Case B

The results of the optimal configuration and design are the same as the previous one (Tables 7 and 8) and the consumptions also, as shown in Table 9.
Nonetheless, as presented in Table 11, NPV is about three times the one obtained for Zaragoza and about twice the one obtained for Marseille with respect to the case A. Even with the same investment as in case A, the NPV are significantly higher: +76% in Marseille and 3 times more in Zaragoza. Furthermore, Marseille's aggregator is still the most profitable. In this case, the savings for the customer are about 39% with respect to the reference system for both locations, as shown in Table 10. This clearly demonstrated an interest for both parts: the customers and the aggregator.
However, in return of a lower initial energy price (70% instead of 95%), and though its revenue will be larger in the end, the aggregator has to accept a longer payback period: 17 and 13 years for Zaragoza and Marseille respectively (Fig. 11). Obviously, this could be reduced, without hampering the boons for the customer, either by using another initial price (for instance 80%) or by modifying the annual energy increase defined in section 2.3.2 or in Eq. 2.16b.



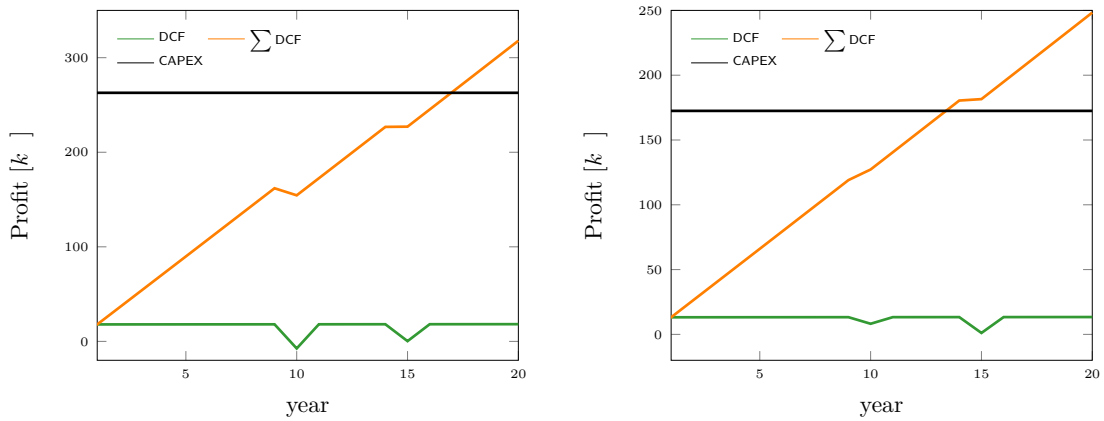
(a) Zaragoza (b) Marseille

Figure 11 – Economic projection of the profitability in case B

4.3 Case C

Table 7 and Table 8 show respectively capacity and investment costs associated to this configuration. In this case the same components are selected but the optimal sizing is different. The most important

difference lies in the PV system which increases by 70% and 107% in Zaragoza and Marseille respectively. CM and GB capacity are stable: -7% in Zaragoza and -10% in Marseille for the former, and +7% in Zaragoza and +2% in Marseille for the latter.
Concerning energy consumption, purchased electricity and gas consumption decrease by 61% and 13% respectively compared to the reference system in Zaragoza, whereas, in Marseille, they decrease by 15% and 46% respectively (see Table 9). More electricity is sold to the grid in Marseille than in Zaragoza, though the irradiation is higher, due to a better self-consumption.
Regarding the economic results in Table 11, there are no differences with the previous case from the customers point of view. However, for the aggregator, its NPV now increases compared to case B (+18% and +9% in Zaragoza and Marseille respectively), which was already better than case A. Investment costs increase by 19% and 39% in Zaragoza and Marseille respectively, mainly because of the increase in PV capacity installed.
Regarding the economic projection of the investment, the payback period is now 17 and 14 years for Zaragoza and Marseille respectively (Fig. 12). These values come once again from the lower initial energy prices which delay the return on investment, but they are also due to a higher initial investment (+19.5% and + 39.3% for Zaragoza and Marseille). In other words, the PP is not singularly affected, compared to case B, even with these higher CAPEX. Therefore, this configuration is particularly interesting for the aggregator, as shown by the associated NPV. Finally, there is no noticeable effect for the customer, and it is still more beneficial than the reference situation.



(a) Zaragoza (b) Marseille

Figure 12 – Economic projection of the profitability in case C

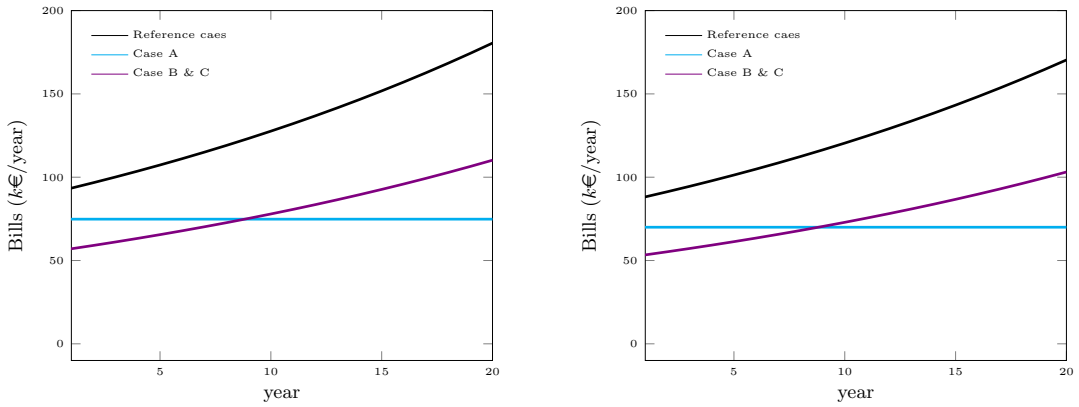
When looking now at the environmental impact, Table 12 shows the $CO_{2\,\mathrm{eq}}$ emissions per year: in Spain, 81% is due to combustion, 14% to electric grid and 5% to equipment. In France, 74% is due to combustion, 16% to electric grid and 10% to the equipment. Thus, appliances have a higher impact on the total $CO_{2\,\mathrm{eq}}$ emissions in Marseille (9.7%). Concerning the total GHG emissions, they decrease by 14% in Zaragoza whereas in Marseille they decrease by 36% compared to reference. In this case, electricity sale to the grid allows higher emissions reductions with more impact in Zaragoza than in Marseille.

5 Discussion

Cost of the contracted power from the membership fees apart, the cost for the reference system is of about 1 717 k (34.3 k /dwelling) for France and about 1 819 k (36.4 k /dwelling) for Spain. The difference between the total cost of the energy bills for the reference system and the revenue of the aggregator corresponds to potential savings for the customer.
For the three business models tested, the results show savings for the customers of approximately 40% compared to reference, as shown in Table 10 and observable on Fig. 13. In other words, it is possible to achieve significant savings for the consumers; in addition, these latter are released from the burden of the financial management of such systems. In fact, these boons could also be singularly higher since the retained projection was finally very conservative. Indeed, from 2020 to 2021, energy prices were tripled in Spain and it is not sure that such variations could not occur again, or even that the expected decrease will lead to lower values than the present projections. Furthermore, due to the European legislation, the gross price is correlated to the last marginal cost of production, which usually correspond to the use of combined cycle gas turbines. More explicitly, the electricity price is influenced by the fluctuations of the gas price, even for countries like France where the main part of the electricity comes from nuclear and hydropower plants.
Concerning economic aspects, NPV are always positive. This clearly demonstrates the sustainability of polygeneration systems managed by a third party between national grids and residential consumers, whose consumptions are aggregated. From the aggregator viewpoint, higher NPV are achieved when a variable price is applied to the customer, but at the cost of a longer payback period. The possibility to resell extra-production of electricity brings another source of revenues, increasing the NPV of 18% and 9.2% in Zaragoza and Spain respectively. The practical conclusions are twofold. First, incentives are not necessarily required but, second, it clearly simplifies both the management of the system and allows for complementary earnings for the aggregator.

Regarding the chosen production units, the optimal configuration always contains for both locations a combination of PV, CM, reversible HP, GB and TSQ; in Zaragoza, TSR is also selected. The dependency of the pricing strategy on this sizing is finally not very strong (case A and B being relatively close), yet the resale of electricity plays a more important role. Meanwhile, technologies such as WT, ST and single-effect AbCh are not chosen anywhere. Similarly, no special tropism is observed toward batteries. This underlines the necessity to think carefully of the associated business models, or to specific tariffs or incentives if such technologies are to have a significant place in the energy paradigm.
In practice, PV and CM enable the reduction of the contracted power from the electric grid and, hence, the corresponding costs. Nevertheless, the results show that there is a higher dependency on the electric grid in Marseille, due to lower electricity prices. On the thermal side, the reversible HP capacity is higher in Zaragoza because of its higher cooling demand. Consequently, due to the support of the reversible HP, cogeneration module and TSQ and GB capacities tend to be lower in Zaragoza, although the heating demand is higher in Zaragoza. Moreover, yet unsurprisingly, reversible HP are better exploited where cooling and heating demands are more balanced.

Lastly, all scenarios decrease the GHG emissions. When selling electricity is forbidden, $CO_{2\,\mathrm{eq}}$ emissions reduction is of 6% and 33% in Zaragoza and in Marseille respectively. In absolute terms, this means reductions about 7.1 $\mathrm{t}_{CO_{2\,\mathrm{eq}}}$ in Zaragoza and 21 $\mathrm{t}_{CO_{2\,\mathrm{eq}}}$ in Marseille compared to the reference system. However, when selling electricity is allowed, $CO_{2\,\mathrm{eq}}$ emissions reduction, compared to the previous cases, is of 8.5 $\mathrm{t}_{CO_{2\,\mathrm{eq}}}$ in Zaragoza and only of 2.2 $\mathrm{t}_{CO_{2\,\mathrm{eq}}}$ in Marseille. Therefore, selling electricity in Zaragoza



(a) Zaragoza (b) Marseille

Figure 13 – Yearly bill for the 50 dwellings along the years

has a higher impact. It is also important to notice that the lower $CO_{2\,\mathrm{eq}}$ emissions from the electric grid in France are more significant to explain the lowest pollution than the lower demand in heating and cooling.

6 Conclusion

This paper studied the economic viability and social interest of an aggregator, third party between the classic distribution grids and several tens of customers. By proposing to install a set of technologies, ranging from PV and WT to ST, HP or CHP, or GB and AbCh as well as thermal (hot and cold) or electrical storages, this new economic agent can either propose to fulfill alone the demand of the consumers or to rely partly on the external grids. An optimization is conducted to find the most profitable situation so as to provide electricity, heat and cold to a district of 50 dwellings. To highlight the possibilities of such an organization, three various business model were tested: one with a constant energy price and two others considering different variable energy prices. Meanwhile, the resale of the extra-electricity produced can be authorized or not. Finally, two locations have been tested, Zaragoza in Spain and Marseille in France, so as to study the influence of the local regulations on the optimal configuration for relatively similar demand (with slight variations, principally for the cooling demand).

The results show that all these configurations lead to a similar polygeneration system. This latter combines PV with CM and reversible HP, as well as a GB and a TSQ. In the Spanish case, TSR is also present. It is worth highlighting that WT, ST and batteries are not enough cost-effective to be selected, meaning that incentives or specific pricing could (or should) be considered to promote their use.
The most important and interesting result demonstrated is that a win-win situation is achievable, where both the consumers and the aggregator can develop a doubly beneficial situation. In comparison with the reference case, the savings for the customers are always greater than 30%, which is enough to be really accountable. Besides, it is always possible to get a positive NPV, which shows the economic viability of the concept. All in all, an added-value is found and there are some interests for both parts: the customers do not have to support the expenditure and operational costs and could still change their

592 energy providers, the aggregator can generate sufficient revenues. The most favorable situation for its
593 incomes is with a variable pricing, and with the possibility to resale the extra-production of electricity.
594 Eventually, reductions of the GHG emissions are achieved but with a great variation between France,
595 where significant decrease around 30% are obtained, and Spain, where they are diminished between 6
596 and 13%.
597
598 In the following of this work, it is planned to extend the study to smart mixed grids, that is to say to
599 electrical grids and heat networks operated in a smart grid context. Indeed, the demand side management
600 techniques could be used for all types of energy and thus give an interesting leeway to better manage
601 the polygeneration system and/or increase the self-sustainability and self-consumption and/or decrease
602 the total installed capacity of several technologies (production units as well as storage). Moreover,
603 another important mechanism is to be considered: the price-elasticity of the demand which can lead to
604 severe modifications of the demand, similarly to demand response strategies, and is worth investigating.
605 Last, the demand part could be refined, using for example the multi-level thermal request prediction
606 developed by Guelpa *et al.* [106] to benefit from a compact model for the buildings demand. Added to
607 this, it would be instructive to either use or to perform a comparative analysis using demand profiles
608 that integrate one or several scenarios of the climate evolution in the next 30 years. For instance, a
609 downscaling approach could be used [107] for such a purpose. Finally, the present results also give an
610 impetus for a more refined and extended economic study of the role and added-value of the aggregator
611 between the customers and the classic energy providers, but also on its positioning between the transport
612 and distribution operators.

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Chapitre 6

Conclusion générale

Pour commencer, on peut rappeler que le principal objectif de la thèse était de concevoir un modèle permettant de gérer en temps réel des réseaux multi-énergies basé sur du DLC et de développer un logiciel basé sur celui-ci. Ensuite, l'objectif était d'exploiter ce logiciel afin de réaliser des simulations sur l'utilisation coordonnée du DLC et des énergies renouvelables. On reviendra brièvement sur les aspects saillants du travail effectué pendant 3 ans ainsi que sur les résultats obtenus avant de conclure.

6.1 Modèle

On peut considérer que le modèle est terminé : les différents concepts et mécanismes utilisés se sont révélés adaptés au problème abordé. Le modèle repose sur 3 éléments clés : les appareils, les contrats et les stratégies. D'abord, les appareils représentent les objets connectés à un réseau d'énergie et qui peuvent consommer, produire, convertir ou stocker de l'énergie. Ensuite, les contrats définissent les règles entre les appareils et les agrégateurs (les gestionnaires de réseau tels que définis dans l'introduction, section 1.4.1). Ces derniers, enfin, reposent sur une stratégie pour équilibrer les réseaux dont ils ont la charge : c'est elle qui choisit d'effacer/produire/stocker/déstocker/acheter/vendre de l'énergie en fonction d'un objectif qui lui est propre. Tous les appareils et tous les agrégateurs appartiennent à un agent, qui représente leur propriétaire. Les agents servent à réaliser des bilans intermédiaires et ne jouent pas un rôle actif : par exemple, ils permettent d'étudier les flux d'argent et d'énergie à l'échelle d'un foyer composé de plusieurs appareils. On peut également définir des hiérarchies d'agent, afin de représenter des organisations établissant des bilans à plusieurs niveaux, comme les différents sites d'une université.
Lors d'un tour, les appareils envoient un message contenant leur demande/offre d'énergie et leurs contraintes physiques à leurs contrats. Les contrats complètent ce message en y ajoutant le prix de la transaction et en précisant à l'agrégateur les possibilités dont il dispose. Ce dernier, comme son nom l'indique, agrège toutes les requêtes et sa stratégie décide en premier lieu s'il souhaite échanger. Le choix a été fait de limiter les échanges à un unique agrégateur jouant le rôle de supérieur. L'agrégateur de rang inférieur est lié à son supérieur par un contrat et se comporte exactement comme un appareil, en formulant une demande/offre d'énergie. Dès qu'un agrégateur connaît les quantités qu'il va échanger, il répartit l'énergie entre les différents appareils à sa charge et leur envoie un message notifiant sa décision. Ce second message permet aux appareils de s'adapter à la décision de l'agrégateur : par exemple, s'ils ne sont pas servis, ils savent qu'ils doivent reporter leur demande. Ce second message est également transmis aux contrats car certaines compensations versées aux agents acceptant de participer au DLC dépendent de l'effort fourni par l'agent.

6.2 Logiciel

Ensuite, `PEACEFULNESS`, le logiciel que j'ai développé, est fonctionnel et permet, dans son état actuel, de réaliser des études de cas. En effet, tous les principaux éléments du modèle sont implémentés : ap-

pareils, agrégateurs, stratégies, contrats, agents. On va revenir ici sur les appareils, les contrats et les stratégies. D'ailleurs, si les appareils, les contrats et les stratégies disponibles ne sont pas exhaustifs, l'architecture est conçue pour faciliter les ajouts.

Du point de vue de l'agrégateur, tous les appareils ont un comportement identique. Cependant, le fonctionnement interne des appareils est protéiforme. D'abord, les appareils de consommation fonctionnent à l'aide d'un double profil : le premier représente le comportement des utilisateurs et le second les caractéristiques techniques. Certains appareils incluent en plus un modèle physique et utilisent des données météorologiques : aujourd'hui, il s'agit du chauffage, de la climatisation et des chauffe-eaux. De plus, le choix a été fait d'agréger la consommation de certains appareils domestiques, soit parce que les énergies en jeu sont faibles, soit parce qu'ils ne sont pas éligibles à une action ciblée de l'agrégateur. L'objectif était de réduire la masse d'information à traiter par l'agrégateur et de simplifier la modélisation. Enfin, un dernier obstacle restait à résoudre : la différence entre les profils de consommation individuels, plutôt discontinus (notamment autour des heures de départ/arrivée dans le foyer) et les courbes de consommation observables à une échelle macroscopique, beaucoup plus continues. Plutôt que de démultiplier les profils d'appareils et d'utilisateurs, le logiciel propose de randomiser les profils à l'aide d'une loi normale : un tirage aléatoire est réalisé lors de la création de chaque appareil, dans lequel les valeurs nominales servent de moyennes et dans lequel l'écart-type est choisi par l'utilisateur. Néanmoins, seuls des consommations domestiques ont déjà été modélisées : aucun profil industriel ou commercial n'est disponible.
Les appareils de production s'appuient toujours sur un profil technique et peuvent avoir recours à un modèle physique et à des données météorologiques. Il est à noter que si les technologies renouvelables sont modélisées finement, les dynamiques de démarrage/arrêt des centrales pilotables ne sont pas intégrées pour le moment. Les appareils de conversion ont la particularité d'être rattaché plusieurs agrégateurs, se comportant en consommateur pour l'un et en producteur pour l'autre. Une technique similaire est employée pour modéliser les dispositifs de cogénération. Enfin, une solution a également été trouvée pour le stockage : il se présente à la fois comme producteur ou consommateur potentiel et le choix entre l'un et l'autre est déterminé par un contrat spécifique. L'idée sous-jacente est que le propriétaire du stock définit préalablement les règles d'utilisation avec l'agrégateur et que le contrat découle de celles-ci. Malheureusement, l'implémentation tardive des appareils de stockage n'a pas permis de les intégrer à nos simulations.

Les contrats, quand à eux, restent pour le moment plutôt simples : en règle générale, ils se contentent d'accorder des tarifs plus intéressants (acheter pour moins ou vendre pour plus) aux agents acceptant de fournir de la flexibilité à l'agrégateur. Néanmoins, des mécanismes plus sophistiqués ont été essayé avec succès : en plus des contrats spécialisés évoqués ci-dessus pour les convertisseurs et les stockeurs, l'une de nos études intègre un contrat proposant des compensations proportionnelles aux efforts fournis. Par ailleurs, si inventer de nouveaux mécanismes contractuels est relativement aisé, il est important de les co-concevoir avec des économistes : identifier les liens entre niveaux de prix, mécanismes de compensation, comportement des consommateurs, producteurs ou agrégateurs est crucial. Sinon, il y a un risque non-négligeable de ne pas identifier des effets indésirables du DLC ou, au contraire, certaines conséquences inattendues et positives.

Plusieurs stratégies ont été proposées. Elles se différencient en deux points : leur politique en terme d'échanges extérieurs et leurs choix de priorités lors de la distribution de l'énergie. Pour le moment, les stratégies disponibles se basent sur un quadruple bilan : la quantité d'énergie qui doit absolument être consommée, celle qui doit être produite et les quantités d'énergies à consommer ou produire que l'on peut choisir de ne pas satisfaire. À noter que lorsque l'on refuse une demande/offre d'énergie, on peut la voir ressurgir lors des prochains pas de temps : on appelle cela l'effet rebond. Actuellement, aucune prédiction, ni pour la consommation, ni pour la production, n'est prise en compte par les stratégies et pour cause : elles ne sont pas implémentées dans le logiciel. Si quelques réflexions préliminaires ont pu être menées, nous n'avons à ce jour pas de solution fonctionnelle pour les intégrer dans `PEACEFULNESS`. De même, nous avons fait le choix de ne pas avoir recours à des techniques d'optimisation dans nos stratégies, afin de garder des temps de calcul faibles mais il serait intéressant d'essayer, afin de pouvoir confirmer ou infirmer notre choix initial : en effet, on peut espérer que l'emploi de techniques d'optimisation améliore les décisions prises et donc les performances du réseau.

Enfin, d'un point de vue plus général, on envisage d'ajouter plus d'informations dans les communications entre les appareils, les contrats et les agrégateurs. En particulier, on pourrait indiquer les émissions CO_2 associées à telle ou telle technologie afin que les agrégateurs puissent les prendre en compte dans leur décision.

6.3 Études de cas

Nous avons eu l'occasion de nous servir de `PEACEFULNESS`pour réaliser des cas d'études. La première étude, présentée dans le chapitre **??**, porte uniquement sur le DLC et son impact sur diverses métriques dans 2 réseaux intégrant une part importante de production renouvelable non-contrôlable. De plus, nous avons comparé dans cette étude deux stratégies différentes, une basée sur des critères physiques et une basée sur des critères économiques, mais poursuivant le même objectif : réduire la dépendance vis-à-vis du réseau.
Dans les résultats des simulations, on peut observer en premier lieu que le DLC a des effets prévisibles : les pics de consommation, la dépendance vis-à-vis du réseau électrique et les factures des consommateurs diminuent. Par contre, dans ce contexte d'une production peu souple et en l'absence de stockage, les consommateurs subissent des taux élevés d'effacement/reports de consommation car ils sont les principaux leviers de flexibilité de l'agrégateur. Les deux approches testées, physique ou économique, renvoient des résultats similaires : si cette observation était généralisable, cela permettrait d'offrir une certaine liberté dans le choix de l'approche. Enfin, on observe des effets de seuil : au-delà de certains seuils de participation au DLC, l'évolution de plusieurs métriques devient beaucoup plus faible. Cela s'explique ainsi : une fois qu'on a suffisamment de flexibilité sur la demande pour auto-consommer la production renouvelable, on ne peut plus valoriser efficacement toute flexibilité supplémentaire. Cela signifie qu'il serait inutile que tout le monde participe au DLC ou même au DSM en général.

Dans un deuxième temps, dans le chapitre **??**, en collaboration avec Dr Ramousse et Dr Fitó du LOCIE, nous avons tenté d'intégrer le DSM en général (*i.e.*pas uniquement restreint au DLC de `PEACEFULNESS`) dès la phase de dimensionnement des unités de production. Pour cela, nous avons proposé une méthode itérative, indépendante des outils d'optimisation et de DSM utilisés. On fait un premier dimensionnement à l'aide de profils de consommation non modifiés. On fait ensuite une simulation de DSM avec premier dimensionnement, qui fournit de nouveaux profils de consommation. Tant que les profils de consommation changent, on refait un dimensionnement qui donne lieu à une nouvelle simulation de DSM. Nous avons ensuite testé cette méthode sur un cas simple : les seules technologies renouvelables autorisées étaient des panneaux PV et des collecteurs solaires thermiques. Plusieurs configurations ont été étudiées : deux méthodes de dimensionnement, deux stratégies et deux niveaux de DSM.
Parmi les différents résultats, on peut retenir en premier que la méthode a convergé en 2 itérations dans tous les scenarios testés. On s'attend par contre à une augmentation du nombre d'itérations nécessaires dans des configurations plus complexes, notamment celles incluant de nombreuses technologies de production et de stockage. Dans tous les scénarios, on constate une diminution de la puissance installée. Néanmoins, l'utilisation d'une telle méthode dans la vie réelle nécessiterait de pouvoir prédire de manière fiable le taux de participation des consommateurs à des programmes de DSM, ou tout du moins de pouvoir estimer un taux minimum fiable de participation. On constate également, comme dans l'étude précédente, un taux élevé d'effacement/report pour les consommateurs.

`PEACEFULNESS`a aussi été utilisé, bien qu'avec un rôle moins central, pour réaliser une dernière étude, en collaboration avec Dr Pinto et Pr Serra de l'université de Saragosse et présentée dans le chapitre **??**. Dans celle-ci, on optimise le dimensionnement d'un système énergétique destiné à satisfaire la consommation de 50 résidences. Ce système énergétique est possédée par une compagnie intermédiaire et le critère de l'optimisation est le NPV. Différentes configurations sont testées. D'abord, on s'intéresse à deux villes situés dans des pays différents, Saragosse et Marseille : le climat, les courbes de consommation, les prix, les niveaux d'émission de CO_2 changent entre les deux villes. Ensuite, on étudie trois business model différents pour la compagnie intermédiaire.

Quelle que soit la configuration, les équipements choisis sont similaires, même si les capacités installées varient. Toujours dans toutes les configurations, on observe à la fois que la compagnie est viable et que les consommateurs réduisent leurs factures.

6.4 Conclusion générale et perspectives

De manière générale, les objectifs de la thèse ont été atteints : d'abord, le modèle et le logiciel développé sont fonctionnels. Certes, ce dernier est largement améliorable, mais le but de la thèse n'a jamais été d'en fournir une version complète : par exemple, le stockage était initialement en-dehors du champ de cette thèse. Si on a pu réaliser différentes études de cas, on se gardera bien de fournir des conclusions fermes et définitives sur les effets du DLC, pour plusieurs raisons. Déjà, rappelons que l'impact du DSM en général et du DLC en particulier dépendent de nombreux facteurs : popularité du DSM (ou du DLC), mécanismes de compensation et tarification, courbes de demandes, technologies en présence, stratégies de gestion adoptées et climat. Ainsi, il faudrait un nombre très important de simulations pour parvenir à des conclusions générales. De plus, nos simulations ne peuvent pas se comparer à une expérience de référence et il est ainsi compliqué de mesurer l'exactitude de certains choix de modélisation. Toute notre travail est donc en attente d'une confirmation (ou d'une infirmation) expérimentale.

Ces quelques constats fournissent de nombreuses directions pour poursuivre ce travail. Déjà, ajouter plus de technologies, de contrats et de stratégies dans le logiciel. Pour ces dernières, on s'attend à ce que l'ajout de modèles prédictifs pour la production et la consommation améliore significativement les résultats des simulations faites avec `PEACEFULNESS`. D'ailleurs, à propos des simulations, on a plusieurs fois indiqué dans ce document qu'il en faudrait beaucoup pour réellement avoir une idée des effets du DLC. On peut songer à d'autres études ciblées et faites à la main comme celles présentées ici, mais aussi à un procédé automatisé : un nombre très élevé de cas d'études, dans lesquels tous les éléments varieraient. On aurait alors une masse importante de données que l'on pourrait exploiter avec des approches de type *big data*. On serait peut-être alors en mesure de dégager des relations ou d'identifier des mécanismes qui seraient précieux dans la perspective d'une utilisation réelle du DLC. Utiliser `PEACEFULNESS`pour piloter des réseaux réels, d'ailleurs, nécessitera de trouver une réponse (au moins) aux questions suivantes : Quels équipements électroniques ? via des prises contrôlées ou via l'intégration directe dans les appareils, comme pour les ballons d'eau chaude ? Comment gérer les avaries et les imprévus, notamment en terme d'impact sur le consommateur ? Par quels moyens communiqueront les données ? Comment s'assurer de la confidentialité des données des consommateurs qui seront mises en circulation et potentiellement stockées ? D'ailleurs, au-delà des problématiques de pure confidentialité, les agrégateurs tels que nous les avons définis seront probablement considérés comme des "opérateurs d'importance vitale" et par conséquent soumis à une législation renforcée en terme de cybersécurité. Dans les faits, cela signifie que la mise en place d'un essai réel (comprendre agir sur la consommation de gens en chair et en os) exigera une vigilance particulière quand à ces questions.

Plus largement, certains problèmes et interrogations ne pourront être traités par les sciences naturelles, et c'est pour cela que le projet s'est fait en collaboration avec des économistes. Par exemple, la relation liant l'effort consenti par les consommateurs aux compensations financières à fournir sera cruciale pour concevoir des programmes de DLC réalistes. On doit aussi s'interroger sur les effets rebonds, qui sont absents de nos simulations. Enfin on aurait besoin de sociologues pour répondre aux questions suivantes : quelle part de la population serait prête à accepter de participer à de tels programmes de DLC, malgré leurs défauts (perte de contrôle, intrusivité) ? À quelles conditions ?

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