eneuron

optimising local energy communities

Report on the energy hub concept and the multi objective programming approach of an energy hub

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D4.1: Report on the energy hub concept and the multi objective programming approach of an energy hub
WP4, Task 4.1

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Technical References

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[1] PU = Public
PP = Restricted to other programme participants (including the Commission Services)
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Summary

Due to the recent fast growth of Distributed Energy Resources (DER) and conversion technologies, numerous planning and evaluation models and approaches are available in the literature to enhance local integration of DER under the energy hub concept. However, most of the works address the design problem by using a limited number of aspects to achieve a single objective, and focuses primarily on the electricity sector.

This deliverable aims to provide an in-depth analysis of the literature surrounding the existing state-of-the-art approaches that are related to multi objective optimization of a multi-carrier energy hub. This systematic review highlights the limitations and identifies needs for further research and enhancement.

To be successful in this, the multi objective optimization approach of an energy hub has been studied under different prisms and individual topics to make sure that a holistic perception is captured.

Through this process, an extensive review has been concluded but also different research pathways were identified to be used as needed by eNeuron to serve its objectives. The main outcomes of this deliverable are not only the ones needed as feedback for the next tasks of eNeuron but also a service to the R&I community as a useful source of systematic review and insights for the timely issue of the optimal design and operation of multi-carrier energy hubs.

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Abbreviations and acronyms

Acronym	Meaning	Acronym	Meaning
AC	Alternating Current	**LEC**	Local Energy Communities
ACs	Air Conditioners	**LHTES**	Latent Heat Thermal Energy Storage
ADMM	Alternating Direction Method of Multipliers	**LHV**	Low Heating Value
AFC	Alkaline Fuel Cells	**LMO**	Local Market Operator
AFIR	Alternative Fuels Infrastructure Regulation	**LP**	Linear Programming
aFRR	Automatic Frequency Restoration Reserves	**MAGA**	Multi Agent Genetic Algorithm
AGC	Automatic Generation Control	**MCFC**	Molten Carbonate Fuel Cells
AI	Artificial Intelligence	**MCS**	Megawatt Charging System
B2B	Business-to-Business	**MES**	Multi-Energy System
B2C	Business-to-Consumer	**MES**	Multi-Energy System
BESS	Battery Energy Storage System	**mFRR**	Manual Frequency Restoration Reserve
BIPV	Building Integrated Photovoltaic	**MGT**	Micro Gas Turbine
BMS	Battery Management System	**MILP**	Mixed-Integer Linear Programming
BRP	Balancing Responsible Party	**MINLP**	Mixed-Integer Non Linear Programming
BS	Bill Sharing	**MMR**	Mid-market Rate
BSP	Balancing Service Providers	**MOEAs**	Multi-objective evolutionary algorithms
C2C	Consumer-to-Consumer	**MPC**	Model Predictive Control
CAES	Compressed Air Energy Storage	**MSGA-II**	Multi-Strategy Gravitational Search Algorithm
CAPEX	Capital Expenditure	**MV**	Medium Voltage
CCS	Carbon Capture Storage	**NLP**	Non Linear Programming
CEC	Citizen Energy Communities	**nZED**	Net-zero energy districts
CHP	Combined Heat and Power	**O&M**	Operation and Management
CHP	Combined Heat and Power	**OCPP**	Open Charge Point Protocol
COP	Coefficient of Performance	**OLTC**	On Load Tap Changer
CSP	Concentrating Solar-Thermal Power	**OPF**	Optimal Power Flow
CVaR	Conditional Value-at-Risk	**OWC**	Oscillating Water Column
DC	Direct Current	**P2G**	Power to Gas
DER	Distributed Energy Resources	**P2H$_2$**	Power to Hydrogen
DES	Distributed Energy System	**P2P**	Peer to Peer
DHC	District Heat and Cooling	**PAFC**	Phosphoric Acid Fuel Cells
DHW	Domestic Hot Water	**PCM**	Phase Change Material
DR	Demand Response	**PEMFC**	Polymer Electrolyte Membrane Cells

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DRP	Demand Response Program	**PHEV**	Plug-in hybrid Electrical Vehicle
DSO	Distributor System Operator	**PMSM**	Permanent Magnet Synchronous Machine
DSO	Distribution System Operator	**PV**	Photovoltaic
EC	Energy Community	**QP**	Quadratic programming
EFP	Energy Flow Problem	**QPSO**	Quantum Particle Swarm optimization
EH	Energy Hub	**R&D**	Research and Development
ELV	Emission Limit Values	**REC**	Renewable Energy Community
EMF	Electromagnetic Field	**RES**	Renewable Energy Sources
EPA	Environmental Protection Agency	**RR**	Regulating Reserve
ESP	Energy Sharing Provider	**SCTES**	Sensible Cold Thermal Energy Storage
ETIP-SNET	European Technology & Innovation Platform - Smart Networks for Energy Transition	**SDP**	Semi-definite programming
ETS	Emissions Trading Scheme	**SDR**	Supply and Demand Ratio
EV	Electric Vehicle	**SHTES**	Sensible Heat Thermal Energy Storage
EV	Electrical Vehicle	**SOC**	State of Charge
FC	Fuel Cell	**SOCP**	Second-order cone programming
GHG	Greenhouse Gas	**SOFC**	Solid Oxide Fuel Cells
GHV	Gross Heating Value	**TCHCES**	Thermochemical Heat and Cold Energy Storage
GIS	Gas Insulated electrical Substation	**TEN-T**	Trans-European Transport Network
GPDR	General Data Protection Regulation	**TOU**	Time of Use
GT	Gas Turbine	**TRL**	Technology Readiness Level
GWP	Global Warning Potential	**TSO**	Transmission System Operator
HER	Heat-To-Electricity ratio	**UNIDO**	United Nations Industrial Development Organisation
HP	Heat Pumps	**UPS**	Uninterrupted Power Systems
HVAC	Heating, Ventilation and Air Conditioning	**UV**	Ultraviolet
ICE	Internal Combustion Engine	**V2B**	Vehicle to building
ICT	Information and Communication Technologies	**V2G**	Vehicle to grid
IE	Industrial Emissions	**V2H**	Vehicle to home
IEHS	Integrated Electricity and Heat Systems	**VaR**	Value-at-Risk
IPC	Integrated Pollution Control	**VRE**	Variable Renewable Energy
KPI	Key Performance Indicator	**WC**	White certificates
LAES	Liquid Air Energy Storage	**WP**	Work Package

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LCTES	Latent Cold Thermal Energy Storage	**WT**	Wind Turbine

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1 Introduction

This report is the first outcome of the WP4- Analysis, design and operation optimisation of the local energy systems: emergence of energy hubs related to first Task i.e. T4.1 - Identification and analysis of the multi-objective problem and the innovative approach of energy hub. This report will formulate the baseline for the next activities of this work package that are namely:

- T4.2 - General methodology for optimal design and operation of an energy hub: This report will provide objective functions, equality/inequality constraints and other optimization background information required for T4.2 to build the methodology for the optimal operation and design of an energy hub.
- Innovation and Research actitivites of the eNeuron project. This report will provide also the state of the art and the innovation approaches to different research questions related to the multi-objective optimization of energy hubs. This can be useful not only for the eNeuron project research objectives under T4.3 - eNeuron tool development, but can be used by the R&I community as well for baseline of their own research.

1.1 Purpose and scope of the document

T4.1 aims to provide an in-depth analysis of the literature surrounding the existing state of the art approaches on the optimal design and operation of multi-carrier energy hubs, and define a path of how these can be improved and extended to fit the eNeuron approach.
The scope of the document is to provide feedback to the Task T4.2 - General methodology approach for optimal design and operation of an energy hub.
Thus, the purpose of the document is to provide a thorough state of the art report and identify potential innovation approaches to research questions related to the formulation of the multi-objective optimal design and operation problems for multi-carrier energy hubs. Final goal is the solid definition of the path that eNeuron must take in order to build upon previous models, tackle any weaknesses and stand out.

1.2 Structure of the document

The structure of the document is as follows:

Next section presents the process for this deliverable development and the main topics of interest that were studied under 4 different clusters. Next chapters tackle each cluster by providing analysis of previous works, highlighting the limitations and providing innovation pathways when relevant.

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Chapter 7 presents the eNeuron approach overall based on the baseline established by previous chapters and the last chapter concludes the deliverable.

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2 The process of the report development

This section provides information related to the process followed by the partners in order to collaboratively produce material that built this report. The process' steps are listed below:

- **Collect** all the documents related to multi-objective problems, multi-carrier/multi-energy systems and energy hubs. In detail, 117 related documents were collected from the most popular and impactful research repositories of the R&I community.
- **Identify** a list of topics of interest for focusing on. The energy hub concept is a multi-facet research question that entails different topics to be further investigated. So, an exhaustive list of 19 topics of interest that are related to eNeuron has been developed. Within this list, the topics have been further categorized as "setting the background" topics or/and "research and innovation" topics. Background topics are the ones that formulate the state of the art of this report whereas "research and innovation" topics are used to formulate the further innovation pathways and the research questions. Of course, a topic can be characterized as both "background" and "research".
- **Extensive review** on the topics for each of the documents.
- **Compilation** of brief reports per topic for both state of the art and the innovation approaches.
- **Deliverable 4.1** development with plenty of insights that are related to the main research question of the **multi objective optimization of an energy hub** that will formulate a substantial input for T4.2

Figure 1 The collaborative process of developing this deliverable

Based on the previous steps, the topics of interests are presented below. The topics have been aggregated under clusters in terms of relevance and for efficient reporting. Based on these clusters, the different sections of this report have been formulated.

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Table 1 – The list of the topics of interest and the clusters identified

Multi objective optimization of an energy hub		
Clusters	**Topic of interests**	**Setting the background (B) or Research (R) category**
1-Energy hubs	Energy hub technologies and energy carriers	**B**
2-Optimization related topics	Multi-objective Optimization Methods	**B+R**
	Optimization Solvers & Frameworks	**B**
	Optimization problem formulation	**B**
	Optimization Objective Functions	**B+R**
	Optimization Constraints	**B**
	Heuristic methods	**B**
	Uncertainty	**B**
	Risk aversion	**B**
3-Markets and Business models	Energy and balancing markets	**B+R**
	Peer-to-peer (P2P) architectures	**B**
	P2P market and pricing schemes	**B**
	Business models	**R**
4-Technical collateral concerns	Temporal and Spatial scopes	**B**
	Long-term system planning	**B**
	Implementation Status	**B**
	Services provided to the network	**R**

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	Management of flexibility resources	**R**
	Simulation methods for Electrical Vehicles	**R**

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3 Cluster 1-Energy Hubs

The integration of different carriers such as electricity, gas, and water under the Energy Hub (EH) concept has attracted researchers' attention in recent years considering a series of global, economic and environmental advantages.
An overview of such advantages can be seen in the table below:

Table 2 The overview of Energy Hubs advantages

Advantages categories	Main advantages of energy hubs
Global advantages	• Energy hub concept in multi-carrier energy systems can lead to a better performance of the system with no interconnections with surrounding systems. • No size limitation. The size of an energy hub can vary from building level (single house) to a community level (city – island) • Increased system reliability • Increased load flexibility
Economic advantages	• Reduced operating costs • Reduction of electrical grid congestion
Environmental advantages	• Reduction in greenhouse gas (GHG) emissions • Reduction of fossil fuels use with the increased renewable energy penetration • Increase of energy efficiency

The optimal operation and interconnection of different energy carriers can bring the use of local resources to the maximum possible point, in the most economical way, aiming at maximizing the efficiency of the system. On top of that, EHs hosting storage facilities, enable conversions between different energy carriers for greater flexibility in energy supply.
Within this cluster, a short review on the energy hubs content i.e., carriers and technologies, is given. The main objective is to have a mapping of the most popular energy hubs configurations found in the literature. So, this section aims to identify any limitations on these configurations and how the eNeuron project can enhance the study on these so to consider them under the eNeuron energy hub multi-objective problem formulation.

3.1 General overview of the EH configuration

Under the EH concept, different technologies and carriers are combined and presented in the literature. According to the different objectives of the papers and their purpose, the utilization of the carriers and the technologies "mix" may differ.

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As far as the carriers are concerned, most of the papers have as a backbone the electricity carrier and they are aiming to optimize its usage, taking under consideration the interactions coming from the other carreirs as well. So, the majority of the research papers have a blend of electricity, district heating/cooling and natural gas. For Heating, Ventilation and Air Conditioning (HVAC), natural gas is the main carrier by means of boilers and combined heat and power (CHP).
So, energy hubs in the bibliography may include renewable energy technologies, however some technologies such as wave/tidal and geothermal are not included and not mentioned at all.

3.1.1 State of the art of the EH configuration

The energy carriers

All the reviewed papers present the multi-carrier energy systems under the energy hub concept and underline the importance of the optimal operation of these systems with the proper interaction of the different carriers. In all reviewed papers, electricity generation, both from RES and conventional power generation units, is considered as a back bone carrier. Then, the **electricity** carrier is combined with other energy carriers. The most widely considered carriers other than electricity are **natural gas**, **heating/cooling**, **hydrogen,** and **domestic hot water**. In the table below, the distribution of the carrier combinations throughout the references are shown.

Table 3 The distribution of carrier combinations in the literature

		Energy carrier combinations				
		Electricity	**Heating/Cooling**	**Hydrogen**	**Natural gas**	**Domestic Hot Water**
Reference	[1] [2], [3],	√				
	[4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] [17]	√	√			
	[9] [18]	√	√	√		
	[16] [19] [20] [21] [22] [23] [24]	√	√		√	
	[25] [26] [27] [28] [29] [30]	√	√		√	√

The technologies

Furthermore, in the literature, different energy carrier generation technologies are considered. In particular, regarding the electricity carrier, both renewable energy sources and conventional energy technologies have been considered as energy carrier generation technologies. In most cases, the largest amount of energy comes from renewable energy sources [31][32][33][34]. Renewable energy sources include PV systems, wind turbines, solar thermal and biomass, in cooperation with

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other generation technologies such as diesel generators, natural gas generators, and fuel cells. Energy generation technologies of the electricity carrier, interact with the generation technologies of the other energy carriers. Regarding the Heating/Cooling carrier, the most considered technologies are CHP ([5], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [35]) and gas boilers ([5], [6], [7], [9], [10], [11], [13], [15], [17], [18], [35]). Other thermal generation technologies considered are heat pumps ([7], [8], [13], [15], [18]), and chillers ([7], [12], [15], [18]). In addition, power-to-gas (P2G) is considered in [9], and [36] include gas-fired generation too.

As far as hydrogen technology is concerned, most of the papers dealing with this energy carrier consider hydrogen production by electrolysis [4], [6] and its later use by means of fuel cells to produce electricity, and in some cases heat [37]. In a few papers, the hydrogen produced by electrolysis is used in a methanation process to produce methane, which can be injected into the natural gas network [14]. In the table below, the distribution of the different technologies per carrier is shown.

Table 4 The distribution of technologies per carrier as per the bibliography

	Energy carriers				
	Electricity	**Heating/Cooling**	**Hydrogen**	**Natural gas**	**Domestic Hot Water**
Technologies	PV systems	CHP	H_2 generator	P2G	Heat recovery from CHP
	Wind turbines	Gas boiler		Methanation processes and devices	Solar thermal
	Solar thermal	Heat Pumps			Gas boilers
	Biomass	Absorption chillers			Biomass boilers
	Diesel generators				
	Fuel cells				

Storage

Regarding the storage facilities in most of the reviewed papers, [34], [37], [38], [39], [40], [41], [42], [43], [44] the configurations presented include at least electrical storage capabilities, combining in several cases other forms of storage such as thermal storage, natural gas storage etc. On the other hand, in rarer cases [32], [45] storage such as hot water storage for heating purposes has been employed. It is important to note that in many cases both electricity and thermal storage are considered. In addition, fuel cells with H_2 storage are considered for storage purposes in some cases [46], [47]. In the table below, the storage facilities per carrier combination are shown.

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Table 5 Storage facilities per carrier combination in bibliography

	Energy carriers				
	Electricity	**Heating/Cooling**	**Hydrogen**	**Natural gas**	**Domestic Hot Water**
Storage facilities	Batteries	Thermal Storage	H_2 storage	Natural gas storage	Thermal Storage
	Flywheel	Electric boiler			
	Supercapacitors				
	Electric Vehicles				
	Compressed Air Energy Storage (CAES)				
	Liquid Air Energy Storage (LAES)				

Flexibility

Regarding the appliances - apart from the non-interruptible ones - three types that are offering flexibility are mentioned: shiftable appliances, shapeable appliances and thermostatically controlled appliances.

Shiftable appliances are flexible and can shift consumption between time intervals. The operation of these appliances can be shifted to off-peak periods without affecting the comfort of the consumer.

Shapeable appliances are flexible appliances that can change their shape in order to store energy or minimize their consumption. An example of such appliances are the phase change materials (PCM) that can be used for energy storage.

Thermostatically controlled appliances are the appliances that can be controlled by a thermostat such as heating and cooling loads in buildings. The main objective of this control is the minimization of the energy consumption.

Some papers also discuss the benefits and challenges related to the integration of the energy carriers and the creation of a network of interconnected energy hubs.

The main benefits are as follows:

- Advanced security of energy supply.
- Increased provision of system services to neighbouring systems such as balancing and ancillary services.
- Reduced RES curtailment and therefore reduced GHG emissions.

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- Increased system reliability.
- Increased load flexibility.

On the other hand, the main challenges of the integration of the energy carriers and the interconnection of energy hubs that need to be addressed are listed below:

- Cost of the required infrastructure and the connecting technologies.
- The ownership of the interconnected networks that has to be defined in a proper way.
- Advanced communication, data acquisition and management infrastructure that is needed for the optimum operation of the interconnected networks.
- High initial investment with a long time for payback.
- Lack of cases and proper business models.
- *Regulatory challenges*: Regulations regarding functionalities and operation, including roles and responsibilities that have to be defined.
- *Social challenges:* Public acceptance of the interconnection and the interaction between the energy hubs.

3.1.2 Limitations

Based on the literature, there are some important limitations and challenges related to the energy hubs and multi carrier energy systems configuration that need to be addressed in order to optimize the planning and operation of such systems in the next future.
The most important challenges and limitations are described below:

- Past research papers focus on the electricity carrier as a backbone while limited other carriers are considered.
- The interaction of different energy carriers affects the nonlinearity and nonconvexity of the problem and thus the existing commercial solvers require more computation resources and solution time and are sensitive to initial conditions.
- The optimal placement and sizing of the different energy technologies in the EH is an important aspect for the optimization of multi-carrier energy hubs, however in many cases is not described or is not taken into consideration.
- Accordingly, energy storage is of high importance and energy hub future models need to pay more attention to the optimization of the sizing and placement of different storage technologies, as well as to the use of emerging technologies and potential alternative storage means like Electric Vehicles (EV) and hydrogen.

It is really important, though, to note that past work considered in a few cases multi-objective problems and multi carrier systems at the same time. This fact leads to a more challenging problem to be formulated with more complexities to handle. The figure below shows this overall limitation of the models found in the past bibliography.

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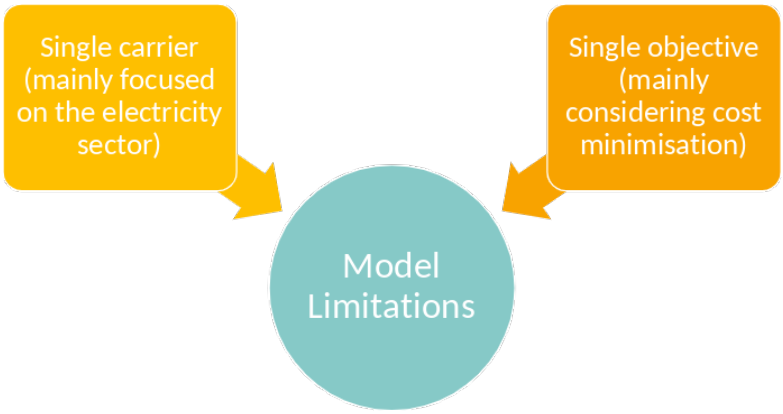

Figure 2 Existing model limitations for the multi-carrier energy systems

3.1.3 Conclusions and eNeuron approach

It is really important to mention that eNeuron aims to cover aspects related to multiple carriers and beyond electricity including, gas, H_2, water, heat, cooling and of course all conversion technologies involved as already described in deliverable r "D2.2 Technical solutions for multi carrier integrated systems under the LEC concept: A review". Also, eNeuron puts forward case studies that not only have as main carrier other than the electricity but also case studies where the electricity carrier is absent. By including different carrier combinations and different types of conversion technologies as well eNeuron will formulate a general applied multi-objective optimal problem formulation that can be scalable and replicable. In the table below, the enhanced approach of the eNeuron project as regards the EH configuration is shown providing a straight comparison with what offered in the bibliography so far.

Table 6 Comparison of EH configuration between eNeuron and bibliography

	Energy carriers and technologies						
	Electricity	**Heating/ Cooling**	**Hydrogen**	**Natural gas**	**Domestic Hot Water**	**Storage**	**Tran sport**
eNeuron approach	PV	Natural gas boiler	Electrolyzer	Gas boiler	Heat recovery from CHP	Batteries	Electr ic Ferrie s / Boats
	Wind	Heat pump	H_2 storage	P2G	Solar thermal	Supercaps	Electr ic Vehicl es

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	Micro-Hydro / Hydro	Hybrid heat pump	Fuel Cells	Methanation processes and devices	Gas boilers	Flywheels	
	Wave/Tidal	Electric boiler			Biomass boilers	Compressed Air Energy Storage (CAES)	
	Geothermal	Steam boilers				Liquid Air Energy Storage (LAES)	
	Fuel cells	Solar thermal for hot water				Electric Vehicles	
		Geothermal				Thermal Storage	
		Absorption chiller				Fuel Cells	
		Biomass boiler					
		CHP (including electricity generation)					
Bibliography	PV systems	CHP	H_2 generator	Gas boiler	Heat recovery from CHP		
	Wind turbines	Gas boiler	Electrolyzers	P2G	Solar thermal		
	Solar thermal	Heat Pumps	$P2H_2$		Gas boilers		
	Biomass	Absorption chillers			Biomass boilers		
	Diesel generators						

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4 Cluster 2-Optimization related topics

4.1 Multi objective optimization methods

Within this section, the optimization methods that have been used for solving the analysed multi-objective problems related to the interaction, operation or planning of multi-energy systems are analyzed.

Multi-objective optimization deals with a class of optimization problems where competing objectives have to be assessed simultaneously, and can be achieved employing diverse optimisation methods, such as genetic and evolutionary algorithms, linear or non-linear programming depending on the complexity of the problem to be solved. It differs from usual optimization problems where a single objective is assessed.

4.1.1 State of the art

When dealing with a multi objective problem, obtaining a unique solution is only possible if the objectives are not conflicting with each other, but in most real cases, this does not happen. Different methods often **simplify the multi objective** into a single objective problem by altering the objective function or adding specific constraints.

A very simple version of this approach is to add the second objective to the first one using a conversion factor. This can also be done in case that there are more than two objectives. For energy system models for example, this could mean including the emission minimization in the cost minimization objective using emission costs. This is the approach used in [20] and [48].

Another similar method is to combine the different objectives into a weighted sum of the objectives [49][50][51]. The weighting factors can be varied to get a better representation of the Pareto front. To facilitate the process and the understanding of the weights, objectives can be normalized [50][51].

A third alternative is to use the epsilon constraint method [41][52][53]. In this method, a primary objective is used, while the other objectives are converted into inequality constraints where the right-hand side is a factor that is varied to get different solutions.

Meta-heuristic models can also be used for multi-objective optimization [52] but they do not guarantee optimality (noninferiority for multi objective problems) of the solutions found.

Due to the multiple objectives, there is no single optimal solution but a set of noninferior solutions (a 1D set for 2 objectives, a 2D set for 3 objectives, etc). This set is called the Pareto front and it can be used to assess solutions by the relative importance of the objectives. Noninferior solutions are solutions where one objective cannot be improved without making another objective worse.

The following table shows the multi-objective optimization methods adopted in the literature. It can be noted that the most popular method is the weighted sum.

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Table 7 Multi-objective optimization methods

Multi-objective Optimization Methods	Brief Description	Document
MO-MFEA-II	The multi-objective multifactorial evolutionary algorithm II (MO-MFEA) is a multitask method. In particular, the parameter random mating probability acquiring the form of a symmetric matrix is uninterruptedly learned and revised online to optimally mandate knowledge transfers between different tasks. In this case, the convergence characteristics are simplified, achieving optimized operation strategy for each task.	[33]
Pareto-based multi-objective evolutionary algorithms (MOEAs)	A Pareto-based multi-objective solution uses evolutionary algorithms to find non-dominated solutions on the Pareto-front which considers multiple objective functions at the same time with trade-offs.	[20] [48] [54] [55]
Modified Teaching-Learning Based Optimization algorithm is used (MTLBO)	In MTLBO algorithm, the methods of teaching phase and learning phase are respectively modified to enhance the disturbance potential of search space, and a new "Self-Learning" method is presented to enhance the innovation ability of the learner and the global exploration performance.	[56] [57] [58]
NSGA-II algorithm	The Non-Dominated Sorting Genetic Algorithm II (NSGA II) is employed to guarantee the feasibility and the accuracy of the model solution. In this methodology elitism and a new maintenance methodology are used to increase diversity. A classification of the solutions according to an order of dominance is used. The assignment of a level or a front of dominance to all the solutions of one population is basics of the NSGA II.	[34] [40] [55] [59]

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	This method is more appropriate for dealing with nonlinear problems which is more difficult and complicated to overcome with other multi objective optimization methods	
VIKOR	To select the optimal solution from Pareto solutions the multi-criteria decision-making method, VlseKriterijumska Optimizacija I Kompromisno Resenj (Vikor) can be employed. This technique is specific to select alternatives with respect to conflicting criteria based on an aggregating function which measures the distance to the best solutions.	[34]
Ɛ-constraints	The Ɛ-constraints is a constraint-based method. The idea is to optimize one of the objective functions, while the others are converted into constraints of the problem. This approach is influenced by the choice of the constraint; besides it can also solve non-convex optimization problems.	[38] [35] [41] [46] [53] [60]
Weighted-sum method	A single objective function is formulated as a weighted sum of the objective functions. This method is employed to find the Pareto frontier. The latter consisting of the best feasible trade-offs between the objectives can be discovered by varying the weight in the interval 0–1.	[25] [26] [27] [28] [29] [30] [49] [50] [51] [55] [58] [61] [62] [63] [64]
Compromise programming method	The application of the compromise programming method aims to the modification of the decision model to include only one objective. The optimum solution can be identified as the one with the shortest distance to the optimum value.	[47] [65]

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4.1.2 Limitations

Based on the previous section, the most important limitations of analyzed multi-optimization methods are summarised below.

The main limitation of the Ɛ-constraints method and compromise programming method, is that they require to transform multi-objective problems into single-objective problems. Furthermore, the weighted sum method, as can be seen in Table 7 is the most common approach because is the simplest and most straightforward way of obtaining multiple points on the Pareto-optimal front. However, the limitation of this approach is that it is hard to select a weighting criterion ensuring that the points are spread evenly on the Pareto front.

4.1.3 Conclusions and next steps for eNeuron

In the literature, there are several techniques for dealing with the complexity of solving multi-objective optimisation problems, such as the weighted sum method, the ε-constraint method, the weighted metric method, and using meta-heuristics algorithms in order to find the Pareto optimality of the problem. However, choosing the most suitable approach depends on the complexity and the scalability of the problem.

In order to decide the best approach to solve a multi-objective optimisation problem, an in-depth study of the algorithms and the problem characteristics has to be performed before applying the optimization method.

Therefore, it has to be considered that the selected method:

1. Always finds the Pareto optimality.
2. Provides all of the Pareto optimal solutions.
3. Considers weights to express preferences.
4. It does not depend on the continuity of the problem functions.
5. Employs the utopia point or its approximation.

By considering the nature of the different flexibility resources (i.e., uncertainty related to the weather, demand response, and prices) in the energy hubs, the method that transforms the multi-objective problem into a single-objective problem in order to be easily solved shall be investigated.

4.2 Optimization Software and Solver

Based on the state of the art, the optimization frameworks that have been used in the bibliography are gathered in the table below.

Table 8 Optimization solvers and frameworks used in bibliography

Optimization Solver	Framework	Document	Total
Not Applicable*	MATLAB	[7] [33] [37] [40] [56] [66] [67] [68] [69] [70]	12
Gurobi	MATLAB	[13] [31] [50] [71]	4
BMIBNB	MATLAB (YALMIP toolbox):	[71]	1

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Not Applicable*	Dest + MATLAB: The software employed to solve the problem is MATLAB The software Dest is used to simulate the standard model building.	[38]	1
CPLEX	MATLAB (YALMIP toolbox): The whole formulation is implemented in MATLAB with YALMIP solution toolbox calling CPLEX in the MATLAB operation.	[72][73]	2
Not Applicable*	MATLAB + GAMS: MATLAB was used to develop the system operation model. GAMS was used for the optimization phase.	[20][52]	2
CPLEX	MATLAB	[5][14][41]	3
CPLEX	GAMS	[9][10][11][12][16] [42][43][46][74][75][76] [77][78][79][80] [81]	16
DICOPT		[2][15][18][22][32][34] [73][82]	5
BARON		[80]	1
CPLEX	IBM ILOG CPLEX	[25][26][27][28][61][29] [62][30][83][84][19][85]	12
Not Applicable*	X-press	[65]	1
Not Applicable*	LINGO	[47]	1
Not Applicable*	MATPOWER TOOL	[3][59]	2
CVXPY	Python	[86]	1
Gurobi + SCENRED tools (tool for the reduction of scenarios modeling the random data processes.)	Python + GAMS	[24][45][53]	3
Not Applicable*	Python (RLLab)	[87]	1

* Optimization solver was not mentioned in these documents.

For papers [88] and [64] it was not possible to identify the framework used for the modeled implementation.

In particular, the optimization solver most used is the CPLEX combined with different optimization frameworks, while GAMS and IBM ILOG CPLEX are the most common and popular and powerful

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optimization frameworks able to produce accurate and logical outcomes. The popularity of solvers and frameworks used in papers are shown in the figure below.

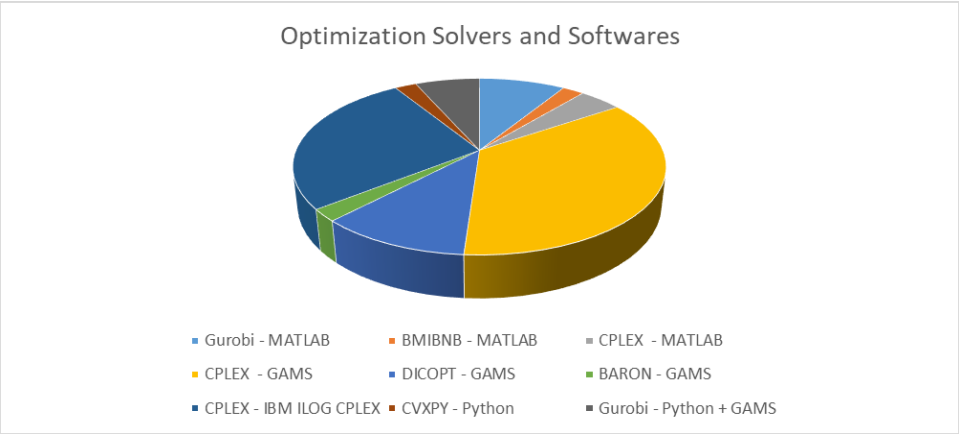

Figure 3 The combination of optimization solvers and frameworks use in the references analysed.

The combination of framework and solver that is going to be used in the eNeuron Project is Python and CPLEX, respectively.

4.3 Optimization Problem formulation

The aim of this section is to identify how the optimization problem in the literature has been formulated to study the EH's operation or design.

The concept of energy hubs entails a multi-energy system with multiple energy carriers working simultaneously. Optimization models found in the literature regarding EHs may be focused on the optimal design and/or operation of them. It has to be mentioned that eNeuron project will tackle both design and operation of EHs. The table below presents the main categories of the different optimization methods.

Table 9: Main categories of optimization methods.

Different Types of Optimization Methods			
Linear Programming (LP)	***Nonlinear Programming (NLP)***	***Mixed Integer Linear Programming (MILP)***	***Mixed Integer Nonlinear Programming (MINLP)***

Having said that, different methods have been identified in the literature as follows:

- ***Linear programming***

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- ***The Mixed-Integer Linear Programming (MILP)*** is used for addressing linear optimization problems with continuous and integer variables that can be continuous or binary.
- ***The Mixed Integer NonLinear Programming (MINLP)*** is used for addressing with continuous and integer variables a very general class of optimization problems that are characterized by non-linearity in the objective functions and/or constraints.

4.3.1 State of the art

This section reviews the different formulations proposed in the bibliography for the optimal design and operation problems of multi-carrier energy systems. Based on the documents that have been reviewed, it is shown that most papers formulate the optimization problems as mixed integer non-linear programming (MINLP) and mixed-integer linear programming (MILP) problems.

LP

The simplest problem formulation are linear programming (LP) problems. LP problems are optimization problems where all involved variables are real and all equations (objective function and constraints) are linear. LP problems can be solved through various methods which guarantees optimality (the simplex or interior point methods for example).

MILP

MILP problems [89][90][41] are LP problems which include integer variables. MILP problems are harder to solve than LP ones but can also be solved to optimality using appropriate solution techniques (branch-and-bound, branch-and-cut for example) provided there is no computation time limit. Binary variables are the most widely used type of integer variable in MILP problems. Binary variables can be used for several purposes. In some cases they represent a yes/no investment decision in a certain technology [89], [90], [41]. They allow to easily consider fixed investment cost in the objective function for example. Binaries can also be used to decide on the status (on, off) of an energy conversion unit in each period of the problem's time horizon [41]. Similarly, they can be used to consider start-up costs and minimum uptime or downtime of an energy conversion unit [89]. [90] also uses binaries to control investment in a grid connection and ensure no simultaneous import and export of electricity. Limiting the number of binary variables allows to limit the computation time. Many papers address the problem of energy hub optimization using MILP formulations [5], [6], [7], [8], [9], [12], [13], [14], [16], [17], [18], [19], [20], [21], [41], [43], [68], [70], [72], [75], [76], [78], [79], [81], [84], [85], [91], [92], [93], [94], [95], [96], [97], [98].

In [78] a MILP model of a Multi-Energy System (MES) considering CHPs, heat pumps (HPs), air conditioners (ACs), EVs, renewable energy sources (RES) and community energy storage (CES) is presented, with the main objective to minimize the overall operating cost of the system. The authors

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of [5] propose a MILP model to minimize the EH's total cost. Similarly, but considering also the optimal size of an EH is done in [6]. The authors of [7] formulate the optimal sizing problem of multi-energy urban energy hub as a multi-objective MILP problem aimed at minimizing both costs and emissions. Authors in [8] give an overview on the integrated electricity and heat systems (IEHS) modelling and solution methods for the optimal operation and compare the main differences between the possible solutions. In [68], a new MILP framework is proposed for the robust optimization of smart multi-energy districts under uncertainty with different energy conversion and storage devices (e.g., PV, EHP, CHP, electric and thermal energy storage and gas boilers) and detailed integrated electricity, heat and gas network mathematical models.

In [19] the day-ahead scheduling of a multi-carrier energy system is formulated as a MILP problem aimed at minimizing the system's operation cost. The MILP problem is solved on a rolling horizon basis under a Model Predictive Control strategy so as to cope with uncertainty. The authors of [85] use a MILP formulation for the optimal operation of a multi-carrier energy hub considering downside risk constraints.

Reference uses a MILP formulation for the optimal design of an industrial manufacturer's multi-carrier energy system. Reference [21] uses a MILP formulation for the optimal operation of a multi-carrier energy system under different electricity, heating and cooling scenarios. The electricity, heating and cooling load balance constraints are reformulated using a chance-constrained approach so as to control the robustness of the model's solutions. Authors in [18] and [13] propose a planning model for a multi-energy microgrid formulated as a MILP problem, while in [14] the day-ahead scheduling of an electricity-hydrogen-gas-heat integrated energy system (EHGHS) is formulated as a scenario-based MILP problem. In reference [92], the potential for improvement of a residential multi-carrier microgrid is analysed via scenario-based simulations under different management strategies. The operation of the microgrid is simulated using a MILP formulation with the objective of increasing the self-sufficiency rate. References [95] [97] and [98] use MILP formulations for the optimal design of multi-carrier energy systems from scratch, i.e. with no predetermined system's structure, carriers or technologies mix. Reference [96] proposes a robust MILP (RMILP) model for the optimization of the operation of a multi-carrier energy systems.

MINLP

Several papers formulate the optimization problem as a mixed integer non-linear programming (MINLP) problem because of the non-linear characteristics of the objective functions and/or constraints [9], [22], [36], [40], [44], [55], [56], [57], [58], [59], [60], [63], [99]. MINLP problems are still today very challenging, especially if they are non-convex, i.e. the objective functions and/or constraints are defined by non-convex functions. Usually MINLP problems are relaxed and reformulated as e.g. mixed-integer second-order cone programming (MISOCP), mixed-integer quadratically constrained (MIQCP) and MILP problems and solved by appropriate decomposition techniques. In [11] the network-constrained scheduling problem of a multi-carrier energy system is formulated as an MINLP problem, which is reformulated as an MISOCP problem and solved by the use of the partial surrogate cuts method.

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The authors of [80] formulate the day-ahead scheduling problem of four urban multi-carrier energy hubs as a MINLP problem, which is reformulated as an MISOCP problem. Then, a fully-distributed consensus-based alternative direction method of multipliers with a limited amount of information exchange between the hubs is developed to decompose the centralized scheduling problem into energy hub-based decision making subproblems. The coupling variables between the energy hubs are then decomposed through the use of a set of consensus variables and constraints. The consensus constraints are introduced in the objective function, each multiplied with the corresponding Lagrange multiplier, so that the problem can be solved iteratively in a decentralized fashion. At each iteration, each energy hub solves its own MISOCP problem with fixed consensus variables and Lagrange multipliers and shares the resulting coupling variables with the adjacent energy hubs. The consensus variables and Lagrange multipliers are updated after each iteration. The iterations terminate when the coupling and consensus variables are close enough to each other. Each MISOCP problem is in turn decomposed into a SOCP problem and a mixed-integer quadratic programming (MIQP) problem, which are solved sequentially and iteratively, using the results of each program as input variables to the other. The iterations end when the relaxed continuous variables of the SOCP problem and the corresponding integer variables of the MIQP problem are close enough to each other. The authors state that the MISOCP problem solved by each energy hub at each iteration may be infeasible in some cases and suggest a procedure to guarantee the convergence of the solution strategy. The authors of [48] present a nonlinear constrained optimization problem for the optimisation of the couplings/connections among the different networks of a multi-carrier energy system, due to the consideration of non-linear constraints such transmission line power flows, aiming the ideal interconnection between different energy infrastructures. The authors highlight the usual complications that may appear when using MINLP formulations, such as the solution dependency of the initial values of variables or the large number of suboptimal solutions that are not all technically reasonable or feasible. The necessary procedures to overcome the above-mentioned problems usually require ad-hoc solutions that cannot be implemented elsewhere.

MILP&MINLP

More particularly, some papers such as [100] and [54] present the general mathematical formulation for **both linear and non-linear problem** and describe the methodology for solving a multi-objective optimization problem. Paper [100] analyses the optimal scheduling of a coupled electrical-natural gas network feeding a distributed electrical load in combined day-ahead market and real-time operating conditions. The problem is formulated via a Data-driven Distributionally Robust Optimization (DDRO), taking into account wind data uncertainty. On the other hand, paper [54] presents a review of existing optimization techniques and their applications in power systems, with a special focus on multi-objective optimization in power system planning. Also, in the case of [10] the multi-objective optimization problem is solved in two stages, in the first stage through a MILP and for the second stage a MINLP is implemented. In [82], the optimisation problem is formulated as a MINLP model. In [101], all the mathematical expressions in the optimisation problem are formulated as linear equations. However, the employed solution method uses a non-

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linear model (Bacterial foraging optimisation) to solve the problem. In [71], the optimisation problem for the day-ahead dispatch is formulated as a MILP model, whereas the intraday scheduling is formulated as a non-linear model. In [66], a bi-level optimisation model is employed. The upper level is not formulated via an objective function but is solved through an iterative algorithm. In [86], the optimisation problem is defined through a second-order cone program (SOCP) relaxation
The table below summarizes screened documents according to the approach used for the formulation of the optimization problem.

Table 10 Formulation of the optimization problem in the bibliography

Approach	Document
Linear Programming (LP)	[28] [33] [37] [41] [47] [89] [90] [102]
Mixed-Integer Linear Programming (MILP)	[5] [6] [7] [8] [9] [12] [13] [14] [16] [18] [19] [20] [21] [25] [26] [27] [29] [30] [31] [38] [41] [42] [43] [45] [46] [49] [50] [51] [61] [62] [65] [68] [70] [72] [73] [75] [76] [77] [78] [79] [81] [83] [84] [85] [91] [92] [93] [94] [95] [96] [97] [98] [102] [103]
Mixed Integer NonLinear Programming (MINLP)	[9] [11] [15] [22] [32] [34] [36] [40] [44] [48] [55] [56] [57] [58] [59] [60] [63] [64] [80] [99]

4.3.2 Limitations

From the review above it seems that mixed-integer linear formulations are the most widely used to optimize the design and operation of multi-carrier energy systems. Nevertheless, some of the different variables that may be present in EHs, respond to a non-linear behaviour, e.g. power flow variables, and to non-convexities, e.g. commitment status of energy conversion and storage units. The accurate representation of the physical phenomena taking place in the energy conversion and storage units of a multi-carrier energy system and of the their design and operational decisions requires the use of MINLP formulations. As mentioned above, the solution of MINLP problems is still today a challenging and computationally hard task. Usually, MINLP problems are relaxed and reformulated as MIQCP, MISOCP or MILP problems and solved by the use of proper decomposition techniques. The solutions of such approaches are not guaranteed to be optimal nor do they represent with precision some physical phenomena taking place in the energy conversion and storage units of the multi-carrier energy system.

These limitations shall be considered by eNeuron project to formulate the optimal design and operation layers of the eNeuron tool, considering both the energy hub and micro energy hub levels

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4.4 Optimization Objective Functions

The objective of this section is twofold. On the one hand, to identify the objective functions used for the design and managementt of the energy hubs; and on the other hand, collect the set of technical, economic, environmental parameters related to the planning and operation of the Energy Hubs.

Specifically, the objective of this section is to identify what are the objective functions that minimize/maximize a combination of technical, economic or environmental aspects related to both planning and short-mid-long term operation basis of the Energy Hubs.

This topic of interest has a significant importance since it will set the background of potential objective functions on which eNeuron can build on and identify the set of related information needed to feed it.

4.4.1 State of the art on the objective functions

The reviewed papers discuss about different optimisation approaches leading to single or multi-objective functions with a twofold main focus, system cost minimization and the optimisation of the environmental parameters (mostly CO_2 reduction). MILP models are the most common solving tool of these kind of problems, over fuzzy logic and other non linear and linear programming models.
A great part of the papers aim to minimise several objective functions. The majority of EHs use electricity and gas as energy carriers and its coordination is done by means of an optimisation model in which both economic and environmental objectives may be considered. The aim of [91] is to minimize the operation cost of the interconnected energy hubs (with electrical and gas demands) as well as the freshwater amount. The study in [76] proposes a multi-objective optimisation problem and fuzzy decision-making approach to minimise the procurement costs as well as reducing carbon emission of interconnected multi-energy hubs. The authors of [71] seek a compromise between operation cost and exergy efficiency by means of a three-stage optimization. In [34] a non-domination based genetic algorithm (NSGA) for multi-objective optimization to address economic benefits and energy efficiency is presented. In reference [38] a fuzzy multi-objective decision and two-stage adaptive robust optimisation methods are detailed. In document [58] authors proposed a multi-objective optimisation problem to minimise the operational cost and the total emissions of a system, while the authors in [40] identified a multi-objective optimisation approach, firstly looking forward to an economic target and then to a second objective related to the reliability of the system. The studies within [26], [28], [47] deal with the minimisation of energy costs and the minimisation of CO_2 emissions. Similarly, the analysis in [30], [65], [46], [31] [61], [62], and [33] present a multi-objective optimisation problem with a common first objective, the minimisation of CO_2 emissions, but with different second objectives such as minimisation of the total annual cost as the sum of

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annualized investment costs of all technologies, the minimisation of energy costs and O&M costs of all technologies in the EH, and the maximization of the EH operator's profit also in the role of aggregator.

Reference [8] considers the objectives related to maximisation of economic efficiency, social welfare or accommodation of renewables.

On the other hand, some papers present a single objective optimisation problem. Documents as [9], [13], [18], [48], [64], [66], [77], [84], [104], [105] aim to minimise the operational cost of the EH, while papers [14] and [15] deal with the minimisation of total investment and operating costs.

The following tables summarizes the objective functions based on the state of the art related to this topic.

Table 11 Objective functions in multi objective optimization in bibliography

Reference	Multi-objective optimization function
[82]	• Minimisation of operational cost • Minimisation of freshwater amount
[33]	• Energy loss minimization • Minimisation of operational cost • Minimisation of CO_2 emissions
[34]	• Minimisation of operational cost • Maximisation of the total energy efficiency
[38]	• Minimisation in investment, operation and carbon emission costs • Maximisation of the grid integration level
[25] [27] [71]	• Minimisation of energy costs • Maximisation of exergy efficiency
[26] [28] [47] [76]	• Minimisation of energy costs • Minimisation of CO_2 emissions
[61], [62]	• Minimisation of CO_2 emissions • Maximisation of the EH/aggregator operator's profit
[29]	• Minimisation of the total annual cost as the sum of annualized investment costs of all technologies, energy costs and O&M costs of all technologies in the EH • Minimisation of total primary energy input to the EH
[30] [31] [46] [65]	• Minimisation of CO_2 emissions • Minimisation of the total annual cost as the sum of annualized investment costs of all technologies, energy costs and O&M costs of all technologies in the EH
[86]	• Minimisation of the generators' cost function in addition to the thermal losses and crowdsources' disutility function designated to compensate for the inconvenience caused by rescheduling shapeable load

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	• Minimisation of the deviation cost of generation from the day-ahead operating point, the network's thermal losses and the budget which the operator has allocated to spend on the real-time incentives at the feeder level
[16]	• Minimisation of the unit commitment cost (start-up and shut-down cost of the CHP units, heat pumps and natural gas boilers), the cost of purchased electricity and natural gas and the dispatch cost • Maximisation of the robustness of the solutions, i.e. by finding the worst-case in terms of the increase in the cost due to the uncertainty

Table 12 Objective functions in single objective optimization in bibliography

Reference	Single-objective optimization function
[83]	Maximisation of the EH/aggregator operator's profit
[9] [13] [18] [48] [64] [66] [77] [84] [104] [105]	Minimisation of operational cost
[2]	Maximisation of the utilities of the customers in a P2P energy sharing trading
[3]	Maximisation of the social welfare given by the sum of the profits of all participants in the P2P energy trading
[73]	Minimisation of the total energy expenditure of all individual customers in the microgrid
[67]	Minimisation of the total social energy cost to derive the optimal energy sharing profiles for the building cluster.
[14]	Minimisation of the cost of device operation, energy storage, energy transaction, and curtailment power of wind and photovoltaic
[15]	Minimisation of the total investment cost and total operating costs of energy technologies in the EH

It can be seen that when it comes to single-objective optimisation functions the minimisation of cost be it investment cost or operation cost is dominant. The maximisation of revenues for the different actors of the energy value chain is also a common pursue. For the multi-objective optimisation functions, most cases pursue two different objectives. The first is cost-related and the second is environmental related e.g. CO_2 emissions reduction, the maximum integration of renewable sources. Only one reference [33] combines three different objectives i.e. cost-related, environmental-related and technical-related. As already mentioned, the more objectives one problem formulation sets the more complex is the resolution as the objectives can be contradictory at a certain point.

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4.4.2 Limitations

The objective function is the central part of any optimization problem and defines its general target and the influencing parameters and variables. In the references analysed, the main objective is -in most cases- related to economic targets expressed as maximisation of revenues or profits or similarly the minimisation of the costs (capital and operational) and the minimisation of energy losses.

In single-objective optimization, the space of solutions is usually easily identifiable while there is a unique optimal solution. The introduction of additional functions target in an optimization problem (multi-objective optimization) and the requirement of simultaneous optimization of each, results in both an increase in the number of solutions (the best solution is not one but many) as well as difficulty in accurately determining the space of the solutions.

In order to achieve the optimal operation of a multi carrier energy hub, a multi-objective optimization approach must be implemented using two or more optimization functions. The optimal configuration for a multi-energy system is a complex problem due to the wide variety of technology options, variation in energy prices, significant daily and annual fluctuations in energy consumption. Additionally, as environmental issues are becoming increasingly important in the analysis of these systems, they should be taken also on board through the appropriate variables. However, when it comes to such a complex problem, the issue of conflicting objective functions may arise.

4.4.3 Conclusions and the innovative eNeuron approach

Based on the previous findings, eNeuron project will consider a multi-objective problem formulation with different objective functions, evaluating the feasibility of the results. The minimization of the cost (including operating cost, investment cost, purchase cost of the energy etc.) will be surely taken under consideration together with the minimization of the CO_2 emission. The main innovation of this multi-objective problem will lie on the following:

- Consider at the same time economic and environmental aspects in building the functions.
- Consider local optimization problems at the local level of mEH (lower level).
- Consider global optimization at the level of EH (upper level).
- Consider the stochastic daily operation of the integrated systems.
- The two levels (lower and upper level at mEH and EH level respectively) harmonically co-exist and not cancel each other's operation. Time span and functional constraints are carefully designed.

This approach will ensure both the short- and long-run sustainability of local integrated energy systems, by identifying trade-off solutions between the economic and environmental priorities, and

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providing valuable information on the correlations between the benefits and impacts of DER integration at the local level.

4.5 Optimization Constraints

Constraints have a central role in optimization problems. Indeed, they limit the solution space while defining the operation of the components of the modelled system. In energy system models, they are used to define the performance charactersitics and limitations of the considered energy conversion and storage devices and of the elements through which the energy carriers are transported and distributed. They also regulate the interaction between the system and the considered commodity and ancillary services markets. Due to the complexity of the interaction of the active resources in the energy hubs and the surrounding energy systems, it is necessary to define a set of physical, technical, economic and environmental constraints that allow delimiting the optimisation problem to viable search space.
So, the aim of this section is to identify the equality and inequality constraints that have been used in the analysed optimisation problems in the bibliography so far. The constraints can be classified into four categories: **technology constraints**, **network constraints**, **market constraints** and **other constraints**.

4.5.1 State of the art

The aim of constrained optimization problems is to find the optimum (minimize or maximize) of an objective function within a feasible region defined by a set of constraints. The constraints can be of two types: **inequality constraints** or **equality constraints.**

As mentioned above, from the screened documents, a classification of constraints has been realized, grouping them in: technology constraints, network constraints, market constraints and other constraints.

Some models simply describe energy conversion and storage technology constraints from their efficiency and limits. Other models have a more complete description of the various technologies that they consider.
In addition to the technologies transforming or storing energy, some models also add details to the modelling of loads. Electric vehicles, combining load and storage, are often modelled. A major reason to add details to the modelling of the loads is to model their flexibility potential coming from the end-points' side.

The network constraints represent mainly import and export limits to the different grids or markets. Other constraints, such as the difference in temperature between the inlet and outlet of heat pipes, gas and power flow equations, can also be found more rarely. Additionally, energy balances ensure

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the balance between the loads and exports on the one hand and the generation and imports on the other.

Market constraints are less common in the reviewed documents. They are sometimes used to represent the estimation of the internal price in models including P2Penergy sharing. Another type of market constraints is the constraint on not to buy and sell energy at the same period.

Tables below present the different constraints with the related references.

Table 13 Technology constraints

Operation constraints **(e.g. Capacity (generation, charging/discharging) and ramp-rate constraints of energy conversion and storage devices, storage capacity limits of energy storage devices, availability of generating units constraints modelling the performance (e.g. input-output curves, dynamics) of energy conversion and storage devices, constraints for the computation of the state of charge and depth of discharge of energy storage devices, constraints to compute the status (on/off, charging/discharging, starting-up/shutting down) or the up- and down-time of energy conversion and storage devices, constraints to compute and limit the capacity of energy conversion and storage devices for providing ancillary services, heat-to-power ration of CHP units, limits on the amount or percentage of load that can be shifted to other periods, constraints used to compute the pollutant emissions of energy conversion units**)	[2] [5] [8] [9] [10][11] [12] [13] [14] [15] [16] [17] [18] [19] [21] [22] [23] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [36] [37] [38] [40] [41] [42] [43] [44] [45] [46] [47] [49] [50] [51] [53] [55] [56] [57] [58] [59] [61] [62] [63] [65] [66] [68] [69] [70][71] [72] [73] [74] [75] [76] [77] [78] [79] [80] [81] [82] [83] [84] [85] [86] [88] [89] [90] [95] [101] [104] [106] [107]
Design constraints (e.g. device availability and available sizes in the market)	[27] [29] [30] [53]
Selection of the technologies in the configuration	[46] [96], [97], [98]

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Table 14 Network constraints

Network flow constraints	**Electricity (active and reactive power), thermal, gas, heating, cooling, domestic hot water, flows**	[2] [3] [5] [7] [9] [10] [11] [13] [18] [21] [22] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [37] [38] [41] [42] [43] [44] [45] [46] [47] [49] [50] [53] [61] [62] [65] [67] [70] [71] [72] [73] [75] [76] [77] [78] [80] [82] [83] [86] [88] [89] [90] [96] [101]
	Network usage charge between the seller and the buyer	
	Lower and upper limits of imported/exported energy and natural gas from/to utility companies	
	Non-convex branch flow model to model distribution network	
Transmission limits (active and reactive power limits in electricity networks, maximum mass flow rate in gas and heating networks, power, gas and thermal flow equations, single flow direction.	Boundaries of the active and reactive power in the transmission lines.	[36] [48] [50] [60] [78]
	Gas flow equations in active and passive pipelines.	
	Single direction for flow of energy in pipeline and pipeline capacity	
Nodal (at energy hub or micro energy hub level) limitations	Mass balances for each node	[5] [8] [16] [36] [51] [63] [66] [82]
	End-users' constraints	
	Active and reactive power balance equations in the hub.	
	Maximum and minimum nodal voltages, maximum and minimum gas pressure, maximum and	

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	minimum supply and return temperature.	
	Constraint on feed in power when grid security concerns	

Table 15 Market constraints

Energy trading balance between crowdsources	[86]
Prevent buying and selling electricity at the same period	[22] [53] [77]
Selling electricity by-product on the spot market	[51]
Estimation of the internal price	[66] [84]
Constraints related to the mutual energy sharing: • **The energy shared by building n with building m must equal the energy shared by building m with building nThe price paid for the energy shared by building n with building m must equal the price paid for the energy shared by building m with building n**	[5] [27] [67] [72]

Table 16 Other constraints

Inequality constraints about the trading participants and the platform service charge	[3]
Target renewable penetration level	[36]
Epsilon and integer cut constraints	[89]

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4.5.2 Conclusions

One of the main limitations of bounding the optimisation problem is the nature of the constraint itself. The difficulties mentioned in section 4.3.2 as regards the use of MINLP formulations are of course relevant to the constraints formulation. In eNeuron project all relevant constraints shall be considered to formulate the optimal design and operation layers of the eNeuron tool, considering both the energy hub and micro energy hub level and will be defined under T4.2.

4.6 Heuristic methods

The aim of this section is to identify the main heuristic/meta-heuristic methods employed to solve the related mathematical problems in the literature. It is important to identify how these methods are used together with traditional methods presented in previous sections to overcome barriers due to the complexity of the problem.

4.6.1 Problem formulation and motivation

Heuristic methods can be defined as a procedure for solving a well-defined mathematical problem by an intuitive approach in which the structure of the problem can be interpreted and exploited intelligently to obtain a reasonable solution. Heuristic, unlike optimization methods discussed in previous sections, are not able to guarantee the optimality of the decisions but can, if designed and tuned correctly, provide enough adequate solutions faster and/or with less computational resources than by using an optimization model. Ref. [54] mentions its utilization in power systems, with special focus on multi-objective optimization in power system planning. The heuristic methods discussed in this literature review were categorized into **simple heuristics** and **meta-heuristics.**

Table 17: Categorization of heuristic methods

Heuristic method	Characteristics	Examples
Simple heuristics	• Faster calculation of solution. • Prone to get stuck in local optima.	• Local search. • Greedy algorithms. • Hill climbers.
Meta-heuristics	• Attempts to obtain a better solution in a pre-defined neighbourhood. • Many methods are based on biological metaphors.	• Evolutionary Algorithms. • Genetic algorithms. • Simulated Annealing. • Particle Swarm. • Tabu Search. • Ant Colony. • Hybrid Algorithms.

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Simple heuristics come in the form of local search, greedy algorithms, and/or hill climbers. Meta-heuristics try to go beyond the local search of the best solution. Many of them are based in some biological metaphor bio-inspired and are in the form of genetic algorithms (GA) and evolutionary algorithms (EA) algorithms, simulated annealing, tabu search, ant colony, hybrid algorithms, fuzzy programming, neural networks, etc. Heuristic/Meta-heuristics methods can be used in various aspects related to energy hubs, for example for the operation/control of the energy hubs [59] as they are often able to handle problems in shorter computational time. As eNeuron will deal with multi-energy carriers and considering energy communities, it is important to keep in mind the different algorithms to solve large scale problems in an efficient time.

4.6.2 State of the art

In Ref.[108], a review of the literature on optimal management of energy hubs is performed. It reports that heuristic are common methodologies for such problems and highlights in particular two papers using this kind of methods for solving optimal energy flow problems (OEF) which are the ones done in [59], which utilized a multi agent genetic algorithm (MAGA) for decomposing the multi-carrier optimal power flow problem into a separate OPF problem, while the other one [56], which proposed using a modified teaching–learning-based optimization algorithm for solving optimal power flow problem in multi carrier energy systems

The environmental/economic dispatch problem involves conflicting objectives and it is known to be highly constrained. To tackle this challenge, in [63] a hybrid multi-objective optimization algorithm is presented based on particle swarm optimization (PSO) and differential evolution (DE). They showed the effectiveness and potential of the algorithm comparing with different techniques reported in literature and by the application to standard IEEE 30-bus test system. A new method combining traditional optimization and meta-heuristic method is presented in [88]. It combines the convex optimization and meta-heuristic in a method named scenario-based branch and bound. This method is used in order to obtain reliable solutions in a model predictive based MINLP with coupled timesteps. The meta-heuristic used is a modified version of the real coded genetic algorithm (RCGA). RCGA is chosen over GA because it converges faster. The meta-heuristic is used to solve single steps independently and their compatibility over the prediction horizon are checked afterwards.

The review paper about the planning of distributed energy resources problem [55] mentions that these problems are usually difficult to solve using traditional mathematical methods, so EA are a good alternative . EA handle sets of possible solutions simultaneously, and as a result, permit identification of several solutions of the Pareto front at once. Hence, EA are recognized as a natural way of solving multi-objective problems efficiently.

A control elitist genetic algorithm is used in [52]. Meta heuristic creates a set of candidate solutions (population), checks the value of the objective function for each of them and applies a heuristic for generating a second population. The heuristic varies between the methods but is often based on the most promising elements of the previous generation. Those steps are repeated until a stop

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criterion is satisfied. The energy storage system (ESS) scheduling problem consists of deciding whether the ESS should be charged or discharged and at which rates. This problem arises in the microgrid energy management (MGEM). In [75] a fuzzy inference system has been used to solve it in efficient time. In [101] a Modified Bacterial Foraging Optimization (MBFO) was used to solve ESS considering the economic and environmental objective functions simulating the trade-off between conflicting objectives.

Other methods are used in the context of local energy markets [104]. They specifically occur when modelling multiple agents competing in a market or in decentralized or distributed approaches such as in [86]. In [86], different optimisation models such as Alternating Direction Method of Multipliers (ADMM), Stackelberg game and Nash game were utilized. Meta-heuristics can also be applied to planning problems, as in [17]. There, the robust planning of the energy system of an energy hub is tackled using Quantum Particle Swarm optimization (QPSO). This meta-heuristic is also compared to the performances of PSO and GA approaches and shows the superiority of the proposed method in terms of convergence speed and global search ability. Similarly, [52] uses an Elitist Genetic algorithm (a variant of NSGA II) in a multi-objective planning problem. The objective considered are minimization of the primary energy demand and investment costs.
In P2P systems energy sharing has the potential to facilitate local energy balance and self-sufficiency. In [84] an evaluation of the performance of some P2P energy sharing systems based on multiagent-based simulation framework was performed. To facilitate the convergence of the algorithm two heuristic techniques were considered: a step length control and a learning process involvement.

As already mentioned in the limitations of objective methods section, in a multi-carrier energy system the operation management considering multi-objective functions are large size problems, and in general are non-linear, non-convex, non-smooth, and high-dimension optimization problem that mathematical techniques could be trapped in local minima. Hence, a well alternative to deal with large size problems is to use evolutionary techniques instead.

In [57] and [58], a novel variation of a fuzzy decision making method was proposed, merged with the well-known modified teaching-learning based optimization algorithm. Ref. [34] developed a multi-strategy gravitational search algorithm (MSGA-II) for optimizing the operation of integrated energy systems with electro-thermal demand response (DR) mechanisms.

A summary on the utilized heuristics methods per reference can be seen on Table 18.

Table 18: Heuristic methods used per reference

Reference	Purpose	Method
[75]	Scheduling of ESS	Fuzzy inference system
[101]	Optimize operative costs	Modified Bacterial Foraging Optimization (MBFO)

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[34]	Optimize electro-thermal DR	Multi-strategy gravitational search algorithm (MSGA-II)
[84]	P2P exchange	Step length control and learning process involvement
[86]	P2P exchange	Alternating Direction Method of Multipliers (ADMM)
[54]	Planning	Does not apply (literature review)
[55]	Planning	Does not apply (literature review)
[59]	MO-OPF	Multi Agent Genetic Algorithm (MAGA)
[63]	Environmental/Economic dispatch	particle swarm optimization (PSO) and differential evolution (DE)
[56]	MO-OPF	Modified teaching–learning-based optimization algorithm
[57]	MO-OPF	Fuzzy decision making
[58]	Minimize costs and emissions	Fuzzy decision making
[108]	Operation and control of EH	Does not apply (literature review)
[88]	Scheduling of DER	Scenario-based branch and bound
[17]	Planning	Quantum Particle Swarm optimization (QPSO)
[52]	Optimize RES mix	Elitist Genetic algorithm
[104]	Energy markets	Does not apply (literature review)

4.6.3 Conclusions

As seen above, heuristic/meta heuristic methods can offer a robust solution when it comes to the challenging multi objective problem formulation for multi carrier energy systems. Variations of genetic and evolutionary algorithms are common techniques in the bibliography. As eNeuron problem expands in two levels, these methods could be combined with the traditional methods putting forward a new heuristic/metaheuristic approach dealing with real-time models and large size networks. However, a significant limitation when using heuristics techniques to solve the multi-objective optimisation problems is the complexity for setting up their parameters to afford a well performance. This and the fact that it is not possible to obtain the optimal solution with these techniques are issues that need to be consiedered.

4.7 Uncertainty

EHs are becoming key actors in the development of multi-energy systems, and most of them face a high penetration of variable renewable generation. Therefore, the models devised for the optimal operation or optimal design of such EHs must deal with the uncertainties of the different components that the EH may have, being higher the impact for the short-term scheduling of the

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EHs. Thus, it is necessary to review how the different sources of uncertainty are usually modelled and the methodologies proposed to solve the EH optimization models.
The aim of this section is to identify the different sources of uncertainty that have been considered in the bibliography e.g.,.renewable energy resource, load, price, etc. and how the uncertainty has been dealt within these documents.

4.7.1 State of the art

When considering uncertainties, most of the analyzed research has considered in some way the behavior of variable renewable energy (VRE), be it wind or PV, or the variations in consumption pattern among different users, be it by the representation of electrical and/or thermal loads. Added to this, some of the references have also considered variations in the market energy price. In order to categorize these references according to the uncertainties that were tackled, a summary is done in Table 19:

Table 19: Uncertainties considered in the analyzed references

Uncertainties	Reference
Renewable generation	[10] [14] [17] [24] [26] [36] [40] [44] [51] [53] [60] [67] [68] [72] [78] [83] [85] [86] [100] [104] [106] [107]
Consumption	[6] [14] [16] [22] [24] [25] [26] [38] [40] [41] [44] [51] [53] [74] [60] [65] [67] [68] [69] [85] [86] [87] [95] [104] [105] [107] [109] [110]
Storage and EVs	[5] [17] [19][75] [100]
Energy price	[3] [5] [24] [25] [26] [44] [51] [53] [74] [96] [60] [69] [83] [85] [87] [95] [104] [105] [109] [110] [111] [107]
Failure	[40]

In order to solve the problematic these uncertainties present, different methodologies have been proposed in the literature, that can be divided in 3 categories, as explained in [56], which are:

- Stochastic optimization: it discretizes the continuous stochastic parameters into a tree of scenarios, in whose nodes uncertainty is assumed to be known.
- Robust optimization: it defines the solution according to the more adverse scenarios regardless of the probability of occurring.
- Chance constrained optimization: it introduces probabilistic constraints for obtaining a trade-off between the optimal value and the robustness of the solution.

A summary on the utilized methods is shown on Table 20:

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Table 20: Methods for handling uncertainties per reference

Method	Reference
Monte Carlo simulation	[5] [6] [22] [26] [31] [37] [53] [60] [76] [77]
Roulette wheel mechanism	[26] [83]
Reinforcement learning	[24] [74] [69] [87] [107]
Robust optimization	[96] [68] [100]
Latin hypercube sampling	[33]
Sampling average approximation	[66]
Robust box uncertainty set method	[38]
Fuzzy inference system	[75]
Distributionally robust chance constrained model.	[72]
Spectral clustering scenario reduction	[14]
Min max min robust framework	[16] [53]
Quantum Particle Swarm Optimisation	[17]
Model predictive control	[19] [88]
Downside risk constraints method	[85]
Big M method	[95]
Sensitivity analysis	[51]
Stochastic optimization	[10] [78] [83] [106]
Probability density function	[17] [40]
Objective wise worst-case optimization	[53]
Robust optimization with min max expected regret criterion	[53]

Of the analyzed references, the most frequent methodology uses stochastic optimization models. From these, the utilization of the Monte Carlo Simulations has stood out as the most common way of dealing with uncertainties, which randomly samples scenarios from historical data or probability distributions, albeit other sampling methods have also been utilized, as it is the case of [33] with Latin Hypercube Sampling or [68] with sampling average approximation, for example.

As for other works that use stochastic optimization models, the authors of [68] propose a two-stage framework that combines a stochastic optimisation model and robust techniques, to identify solutions of the problem that are robust and flexible in terms of uncertainty. In the case of [19], a two-step approach is used for the operation of an EH, using stochastic optimisation in the first step and a Model Predictive Control (MPC) strategy in the second step. The authors of [85] propose a stochastic optimisation combined with a novel risk assessment approach called the downside risk constraints method for the modelling of the risk imposed by uncertain parameters.

Robust optimisation techniques are found in the works of [16], [17]. The authors of [16] consider the uncertainty of each variable through a suitable uncertainty set or prediction interval that is defined as a function of the forecast value and the forecast error. The authors consider different degrees of robustness and different magnitudes of the forecast error. In [17] the authors use a

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robust method based on a Quantum Particle Swarm Optimisation (QPSO) approach to solve the optimisation model.

As for chance constrained optimization, the authors of [72] solve the optimisation problem using a distributionally robust chance constrained model. Also, the authors of [75] made a forecast of uncertain parameters that were then used in a fuzzy inference system to make charging and discharging decisions for a storage system with the goal of simplifying the optimization of the energy system.

4.7.2 Conclusions

As seen in the referenced literature, the utilization of VRE as well as consumption patterns and energy market price dynamics bring an array of uncertainty to the modelling and optimization of the EH. In order to solve this, the methodology implemented needs to fulfil a robust solution while still vying for a result close to the optimal value. From the research that has been analyzed, the preferred choice when dealing with uncertainties has been with the use of stochastic optimization models, of which the utilization of Monte Carlo simulations is of interest.

4.8 Risk Aversion

Risk management is a procedure for shaping a risk distribution. Popular functions managing risk are value-at-risk (VaR) and conditional value-at-risk (CVaR) used to provide a risk-hedging strategy measuring and controlling the level of risk exposure. Risk management is highly associated with the uncertainty management discussed in the previous section involving renewable variations and electricity load forecasting errors. It could be defined as the potential that an energy producer (energy hub or micro-hub, virtual power plant or LEC) will fail to meet its obligation in accordance with agreed terms (not producing or demanding the foreseen amount of energy from the energy market for a specified hour) [75]. The intermittent and stochastic characteristics of renewable energy resources bring new challenges on the scheduling of power systems [82]. Therefore, uncertainty management becomes key and is usually considered by means of robust optimization and stochastic optimization.

Risk is typically defined in terms of returns' "variance" from the mean return. The more widely dispersed real returns are around the average, the riskier the asset is. This is used within energy markets to evaluate the amount of renewable energy to be bought or sold in different periods and the associated price.

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4.8.1 Problem formulation and motivation

Risk-averse formulations interpolate between the classical expectation-based stochastic and minimax optimal control. This means that they are flexibly managing uncertainty from the worst case up to the expected (risk neutral). This way, risk-averse problems aim at hedging against extreme low-probability events without being overly conservative.

There are two main approaches followed to deal with this issue in the literature: the first one considers risk metrics that provide a grade of risk to moderate the decision; the second one is through distributionally robusts optimization. In general, the decision maker may trade performance for safety by interpolating between the conventional stochastic and worst-case formulations looking forward robustness to load and renewable power prediction errors.

4.8.2 State of the art

Value-at-Risk

Value at risk (VaR) is a statistic that quantifies the extent of possible financial losses within an investment operation. VaR modelling determines the potential for loss in the entity being assessed and the probability that the defined loss will occur [76].
The VaR of X with confidence level α ∈]0, 1[is:

$$VaR_{\alpha}(X) = \min \{z \mid FX(z) \geq \alpha\}. \qquad (1)$$

By definition, $VaR_{\alpha}(X)$ is a lower α-percentile of the random variable X. Value-at-risk is commonly used in many engineering areas involving uncertainties. For normally distributed random variables, VaR is proportional to the standard deviation.

If X ∼ N(μ, σ2) and FX(z) is the cumulative distribution function of X, then [75],

$$VaR_{\alpha}(X) = F -1 X (\alpha) = \mu + k(\alpha)\sigma, \qquad (2)$$

where k(α) = √2 erf−1(2α − 1) and $\mathrm{erf}(z) = (\frac{2}{\sqrt{\pi}}) \int_0^z e^{-t^2} dt$

Conditional Value-at-Risk

Conditional Value at Risk (CvaR) is a risk assessment measure, used for effective risk management, that quantifies the amount of tail risk an investment portfolio has over a specific time frame.

CvaR is a weighted average of VaR and CvaR+, and attempts to address the shortcomings of the VaR model.

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$$CvaR = \lambda\ VaR + (1-\lambda)\ CvaR+\ ,\ 0 \leq \lambda \leq 1 \qquad (3)$$

While VaR represents a worst-case loss associated with a probability and a time horizon, CvaR is the expected loss if that worst-case threshold is ever crossed [101].

The CVaR of X with confidence level α ∈]0, 1[is the mean of the generalized α-tail distribution [76]:

$$CVaR_a(X) = \int_{-\infty}^{\infty} Z dF_X^a(Z) \qquad (4)$$

$$\text{Where } F_X^a(Z) = \begin{cases} 0\ ,\ when\ \ Z < VaR_a(X) \\ \frac{F_X(Z)-a}{1-a}\ ,\ when\ Z \geq VaR_a(X) \end{cases} \qquad (5)$$

Markowitz portfolio theory

Markowitz Portfolio Theory (MPT) uses complex mathematics to diversify a portfolio in such a way that it earns a particular return with the smallest amount of risk.

In [37], the presence of uncertainties in zero-carbon multi-energy system (ZCMES) influences its scheduling performance and brings some particular operation risk. Thus, in the operational-cost objective function, the Markowitz's mean-variance theory is employed to simultaneously minimize and maintain a balance between economy and risk.

Information gap decision theory

The information gap decision theory (IGDT) is a practical strategy with no need to probability distribution function of uncertain parameter, that models the positive and negative aspects of uncertainty based on the known and unknown information. Positive and negative outcomes that uncertainty may cause are modelled using two functions of information gap decision theory called robustness and opportunity functions [71].

In [43] IGDT may be used either from risk-averse or risk-seeking perspectives. In risk averse IGDT, the decision maker would be satisfied if the cost is equal to or less than a pre-specified critical value.

Distributionally robust and risk averse approaches to multistage stochastic programming

To handle uncertainty in generation in the power system, various optimization methods have been implemented such as scenario-based optimization (SO) and robust optimization (RO); however, they provide major drawbacks. By combining the advantages of SO and RO, the distributionally robust optimization (DRO) methods have been proposed to solve the optimization problems with uncertainties (renewable generation and loads). There are different approaches to solve this kind of problems typically reducing the constraints formulation to be solved via MILP, where the

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distribution information is useful to obtain a less conservative solution. Although treating the uncertainties from different sources independently leads to over-conservative strategies. Data drive solutions are then developed to coordinate the scheduling of multi-energy coupled systems (MECS) in which the correlation and distribution characteristics of the uncertainties are considered to reduce the conservativeness of decision-making. By this means, the operation reliability of coordination scheduling of MECS can be realized

In this way, in [100] the data-driven robust optimization (DDRO) method allows to address the uncertainty while obtaining less conservative minimum cost solutions.

In [85] a stochastic model for risk evaluation is presented. The novel and flexible methodology presented allows to reduce the risk associated to the uncertain environment slightly increasing the operation cost. This is shown in some tables where the various operation cost of hybrid energy system (HES) in each scenario are compared with the risk control parameter.
Table below presents the risks with the related parameters.

Table 21: Risks and related parameters.

Risks	Related parameters
Financial risks	• Electrical loads • Thermal loads • Sun irradiation • Electricity prices
Reliability and power quality risks	• Deviations of demands • PV power • Wind power • Electricity prices.

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5 Cluster 3-Markets and Business Models

The aim of this section is to identify the way of interaction of mEH and EH with the market regime. Electricity markets are always addressed to purchase electricity for satisfying local demand and, at certain times, sell the energy excess or make arbitrage. So, the attention is given to papers that are capturing this relation and how the mEHs- HEs schedule beforehand the daily and real-time operation for participating in the markets. Apart from the different types of electricity markets, the attention is also given to commodity markets such as natural gas market. As seen in the next, the natural gas market is also considered when thermal loads are included but this is limited to the knowledge of natural gas price rather than a market structure.
It should be highlighted that the market participation of the mEH in eNeuron should be designed and highly adapted to the existing (or proposed) market mechanisms considered in the literature and aligned with the business models that will be developed under WP3.

5.1 Energy and Balancing markets

The aim of this subsection is to identify the energy and balancing markets in which the energy or micro-energy hubs have been assumed to take part in the screened documents. Other commodity markets may be considered as well.

5.1.1 State of the art

Despite that all consulted literature considered electricity markets to purchase or sell electricity, **a clear market framework is not presented** which should include the main features of market mechanisms such as market bids, closure times, market clearing process, real-time power set-point or grid needs, ideally taking into account potential national particularities. Sorely the reference [71] considers a multi-stage optimization with three temporal horizons: day-ahead dispatch with 1-hour resolution, and intraday operation with 15-min and 5-min beforehand scheduling intervals, to adjust short-term cost and efficiency based on forecast updates of local generation and load. This market design representation is closer to the realistic market dispatch.

All cases analysed take part in the electricity market in two ways:

- Firstly, in order to maintain reliability and stability in EHs' operation, grid constrains in the strategy of optimal coordination of the energy flows are included. In order to guarantee the stability and energy balance of the EHs the optimization models have to impose constraints associated to the electricity grid and load balancing. These constrains include line

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transmission capacity [100], [106], power and energy balance [100], [5], [88], [22], electrical demand [106], and maximum and minimum values of lines voltage [22]. For more details regarding the constraints please see section 4.5.

- Secondly, the EHs take part in the **day-ahead electricity market** taking into account different costs i.e. in [100] the authors have considered generation cost, start-up/shutdown cost, upward/downward reserve cost and real-time operation cost (regulation cost, curtailment/shedding penalties). In its simplest version, literature use the historical day-ahead electricity price to model the electricity market. This is the approach used in [89], [51]. Local electricity market models usually use an intraday timescale and only a few combines multiple timeframes [104]. Figure 4 illustrates the working schedules on the day-ahead and intraday markets:

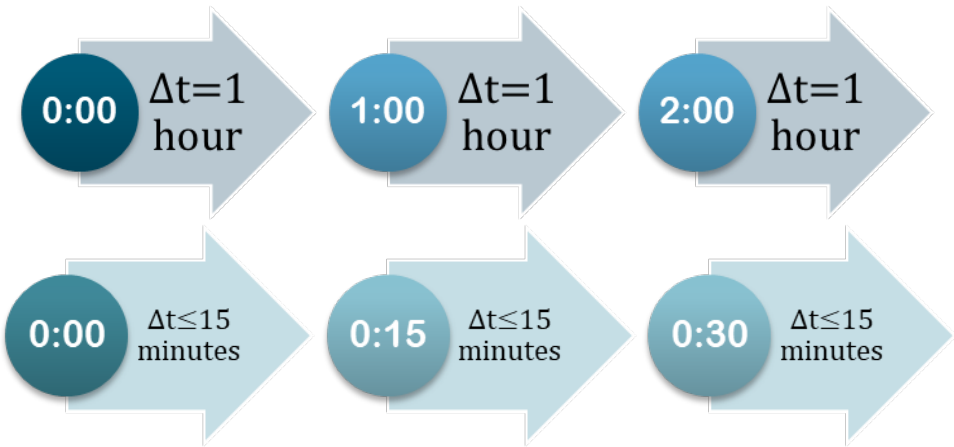

Figure 4:Day-ahead and intraday bidding schedules

No balancing market (such as frequency balancing services, voltage control or grid congestion management) is considered in the literature. In [5], the energy hub is allowed to purchase or sell electricity so as to meet its own electricity and heat demand or to minimize the cost. The price at which the electricity is purchased by the EH is referred as “real-time electricity prices”. The price at which the electricity sold by the energy hub is valued at 90% of the previous price. The research presented in [106] shows a brief consideration about the day-ahead market, where the system operation costs are minimized thanks to the simultaneous dispatch of energy and reserve, but this study does not perform a deep market analysis. The model used in [88] considers the market energy price (day ahead vs real time) to reduce energy utilization from utility grid and in [22] the upstream grid energy price is compared to the optimal schedule to buy or sell electricity to the grid.

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In [39] that it is a review work related to net-zero energy districts (nZED) problems, they mentioned that it is common to consider the energy balancing in these type of problems. An example of how the electricity market works in Ontario Canada under demand response services is studied in [20]. In the case studies presented in [17] and [18] the hubs can sell/purchase electricity to/from the distribution network. In [14] they introduced the possibility of selling heat and electrical power to external networks in their model through the objective function. Due to the Heat-To-Electricity ratio (HER) that is clearly different depending of the type of building (residential, industrial), in [93] they considered two cases to test the behaviour of their Integrated Demand Response system (IDR). Following another approach, reference [15] considers the energy hub participating in Demand Response Programs (DRPs) by changing its behaviour in response to a time of use (TOU) tariff. As there is a big difference in a day-ahead and real-time prices, in [72] a design for day-ahead EH energy management with multiple uncertainties and taking account risks in intra-day real-time transactions has been performed. Ref. [86] presents a useful open platform that allows to the users of EHs to add key performance indicators (KPI) to analyse different scenarios related to energy markets.

Nonetheless, other studies [34], [61], [62], [71], [76], [82] take into consideration the fluctuation of hourly wholesale electricity prices, which has direct influence on the objective functions, while in [38], placed in China, the electrical power purchase price is considered relatively stable. Similarly, in [105], [44], the energy hub can import energy from the wholesale market and export excess energy to the wholesale market. In [94], energy market prices are described containing a nodal energy pricing strategy using the flow-tracing method.

As mentioned before no balancing services has been addressed at all in the consulted literature, while several market mechanisms for energy flexibility inside EH are included. Only authors in [62] consider additional revenues for selling the electrical flexibility collected from PEVs in V2G mode into the wholesale market, but not in a concrete balancing market mechanism. Furthermore, [61] and [76] address demand response mechanisms through TOU prices to end-users as an incentive scheme to reduce the operational costs by shifting load from high to low price times, while in [34] both electrical and -thermal loads enhance the flexibility of demand side load management. In addition, white certificates (WC) derived by the related Italian incentive scheme are included for CHPs in [61]. Some of the work referenced make mention on utilizing forecasts for unit commitment for the next day [62] or bidding for the day-ahead market through the figure of an aggregator, which opens the possibility for a more active role in such market and others in which the energy hubs may offer both its aggregated flexibility and excess generation [30].

Regarding the gas market, only natural gas price and thermal load is considered in the optimized operation of the energy hubsn [34], [38], [48], [61], [62], [71], [76], [82] but without an itself gas market structure.
Models presented in [22], [100] and [106] consider gas prices in their optimization costs algorithms.

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5.1.2 Limitations

The most important limitation found in the literature as already mentioned is that none of the papers considers the participation of the studied energy hubs in **electricity balancing markets**. The only electricity market considered is the day-ahead electricity spot market. Only a few papers consider such a market.

A second limitation found in the listed papers is the lack of a **realistic electricity market setting**. Generally, for an energy hub to sell/purchase electricity in the day-ahead electricity spot market the market agent representing the energy hub (it can be its owner or another company acting as representative) must submit selling/buying bids before the market gate closure (usually the day before the electricity delivery/withdrawal). In-between the gate closure time of the day-ahead electricity spot market and the time of delivery of the energy cleared in such a market several intra-day electricity markets are celebrated where the market agent representing the energy can submit selling or buying bids so as to modify the generation schedule of the day-ahead electricity spot market or the previous intra-day market.

The reasons for participating in the intra-day markets are diverse: some market agents update their generation schedule in the intraday markets since better forecasts (of e.g. the demand or the renewable generation) are made available as the time of delivery approaches; some others do it as a consequence of unexpected contingencies which render some of their generation or consumptions devices unavailable; and quite a few market agents attempt to get some extra revenues by the "cross" price arbitrage between the day-ahead electricity spot market and the intraday markets and between the different sessions of the latter. Finally, in real-time, if the amount of energy transferred to/withdrawn from the grid by the energy hub differs from the energy scheduled in the last market, or market session, in which the agent has participated, the excess/deficit energy is computed as an upward/downward imbalance.

The electricity production/consumption scheduled in each market or market session in which the agent has participated is remunerated/charged at the market clearing price (usually marginal), whereas the upward/downward imbalances are remunerated/charged at the imbalance price (usually different upward and downward). None of the revised papers consider the entire process as described above. Most of them use a single electricity price, presumably corresponding to the day-ahead electricity spot market. In some papers, the uncertainty of the electricity price is considered by means of stochastic or robust optimisation approaches.

The third limitation found in the revised papers is analogous to the second one but referred to the natural gas market setting. The delivery and consumption of natural gas is also negotiated both in day-ahead and intraday markets or sessions. The time horizon and temporal resolution of the day-ahead and intraday gas market sessions are not the same as those of the day-ahead and intraday

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electricity markets. Gas imbalances are also computed in the gas market. The gas sold/purchased in each market or market session in which the agent has participated is liquidated at the market clearing price (usually marginal), whereas the excess/deficit gas imbalances are liquidated at the imbalance price (usually different for excess and deficit imbalances). None of the revised papers consider the entire process as described above. All papers where the gas price is considered use a single gas price, presumably corresponding to the day-ahead gas market price. The uncertainty of gas prices is not considered in any of the revised papers.

Limitations related to other carriers markets (e.g. heat market) or multi-carrier markets are not mentioned in this document since such markets are not yet mature enough.

5.1.3 Research questions per limitation

Two common research questions arise as regards the aforementioned limitations:

1. **How can** the participation of energy hubs in markets (electricity balancing markets, a realistic electricity market setting, a realistic gas market setting) **be considered** in the optimisation models used to define their optimal operational schedule and design?
2. **Is it worth to consider** the participation of energy hubs in electricity balancing markets/a realistic electricity market setting/a realistic gas market setting in the optimisation models used to define their optimal operational schedule and design?

5.1.4 Innovation paths per limitation

Consideration of electricity balancing markets in the determination of the optimal operational schedule and design of energy hubs

In order to get an answer to the questions of how and whether it is worth to consider the participation of the energy hub in the electricity balancing market so as to determine its **optimal operational schedule**, a potential path would comprise the following tasks.

a. Revise the rules of the balancing market

b. Identify the known and unknown balancing market variables (prices, volumes, etc.) at the time when the market agent must submit bids to participate in the balancing market

c. Define the algebraic formulation of the problem of determining the optimal operational schedule of the energy hub participating in the electricity balancing market and code it in a suitable programming language (e.g. GAMS, CPLEX or Julia). The constraints and limitations of the balancing market should be formulated in as much detail as possible.

d. Find or devise an adequate solution procedure to solve the problem. This might require reformulating the problem so that it can be solved by the chosen solution procedure.

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e. Validate the problem's formulation and solution procedure from a set of computational experiments (assuming perfect knowledge of the unknown balancing market variables) and evaluate the computational performance of the model. Modify the formulation and/or solution procedure if necessary.

f. Once the problem's formulation and solution procedure have been validated, choose a set of representative daily cases and run the model without and with considering the participation of the energy hub in the balancing market (assuming perfect knowledge of the unknown balancing market variables).

g. From the results obtained in task f check whether it may be worth to consider the participation of the energy hub in the balancing market using the formulation and solution procedure validated in task e.

h. If the answer in step g. is yes:

1. Statistically analyse the unknown balancing market variables at the time when the energy hub must submit bids to participate in the balancing market.
2. Develop forecasting models of the unknown balancing market variables.
3. Reformulate and recode the problem (e.g. as a multi-stage stochastic or robust optimisation problem) if necessary as a function of the analysis in task h.1 and repeat tasks e and f.
4. Repeat tasks e and f assuming imperfect knowledge of the unknown balancing market variables.
5. From the results obtained in task h.4, conclude whether it is worth it to consider the participation of the energy hub in the balancing market using the formulation and solution procedure validated in task e.

In order to get an answer to questions of how and whether it is worth to consider the participation of the energy hub in the electricity balancing market so as to determine its **optimal design**, a potential follow-up path would comprise the following tasks:

i. Choose a set of representative daily cases and run the model without and with considering the participation of the energy hub in the balancing market (assuming perfect knowledge of the unknown balancing market variables), and considering different energy hub designs.

j. From the results of task i, conclude whether or not the optimal design notably changes when the participation of the energy hub in the balancing market is considered to determine its optimal design.

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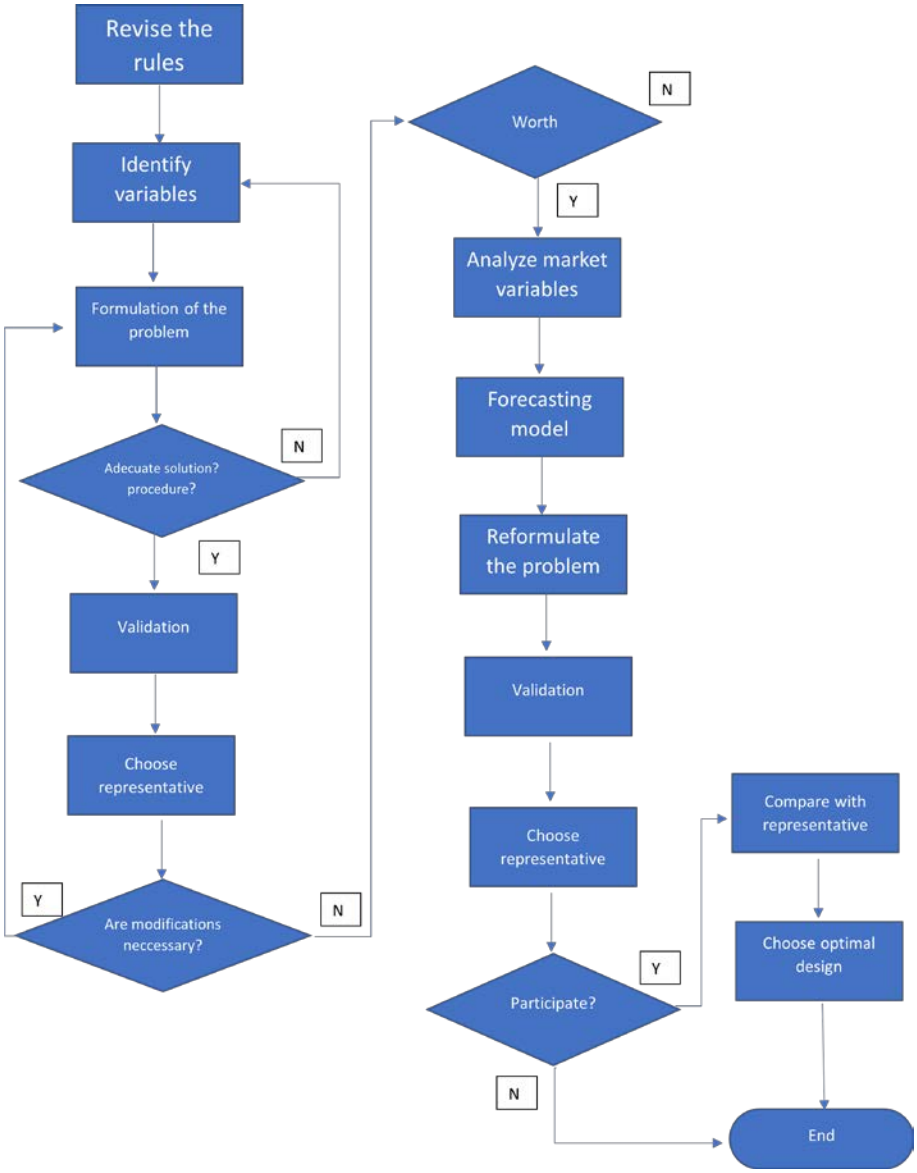

Figure 5: Flowchart of decision making process for EH to participate in balancing markets

<u>Consideration of a realistic electricity market setting in the determination of the optimal operational schedule and design of energy hubs</u>

In order to get an answer to the questions of how and whether it is worth it to consider a realistic electricity market setting so as to determine the **optimal operational schedule** of an energy hub, a potential path would comprise the above tasks a-h, focusing on the electricity market setting (realistic electricity market sequence considering day-ahead electricity spot and intraday markets and energy imbalances) rather than on the participation on the energy hub in the balancing market.

In order to get an answer to the questions of how and whether it is worth it to consider a realistic electricity market setting so as to determine the **optimal optimal design** of an energy hub, a potential path would comprise the above tasks i-j, focusing on the electricity market setting instead of on the participation on the energy hub in the balancing market.

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Consideration of a realistic gas market setting in the determination of the optimal operational schedule and design of energy hubs

In order to get an answer to the questions of how and whether it is worth it to consider a realistic gas market setting so as to determine the **optimal operational schedule** of an energy hub, a potential path would comprise the above tasks a-h, focusing on the gas market setting (realistic gas market sequence considering day-ahead and intraday sessions and gas imbalances) rather than on the participation on the energy hub in the balancing market.

In order to get an answer to the questions of how and whether it is worth it to consider a realistic gas market setting so as to determine the **optimal optimal design** of an energy hub, a potential path would comprise the above tasks i-j, focusing on the gas market setting instead of on the participation on the energy hub in the balancing market.

5.1.5 Approach for eNeuron

The eNeuron project should consider the research questions mentioned in section 5.1.3 (How can the participation of energy hubs in different markets be considered in the optimisation models and whether their participation is actually worthy) so as to develop the optimal operation and design layers of the eNeuron tool.

Developing a tool applicable to every energy hub, participating in different electricity, gas, and electricity balancing markets is not possible. However, the electricity and gas market settings in most EU countries is similar. As regards the electricity balancing markets, some of them are identical or similar across quite a few EU countries (e.g. the frequency containment reserve market in Austria, Belgium, Slovenia, Switzerland, Germany, Western Denmark, France and the Netherlands operates as a single market).

The eNeuron team should address the research questions mentioned above in at least 1 case study (which might be based on 1 of the eNeuron pilots). It would be also advisable that the optimal operation and design layers of the eNeuron tool, or a version of it, would be developed considering these research questions, at least for such a case study. Specifically, the optimal operation layer might require to be subdivided into several sublayers so as to deal with the intraday operation of the energy hub in the electricity and gas intraday markets, and in the electricity balancing markets.

5.1.6 Further research questions

The interaction between the energy and balancing markets through their corresponding agents with the energy hub and its participating actors needs to be addressed, as the previous literature has

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been lacking in this regard. This may be realized by means of incentives, local markets, peer-to-peer markets, etc. The literature on the participation of energy hubs in local heating markets is scarce. Therefore, further research in this topic is needed in order to fully exploit the benefit of the local resources within it.

The real-time control of each element in the energy hub (generation, storage and consumption units of various energy carriers) will require an almost continuous update of the relevant set-point (e.g. power set-point of electricity storage units). As this might be computationally challenging, there is the need for elaborating an efficient scheme that can make such decisions and translate them into corresponding actions within the corresponding time constraints.

There have also been discussions about participating in the electricity market with the energy hub as a single actor. So, there would be the interest on how a more decentralized structure with independent actors can benefit from this, as the literature that did consider P2P schemes did not delve deep into interacting with actors outside the local energy community.

It is of utmost importance to establish a clear market framework that addresses the main features of existing electricity markets such as market bids, closure times, market clearing process; and closer to the operation, the intraday redispatch of DERs should be considered and real-time power setpoints or grid needs should be followed.

For the scheduling and dispatch of DERs, it would be of interest to evaluate not only the wholesale electricity market, but instead include in the decision-making other energy carriers that could be of interest, such as the balancing market features, as well as features and constraints related to other energy carriers (thermal, gas, etc.) or the many services that can be provided within this structure (ancillary services, P2P markets, etc.).

Only one paper [18] includes time-of-use prices for natural gas purchased from the natural gas distribution system and heat purchased from the district heating system into its objective function. In addition, in [14] authors introduce the possibility of selling heat to external network in their model through the objective function too. This opens up the possibility of a more predominant role of the heating sector, for which a scheme where local heat resources can be introduced would be of special interest.

5.1.7 Conclusions

The role of EH as an aggregated entity comprised of different users and energy resources is an interesting prospect and it could bring more economic benefits. For this reason, an analysis on the energy markets in which they would be able to participate is a must, as well as identifying what demands in a technical matter for them to participate in.

It was found that most of the reviewed literature was lacking in identifying the ways in which energy hubs may interact with different energy markets, having thus a need for devising ways that this would be enabled with multiple energy carriers and not solely for the electricity sector. Furthermore, the constraints for each energy carrier for participating in such markets need to be elaborated more extensively.

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eNeuron project should consider realistic market designs for electricity markets and beyond. Not only daily wholesale market should be considered, but also real-time market to adjust the intra-daily operation of the distributed energy resources according to the updated forecasting, including TOU schemes or other mechanisms for demand response outside the EH. Moreover, the external grid will become more unstable and weaker with the increase of EHs and renewable sources. Thus, the EHs are key actors, who have flexible capabilities, to provide balancing services to the external grid, while at the same time additional revenues are obtained and the energy cost is reduced.

5.2 P2P architectures

There are three main general architectures for developing a P2P system: centralized, distributed, and decentralized. The objective of this section is to identify the characteristics of each of them and their main advantages and disadvantages, so that it is possible to identify what best matches the project needs.

5.2.1 Problem formulation and motivation

The progressive transition of the electricity sector from a conventional hierarchical structure to a decentralized one, opens new opportunities for DERs connected to distribution networks – distributed generation, storage, and controllable demand –to provide value for both the grid operators, that can benefit from an additional source of flexibility to operate their networks, and prosumers (DER owners) that can reduce their energy cost, by using on-site generation and make profit, by selling the generation excess.

However, the effective integration of DERs is a challenge that requires the definition of new optimized instruments, market structures and business models. In this context, a novel energy distribution model has emerged, the so-called P2P concept. The peers, who are organized in a local energy community, exchange energy among them with the aim of reducing costs of buying electricity and increasing benefits of selling electricity, minimizing in this way the net energy exchange with the main network. At the same time, it is ensured that the system is operating safely and efficiently.

There can be different P2P architectures, as a function of the characteristics of the trading process and the communication of information among the participants.

5.2.2 State of the art

In the literature, three main P2P architectures are proposed, as a function of where the decisions of the energy trading process are taken and as a function of the communication characteristics.

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In a centralized P2P architecture, there exists a centralized coordinator in charge of deciding the energy transactions among the peers in the community and the price of these transactions. Peers have only communication with the coordinator. Once the transactions have been made effective, the centralized coordinator is in charge of distributing the obtained revenues among the participants [1], [22], [23], [104], [112]. Reference [3] proposes a novel centralized P2P energy trading model named operator-oriented P2P trading, to lower the barriers to enter into transaction, while accommodating various customers. The operator, instead of each participant, decides the marginal/trading price and trading schedules. In [86], another centralized P2P architecture is proposed where the network operator has direct control over the DERs of crowdsources and it is in charge of deciding the incentive prices for the real-time operation. Reference [78] defines a centralized system that searches optimization of the costs of electricity and gas of a neighbourhood, including CHPs HPs, HVACs, EVs, RES and a community energy system.

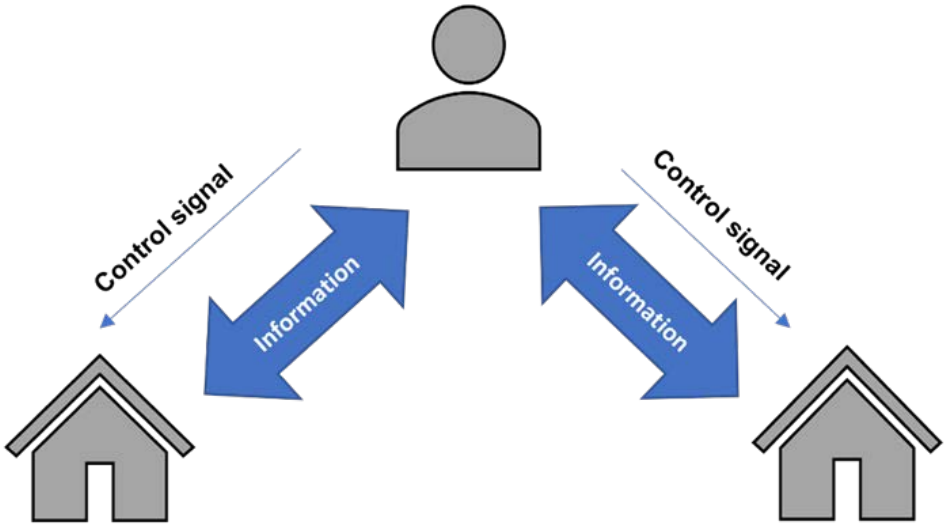

Figure 6: Centralized P2P architecture

In a decentralized P2P architecture, peers can directly communicate with each other without the involvement of a centralized coordinator. The decision-making process about the amount of energy exchanged and the price are taken by each peer [1], [104], [112]. In addition to the centralized architecture described above, reference [86] also proposes a decentralized architecture for the day-ahead operation in which direct energy trading between crowdsources is carried out. These energy transactions are included within the optimization algorithm of the network operator as constraints. Reference [2] also defines a decentralized architecture where customers can trade and exchange energy with other customers. All customers can communicate with each others using a two-way communication system. Minimum information is shared between customers in order to protect their privacy. Reference [67] considers a fully decentralized P2P system where smart energy buildings can share energy among them without the need of having a coordinator.

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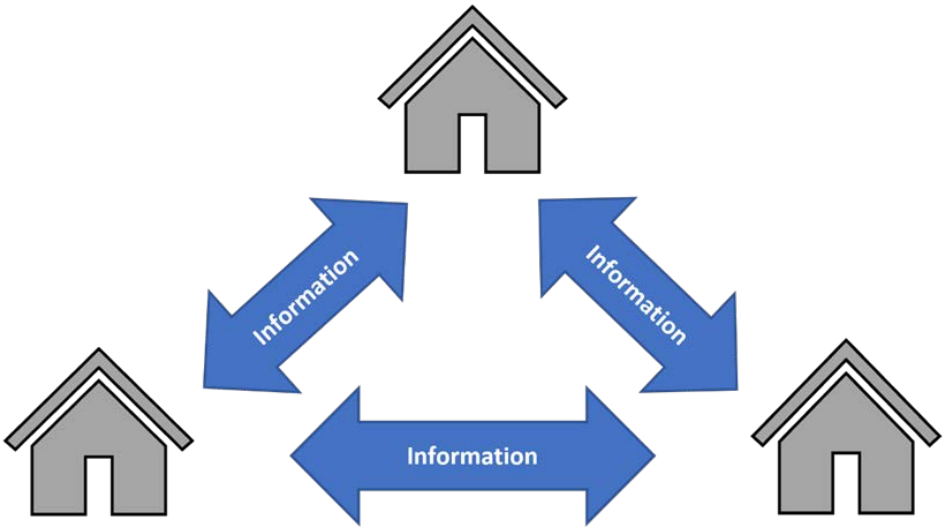

Figure 7: Decentralized P2P architecture

In a distributed P2P architecture, there exists a coordinator that communicates with each peer and manages the energy trading market set for the transactions among them. However, in contrast to a centralized P2P architecture, the coordinator does not have control over the amount of energy exchanged. It just tries to influence participating peers by sending suitable price signals. It represents a hybrid approach between the centralized and the decentralized P2P architectures [1], [104], [112]. Reference [84] proposes a distributed architecture where the operator only provides a local market platform with necessary functions, in which all the prosumers trade or share energy with each other in order to maximise their own benefits individually. Therefore, prosumers have full control of their own DERs, and no additional incentives are needed to motivate prosumers to participate. Moreover, reduced computational time and communication infrastructure are required due to its distributed nature.

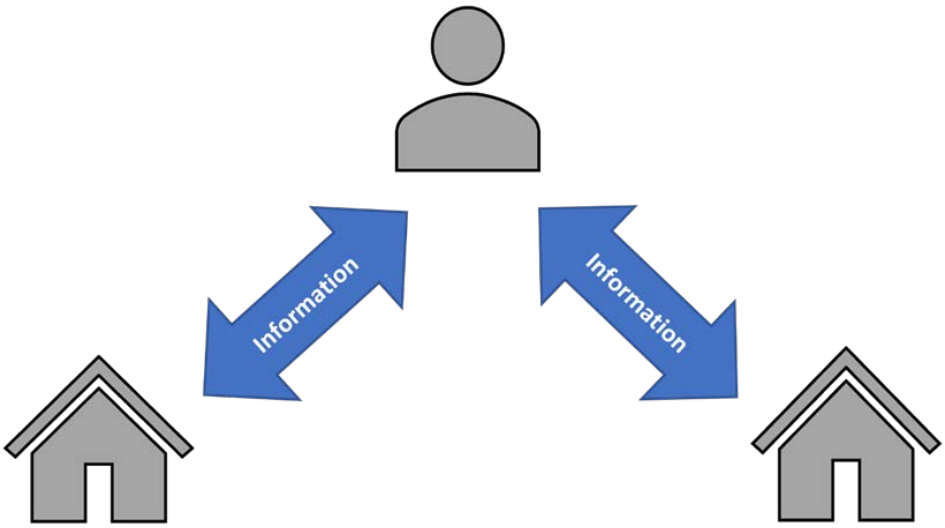

Figure 8: Distributed P2P architecture

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In [66], a distributed P2P architecture is also provided including two types of agents: 1) P2P PV prosumers that trade energy among them and 2) Energy Sharing Provider (ESP) in charge of coordinating the sharing activities. [73] defines a P2P distributed architecture in which the transaction process is implemented based on blockchain technology. Four stages are developed: 1) In the stage of the customer demands, users forecast the electricity demand and energy generation at time slot t based on reality and form the demand information. 2) In the stage of the initiation of the transaction, if the user's net load (load demand minus energy generation) is positive, correspondently, a purchase order will be generated by the P2P energy trading platform, otherwise an electricity sale order will be generated. After that, the orders will be sent to the microgrid through the distributed network. 3) In the stage of the security check, firstly, the orders will be verified by the microgrid scheduling and balance management system, under the constraints of energy balance, the real-time electricity price of the main grid, and the minimum operational cost of the system. Secondly, the optimal P2P purchasing and selling prices will be calculated by MILP optimization, and published to the users. 4) In the stage of execution of trading, after the orders have been completed, for each participant, the microgrid operator will settle charges of internal orders (orders within the microgrid) at designated P2P purchasing and selling prices and external orders (orders with main grid) at clearing prices. [77] considers a distributed P2P architecture where multi-carrier Energy Hubs (EHs) take part in a local market managed by a non-profit entity named local market operator (LMO). EHs have also access to district markets (electricity utility, gas utility, district heating, district cooling), in which they can trade various forms of energy. However, EHs first try to exchange the maximum energy in the local markets because market clearing prices are assumed to be more beneficial for both sellers and buyers.

Some other studies focused on the P2P electricity market and their pricing structure in which peers are able to sell their excess production and bargain for a better electricity price than the one offered by the retailer [27], [28], [61], [29], [62], [30], [65], [46]. These seem promising when studying further uses for energy hubs, in which consumers with flexible demands can play a part.

Table 22: Comparison of P2P architectures

Centralized architecture	Decentralized architecture	Distributed architecture
• Provides direct setpoints to which the consumption must adjust to. • Allows for an easier network operation. • Most intrusive method. • Allows for a coordinated response.	• No supervisory figure in the energy exchange. • Minimal exchange of information. • Not able to perform coordinated actions for external actors.	• Allows a certain degree of influence on consumer patterns. • Cannot establish a specific setpoint. • Less demanding on communication infrastructure.

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5.2.3 Limitations

Centralized P2P architecture has several advantages such as maximizing the total welfare of the community and better support for grid operator services. However, it has more complexity in management and can imply a very high computational burden if many peers are involved. In addition, there could be confidentiality problems as prosumers have to provide all information to the centralized coordinator [1], [104], [112].

Decentralized P2P architecture has the advantage that the decision-making process is carried out at the prosumer level and therefore they have full control of their DERs. In addition, it is a very scalable architecture. In contrast, as there does not exist a coordinator, the overall welfare of the community is less optimized [1], [104], [112].

Distributed P2P architecture shares the advantages of the previous two architectures. There exists a coordinator that through sending suitable price signals influences the participation of the prosumers while the decision-making process is still maintained at the prosumer level. The amount of information to be exchanged with the coordinator is less than in a centralized architecture, so prosumers can maintain better their privacy. It is very scalable and more compatible with existing regulatory framework [1], [104], [112].

5.2.4 Conclusions and eNeuron approach

For the e-Neuron project, the distributed P2P architecture is of utmost interest. It avoids the complexity of bilateral negotiations between peers, but at the same time peers are in full control over their assets and how they want to optimize and operate their energy resources. In addition to this, having one central marketplace for energy trading among peers, allows implementing grid related requirements more easily, since the pricing mechanism might be adapted to incorporate grid needs. A very important issue here is to define proper market and pricing schemes which incentive prosumers to participate and help to reach the maximization of the overall welfare of the community and support for grid operator services

5.3 P2P pricing schemes

The aim of this section is to identify market and pricing schemes to be applied in a P2P market that would allow for optimizing the social welfare in a P2P scheme and whether it is possible to replicate it to what is currently expected for the local energy hubs proposal.

5.3.1 Problem formulation and motivation

One way of incentivizing the use of local DER within a community has been with the implementation of P2P mechanisms, by which prosumers may buy and sell electricity to their other peers at a better

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price than the one offered by the retailer. For this reason, it is of importance to establish the way in which the price is established among peers that may benefit every party involved within the exchange.

For this, it would be of interest that such mechanism can be replicated in a way that also benefits the introduction of different energy actors, as currently most EH schemes that have been introduced have done so in ways that do consider demand response as a source of flexibility but do not neccesarily portray consumers and prosumers as the independent actors they are and who need to be offered incentivizes for them to participate and offer their assets [15], [18], [39], [78]. So, it is imperative to establish a scheme that allows users within the community to exploit these resources alongside with the ones already included in most P2P mechanisms.

It has to be taken into consideration that the deployed market mechanisms and pricing schemes will be shaped accordingly to the adopted P2P architecture. As explained in section 5.2.2, three main P2P architectures have been proposed in the literature as a function of where the decisions of the energy trading process are taken and as a function of their communication characteristics, namely: centralized P2P, decentralized P2P and distributed P2P.

5.3.2 State of the art

In the literature, different mechanisms have been developed for obtaining an optimal pricing scheme. The adopted approach depends on the kind of P2P architecture implemented.
As regards the price schemes [84] evaluates three different pricing mechanisms for a distributed P2P architecture:

1) Supply and demand ratio (SDR) mechanism: as the name implies, defines internal prices with a function dependant on the ratio between supply and demand.
2) Mid-market rate (MMR): the internal trading price gets averaged between the buying and selling price, with any mismatch between supply and demand being covered by the grid.
3) Bill sharing (BS): the energy costs and income is shared evenly among prosumers according to the amount they consume and generate.

Among the studies considered, [66] proposes an SDR pricing mechanism for a distributed approach in which the internal selling price varies between the grid buy and grid sell prices, and the internal buying price is defined as an average value considering the cost of internal selling of energy, utility grid charges and ESP charges. In [73], an improved MMR model based on the coalition game theory is used. For that, the reference price of P2P transactions is set as the mean value of the electricity purchasing and selling price of the main grid, and the purchasing and selling price of electricity in the P2P market is based on three different scenarios as a function of the ratio between energy generation of the prosumers and the overall demand in microgrids (equal, lower or higher).

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Several papers develop approaches based on optimization algorithms. [2] develops a two-stage optimization approach based on the Nash bargaining theory to be applied in a decentralized P2P architecture. The first stage of the optimization aims to maximize the social utility function whereas the second one aims to obtain the optimal payments for each peer. A distributed algorithm based on ADMM is designed to solve the problem. [3] provides an operator-oriented P2P energy trading model (centralized P2P architecture) based on an optimization algorithm whose objective is to find the optimal trading schedule that maximizes social welfare while preventing imbalance in revenues between buyers and sellers. To guarantee the profits of the participants, it considers consumers/prosumers with different marginal prices (block, rated price, time of use, real-time pricing and critical peak pricing) plus the costs associated to the utilization of the network when establishing the price.

Bilateral contract-based models represent another kind of pricing mechanism found in the literature. [86] proposes bilateral contracts to agree a “contract price” between the utility and the peers that provide full control of their resources to the grid operator in a centralized P2P architecture. [86] also proposes bilateral contracts for agreeing a price between two peers that exchange energy between them in a decentralized architecture.

Finally, several papers develop auction-based models. In [77] a double auction-based approach is implemented for a distributed P2P architecture. EHs independently decide on the amount and price of energy to be traded in the local markets and express their interest in local trading through submitting their offers/bids to the local market operator (LMO). [104] mentions auction-based approaches are also viable methods for clearing local electricity markets. Auction-based approaches benefit from the fact that the market-clearing follows an automated set of rules and can be solved in a distributed fashion by the involved agents.

5.3.3 Limitations

From a technical perspective, a P2P marketing scheme would need to consider any network constraints that might be present, possibly limiting the profits of individual users and thus making it less attractive. The network usage cost needs to be considered properly, as even on the most decentralized scheme, a common network will always be used, be it on an autonomous microgrid or along the distribution network, as the electricity will not flow solely between the two peers but instead shared within the common network, thus the final price should also include some of the costs associated with its utilization[3].

From a market perspective, it should be highlighted that the maximum individual profit may not always align itself with the social welfare, thus the pricing scheme would require some collaboration among actors instead of having counter-productive actions. This would create a mechanism that may help the network overall but would still be attractive for new actors [23].

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Also, the way users interact with the retailer may need to be considered, as some of these offer varying tariff schemes and thus this becomes another variable to take into consideration for the pricing scheme, as the attractiveness of the P2P model is that electricity can be sold with a higher profit and bought at a cheaper price to the ones that would otherwise be offered by the retailer.

Another issue to tackle is the one related to the legal framework, by which the P2P scheme may end up being affected, as the prosumers would need to be covered as an active actor that is capable of selling electricity and not solely as a client that can get their tariff with the retailer reduced due to the exported electricity.

Although P2P exchange across different energy communities is mentioned as possible in the literature reviews presented by W. Tushar et al [112] and T. Sousa et al [1], on P2P architecture models, there is no mention in the studied works of possible concrete market mechanism for establishing such an exchange among different communities. Also, the energy exchange between the energy community and the distribution network was seen as something to be reduced as much as possible . These reviews show the need to better portray such dynamics of P2P pricing mechanisms in later studies.

There is also the need for adapting these P2P pricing schemes in a way that the interaction between users using different energy carriers is facilitated in order for them to be able to increase their profits while optimizing the social welfare as the current works studied on energy hubs do not contemplate an active role for consumers and prosumers[15], [18], [39], [78].

Finally, from the mathematical point of view, several algorithms proposed in the literature can show convergence problems. This is the case of price-based schemes such as SDR, MMR and BS. These are based on iterative bidding processes in which the bids provided by the prosumers change in response to the dynamic internal price. It is possible that the energy bids and internal price values do not converge to a fixed point after a finite number of iterations. So, it is necessary to implement mechanisms that ensure the convergence of these algorithms in an acceptable time [84].

5.3.4 Conclusions and eNeuron approach

There have been fruitful studies on the maximization of social welfare and increase of individual profits on P2P schemes, which allow users to negotiate the excess electricity that is being produced as well as to choose who they are going to buy it from. Still, the interaction between users with other outside actors is either reduced to the minimum that is needed or non-existent. When considering this, it could be stated that there is a possibility enlarging the scheme in a way that allows users to engage with local but centralized resources as well as with the exchange with different energy carriers.

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In eNeuron, a distributed P2P architecture will be implemented so price-based schemes like SDR, MMR or BS should be investigated. It is important to take into account that these algorithms can have convergence problems so the appropriate mechanisms to avoid them should be included.

5.4 Business models

The aim of this section is to identify the existing business models in multi-carrier energy hubs and provide an overview on how these would ensure their economic viability.

5.4.1 State of the art

In most of the reviewed papers, the business models are based on different objectives of the system under study e.g. the minimization of the total operating cost, as well as the cost of emissions, cost of power loss and carbon dioxide emissions.

Having said this, main insights can be summarized in the following way: In [86], the main objective is to minimize electricity costs by employing local resources from the community energy system in a way that it does not violate any network constraint. In [67], the model employs a transactive energy scheme as a business model. Each building tends to charge more for the energy supplies to other buildings and pay less for the energy demands from other buildings, therefore the clearing prices should be equilibrium prices such that each building will pay/charge for the energy demands/supplies.

In [77], EHs have access to district markets, in which they can trade various forms of energy. Additionally, they have access to a local market, which allows EHs to trade energy among themselves in a P2P market. EHs first try to exchange the maximum energy in the local markets because market clearing prices are assumed to be more beneficial for both seller and buyer EHs than the prices of district markets.

The energy hub analysed in [5] is supposed to decide on the electrical and thermal load dispatch, both for the electricity, heat generation and storage units to meet a specific electricity and heat demand at minimum cost. The energy hub is allowed for such a purpose to purchase/sell electricity from/to the grid.

The business model is focused on the reduction of the fuel cost and emission in [63], of the net present value of costs and the probability of power supply losses in [40], and of the total cost of operation in [56], [96]. In papers [57], [59], [48] the business model is focused on the reduction of the total cost of generation and the total emission and in [68] it is based on the reduction of the expected time-ahead energy costs.

In [73] the business model aims to minimize the total energy expenditure of all individual customers in the microgrid.

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To conclude, as noted in [104] business models for energy sharing via local electricity markets are still very rarely put into commercial practice. The paper presents the existing barriers in current regulatory frameworks with a focus on the Portuguese energy market after analysing the peer-to-peer energy sharing business model of the project Community S (S for sharing, solar, storage, sustainable and smart). In [1], three business models are discussed: C2C (Consumer-to-Consumer), on which a distributed P2P scheme would be based, B2C (Business-to-Consumer), which could portray a traditional scheme in which the consumer buys electricity from the retailer, and B2B (Business-to-Business), which would imply an exchange between different commercial entities. Regarding the P2P energy trading, in [3] the business model is focused on the maximization of the profits (P2P energy trading).

Table 23: Business model per reference

Reference	Business model	Objective
[3]	B2C, C2C	P2P exchange
[5]	B2C	Minimize costs and emissions
[36]	B2C	Maximize revenue
[48]	B2C	Minimize costs and emissions
[52]	B2C	Maximize RES output
[54]	B2C	Minimize costs and emissions (literature review)
[56]	B2C	Minimize operational costs
[57]	B2C	Minimize costs and emissions
[60]	B2C	Minimize operational costs
[61]	B2C	Minimize costs and emissions
[65]	B2C	Minimize costs and emissions
[69]	C2C	P2P exchange
[70]	B2C	Minimize energy costs
[75]	B2C, C2C	P2P exchange, minimize energy costs
[78]	B2B, B2C	Trade between EH, minimize costs and emissions
[87]	B2C, C2C	P2P exchange

5.4.2 Limitations

Based on the papers reviewed regarding this topic, the business models in most of the cases focus on the reduction of the cost of the purchased energies and the total investment and operating costs of the energy systems. In some papers, carbon emission cost is taken into consideration as well.

Different business models should be evaluated in this project, including multi-carrier technical and economical optimization (e.g., cost optimization and maximization of the self-consumption) and for example ancillary services supplied to the different system operators.

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Most of the literature on energy markets and P2P schemes have been limited only to a single energy carrier, which is electricity, or do not go in depth in the peculiarities of other energy markets. This means there is a need for further depeloping business models that could reflect the different energy carriers present in the EH.

5.4.3 Approach for eNeuron

The eNeuron tool should provide innovative business models including the optimization of the operation of multi-carrier energy communities. This means to fully exploit its potential in participating in different energy markets, having each their peculiarities. Of these, the electricity carrier has been the most analyzed carrier in the literature, proving further potential on P2P trading, as well as the participation in wholesale and balancing electricity markets. It is imperative to also highlight that the structure of these business models will shape any optimal placement and sizing of the different technologies being considered.

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6 Cluster 4 - Technical collateral concerns

6.1 Temporal and spatial scope

Temporal and spatial scope are important parts of energy system models. Indeed, they define the range of applications that a model can be used for. Typically, the higher the resolution, the more detailed and precise the results, but the more complex and time consuming it becomes to find an optimal solution. Some models are therefore made with specific application ranges in mind, which is often reflected by the choice of case studies using the model.

The aim of this section is to identify the temporal scope, the spatial scope and the temporal resolution of the models used in the literature. Typical temporal resolutions are hourly, but some models implement higher or lower resolutions. Typical temporal scope is one year but it is important to identify whether it is actual or derived from the use of representative days or hours. It is common to find the use of one day per season. The spatial scope is also crucial to understand the models. Temporal and spacial scopes are relevant for to the scalability of the energy system models .

6.1.1 Problem formulation and motivation

Energy system models must represent the conditions, both spatial and temporal, of the market they take place in. The spatial scope of markets ranges from a continent to a couple of buildings, in the case of local energy markets, or even to a single building. It is important that the spatial scope is customized to the problem that needs to be addressed, especially when the model is to be implemented in real-life cases.

The temporal scope encompasses both the length of the time horizon and the time resolution considered in the model. The time horizon can range from several years to a single day or hour while the time resolution is very often hourly time-steps but can also be shorter for representing real time operation.

When choosing the scope of a model it is important to bear in mind that a finer granularity (temporally and spatially) implies a higher computational and data acquisition burden. Indeed, the more detailed the model is, the more time it will take to be solved. Similarly, the more detailed the model is, the more data will be necessary to execute it. This can especially be a problem in the context of research when one does not always have access to detailed data from TSO, DSOs and other consumers.

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6.1.2 State of the art

In this section, we will discuss the different temporal and spatial scopes that are found in the literature. However, not all models report those elements explicitly despite their importance.

The most commonly used time horizon among the papers considered in this study are one year and one day. Many documents use one year ([1], [17], [24], [27], [30], [36], [37], [41], [45], [46], [47], [51], [52], [53], [61], [65], [89], [70], [81], [90], [91], [92], [95], [102]), e.g., documents that focus on long-term energy system planning. However, this is not always done in the same way. Indeed, a complete year can be too computationally challenging, and some models reduce the complexity by representing a year with representative days. The number of representative days varies depending on the model; [37], [27] and [30] simplify the annual scope by the use of one representative day per season, while [65] uses one week per month to study a whole year. [90] uses three days for each month in a year corresponding to weekday, weekend and peak, while [47], [53] and [50] use only three typical days in total.

Models with a stronger operational focus use more detailed descriptions and may choose to only use a horizon of one day, such as ([1], [5], [9], [10], [11], [14], [15], [16], [19], [20], [26], [28], [29], [32], [33], [42], [43], [58], [60], [62], [64], [66], [71], [72], [77], [78], [80], [83], [85], [96], [100], [101], [106], [107]). Other models need to account for the future trends in price and demands for example and use longer horizon, 5 years in the case of [74] and [49]. In addition, [49] compares the use of four day-types (summer weekday, summer weekend, winter weekday and winter weekend) and 39 day-types (weekdays, Saturday and Sunday for 13 four weeks periods). Finally, some documents use various particular horizons, like 7 weeks in [69].

In addition to the time horizon, the literature adequately describes the time resolution used in the various cases.

The most common temporal resolution is one hour ([5], [6], [7], [9], [11], [12], [14], [15], [16], [22], [24], [26], [28], [29], [32], [33], [36], [38], [40], [41], [42], [43], [52], [60], [62], [64], [66], [69], [70], [72], [75], [77], [78], [80], [81], [83], [89], [90], [92], [95], [96], [100], [101], [107]). An hourly resolution allows to capture some of the variability in the demand and renewable generation and also fits well with the structure of the day-ahead markets. A few models do not use it, as [21], [49] and [88] which use a half hourly resolution because the day ahead market resolution in the UK is 30 minutes. Even finer resolution can also be rarely found, [99], [106] and [79] with 15 minutes, [86] and [67] between 15 minutes and 5 minutes, [21] 1 minute and [87] half a minute. The greater the granularity, the deeper the level of detail and increasing the reliability and accuracy of the model.
Some models use a lower resolution as a way to reduce the computational burden: for example, [50] uses 2h, [51] 4h and [53] divides each day in 6 periods which do not have to be of the same length.

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Table 24 summarizes the different temporal resolutions used in the different papers of the reviewed literature.

Table 24 Temporal resolutions used in the reviewed literature

Temporal Resolution	References
Half minute	[87]
One minute	[21]
Five minutes	[67], [86]
Fifteen minutes	[67], [79], [86], [99], [106]
Half hour	[88]
One hour	[5], [6], [7], [9], [11], [12], [14], [15], [16], [22], [24], [26], [28], [29], [32], [36], [33], [38], [40], [41], [42], [43], [52], [60], [62], [64], [66], [69], [70], [72], [75], [77], [78], [80], [81], [83], [89], [90], [92], [95], [[96], 100], [101], [107]
Two hours	[50]
Four hours	[51]
Six periods for each day	[53]

The spatial scope varies greatly between models due to different goals, locations, technologies and sectors (e.g., residential, industrial, commercial sectors) of the energy system. In addition, it is not always reported precisely in the documents and can focus on different types of information: for instance some documents report a geographical location while others provide a physical description of the local system and others provide no information at all.

Many models focus solely on an individual energy system, be it a single building ([49], [52]) or a single area (neighbourhood, micro energy grid, energy hub for example) [41], [42], [43], [48], [89], [96]. A few models focus more on the interaction between different energy systems inside a larger one. This is the case of [60] where 4 smart energy hubs are included in an IEEE 33 bus network. Similarly, the model presented in [22] is applied in a 33-bus radial distribution network and a 14-node gas network, 3 smart energy hubs and a power-to-gas system. A IEEE 30 bus network is also used in [58] with 5 generators, 4 tap-transformers, and 2 shunt capacitors.

The number of buildings can vary greatly: 4 in [50], 6 in [53], 25 in [81] and [73] in [70]. A different approach is taken in [51] where they consider a grid of interconnected nodes. They report that for their model, using bigger than a three-by-three grid would become intractable. A grid with interconnected nodes also used in [78]. The microgrid considered has 21 nodes, 6 of which are energy hubs each comprising a natural gas boiler, a CHP unit, a heat pump and a heat storage unit. In other nodes of the microgrid there are 3 wind generators, 2 batteries and electrical loads. Table 25 summarises the different spatial scope used in the reviewed papers found in the literature.

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Table 25 Spatial scope used in the reviewed literature

Spatial Scope	References
Single building	[49], [52]
single area	[41], [42], [43], [48], [89], [96]
interaction between different energy systems inside a larger one	[22], [50] [53], [58], [60], [70], [81]
grid of interconnected nodes	[16], [51]

6.1.3 Limitations

The topic of the temporal and spatial scope is closely related to the topic of scalability of models. Indeed, more precise models may require finer resolutions and larger optimization problems. Similarly, applying the models to larger areas has the same effect. Thus, it is important to design optimisation models while thinking of the intended use in terms of scope and resolutions to ensure the computational tractability of the model. Furthermore, the hardware used for solving the model must also be considered when designing the model for the same reasons.
Another limitation related to this topic is the accessibility of data. Increasing the resolutions increases the need for data, which become more difficult to obtain as the temporal resolution and spatial scope grows.

6.1.4 Conclusions

The temporal scope mainly used in the analysed papers is the daily one with an hourly resolution. However, other studies consider other values of planning horizon and annual scopes are fairly common, especially for planning problems. Clustering or representative days or weeks are a common way to reduce the burden coming from using long time horizons. Regarding the spatial scope, there is not a common model for the different studies analysed, since most of them are very different each other in terms of technologies, locations and sectors.

It could be interesting for the eNeuron project to explore a shorter temporal resolution than the most used in the existing operational models.

6.2 Long Term System Planning

Optimization tools are important for determining the optimal expansion strategies of energy hubs. For instance, it is crucial to determine how the expected changes in consumption patterns can be met in the most efficient way.
However, it is quite rare for planning problems to account for the long-term future developments, for example of prices, and their impact on energy system investments. This is due to the difficulty of having quality estimates or forecasts of such parameters.

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Another relevant issue is about the use of data (thermal and electrical loads, etc.) from DBs and literature based on "as usual" technologies, that don't include flexibility and user demand technologies.
A possible solution is to use only sampling from historical data, but this comes with a bias and does not account for example for the changes that will come with climate change. Another solution is to link the models to be capable of handling long term planning of different spatial scale. This can for example provide estimates of future electricity prices.
The aim of this section is summarizing how the long-term planning aspect is handled in the documents focusing on planning multi-carrier Energy Hubs from this review.

6.2.1 Problem formulation and motivation

Accounting for future conditions in planning problems of EHs is difficult but important. Indeed, when planning the energy system of an energy hub, it is important to account for the future changes in commodities prices and demand in a long enough horizon. This is important in the context of climate change and of the energy transition which affects significantly the energy demands and the European energy system. Having a good representation of such parameters is crucial to the quality of the results obtained from a planning model. Changing conditions can be more favourable to certain technologies.

The difficulty of obtaining good forecasts arise from the high level of uncertainty associated with long term forecasts. In addition, models for the planning of local energy systems such as energy hubs often use hourly resolution. This poses additional challenges in the context of future forecasts. Indeed, annual load growth for example can be estimated based on projections from different agencies but incorporating the effects of changes of habits, of new loads and of potential climate impacts at an hourly level is non-trivial.

Usually, optimisation models found in the literature as regards EHs, deal with the design and/or operation of the EHs. Optimisation models dealing with the design of EHs should be able to consider the operational aspects of the EHs also for the long-term planning, as EHs are becoming key actors in the development of multi-energy systems. To evaluate the ability of the optimisation models/tools to consider different future scenarios, a literature review has been conducted.

6.2.2 State of the art

Some of the papers reviewed focus on the optimal design of EHs, while others focus on the optimal operation of them. The work presented in [40] belongs to the former group and presents a method for the optimal design of an isolated EH with a high penetration of variable renewable generation, conducting a simulation of a whole year. The yearly load profile is synthetically generated: starting from a daily load profile, it is replicated for 365 days, and then certain randomness is considered on

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a daily and hourly basis by means of multiplying each hourly load by a factor that considers the daily perturbation and by a factor that considers the hourly perturbation.

The authors of [109] present a review of models and assessment techniques that are currently available to analyse multi-energy systems, and in particular, distributed multigeneration systems. The models analysed in the paper are RETScreen, EnergyPLAN, DER-CAM and eTransport. Except in the case of EnergyPlan, the rest of the models analysed are able to consider system expansion, and in the case of DER-CAM and eTransport, are able to perform an optimal system expansion.

The work presented in [108] provides an analytical review of the management's optimisation of micro and macro smart EHs. The authors remark the importance of long-term planning in EHs, considering networks constraints, environmental issues, variable renewable generation, among others. As authors stated in their document, in addition to the operating optimization of macro energy hubs in a short period of time, long-term planning of these systems is also one of the most important issues.

The authors of [92] conduct a performance evaluation of a real EH at residential scale, considering suitable strategies for the EH's energy management for the operation of a whole year based on forecasts of both solar-photovoltaic and solar thermal based energy production. Furthermore, they present a computational framework aimed at microgrid design, and it has been used to simulate the behavior of the system taking into consideration various system configurations. The authors of [70] propose an EH concept-based method to integrate decentralised energy systems at a neighbourhood scale. The proposed method uses the energy hub concept in the design stage to evaluate optimal design layouts of multi-carrier energy hubs or their optimal operation. Furthermore, authors of this document develop control strategies for balancing supply and demand of an energy hub.

[27] presents a multi-objective optimization model for the design of a multi-carrier energy system to determine its optimal architecture, whereas [61], presents an optimization analysis of the energy generation in a real distributed energy system (DES) coupled to a District Heating (DH) network by maximizing the DES operator profit and minimizing the DEStem greenhouse gases emissions.
In [30], the authors present a multi-objective optimization model for the optimal design of an integrated LEC with multiple energy hubs. In detail, the aim of the optimization problem is to identify the optimal configurations of interconnected DER systems in a LEC to satisfy the users multi-energy demand i,e., electricity, domestic hot water, space heating and space cooling, while considering both cost and emission aspects.
In [31], a multi-objective tool was developed for multi-carrier energy systems design with energy storage technologies of different storage capacities and short- and long-term energy storage strategies. The proposed tool takes into consideration various deterministic and uncertain conditions in order to demonstrate the feasibility of $P2H_2$ technology using dynamic optimization while capturing uncertainties such as technology capital cost, efficiency, lifetime, etc.

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In [39], two main planning concepts related to energy systems are investigated, namely (1) the energy system expansion planning (2) and the operation planning. Authors of this document, hightlight the importance of considering operational details for the optimal expansion planning or design of multi-carrier energy systems.
In [54] and [55], a comprehensive overview of the multi-objective techniques used to solve power system planning problems with cost minimization and increased reliability, in the presence of DER is provided.

Document [95], models the coupling of different energy systems from an input–output perspective. Substantial studies have been carried out on the operation, planning, and evaluation of MES using the EH concept. Joint planning of an MES (considering the operation, planning, and evaluation) takes advantage of the synergy of various energy types to improve the utilization of the assets and reduce the planning cost.

In [74], a method for the optimized selection of the components of a multi-carrier water and energy system and their optimal sizing is presented. It considers the total operational and maintenance cost with emission penalties in order to supply electricity, thermal and potable water demands in a smart island. The model uses a 5-year horizon, allowing it to capture longer-term effects than most similar available models. A five-year horizon is also used in [49], though other horizons can be used. [95] presents an optimization model for the optimal design of multi-carrier energy systems and investigates the planning methods for community level EH for determining the optimal generation, conversion and delivery of electricity, heat, cooling and other services. The proposed model might be easily applied under different future price and demand scenarios and thus implicitly consider the long-term evolution of such variables. The planning horizon used in this work is one year. Similarly, in [90], a single year is used for the design of a multi-energy microgrid. [52] applies the planning problem to a building and considers the building lifetime of 30 years as a horizon. However, it considers the loads, prices, and other parameters to be constant in that period.

Finally, a review is performed in [105] focused on operation and planning optimization problems of Energy Hubs.

6.2.3 Limitations

Typically, the optimisation models proposed in the literature for the optimal sizing of EHs assume strong simplifying assumptions as regards the operation of the EH. In addition, the intra-hourly resolution is generally not considered, and this can lead to an unrealistic result in the case of an EH with high penetration of variable renewable generation. Other limitations as regards the long-term system planning are, among others, to neglect the energy network and to make simplifying assumptions regarding the energy markets considered.

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The long-term changes to parameters that will affect the design of the energy system in planning are not often considered in the literature. One reason is the high uncertainty associated with long term scenarios making it hard to choose reliable data. Even then, considering changes in, for example, the hourly consumption patterns is complex.

Cost reduction of technology (for investment timing problems) is also highly uncertain and dependant on their global adoption. Local energy system planning models alone are not suited for such tasks and should rather be used in relation with other models that can implement learning rates such as the TIMES model, GENeSYS-MOD, or EMPIRE.

6.2.4 Conclusions

Planning of local energy systems such as energy hubs is most often done with a limited understanding of the impacts of the long-term changes in crucial parameters such as costs and demands. For computational reasons, optimization considering the operation of a single year is often chosen. In addition to the computational complexity, implementing longer optimizations timeframe would also require good quality data or scenarios. One solution is to couple to models more specialized in such problems.

6.3 Implementation status

The aim of this section is to find out whether the algorithms/tools proposed in the screened documents for the optimal design and/or operation of energy hubs are being effectively used to make design and/or operational decisions of an existing energy hub, or if they have been implemented only in case studies.

6.3.1 Problem formulation and motivation

Energy hubs are becoming key actors in the development of multi-energy systems that can improve the overall performance of traditional energy systems. In order to evaluate the viability of these systems different configurations of energy carriers and optimization approaches have been proposed in literature. The works analysed show three different levels of implementation: simulation of cases of study, demonstration projects and implementation on existing EHs.

6.3.2 State of the art

The majority of the works analysed present simulations of cases studies, most of them are focused on the optimization of the energy flows between the energy carriers of the energy hubs. The data used for the simulations include measurements from real users such as residential buildings or district communities, or different kinds of users as commercial buildings, cinemas or hospitals. Also, load prediction methods have been used [38] to determine user's energy demands.

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To simulate the optimization of systems composed by multi-energy hubs standard grids configurations (electricity and gas) have been used. In [1], the case of study is based on the IEEE 14-bus system separated into three communities, [3] use the IEEE 18-bus radial distribution system and in [86] the simulations are based on the Southern California Edison (SCE) 56-bus test feeder.

Demonstration projects are presented in [71] and [47]. In the first case the multi-energy system was tested in the SGCC Science and Technology Project, which includes cold, heat, power, and gas sources. The system was externally connected to the distribution network, central heating station, and gas pipe network. The second case corresponds to a multi-carrier system (PV, fuel cell, gas engine, and CHP plant) installed in an eco-campus located at Kitakyushu Science and Research Park (KSRP), Japan. The analysis of pilot projects in Asia, Europe, North America and Australia with P2P energy sharing systems is presented in [23].

The implementation on existing EHs is shown in [79] where different houses in Ontario were used as pilot cases.

The works analyzed show three different levels of implementation: simulation of cases of study, demonstration projects and implementation on existing EHs.

Most of the analyzed documents presented only case studies, whether academical or practical. The maximum number of case studies presented in a single work was five [18], while most of the documents presented between two and three. Also, the size of the considered energy hub varied considerably, from a single building [74], to district-sized large complexes.

Regarding the works where the multi-energy hubs system optimization was validated through simulation, most of them used the IEEE test systems, such as the 6-bus [9] or the 30-bus [36]. Other works were simulated in custom non-real systems [10], [13] or reality-based systems [24], [91], [94], [95], [113].

Demonstration projects were presented in [43], [74], [92], [98], [114]. The methodology developed in the works, was used to actively operate on the energy supply of a residential microgrid called “Leaf House”, the system integration of different technologies for the electrical network (PV+BESS+network) and the heat network (GHP+solar thermal plant+auxiliary boiler) was analyzed. In the document [114], the optimal RES structure sizing for small systems consisting of loads, BESS, PV, gensets (or cogeneration units), was evaluated to allow off and on grid operation of the microgrid. After initial release for the Schneider Electric microgrid service team in the US, the tool has been deployed in Australia, Singapore and France.

In [74], the proposed model was implemented on a commercial building in a smart island. The proposed model goal, was the optimized selection of the components for a multi-carrier water and energy system (MCWES) and their optimal sizing.

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Finally, regarding [43], [98], no significant details about the implementation were provided. Table below summarizes the different implementation levels presented in the literature.

Table 26 Levels of EH implementation in the literature

Levels of implementation	References
Simulation of cases of study	[1] [3] [9] [10] [13] [18] [24] [36] [38] [74] [86] [91] [94] [95] [113]
Demonstration projects	[23] [43] [47] [71] [74] [92] [98] [114]
Implementation of real EHs	[79]

6.4 Services provided to the network

This section aims to identify the potential grid services provided by Local Energy Communities (LECs) to the external network and the corresponding limitations found in the literature, in this regard.

LECs, as the centre of energy system decision, are well-placed to meet local energy needs and bring people together to achieve common goals for well-being. However, LECs aim not only to provide self-sufficiency efficiently to the community users (under the concept of energy islands), but also as a grid-connected system, they are able to provide flexibility through different products such as demand response (DR) or establish local energy markets; and can also be employed to support the grid of neighbouring systems and the external network, by the provision of balancing and ancillary services, congestion relief, voltage support, and grid infrastructure deferral.

As can be extracted from the consulted literature and research trends, LECs are mostly focused on minimizing the investment cost of the community, reduce primary energy consumption, and decrease the CO_2 emissions from a global perspective [41], [52], as well as from a market perspective [72]. As an innovation contributing to the integrated multi-energy system, reduction of system operating cost and increase of system flexibility can be considered indirect network services. Some authors consider this hypothesis, but then they usually don't specify which services they will provide [1].

Recently, peer-to-peer energy sharing mechanisms and price-based DR programs are key research topics as regards the optimization of the operating costs of multi-carrier EHs [14], [16], [46], [76], [84], [111]. In [60] and [106], only some network constraints are considered, but no services are provided. In [20] an electrolyser is controlled to provide DR services to the electricity market in Ontario. DR is also mentioned in [115]. However, DR mechanism is not by itself an ancillary service provided to the grid.

The authors in [75] state that battery energy storage systems (BESS) can provide regulating reserve, a type of ancillary service, by modulating active power for frequency control, to reduce frequency

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deviations caused by sudden changes in renewable generation, enhance the power quality and reduce the power losses. In fact, the BESS is controlled to match the local generation and consumption of the EH and improve the controllability of power flow, although these services are not provided to the external network. In [23], [100], [104] the EH can offer balancing services to the grid, such as: load supply, secondary power reserve, avoid load shedding & curtailment [100]. In particular, for batteries, [102] shows that the provision of balancing services is more profitable than mitigating RES intermittency. In [71], by dispatching the sources at different time intervals, the regulating reserve service is provided to address normal random short-term fluctuations in load. [100] also considers the interesting possibility of grid decoupling in case of a natural disaster.

In conclusion, from the consulted literature, real ancillary services provided to the external network are rarely addressed, despite the EHs having the ability to provide ancillary services which might result in additional revenue streams and ensure a more robust distribution network.

6.4.1 Research questions

The main research gap, in this regard, is to address the possibility of EHs to provide various types of ancillary services to the external network. The **energy management strategies,** which optimize the energy schedule and energy dispatch of DERs, should integrate these new ancillary service features and constraints in the **optimization problem** and later, in the real-time operation dispatch.

LECs should be able to provide flexibility through different products such as DR and can also be employed to support the external network with functions such as balancing and ancillary services, congestion relief, voltage support, and grid infrastructure deferral. To satisfy the energy demand in a stable and continuous way, and to guarantee the safety of the entire electricity system, there are various services to be ensured which are divided into: frequency control, voltage control, congestion management and black-start.

In addition to evaluating the techno-economic benefits of ancillary services for the EH and the external network (revenues, losses, costs, etc.), it is necessary to **assess the impact** on the local energy dispatch, energy transactions between peers and the grid, and performance in real time.

6.4.2 Potential Innovation pathways.

The optimization problem should provide an innovative approach for comprehensive modelling of central assets, connected RES, and emerging technologies in a LEC through the EH concept, while also considering economic and environmental aspects. The features of the ancillary services mentioned before (frequency control, voltage control, local congestion management, etc.) should be modelled, and their interaction with other energy carriers and involved technologies should be included.

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The presence of an independent entity/platform that will manage the trading operations will also contribute to allowing the provision of potential ancillary services upstream to the DSO. The market model and market platform should be designed and developed open to market players, who are able to provide ancillary services: distribution or transmission system operators, balance responsible parties, aggregators, energy retailers, distributed energy resources, prosumers, etc.

When a new functionality wants to be included in the energy community or energy hub to increase the revenues and provide more flexible operation, it should be clarified which specific ancillary service is being approached. Each grid service has their own **features**, energy and power needs, market framework, availability or energy-based price, penalty cost for non-compliance and so on.

Furthermore, the ICT **infrastructure** should be taken into account. The presence of an independent entity/platform that will manage the trading operations is required to allowing the provision of potential ancillary services. An **effective communication** between aggregator/retailer agent and Distribution System Operators (DSOs) and Balance Service Providers (BRP) should be ensured.

6.4.3 Approach for eNeuron

The eNeuron tool will optimize multi-carrier energy systems that will allow optimal integration of the different carriers. A shorter-term optimisation will be developed to calculate the optimal dispatch of resources in an operational time frame (minutes/hours), considering both the limitations and needs of the power system as well as the overarching objectives of the LEC.

The eNeuron tool should ensure the consideration of smart, innovative systems and products enabling the provision of new grid services in a cost-efficient manner. Thus, ancillary services provided to the grid should be considered into the optimization problem and be analysed and validated afterwards.

The different eNeuron pilot demonstrators will be interested in local energy system optimisation for local energy management, grid flexibility management, basic ancillary services provision to the MV grid, local active grid congestion avoidance, and voltage stability support. These functions should be considered and demonstrated, or at least simulated.

6.4.4 Conclusions

There is a lack of studies which address the grid ancillary services provided by a LEC to the external network. Some ancillary services and DR mechanisms are considered inside the EHs, but actual ancillary services provided to the external network are seldom addressed.

The eNeuron tool should ensure the consideration of smart, innovative systems and products enabling the provision of new grid services in a cost-efficient manner, which enable local energy system optimisation for local energy management, grid flexibility management, basic ancillary

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services provision to the MV grid, local active grid congestion avoidance, and voltage stability support.

6.5 Management of flexibility sources

This section aims to identify the management of flexibility resources in the context of Local Energy Communities and the corresponding limitations found in the literature in this regard.

From the revised papers, there have been a specific focus on introducing new energy carriers that could allow for some innovation in their energy hub, such as in the use of hydrogen on a power-to-gas scheme or for exploiting the flexibility of charging electric vehicles, and electrical energy storage.

From **supply-side flexibility**, some of this research has been limited in that regard due to the loose coupling of different energy carriers that was structured within their EH, as in some research the only device that had interaction with both the electricity and heating sector was the combined heat and power (CHP) plant [65], which in turn limits the prospects of the EH as an overall system, as the possible interaction and flexibility that can be exploited from it is greatly reduced. Very often, the supply-side flexibility is managed using only storage systems, such as battery or thermal storage [2], [27], [29], [38], [46], [62], [83], [102], in few cases power-to-X is considered [111].
Another limitation to the flexibility has been emerged from papers [99] and [102]. In particular, the complete self-consumption of renewable electricity is enforced on the whole district, thus forbidding the bi-directional flow of electricity, and forcing the local energy community to consume all the electricity produced by constraining the net load.

The loose coupling of different energy carriers is also shown on the prospect of **demand-side flexibility**, as when considered it goes into load shifting for demand response, having then often only focused on the electrical part, whereas on the consumer side, if there were any other coupling for the electricity and heating sector, there would have been more of an interest in reviewing any flexibility that can be provided from the latter and reflected in the former. [99] considers only the flexibility of thermal load, while assuming electrical and cold ones fixed. [111] considers the flexibility of the cooling load. In some papers, demand-side flexibility is managed through smart charging of PEVs, [62], [18] and on/off electrical appliances [18].

Market mechanisms (peer-to-peer markets, coordinated, decentralized and community control schemes) are addressed in [23], [67], [71], [76] as method for improving the efficiency and flexibility of the EH and increase the active role of prosumers. In several works, demand-side flexibility is addressed by considering incentive-based programs and energy price strategies [12], [23] such as time-of-use electricity price, or time-of-day unit price for electricity for demand response [5], [11],

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[18], [28], [29], [34], [76], [78]. From these works emerges the need to increase economic incentives for energy flexibility.

Finally, it is worth noting that the modelling process of flexibility has to resemble as much as possible the real world; thus, all the constraints must be chosen properly thinking about the accuracy of the expected outcomes. Together with this, the correct formulation of the analysed scenarios must be taken into account, where all the parameters and variables have to be carefully defined according to the real problem solutions to be achieved. Once the previous aspects have been correctly defined, the replicability of the used models can be then ensured for being then applied in other real contexts.

The main limitations emerged are listed below.

- **Limited coupling** between the different energy carriers/sectors. The coupling among sectors improves the flexibility, such as converting gas to electricity and heat and using the excess renewable generation for heating purposes.
- **Limited economic incentives** for energy flexibility. There is a need for the improvement of flexible energy tariffs and supporting incentives in order to stimulate the utilization of flexible buildings/communities/hubs as active instruments to provide energy flexibility for energy grid economy and reliability.
- Constraints related to self-sufficient energy consumption, that could act by limiting the flexibility.
- **Reliability of the constraints** used in the models for representing the real behaviour of the energy system.

6.5.1 Research questions

Based on the limitations extracted from the background report of this topic, this section reports the main research questions about the management of flexibility resources emerged by the papers reviewed.

Overall, questions arise on whether the flexibility of different energy carriers is being fully exploited when seen as from the overall system, and whether there may be room for improvement in the coupling of different energy carriers, so as to exploit the flexibility being provided from different energy carriers by the energy hub as a whole.

When applying the developed solutions to a real-world demonstration, it is very important to ensure that all required information by physical models (DER parameters, usage patterns, weather forecasts, price information, etc.) is accurate enough and is updated when required to ensure that the outputs of the simulations fit the reality. Otherwise, the calculated control signals will not be the optimal ones and the obtained response from the different control actions will not be the

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expected ones. The definition of physical models that accurately represent the actual behaviour of the DERs is another important issue that should be further investigated.

In the following, specific research questions are reported:

- What impact **more complex and decentralized schemes** for energy carriers other than electricity have on the representation of EH and their operation? What control and pricing scheme are adapted to those energy carriers?
- Why often **only storage (battery)** is adopted as a flexibility management measure?
- Why the constraint of an energy community is the self-sufficient energy consumption? This is a strong limitation having a wide view of the national grid with which it is connected.
- Why demand-side flexibility is often only focused on the electrical and/or thermal part without considering both?
- Can be the constraints used in the modelling considered reliable for forecasting the real behaviour of an energy system?

6.5.2 Innovation path per limitation

This section presents the innovation path that can be followed to answer the research questions and overcome the current limitations found in the literature.

- A comprehensive system should be proposed in which different energy converters and branches are identified and which allow for the introduction of a wide array of technologies within the energy hub. Having this done properly allows for the interaction among the electricity, heating, gas and cooling sector in a comprehensive way.
- Decentralized markets with incentives-based programs should be designed that encourage the management of flexibility.

- Multiple energy storage systems must be taken into consideration, along with the flexibility of the loads in order to achieve the optimal operation of an energy hub.
- Bi-directional energy flows should be considered in order to possibly provide flexibility also to the main national grid.
- Flexibility of multiple loads should be modelled.
- Constraints that can provide more reliable results, closer to the real world, as much as possible should be used. In a practical implementation it is necessary to check that the defined physical models represent the behaviour of the DERs accurately by comparing the simulated values with the actual ones. If this is not the case, more complex models should be implemented. If this is not enough, the complexity of the model could be

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increased by adding other state variables (envelope temperature, heater temperature, etc.) or implementing a non-linear model.

6.5.3 Approach for eNeuron

The approach for eNeuron project is to integrate, under the energy hub configuration, several distributed energy sources, including renewables and waste heat from power generation processes to satisfy the thermal demand of the LEC, and multiple energy carriers, such as electricity, heating, cooling, hydrogen, transport etc. at different scales.

Different energy storages should be integrated for enhancing the flexibility, both from the supply and demand sides, and sector-coupling solutions should be adopted by connecting different energy carrier networks (e.g., district heating/cooling networks) with a synergic operation among them.
Demand-side flexible resources should be developed for all energy carriers, paying special attention to the flexibility of the thermal demand. Decentralized markets with incentives-based programs should be designed for encouraging the management of flexibility.

Bi-directional energy flows from/into a national grid to which the energy community is connected should be considered to provide flexibility also to the national grid and incentivize the prosumers' behaviour to be an active part in the future energy scenario.

For the eNeuron pilots, it would be interesting to investigate if a DER model calibration functionality in charge of adjusting the values of the parameters of the DER model with higher uncertainty is required. This could be based on historical measurement data and employ regression techniques such as linear regression or Kalman filters. This is especially important for the parameters of the HVAC system that are the ones with higher uncertainty.

6.5.4 Conclusions

This section aimed to evaluate current measures for the management of the flexibility resources in the context of LECs. From the literature analysed it emerges that the main limitations to the flexibility in the context of LEC are mostly related to the: limited coupling among sectors; limited economic incentives for energy flexibility; presence of constraints that could act by limiting the flexibility; need to represent the real behaviour of the energy system.
From the analysis emerges that energy storages are among the most important and efficient way to manage flexibility, both from the supply and consumer sides, and that adopting the cross-sector coupling solutions would enhance boost their viability. However, nergy storage systems integration would change the energy consumption behaviour, and such change must be considered. Furthermore, for all energy carriers, their flexibility needs to be considered.

Moreover, it emerged that in a practical implementation of the developed solutions, it is very important to ensure that the modelling of the DERs is carried out accurately using the suitable

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models and estimating the more realistic values of their parameters. If necessary, techniques for periodically adjusting the values of these parameters should be developed. For this purpose, simulated values should be compared with actual measurement data. It is also important to check that the defined physical models (e.g. linear models) represents the real behaviour of the DER. Otherwise, the complexity of the model should be increased.

6.6 Simulation methods for Electric Vehicles

6.6.1 State of the art and limitations

The simulation of electric vehicles (EVs) is not a new subject and several approaches have been proposed in the literature [44]. Nevertheless, the development of LECs including PEVs with functions such as controllable charging, and Vehicle-to-Grid operation (V2G), still today pose some challenges.

A major limitation when dealing with the modelling of PEV or plug-in hybrid EV (PHEV) is the way to represent the availability of the vehicles and energy use while they are away. Indeed, those factors are dependent on the user, its behavior and habits.

PEVs could play a dual role: represent loads to satisfy in the Grid-to-Vehicle (G2V) mode, and serving as distributed storage when equipped with Vehicle-to-Grid (V2G) technology. For this reason Evs and PHEVs are often modelled as: batteries [76], [42]; a part of a large equivalent battery storage [44]; different peers in a bilateral trading system based on P2P [1]; part of the end-users' load profile [102]; a flexible/shapeable load for electrical networks [84], [86].

The availability of data regarding PEVs and energy use is an important issue and some assumptions can be done on the availability and status of EV during the day. Some works assume that the vehicles depart and arrive at given times [18], [69]. For example in [69] EVs are assumed to be plugged out at 8 am (approximately full battery) and plugged in at 4 pm (quite empty). From 4 pm to 8 am the battery can store electric energy when it is more convenient (at low price hours) and use its energy at high price hours. In order to assure that at 8 am the PHEV has a good charge level, a dissatisfaction term is considered that is directly proportional to the difference between the maximum level of charge and the level of charge at 8 am. Obviously these assumptions are too simplistic and not realistic. Other works divide the PEVs into clusters [62], each with specific characteristics: (1) battery capacity (2) arrival and departure times at/from the charging stations, (3) the SOC at the arrival time; and (4) the SOC desired at the departure time. Some works as [19] use a probabilistic approach representing the EVs' availability by a normal distribution and a probability function based on survey data. In addition, this data is used in a stochastic MPC for the control of the local energy system, allowing to plan for the EV availability with refined scenarios for each hour. In [5] the uncertainty of the time intervals during which the EV owners are at home and can therefore charge or discharge the EV battery are considered by means of a Monte Carlo approach. The daily driving distance of

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each Electrical Vehicles (EVs) is modelled as a log-normal distribution function. The home arrival and departure times of each EV are modelled each as a normal distribution. The daily driving distance, home arrival and departure time of each EV are randomly generated from such probability distributions.

While many works focus on the operation [19], [65], the investment plan for the community should also be accounted for the EVs. In fact, EVs can pose challenges to the grid in the planning phase due to their additional demand and, in the operation phase, due to potential stability issues.

The most presented papers have a centralized planning approach instead the type of model necessary for incorporating EV in each agent bidding should be addressed.

6.6.2 Research questions per limitation

In order to simulate, in a realistic way, the behavior of PEVs and its role in a LEC, it is essential to have access to dataset, in order to simulate the behavior of the PEVs in a probabilistic and more accurate way. Data will allow to estimate the average departure and arrival time, assess the impact of the month, weekday, hour of the day on the parking habits, etc.

Unfortunately, many datasets related to car parking are not easily accessible, reducing the investigations on this aspect and are often related to cars and not to PEVs/PHEVs. On the one hand, it is normal that most of the mobility data available in the literature refers to conventional ICE vehicles, as the share of EVs is still small. On the other hand, considering that EVs with larger battery capacities are becoming available in the market and that the fast charging infrastructure is increasing in all European countries, the day-by-day behaviour of an EV is very similar to that of a conventional ICE vehicle, except for long trips (above 300-400 km) where intermediate charging will be required for EVs, which may delay the travel time a bit more (comparing to refuelling a conventional ICE vehicle in a gas station). Therefore, the use of conventional vehicle mobility information is realistic, especially when analysing mobility in urban environments.

Even though EVs, when connected to a bidirectional charger, can be considered equivalent to a battery storage system, there are several questions that arise due to differences between the control logic and usage pattern of EVs and chargers.

For example, a battery storage system is usually 100% controllable, and returns almost all of the previously charged electric power. On the contrary, EVs usually cannot be controlled by the grid operator at present, and they will also consume much more electric power than supply to the grid, due to the power being by the vehicle itself. For these reasons the PEVs pose challenges to the grid in the planning phase due the additional demand.

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The inclusion of the EVs in LECs can also make their management more difficult. Even if there is some coordination, there will always be a lot more constraints than a simple battery storage system. Which impact can these constraints and power imbalance have in the results of the simulations, both technically and economically? What are the potential stability issues that can emerge?

Moreover, different types of EV loads should be considered as PHEV and Battery Electric Vehicles (BEVs), the V2G also should be modelled and it is necessary to overcome the centralized planning approach. EVs as they don't have ICE engine, can only inject electricity that has been previously charged from the grid, while PHEVs can be more flexible, as they can also function as a portable generator, being able to generate electricity and charge their battery from their ICE engine.

6.6.3 Innovation path per limitation

The optimization problem should provide an innovative approach for comprehensive modelling of central assets, connected RES, and emerging technologies in a LEC through the EH concept, while also considering economic and environmental aspects. Thus, the simulation of EVs should also follow this innovation approach. Namely, different simulation strategies and constraints levels should be analysed, for example considering interaction between EVs and the LEC, different EVs' usage profiles, different charge/discharge controllability schemes, different types of EVs, etc.

The technical, economic and environmental aspects of these strategies should be compared to evaluate the advantages and disadvantages of different EV simulation methods.

Although, some documents of the literature studying the impact of the EVs on power imbalance and the potential stability issues on LEC, these issues need further investigation. Moreover, additional investigations have to be devoted to the V2G and to the overcoming of the centralized planning approach.

The data related to EVs (departure time, arrival time, SOCs, etc.) in several areas of interest (public parking's, car sharing, etc.), should be collected and shared, in anonymized way, to boost the investigations on the simulation of EVs using probabilistic methods.

6.6.4 Approach for eNeuron

The eNeuron tool will optimize multi-carrier energy systems that will allow optimal integration of the different carriers. The eNeuron tool should provide an innovative and optimized configuration of the LEC as a whole (types, quantities and sizes of all technologies) considering the technical, economic and environmental objectives in the long-term and daily operation schedules considering also the peer-to-peer energy trading.

Accordingly, different EVs (not only cars) implementation schemes should be reviewed, for example from the different pilot sites, but also others. After this revision, the advantages and disadvantages

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of the innovation paths presented in the last chapter should be considered, in order to determine the best EV simulation strategy (or strategies) for the eNeuron tool, from the technical, economic and environmental point of views.

Surveys can be conducted to refine EV user behaviours for the case studies and their implementations in the framework. In addition, the creation of one or more datasets containing anonymized data useful for the simulation of EV behaviour (containing for each EV: arrival time, departure time, SOC, etc.) in different areas of interest (e.g. the pilots sites) and different typology (e.g., public charging stations on the street, charging stations in public/private parking's, car sharing, etc.). Moreover, making this dataset open-access could be very useful for future investigations in this context.

The planning problem with the integration of EV can be addressed by improving the *Integrate tool*. An EV module can be implemented, based on EV availability statistics or dataset described before, in order to provide a simplified EV model based on the observed behavior of EVs.

The potential stability issues can be addressed by *Validation tool* (e.g. anomaly detection functionality) integrated in the workflow but the feasibility of this approach for an in-line detection and control should be verified.

The integration of the PEV in the local energy market is dependent on the chosen architecture and this should also be addressed properly.

6.6.5 Conclusions

This section aimed to evaluate current methodologies to simulate EVs in the context of energy hubs and the corresponding limitations found in the literature.

Nevertheless, there are some questions than can be made due to differences between the control logic and usage pattern of EVs and chargers, which can make their simulation in a LEC very different than a simple battery storage. Different simulation strategies and constraints levels should be analysed, for example considering interaction between EVs and the LEC, different EVs usage profiles, different charge/discharge controllability schemes, etc.

The eNeuron tool will optimize multi-carrier energy systems that will allow optimal integration of the different carriers. Accordingly, different EV's implementation schemes should be reviewed, for example from the different pilot sites, but also others. After this revision, the advantages and disadvantages of the innovation paths presented in the last chapter should be considered, in order to determine the best EV simulation strategy (or strategies) for the eNeuron tool, from the technical, economic and environmental point of view.

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7 Conclusions and the overall eNeuron approach

This deliverable provides an in-depth analysis of the literature surrounding the existing state of the art regarding the multi objective optimization of an energy hub. The final aim is to define a path for how this approach can be fostered and improved to fit the eNeuron approach. The overall approach for eNeuron is summarized based on the main findings of the previous sections and conclusions are reached.

Multi objective optimization of an energy hub		
Clusters and related topics		**eNeuron approach**
1-Energy hubs	Energy hub technologies and energy carriers	eNeuron will take on board all different types of EH configuration in order to compile general solutions that can be replicable and scalable. The main innovation here is that eNeuron will focus not only on cases where electricity carrier is dominant but will develop scenarios with different carriers involved and configuration considering a wide range of conversion technologies.
2-Optimization related topics	Multi-objective Optimization Methods	Based on the literature, eNeuron will choose the most suitable multi-objective approach depending on the complexity and the scalability of the problem.
	Optimization Solvers & Frameworks	Python and CPLEX will be employed in eNeuron solutions. Powerfactory software package will be employed for validation purposes.
	Optimization problem formulation	For developing the eNeuron problem formulation the following will be taken care of: A multi objective problem formulation will be considered taking both economic and environmental aspects on board. This will impact both the structural planning of the LEC and the operation. These formulations will be considered as appropriate at both layers of optimization i.e. lower mEH and higher EH of the LEC. For the exchange of flexibility the peer-to-peer energy trading will be also considered so that prosumers seek for their best interest within their local region. Through this market and its operations, it will be secured that the two levels of optimization should harmonically co-exist and

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		not cancel each other's operation. Time span and functional constraints shall be carefully designed.
	Optimization Objective Functions	Based on the literature review, the objective functions shall be decided considering also the feedback coming from WP3 defining the actors and the business models.
	Optimization Constraints	eNeuron will take under consideration the state of the art and take on board all critical issues under T4.2.
	Heuristic methods	
	Uncertainty	
	Risk aversion	
3-Markets and optimization objectives	Energy and balancing markets	The eNeuron project aims to develop the eNeuron tool that can be applicable in general terms in every EH and local markets. The eNeuron team when developing the solutions will take care of the interaction of the EH with the markets and their realistic operation. To this extent, the short-term optimal operation layer might require to be subdivided into several sublayers so as to deal with the intraday operation of the energy hub in the electricity and gas intraday markets, and in the electricity balancing markets as well.
	P2P architectures	For the e-Neuron project, the distributed P2P architecture is going to be developed and simulated in order to allow to the mEH to trade and also to serve the LEC objectives as dictated by the EH level and transposed through the market. Through this architecture the overall optimization shall be achieved and both levels of the LEC shall interact in the most efficient way.
	P2P market and pricing schemes	In eNeuron, a distributed P2P architecture will be implemented so price-based schemes shall be investigated. Appropriate mechanisms to avoid conflicts and convergence issues shall be employed.
	Business models	The eNeuron project will provide innovative business models having in mind the baseline provided by the extended state of the art review. It has to be mentioned that an exhaustive list of conversion technologies, actors and their roles shall be taken on board to provide the value chain of the integrated grid where different carriers rather than the electricity are existing.

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4-Technical collateral concerns	Temporal and Spatial scopes	eNeuron will address through the complementary pilots as well as the scenarios different time horizons in both the design and operation of the EHs and investigate a high range of different spatial scopes.
	Long-term system planning	Planning of local energy systems such as energy hubs is most often done with a limited understanding of the impacts of the long-term changes in crucial parameters such as costs and demands. eNeuron tool will take on board operational details in the long term planning and structure design layer and will be tight with forecasting tools as well towards this direction.
	Implementation status	eNeuron will try a wide range of use cases in the pilots whereas replicability of these solutions are actively pursued under WP7.
	Services provided to the network	The eNeuron tool ensures the consideration of smart, innovative systems and products enabling the provision of grid services in a cost-efficient manner.
	Management of flexibility resources	Different energy storages are going to be integrated for enhancing the flexibility, both from the supply and demand sides, and sector-coupling solutions will be adopted. Management of flexibiltiy shall be considered greatly for the P2P market simulation.
	Simulation methods for Electrical Vehicles	Both planning and operation strategies for EV shall be examined as a source of flexibility and a good asset participating through the mEH into the market.

These insights will be used as a baseline for the development and further research activities that will take place under the T4.2 task.

It has to be mentioned that besides interesting conclusions for the eNeuron project development, different innovation pathways per topic have been identified that can be exploited for future research endeavours of the partners and the R&I community in general.

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References

[1] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 104, no. January, pp. 367–378, 2019, doi: 10.1016/j.rser.2019.01.036.

[2] A. Jiang, H. Yuan, and D. Li, "A two-stage optimization approach on the decisions for prosumers and consumers within a community in the Peer-to-peer energy sharing trading," *Int. J. Electr. Power Energy Syst.*, vol. 125, no. July 2020, p. 106527, 2021, doi: 10.1016/j.ijepes.2020.106527.

[3] K. Heo, J. Kong, S. Oh, and J. Jung, "Development of operator-oriented peer-to-peer energy trading model for integration into the existing distribution system," *Int. J. Electr. Power Energy Syst.*, vol. 125, no. September 2020, p. 106488, 2021, doi: 10.1016/j.ijepes.2020.106488.

[4] M. R. Akhtari and M. Baneshi, "Techno-economic assessment and optimization of a hybrid renewable co-supply of electricity, heat and hydrogen system to enhance performance by recovering excess electricity for a large energy consumer," *Energy Convers. Manag.*, vol. 188, no. January, pp. 131–141, 2019, doi: 10.1016/j.enconman.2019.03.067.

[5] X. Lu, Z. Liu, L. Ma, L. Wang, K. Zhou, and N. Feng, "A robust optimization approach for optimal load dispatch of community energy hub," *Appl. Energy*, vol. 259, no. October 2019, 2020, doi: 10.1016/j.apenergy.2019.114195.

[6] I. Petkov, P. Gabrielli, and M. Spokaite, "The impact of urban district composition on storage technology reliance: trade-offs between thermal storage, batteries, and power-to-hydrogen," *Energy*, vol. 224, p. 120102, 2021, doi: 10.1016/j.energy.2021.120102.

[7] N. Cannata *et al.*, "Multi-objective optimization of urban microgrid energy supply according to economic and environmental criteria," *2019 IEEE Milan PowerTech, PowerTech 2019*, 2019, doi: 10.1109/PTC.2019.8810776.

[8] M. Zhang, Q. Wu, J. Wen, Z. Lin, F. Fang, and Q. Chen, "Optimal operation of integrated electricity and heat system: A review of modeling and solution methods," *Renew. Sustain. Energy Rev.*, vol. 135, no. January 2020, p. 110098, 2021, doi: 10.1016/j.rser.2020.110098.

[9] A. Ghanbari, H. Karimi, and S. Jadid, "Optimal planning and operation of multi-carrier networked microgrids considering multi-energy hubs in distribution networks," *Energy*, vol. 204, p. 117936, 2020, doi: 10.1016/j.energy.2020.117936.

[10] M. Monemi Bidgoli, H. Karimi, S. Jadid, and A. Anvari-Moghaddam, "Stochastic electrical and thermal energy management of energy hubs integrated with demand response programs and renewable energy: A prioritized multi-objective framework," *Electr. Power Syst. Res.*, vol. 196, no. April, p. 107183, 2021, doi: 10.1016/j.epsr.2021.107183.

[11] H. Chen, M. Liu, Y. Liu, S. Lin, and Z. Yang, "Partial surrogate cuts method for network-constrained optimal scheduling of multi-carrier energy systems with demand response," *Energy*, vol. 196, p. 117119, 2020, doi: 10.1016/j.energy.2020.117119.

[12] T. Liu, D. Zhang, S. Wang, and T. Wu, "Standardized modelling and economic optimization of

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

multi-carrier energy systems considering energy storage and demand response," *Energy Convers. Manag.*, vol. 182, no. September 2018, pp. 126–142, 2019, doi: 10.1016/j.enconman.2018.12.073.

[13] W. Yong *et al.*, "Day-ahead dispatch of multi-energy system considering operating conditions of multi-energy coupling equipment," *Energy Reports*, vol. 7, pp. 100–110, 2021, doi: 10.1016/j.egyr.2021.02.016.

[14] Z. Wang, J. Hu, and B. Liu, "Stochastic optimal dispatching strategy of electricity-hydrogen-gas-heat integrated energy system based on improved spectral clustering method," *Int. J. Electr. Power Energy Syst.*, vol. 126, no. PA, p. 106495, 2021, doi: 10.1016/j.ijepes.2020.106495.

[15] S. A. Mansouri, A. Ahmarinejad, M. S. Javadi, and J. P. S. Catalão, "Two-stage stochastic framework for energy hubs planning considering demand response programs," *Energy*, vol. 206, 2020, doi: 10.1016/j.energy.2020.118124.

[16] M. H. Shams, M. Shahabi, M. MansourLakouraj, M. Shafie-khah, and J. P. S. Catalão, "Adjustable robust optimization approach for two-stage operation of energy hub-based microgrids," *Energy*, vol. 222, 2021, doi: 10.1016/j.energy.2021.119894.

[17] E. Shahrabi, S. M. Hakimi, A. Hasankhani, G. Derakhshan, and B. Abdi, "Developing optimal energy management of energy hub in the presence of stochastic renewable energy resources," *Sustain. Energy, Grids Networks*, vol. 26, p. 100428, 2021, doi: 10.1016/j.segan.2020.100428.

[18] S. M. Nosratabadi, R. Hemmati, and P. Khajouei Gharaei, "Optimal planning of multi-energy microgrid with different energy storages and demand responsive loads utilizing a technical-economic-environmental programming," *Int. J. Energy Res.*, vol. 45, no. 5, pp. 6985–7017, 2021, doi: 10.1002/er.6286.

[19] X. Guo, Z. Bao, and W. Yan, "Stochastic model predictive control based scheduling optimization of multi-energy system considering hybrid CHPs and EVs," *Appl. Sci.*, vol. 9, no. 2, 2019, doi: 10.3390/app9020356.

[20] N. Preston *et al.*, "How can the integration of renewable energy and power-to-gas benefit industrial facilities? From techno-economic, policy, and environmental assessment," *Int. J. Hydrogen Energy*, vol. 45, no. 51, pp. 26559–26573, 2020, doi: 10.1016/j.ijhydene.2020.07.040.

[21] M. S. Javadi, M. Lotfi, A. E. Nezhad, A. Anvari-Moghaddam, J. M. Guerrero, and J. P. S. Catalao, "Optimal Operation of Energy Hubs Considering Uncertainties and Different Time Resolutions," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 5543–5552, 2020, doi: 10.1109/TIA.2020.3000707.

[22] S. E. Hosseini and A. Ahmarinejad, "Stochastic framework for day-ahead scheduling of coordinated electricity and natural gas networks considering multiple downward energy hubs," *J. Energy Storage*, vol. 33, no. October 2020, p. 102066, 2021, doi: 10.1016/j.est.2020.102066.

[23] M. Vahid-Ghavidel, M. Sadegh Javadi, M. Gough, S. F. Santos, M. Shafie-Khah, and J. P. S. Catalão, "Demand response programs in multi-energy systems: A review," *Energies*, vol. 13,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

no. 17, pp. 1–17, 2020, doi: 10.3390/en13174332.

[24] Y. Ye, Y. Ye, D. Qiu, X. Wu, G. Strbac, and J. Ward, "Model-Free Real-Time Autonomous Control for a Residential Multi-Energy System Using Deep Reinforcement Learning," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3068–3082, 2020, doi: 10.1109/TSG.2020.2976771.

[25] M. Di Somma *et al.*, "Operation optimization of a distributed energy system considering energy costs and exergy efficiency," *Energy Convers. Manag.*, vol. 103, pp. 739–751, 2015, doi: 10.1016/j.enconman.2015.07.009.

[26] M. Di Somma, G. Graditi, E. Heydarian-Forushani, M. Shafie-khah, and P. Siano, "Stochastic optimal scheduling of distributed energy resources with renewables considering economic and environmental aspects," *Renew. Energy*, vol. 116, pp. 272–287, 2018, doi: 10.1016/j.renene.2017.09.074.

[27] M. Di Somma *et al.*, "Multi-objective design optimization of distributed energy systems through cost and exergy assessments," *Appl. Energy*, vol. 204, pp. 1299–1316, 2017, doi: 10.1016/j.apenergy.2017.03.105.

[28] M. Di Somma *et al.*, "Multi-objective operation optimization of a Distributed Energy System for a large-scale utility customer," *Appl. Therm. Eng.*, vol. 101, pp. 752–761, 2016, doi: 10.1016/j.applthermaleng.2016.02.027.

[29] "Di Somma M, Caliano M, Graditi G, Pinnarelli A, Menniti D, Sorrentino N, Barone G. Designing of Cost-Effective and Low-Carbon Multi-Energy Nanogrids for Residential Applications. Inventions. 2020; 5(1):7. https://doi.org/10.3390/inventions5010007."

[30] F. Foiadelli, S. Nocerino, M. Di Somma, and G. Graditi, "Optimal Design of der for Economic/Environmental Sustainability of Local Energy Communities," *Proc. - 2018 IEEE Int. Conf. Environ. Electr. Eng. 2018 IEEE Ind. Commer. Power Syst. Eur. EEEIC/I CPS Eur. 2018*, 2018, doi: 10.1109/EEEIC.2018.8493898.

[31] I. Petkov and P. Gabrielli, "Power-to-hydrogen as seasonal energy storage: an uncertainty analysis for optimal design of low-carbon multi-energy systems," *Appl. Energy*, vol. 274, no. January, p. 115197, 2020, doi: 10.1016/j.apenergy.2020.115197.

[32] M. Nazari-Heris, B. Mohammadi-Ivatloo, and S. Asadi, "Optimal operation of multi-carrier energy networks with gas, power, heating, and water energy sources considering different energy storage technologies," *J. Energy Storage*, vol. 31, no. May, p. 101574, 2020, doi: 10.1016/j.est.2020.101574.

[33] T. Wu, S. Bu, X. Wei, G. Wang, and B. Zhou, "Multitasking multi-objective operation optimization of integrated energy system considering biogas-solar-wind renewables," *Energy Convers. Manag.*, vol. 229, no. December 2020, p. 113736, 2021, doi: 10.1016/j.enconman.2020.113736.

[34] Y. Wang *et al.*, "Economic and efficient multi-objective operation optimization of integrated energy system considering electro-thermal demand response," *Energy*, vol. 205, p. 118022, 2020, doi: 10.1016/j.energy.2020.118022.

[35] "Mohammadi-Ivatloo, Behnam, and Farkhondeh Jabari, eds. Operation, planning, and analysis of energy storage systems in smart energy hubs. Cham, Switzerland: Springer International Publishing, 2018."

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

[36] H. Khani, A. Sawas, and H. E. Z. Farag, “An estimation–Based optimal scheduling model for settable renewable penetration level in energy hubs,” *Electr. Power Syst. Res.*, vol. 196, no. April, p. 107230, 2021, doi: 10.1016/j.epsr.2021.107230.

[37] T. M. Alabi, L. Lu, and Z. Yang, “A novel multi-objective stochastic risk co-optimization model of a zero-carbon multi-energy system (ZCMES) incorporating energy storage aging model and integrated demand response,” *Energy*, vol. 226, p. 120258, 2021, doi: 10.1016/j.energy.2021.120258.

[38] R. Yan *et al.*, “Multi-objective two-stage adaptive robust planning method for an integrated energy system considering load uncertainty,” *Energy Build.*, vol. 235, p. 110741, 2021, doi: 10.1016/j.enbuild.2021.110741.

[39] C. B. Heendeniya, A. Sumper, and U. Eicker, “The multi-energy system co-planning of nearly zero-energy districts – Status-quo and future research potential,” *Appl. Energy*, vol. 267, no. November 2019, p. 114953, 2020, doi: 10.1016/j.apenergy.2020.114953.

[40] J. J. Roberts, A. Marotta Cassula, J. L. Silveira, E. da Costa Bortoni, and A. Z. Mendiburu, “Robust multi-objective optimization of a renewable based hybrid power system,” *Appl. Energy*, vol. 223, no. January, pp. 52–68, 2018, doi: 10.1016/j.apenergy.2018.04.032.

[41] P. Gabrielli, M. Gazzani, E. Martelli, and M. Mazzotti, “Optimal design of multi-energy systems with seasonal storage,” *Appl. Energy*, vol. 219, no. June 2017, pp. 408–424, 2018, doi: 10.1016/j.apenergy.2017.07.142.

[42] T. Ma, J. Wu, and L. Hao, “Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub,” *Energy Convers. Manag.*, vol. 133, pp. 292–306, 2017, doi: 10.1016/j.enconman.2016.12.011.

[43] A. R. Jordehi, M. S. Javadi, M. Shafie-khah, and J. P. S. Catalão, “Information gap decision theory (IGDT)-based robust scheduling of combined cooling, heat and power energy hubs,” *Energy*, vol. 231, 2021, doi: 10.1016/j.energy.2021.120918.

[44] A. Maroufmashat, S. T. Taqvi, A. Miragha, M. Fowler, and A. Elkamel, “Modeling and optimization of energy hubs: A comprehensive review,” *Inventions*, vol. 4, no. 3, 2019, doi: 10.3390/inventions4030050.

[45] J. Liu, Z. Xu, J. Wu, K. Liu, and X. Guan, “Optimal planning of distributed hydrogen-based multi-energy systems,” *Appl. Energy*, vol. 281, no. October 2020, p. 116107, 2021, doi: 10.1016/j.apenergy.2020.116107.

[46] A. Maroufmashat, S. Sattari, R. Roshandel, M. Fowler, and A. Elkamel, “Multi-objective Optimization for Design and Operation of Distributed Energy Systems through the Multi-energy Hub Network Approach,” *Ind. Eng. Chem. Res.*, vol. 55, no. 33, pp. 8950–8966, 2016, doi: 10.1021/acs.iecr.6b01264.

[47] H. Ren, W. Zhou, K. Nakagami, W. Gao, and Q. Wu, “Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects,” *Appl. Energy*, vol. 87, no. 12, pp. 3642–3651, 2010, doi: 10.1016/j.apenergy.2010.06.013.

[48] M. Geidl and G. Andersson, “Operational and structural optimization of multi-carrier energy systems,” *Eur. Trans. Electr. Power*, vol. 16, no. 5, pp. 463–477, 2006, doi: 10.1002/etep.112.

[49] D. Cedillos Alvarado, S. Acha, N. Shah, and C. N. Markides, “A Technology Selection and

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement N° 957779

Operation (TSO) optimisation model for distributed energy systems: Mathematical formulation and case study," *Appl. Energy*, vol. 180, pp. 491–503, 2016, doi: 10.1016/j.apenergy.2016.08.013.

[50] L. Li, H. Mu, N. Li, and M. Li, "Economic and environmental optimization for distributed energy resource systems coupled with district energy networks," *Energy*, vol. 109, pp. 947–960, 2016, doi: 10.1016/j.energy.2016.05.026.

[51] A. Rieder, A. Christidis, and G. Tsatsaronis, "Multi criteria dynamic design optimization of a small scale distributed energy system," *Energy*, vol. 74, no. C, pp. 230–239, 2014, doi: 10.1016/j.energy.2014.06.007.

[52] F. Ascione, N. Bianco, R. F. De Masi, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "Multi-objective optimization of the renewable energy mix for a building," *Appl. Therm. Eng.*, vol. 101, pp. 612–621, 2016, doi: 10.1016/j.applthermaleng.2015.12.073.

[53] M. Karmellos, P. N. Georgiou, and G. Mavrotas, "A comparison of methods for the optimal design of Distributed Energy Systems under uncertainty," *Energy*, vol. 178, pp. 318–333, 2019, doi: 10.1016/j.energy.2019.04.153.

[54] M. O. W. Grond, N. H. Luong, J. Morren, and J. G. Slootweg, "Multi-objective optimization techniques and applications in electric power systems," *Proc. Univ. Power Eng. Conf.*, 2012, doi: 10.1109/UPEC.2012.6398417.

[55] A. Alarcon-Rodriguez, G. Ault, and S. Galloway, "Multi-objective planning of distributed energy resources: A review of the state-of-the-art," *Renew. Sustain. Energy Rev.*, vol. 14, no. 5, pp. 1353–1366, 2010, doi: 10.1016/j.rser.2010.01.006.

[56] A. Shabanpour-Haghighi and A. R. Seifi, "Energy Flow Optimization in Multicarrier Systems," *IEEE Trans. Ind. Informatics*, vol. 11, no. 5, pp. 1067–1077, 2015, doi: 10.1109/TII.2015.2462316.

[57] A. Shabanpour-Haghighi, A. R. Seifi, and T. Niknam, "A modified teaching-learning based optimization for multi-objective optimal power flow problem," *Energy Convers. Manag.*, vol. 77, pp. 597–607, 2014, doi: 10.1016/j.enconman.2013.09.028.

[58] A. Shabanpour-Haghighi and A. R. Seifi, "Multi-objective operation management of a multi-carrier energy system," *Energy*, vol. 88, pp. 430–442, 2015, doi: 10.1016/j.energy.2015.05.063.

[59] M. Moeini-Aghtaie, A. Abbaspour, M. Fotuhi-Firuzabad, and E. Hajipour, "A decomposed solution to multiple-energy carriers optimal power flow," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 707–716, 2014, doi: 10.1109/TPWRS.2013.2283259.

[60] M. Majidi and K. Zare, "Integration of smart energy hubs in distribution networks under uncertainties and demand response concept," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 566–574, 2019, doi: 10.1109/TPWRS.2018.2867648.

[61] R. Roberto, R. De Iulio, M. Di Somma, G. Graditi, G. Guidi, and M. Noussan, "A multi-objective optimization analysis to assess the potential economic and environmental benefits of distributed storage in district heating networks: A case study," *Int. J. Sustain. Energy Plan. Manag.*, vol. 20, pp. 5–20, 2019, doi: 10.5278/ijsepm.2019.20.2.

[62] M. Di Somma, L. Ciabattoni, G. Comodi, and G. Graditi, "Managing plug-in electric vehicles in

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

eco-environmental operation optimization of local multi-energy systems," *Sustain. Energy, Grids Networks*, vol. 23, p. 100376, 2020, doi: 10.1016/j.segan.2020.100376.

[63] D. wei Gong, Y. Zhang, and C. liang Qi, "Environmental/economic power dispatch using a hybrid multi-objective optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 6, pp. 607–614, 2010, doi: 10.1016/j.ijepes.2009.11.017.

[64] M. Nunes Fonseca, E. de Oliveira Pamplona, A. R. de Queiroz, V. E. de Mello Valerio, G. Aquila, and S. Ribeiro Silva, "Multi-objective optimization applied for designing hybrid power generation systems in isolated networks," *Sol. Energy*, vol. 161, no. September 2017, pp. 207–219, 2018, doi: 10.1016/j.solener.2017.12.046.

[65] D. Buoro, M. Casisi, A. De Nardi, P. Pinamonti, and M. Reini, "Multicriteria optimization of a distributed energy supply system for an industrial area," *Energy*, vol. 58, pp. 128–137, 2013, doi: 10.1016/j.energy.2012.12.003.

[66] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-Sharing Model with Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, 2017, doi: 10.1109/TPWRS.2017.2649558.

[67] S. Cui, Y. W. Wang, and J. W. Xiao, "Peer-to-peer energy sharing among smart energy buildings by distributed transaction," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6491–6501, 2019, doi: 10.1109/TSG.2019.2906059.

[68] E. A. Martinez Cesena and P. Mancarella, "Energy Systems Integration in Smart Districts: Robust Optimisation of Multi-Energy Flows in Integrated Electricity, Heat and Gas Networks," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 1122–1131, 2019, doi: 10.1109/TSG.2018.2828146.

[69] M. Rayati, A. Sheikhi, and A. M. Ranjbar, "Optimising operational cost of a smart energy hub, the reinforcement learning approach," *Int. J. Parallel, Emergent Distrib. Syst.*, vol. 30, no. 4, pp. 325–341, 2015, doi: 10.1080/17445760.2014.974600.

[70] K. Orehounig, R. Evins, and V. Dorer, "Integration of decentralized energy systems in neighbourhoods using the energy hub approach," *Appl. Energy*, vol. 154, pp. 277–289, 2015, doi: 10.1016/j.apenergy.2015.04.114.

[71] P. Li *et al.*, "Intraday multi-objective hierarchical coordinated operation of a multi-energy system," *Energy*, vol. 228, p. 120528, 2021, doi: 10.1016/j.energy.2021.120528.

[72] J. Cao, B. Yang, S. Zhu, C. Ning, and X. Guan, "Day-ahead chance-constrained energy management of energy hub: A distributionally robust approach," *CSEE J. Power Energy Syst.*, pp. 1–12, 2021, doi: 10.17775/cseejpes.2020.04380.

[73] H. Huang, S. Nie, J. Lin, Y. Wang, and J. Dong, "Optimization of peer-to-peer power trading in a microgrid with distributed PV and battery energy storage systems," *Sustain.*, vol. 12, no. 3, 2020, doi: 10.3390/su12030923.

[74] H. Zou, J. Tao, S. K. Elsayed, E. E. Elattar, A. Almalaq, and M. A. Mohamed, "Stochastic multi-carrier energy management in the smart islands using reinforcement learning and unscented transform," *Int. J. Electr. Power Energy Syst.*, vol. 130, no. December 2020, p. 106988, 2021, doi: 10.1016/j.ijepes.2021.106988.

[75] V. V. S. N. Murty and A. Kumar, "Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems," *Prot. Control Mod. Power Syst.*,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

vol. 5, no. 1, pp. 1–20, 2020, doi: 10.1186/s41601-019-0147-z.

[76] J. Salehi, A. Namvar, and F. S. Gazijahani, "Scenario-based Co-Optimization of neighboring multi carrier smart buildings under demand response exchange," *J. Clean. Prod.*, vol. 235, pp. 1483–1498, 2019, doi: 10.1016/j.jclepro.2019.07.068.

[77] M. Khorasany, A. Najafi-Ghalelou, R. Razzaghi, and B. Mohammadi-Ivatloo, "Transactive energy framework for optimal energy management of multi-carrier energy hubs under local electrical, thermal, and cooling market constraints," *Int. J. Electr. Power Energy Syst.*, vol. 129, no. July 2020, p. 106803, 2021, doi: 10.1016/j.ijepes.2021.106803.

[78] A. Çiçek, İ. Şengör, A. K. Erenoğlu, and O. Erdinç, "Decision making mechanism for a smart neighborhood fed by multi-energy systems considering demand response," *Energy*, vol. 208, 2020, doi: 10.1016/j.energy.2020.118323.

[79] M. C. Bozchalui, S. A. Hashmi, and S. Member, "Smart grids," *Green Energy Technol.*, vol. 101, no. 4, pp. 119–121, 2012, doi: 10.1007/978-1-4471-2813-7_22.

[80] D. Xu, Q. Wu, B. Zhou, C. Li, L. Bai, and S. Huang, "Distributed Multi-Energy Operation of Coupled Electricity, Heating, and Natural Gas Networks," *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2457–2469, 2020, doi: 10.1109/TSTE.2019.2961432.

[81] M. Ghorab, "Energy hubs optimization for smart energy network system to minimize economic and environmental impact at Canadian community," *Appl. Therm. Eng.*, vol. 151, no. February, pp. 214–230, 2019, doi: 10.1016/j.applthermaleng.2019.01.107.

[82] M. J. Vahid Pakdel, F. Sohrabi, and B. Mohammadi-Ivatloo, "Multi-objective optimization of energy and water management in networked hubs considering transactive energy," *J. Clean. Prod.*, vol. 266, p. 121936, 2020, doi: 10.1016/j.jclepro.2020.121936.

[83] M. Di Somma, G. Graditi, and P. Siano, "Optimal Bidding Strategy for a DER Aggregator in the Day-Ahead Market in the Presence of Demand Flexibility," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1509–1519, 2019, doi: 10.1109/TIE.2018.2829677.

[84] Y. Zhou, J. Wu, and C. Long, "Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework," *Appl. Energy*, vol. 222, no. February, pp. 993–1022, 2018, doi: 10.1016/j.apenergy.2018.02.089.

[85] Y. Cao, Q. Wang, W. Cheng, S. Nojavan, and K. Jermsittiparsert, "Risk-constrained optimal operation of fuel cell/photovoltaic/battery/grid hybrid energy system using downside risk constraints method," *Int. J. Hydrogen Energy*, vol. 45, no. 27, pp. 14108–14118, 2020, doi: 10.1016/j.ijhydene.2020.03.090.

[86] S. Wang, A. F. Taha, J. Wang, K. Kvaternik, and A. Hahn, "Energy Crowdsourcing and Peer-to-Peer Energy Trading in Blockchain-Enabled Smart Grids," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 49, no. 8, pp. 1612–1623, 2019, doi: 10.1109/TSMC.2019.2916565.

[87] J. Bollenbacher and B. Rhein, "Optimal configuration and control strategy in a multi-carrier-energy system using reinforcement learning methods," *IESC 2017 - Int. Energy Sustain. Conf.*, vol. 2017–Decem, no. 2, pp. 1–6, 2017, doi: 10.1109/IESC.2017.8167476.

[88] M. Dan, S. Srinivasan, S. Sundaram, A. Easwaran, and L. Glielmo, "A Scenario-Based Branch-and-Bound Approach for MES Scheduling in Urban Buildings," *IEEE Trans. Ind. Informatics*, vol. 16, no. 12, pp. 7510–7520, 2020, doi: 10.1109/TII.2020.2978870.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

[89] S. Fazlollahi, P. Mandel, G. Becker, and F. Maréchal, “Methods for multi-objective investment and operating optimization of complex energy systems,” *Energy*, vol. 45, no. 1, pp. 12–22, 2012, doi: 10.1016/j.energy.2012.02.046.

[90] S. Mashayekh, M. Stadler, G. Cardoso, and M. Heleno, “A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids,” *Appl. Energy*, vol. 187, pp. 154–168, 2017, doi: 10.1016/j.apenergy.2016.11.020.

[91] C. Zhang *et al.*, “A novel methodology for the design of waste heat recovery network in eco-industrial park using techno-economic analysis and multi-objective optimization,” *Appl. Energy*, vol. 184, pp. 88–102, 2016, doi: 10.1016/j.apenergy.2016.10.016.

[92] G. Comodi *et al.*, “Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies,” *Appl. Energy*, vol. 137, pp. 854–866, 2015, doi: 10.1016/j.apenergy.2014.07.068.

[93] Z. Qiu, B. Wang, J. Huang, and Z. Xie, “Optimal configuration and sizing of regional energy service company’s energy hub with integrated demand response,” *IEEJ Trans. Electr. Electron. Eng.*, vol. 14, no. 3, pp. 383–393, 2019, doi: 10.1002/tee.22819.

[94] G. Pan, W. Gu, Z. Wu, Y. Lu, and S. Lu, “Optimal design and operation of multi-energy system with load aggregator considering nodal energy prices,” *Appl. Energy*, vol. 239, no. November 2018, pp. 280–295, 2019, doi: 10.1016/j.apenergy.2019.01.217.

[95] Y. Wang, N. Zhang, Z. Zhuo, C. Kang, and D. Kirschen, “Mixed-integer linear programming-based optimal configuration planning for energy hub: Starting from scratch,” *Appl. Energy*, vol. 210, no. May 2017, pp. 1141–1150, 2018, doi: 10.1016/j.apenergy.2017.08.114.

[96] A. Najafi-Ghalelou, S. Nojavan, K. Zare, and B. Mohammadi-Ivatloo, “Robust scheduling of thermal, cooling and electrical hub energy system under market price uncertainty,” *Appl. Therm. Eng.*, vol. 149, no. December 2018, pp. 862–880, 2019, doi: 10.1016/j.applthermaleng.2018.12.108.

[97] T. Ma, J. Wu, L. Hao, W. J. Lee, H. Yan, and D. Li, “The optimal structure planning and energy management strategies of smart multi energy systems,” *Energy*, vol. 160, pp. 122–141, 2018, doi: 10.1016/j.energy.2018.06.198.

[98] W. Huang, N. Zhang, J. Yang, Y. Wang, and C. Kang, “Optimal configuration planning of multi-energy systems considering distributed renewable energy,” *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1452–1464, 2019, doi: 10.1109/TSG.2017.2767860.

[99] M. Capone, E. Guelpa, and V. Verda, “Multi-objective optimization of district energy systems with demand response,” *Energy*, vol. 227, p. 120472, 2021, doi: 10.1016/j.energy.2021.120472.

[100] Y. Zhang, Y. Liu, S. Shu, F. Zheng, and Z. Huang, “A data-driven distributionally robust optimization model for multi-energy coupled system considering the temporal-spatial correlation and distribution uncertainty of renewable energy sources,” *Energy*, vol. 216, p. 119171, 2021, doi: 10.1016/j.energy.2020.119171.

[101] M. Motevasel, A. R. Seifi, and T. Niknam, “Multi-objective energy management of CHP (combined heat and power)-based micro-grid,” *Energy*, vol. 51, pp. 123–136, 2013, doi: 10.1016/j.energy.2012.11.035.

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[102] A. Bartolini, F. Carducci, C. B. Muñoz, and G. Comodi, "Energy storage and multi energy systems in local energy communities with high renewable energy penetration," *Renew. Energy*, vol. 159, pp. 595–609, 2020, doi: 10.1016/j.renene.2020.05.131.

[103] G. Comodi, A. Bartolini, F. Carducci, B. Nagaranjan, and A. Romagnoli, "Achieving low carbon local energy communities in hot climates by exploiting networks synergies in multi energy systems," *Appl. Energy*, vol. 256, no. August, p. 113901, 2019, doi: 10.1016/j.apenergy.2019.113901.

[104] S. Bjarghov *et al.*, "Developments and Challenges in Local Electricity Markets: A Comprehensive Review," *IEEE Access*, vol. 9, pp. 58910–58943, 2021, doi: 10.1109/ACCESS.2021.3071830.

[105] H. Sadeghi, M. Rashidinejad, M. Moeini-Aghtaie, and A. Abdollahi, "The energy hub: An extensive survey on the state-of-the-art," *Appl. Therm. Eng.*, vol. 161, no. December 2017, 2019, doi: 10.1016/j.applthermaleng.2019.114071.

[106] A. Turk, Q. Wu, M. Zhang, and J. Østergaard, "Day-ahead stochastic scheduling of integrated multi-energy system for flexibility synergy and uncertainty balancing," *Energy*, vol. 196, p. 117130, 2020, doi: 10.1016/j.energy.2020.117130.

[107] T. Sogabe, B. Malla, T. Hioki, and K. Takahashi, "Multi-carrier energy hub management through deep deterministic policy gradient over continuous action space," pp. 3–6.

[108] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, M. Hosseinzadeh, H. Yousefi, and S. T. Khorasani, "Optimal management of energy hubs and smart energy hubs – A review," *Renew. Sustain. Energy Rev.*, vol. 89, no. September 2017, pp. 33–50, 2018, doi: 10.1016/j.rser.2018.02.035.

[109] P. Mancarella, "MES (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1–17, 2014, doi: 10.1016/j.energy.2013.10.041.

[110] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, and H. Yousefi, "Energy hub: From a model to a concept – A review," *Renew. Sustain. Energy Rev.*, vol. 80, no. November 2016, pp. 1512–1527, 2017, doi: 10.1016/j.rser.2017.07.030.

[111] A. Arteconi *et al.*, "Thermal energy storage coupled with PV panels for demand side management of industrial building cooling loads," *Appl. Energy*, vol. 185, pp. 1984–1993, 2017, doi: 10.1016/j.apenergy.2016.01.025.

[112] W. Tushar *et al.*, "Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges," *Appl. Energy*, vol. 282, no. PA, p. 116131, 2021, doi: 10.1016/j.apenergy.2020.116131.

[113] D. E. Majewski, M. Wirtz, M. Lampe, and A. Bardow, "Robust multi-objective optimization for sustainable design of distributed energy supply systems," *Comput. Chem. Eng.*, vol. 102, pp. 26–39, 2017, doi: 10.1016/j.compchemeng.2016.11.038.

[114] A. Anwar, P. Beguery, P. Pflaum, J. Huynh, and J. Friedman, "Optimal der Sizing Using Microgrid Design Tool Integrating Model Predictive Control Based Energy Management - A Case Study," *2018 IEEE Energy Convers. Congr. Expo. ECCE 2018*, pp. 3799–3806, 2018, doi: 10.1109/ECCE.2018.8557718.

[115] C. Klemm and P. Vennemann, "Modeling and optimization of multi-energy systems in mixed-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 957779

use districts: A review of existing methods and approaches," *Renew. Sustain. Energy Rev.*, vol. 135, no. July 2020, p. 110206, 2021, doi: 10.1016/j.rser.2020.110206.

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