MODELLING AND OPTIMISATION OF A DISTRICT HEATING NETWORK'S MARGINAL EXTENSION

Axelle Catherine Christel DELANGLE

2 September 2016

Supervised by: Prof. Nilay Shah, Dr. Romain Lambert, Dr. Salvador Acha

A thesis presented to Imperial College London in partial fulfilment of the requirements for the degree of *Master of Science in Sustainable Energy Futures* and for the *Diploma of Imperial College*

Energy Futures Lab

Imperial College London

SW7 2AZ

Abstract

District heating networks have a key role to play in tackling greenhouse gas emissions associated with urban energy systems. In this context, renewed attention has recently been paid to them and there is a global trend towards the acceleration of district heating expansion. If several existing networks even plan to extend, little work has been carried out on district heating networks expansion in the literature. The following thesis develops a methodology to find the best district heating network expansion strategy under given constraints. After analysing the heat demand and establishing buildings connection scenarios, the model developed optimises the energy centre expansion over a twelve years' time horizon. Spatial expansion aspects are also included. The optimisation approach was applied to the case of the Barkantine district heating network in the Isle of Dogs, London.
The model demonstrated that depending on the optimisation performed (costs or greenhouse gas emissions), some connection strategies have to be privileged. It also proved that district heating scheme's financial viability may be affected by the connection scenario chosen, highlighting the necessity of planning strategies for district heating networks. The proposed approach can be adapted to other district heating network schemes and modified to integrate more aspects and constraints.

Acknowledgements

I would like to express my gratitude to my supervisor, Dr. Romain Lambert, for all the time, guidance and interest he provided to my research project. He let me a great degree of freedom in the completion of this thesis while constantly remaining available when I needed his help. I would also like to thank Prof. Nilay Shah and Dr. Salvador Acha, my co-supervisors.

I would like to thank EDF Energy for enabling the possibility of carrying this project forward, as well as Marie-Lou Picherit for the data she provided to me.

I would like to acknowledge the work done by Jorge Corral Acero, which served as a firm starting point for my model. I would also like to thank Aitor Soler-Garcia for his help on electricity prices modelling.

I would like to thank the French State and the Ecole Polytechnique for giving me the means to study in London and to have a great learning experience in the Sustainable Energy Futures course.

Last but not least, I would like to thank my family, my friends and Alexis for their unconditional support and unfailing encouragement throughout the year.

Contents

1 Introduction **1**
1.1 Imperial College - EDF Energy partnership . . . 1
1.2 Project: scope, purpose and focus . . . 1
1.3 Thesis organisation . . . 2

2 Background and literature review **3**
2.1 Strategic importance of district heating . . . 3
2.1.1 Benefits of district heating . . . 3
2.1.2 Heat use in the UK and in the EU . . . 3
2.1.3 Strategic importance of district heating and future targets . . . 4
2.2 Overview of district heating networks . . . 5
2.2.1 What is a District Heating Network ? . . . 6
2.2.2 Heat demand and heat demand mapping . . . 8
2.2.3 Heat production and storage . . . 10
2.2.4 Design and operating parameters . . . 13
2.3 Heat network modelling and optimisation . . . 14
2.3.1 Classical algorithms: why are they relevant for district heating ? . . . 14
2.3.2 Heat network modelling and optimisation . . . 17
2.4 Extension of district heating networks . . . 18
2.4.1 How to identify the areas that are suitable for the extension of the network? . . . 18
2.4.2 How to model their extension? . . . 19
2.5 Conclusion - presentation of the existing network and area . . . 20

3 Heat demand analysis **22**
3.1 Loads selection and clustering . . . 23
3.1.1 Identification of anchor heat loads . . . 23
3.1.2 Heat demand estimation for each load . . . 23
3.1.3 Generation of clusters of interest . . . 24
3.2 Thermal demand data discretisation . . . 25
3.3 Elaboration and presentation of the scenarios . . . 26

4 Design of the energy centre **28**
4.1 General model: Mixed integer linear programming . . . 29
4.1.1 Sets . . . 29
4.1.2 Parameters . . . 29
4.1.3 Variables . . . 31
4.1.4 Main equations and constraints . . . 32
4.1.4.1 Technology sizing . . . 32
4.1.4.2 Working constraints . . . 33
4.1.4.3 Heat and electricity balance . . . 33
4.1.4.4 Storage constraints . . . 34
4.1.4.5 Costs calculations and resource use . . . 34
4.1.4.6 GHG emissions . . . 35
4.1.4.7 Surface required to build the plants . . . 36
4.1.4.8 Initial conditions . . . 36

4.1.4.9 Objective functions . . . 36
4.2 Baseline scenario . . . 36
4.3 Model variations . . . 37
4.4 Input data and assumptions . . . 38
4.4.1 Technologies considered and subsidies . . . 38
4.4.1.1 Combined heat and power plants . . . 38
4.4.1.2 Natural gas boilers . . . 40
Domestic boilers . . . 40
Non domestic boilers . . . 40
4.4.1.3 Heat pumps . . . 41
4.4.1.4 Biomass boilers . . . 42
4.4.2 Electricity prices and variations . . . 42
4.4.3 Consumer types and heat prices . . . 43
4.4.4 Carbon factors . . . 44
4.4.4.1 Fuel allocation to CHPs electricity output . . . 44
The Boiler Displacement Method . . . 44
The Power Station Displacement Method . . . 44
The DUKES displacement Method . . . 44
4.4.4.2 Dynamic grid electricity carbon factors . . . 45
4.4.4.3 Other factors . . . 46
4.4.5 Natural gas and biomass prices . . . 46
4.4.6 Storage modelling . . . 46

5 Pipes network extension **48**
5.1 Investments required for the spatial network expansion . . . 48
5.2 Estimation of the pumping costs required . . . 50

6 Results analysis **51**
6.1 Design of the energy centre . . . 51
6.1.1 Costs optimisation . . . 51
6.1.1.1 General overview . . . 51
6.1.1.2 Detailed costs analysis . . . 53
First version . . . 53
Second version . . . 55
Heuristic models . . . 58
Third version . . . 60
6.1.1.3 GHG emissions . . . 62
6.1.1.4 Surface required in each scenario . . . 63
6.1.1.5 Conclusion: costs optimisation - main differences and outcomes . . . 63
6.1.2 GHG emissions optimisation . . . 64
6.1.2.1 General overview . . . 64
6.1.2.2 Detailed GHG emissions analysis . . . 67
Second model - DUKES method . . . 67
Third model - DUKES method . . . 69
6.1.2.3 Costs associated with the models . . . 71
6.1.2.4 Surface required in each scenario . . . 73
6.1.2.5 Conclusion: GHG emissions minimisation - main differences and outcomes . . . 73
6.2 Network expansion . . . 74

7 Discussion **77**
7.1 Results discussion . . . 77
7.1.1 Energy centre design . . . 77
7.1.2 Spatial network expansion . . . 78
7.2 Methodology discussion . . . 78
7.2.1 Analysis of the demand . . . 79
7.2.2 Time modelling strategy . . . 79
7.2.3 Technology portfolio . . . 79

7.2.4 Spatial network expansion . . . 80

8 Conclusion **81**
8.1 Summary of the key findings . . . 81
8.2 Further work . . . 81
8.2.1 Optimisation of the spatial network expansion . . . 82
8.2.2 Combination of the scenarios using a stochastic approach . . . 82
8.2.3 Sensitivity analysis . . . 82

Bibliography **83**

Appendices **90**
A Buildings connected to the existing district heating network . . . 91
B Potential heat loads to be connected to the Barkantine district heating network . . . 92
C Methodology used to estimate the surface required by each technology . . . 94
D Generation of dynamic carbon factors . . . 96
E Estimation of thermal storage losses . . . 98
F Adjacency matrix built to estimate pipes investment and pumping costs . . . 100
G Heat production and storage capacities selected in models 1, 2, 3 and in the heuristic models . . . 101
H Heat production profiles obtained for Scenario 2 - Model 1 . . . 102
I Heat production profiles obtained in the second model . . . 103
J Heat production profiles obtained in the third model . . . 105
K Heat production and storage capacities selected in models 2B, 2T, 2P, 3B, 3P and 3T . . . 107
L Heat production profiles obtained in model 2T . . . 109
M Heat production profiles for scenario 1, model 3T . . . 111
N Costs associated with the network expansion . . . 113

List of Figures

2.1 Economical benefits of district heating networks 4
2.2 Final energy consumption by sector and end use in the UK, 2013 4
2.3 Trajectories for total domestic heat demand under four levels of change 4
2.4 Share of primary fuels used for district heating networks in the UK 4
2.5 Schematic representation of a district heating network with indirect space heating and hot water supply 6
2.6 Typical district heating network structures 8
2.7 Example of a ring network structure 8
2.8 Composition of heat and electricity demand variability across a year in the UK 9
2.9 Energy balance on a heated building 9
2.10 An example of heat mapping using a GIS system: the London Heat Map 10
2.11 Efficiency of a CHP plant compared to conventional heat and power generation 11
2.12 An example from topping and bottoming cycles 11
2.13 Example of integration of small-scale heat pumps in a DHN 12
2.14 Sizing of the heat source capacities 12
2.15 Typical mode of operation of conventional thermal stores 12
2.16 Optimisation techniques that can be used to solve DHN problems 16
2.17 Schematic representation of the DHNs modelling levels 17
2.18 Leading, matching and lagging approaches that may be used in capacity expansion problems 20
2.19 Isle of dogs location 21
2.20 London Heat Map, zoom on the Isle of dogs area 21
2.21 Schematic representation of the existing Barkantine district heating network 21

3.1 Methodology and data sources used to estimate heat demand and build connection scenarios 22
3.2 Targeted area for the DHN's expansion problem 23
3.3 Anchor heat loads identified in the area of interest 23
3.4 Spatial representation of the potential loads to be connected 23
3.5 Methodology and data sources used to generate hourly heat demand profiles: example of Gainsborough house 24
3.6 Spatial representation of the clusters 25
3.7 Heat demand - Scenario 1, with and without diversity 27
3.8 Heat demand - Scenario 2, with and without diversity 27

4.1 Optimisation model structure 28
4.2 CHPs power consumption as a function of their part load 39
4.3 CHPs electrical output as a function of their part load 39
4.4 Ammonia heat pumps COP as a function of the source temperature for a sink's temperature of 90 °C 41
4.5 Example of electricity import tariffs generated for weekdays using the Tariff Model 43
4.6 Example of electricity import tariffs generated for weekends using the Tariff Model 43
4.7 Dynamic electricity carbon factors used in the model 46
4.8 Natural gas prices used for the model based on DECC projections 46

5.1 Methodology applied to estimate spatial network investment costs 48
5.2 Pipes and nodes layout 49
5.3 Cost of laying out transmission pipes in a hard environment as a function of their diameter 49

6.1 Heat production capacity evolution for scenario 1 . . . 51
6.2 Heat production capacity evolution for scenario 2 . . . 52
6.3 Net Present Value obtained for each model and each scenario . . . 52
6.4 Yearly investment schedule - Scenarios 1 and 2, model 1 . . . 53
6.5 Heat production profiles - Scenario 1, model 1, day 1, years 2 and 5. . . . 54
6.6 Heat production profiles - Scenario 1, model 1, day 1, years 10 and 12. . . . 54
6.7 Heat production profiles - Scenario 1, model 1, day 18, years 2 and 5. . . . 55
6.8 Heat production profiles - Scenario 1, model 1, day 18, years 10 and 12. . . . 55
6.9 Yearly investment schedule - Scenarios 1 and 2, model 2 . . . 56
6.10 Heat production profiles - Scenario 1, model 2, day 1, years 2 and 5. . . . 57
6.11 Heat production profiles - Scenario 1, model 2, day 1, years 10 and 12. . . . 57
6.12 Heat production profile - Scenario 2, model 2, day 1, year 12 . . . 58
6.13 Yearly investment schedule - Scenarios 1 and 2, model 2 heuristic, leading approach . . . 59
6.14 Yearly investment schedule - Scenarios 1 and 2, model 2 heuristic, matching approach . . . 59
6.15 Yearly investment schedule - Scenarios 1 and 2, model 3 . . . 60
6.16 Heat production profiles - Scenario 2, model 3, day 1, years 2 and 5. . . . 61
6.17 Heat production profiles - Scenario 2, model 3, day 1, years 10 and 12. . . . 61
6.18 GHG emissions associated with each model and scenario. . . . 62
6.19 Surface required to install the technologies selected in each scenario . . . 63
6.20 Heat production capacity evolution for scenario 1 . . . 65
6.21 Heat production capacity evolution for scenario 2 . . . 65
6.22 GHG emissions obtained in each model . . . 66
6.23 Heat production profiles - Scenario 2, model 2T, day 1, years 2 and 5. . . . 68
6.24 Heat production profiles - Scenario 2, model 2T, day 1, years 10 and 12. . . . 68
6.25 Daily GHG emissions profiles - Scenario 2, model 2T. . . . 69
6.26 Heat production profiles - Scenario 2, model 3T, day 1, years 2 and 5. . . . 70
6.27 Heat production profiles - Scenario 2, model 3T, day 1, years 10 and 12. . . . 70
6.28 Daily GHG emissions profiles - Scenario 2, model 3T. . . . 71
6.29 Yearly investment schedule - Scenarios 1 and 2, model 2T . . . 71
6.30 Yearly investment schedule - Scenarios 1 and 2, model 3T . . . 72
6.31 Net Present Value obtained for each model and each scenario . . . 72
6.32 GHG emissions obtained in each model . . . 73
6.33 Investments required for the DHN spatial extension . . . 75
6.34 Yearly investment schedule including spatial expansion - Scenarios 1 and 2, model 3 . . . 75
6.35 Yearly investment schedule including spatial expansion - Scenarios 1 and 2, model 3T . . . 76

Appendices . . . 91
1 Loads connected to the existing network . . . 91
2 Potential nodes to be connected to the network . . . 93
3 Evolution of the floor area required by CHPs as a function of their heat output . . . 94
4 Evolution of the floor area required by biomass boilers as a function of their heat output . . . 94
5 Evolution of the floor area required by thermal stores as a function of their heat output . . . 95
6 Projected electricity carbon factors adjusted to 2016 . . . 96
7 Hourly ratios used to calculate electricity carbon factors averaged over the period 2009-2015 . . . 96
8 Monthly ratios used to calculate electricity carbon factors averaged over the period 2009-2015 . . . 96
9 Weekly ratios used to calculate electricity carbon factors averaged over the period 2009-2015 . . . 97
10 Dynamic electricity carbon factors used in the model . . . 97
11 Schematic representation of parameters used to estimate thermal storage heat losses . . . 98
12 Schematic representation of partial thermal storage losses . . . 98
13 Adjacency matrix built to estimate pipes investment and pumping costs . . . 100
14 Heat production profiles - Scenario 2, model 1, day 1, years 2 and 5 . . . 102
15 Heat production profiles - Scenario 2, model 1, day 1, years 10 and 12 . . . 102
16 Heat production profiles - Scenario 2, model 1, day 18, years 2 and 5 . . . 102
17 Heat production profiles - Scenario 2, model 1, day 18, years 10 and 12 . . . 103
18 Heat production profiles - Scenario 2, model 2, day 1, years 2 and 5 . . . 103
19 Heat production profiles - Scenario 2, model 2, day 1, years 10 and 12 . . . 103
20 Heat production profiles - Scenario 1, model 2, day 18, years 2 and 5 . . . 104

21 Heat production profiles - Scenario 1, model 2, day 18, years 10 and 12 . . . 104
22 Heat production profiles - Scenario 2, model 2, day 18, years 2 and 5 . . . 104
23 Heat production profiles - Scenario 2, model 2, day 18, years 10 and 12 . . . 104
24 Heat production profiles - Scenario 1, model 3, day 1, years 2 and 5 . . . 105
25 Heat production profiles - Scenario 1, model 3, day 1, years 10 and 12 . . . 105
26 Heat production profiles - Scenario 2, model 3, day 18, years 2 and 5 . . . 105
27 Heat production profiles - Scenario 2, model 3, day 18, years 10 and 12 . . . 106
28 Heat production profiles - Scenario 1, model 3, day 18, years 2 and 5 . . . 106
29 Heat production profiles - Scenario 1, model 3, day 18, years 2 and 5 . . . 106
30 Heat production profiles - Scenario 1, model 2T, day 1, years 2 and 5 . . . 109
31 Heat production profiles - Scenario 1, model 2T, day 1, years 10 and 12 . . . 109
32 Heat production profiles - Scenario 2, model 2T, day 18, years 2 and 5 . . . 109
33 Heat production profiles - Scenario 2, model 2T, day 18, years 10 and 12 . . . 110
34 Heat production profiles - Scenario 1, model 2T, day 18, years 2 and 5 . . . 110
35 Heat production profiles - Scenario 1, model 2T, day 18, years 10 and 12 . . . 110
36 Heat production profiles - Scenario 1, model 3T, day 1, years 2 and 5 . . . 111
37 Heat production profiles - Scenario 1, model 3T, day 1, years 10 and 12 . . . 111
38 Heat production profiles - Scenario 2, model 3T, day 18, years 2 and 5 . . . 111
39 Heat production profiles - Scenario 2, model 3T, day 18, years 10 and 12 . . . 112
40 Heat production profiles - Scenario 1, model 3T, day 18, years 2 and 5 . . . 112
41 Heat production profiles - Scenario 1, model 3T, day 18, years 10 and 12 . . . 112
42 Annualised connection costs per cluster for various pipes diameters . . . 113
43 Annual pumping costs required per cluster for various pipes diameters . . . 113

List of Tables

2.1 Typical operating modes in a DHN . . . 13

3.1 Repartition of the loads of interest into clusters . . . 25
3.2 Clusters connection order considered for scenarios 1 and 2 . . . 27

4.1 Sets used in the model . . . 29
4.2 Technical parameters used in the model . . . 30
4.3 Economic parameters used in the model . . . 31
4.4 Binary variables used in the model . . . 31
4.5 Other variables used in the model . . . 32
4.6 Hypothesis used to model CHPs I . . . 39
4.7 Hypothesis used to model CHPs II . . . 40
4.8 Hypothesis used to model domestic boilers . . . 40
4.9 Hypothesis used to model non domestic boilers . . . 40
4.10 Hypothesis used to model heat pumps . . . 41
4.11 Hypothesis used to model non domestic boilers . . . 42
4.12 Factors considered in the Electricity Tariffs Model . . . 42
4.13 Heat prices and customers share of the demand considered . . . 44
4.14 Displacement coefficients used in the model . . . 45
4.15 Assumptions used to model storage . . . 47

5.1 Assumptions used to estimate additional pumping costs required by the network expansion . . . 50

6.1 Costs optimisation: summary of the main outcomes . . . 64
6.2 GHG emissions minimisation: summary of the main outcomes . . . 74

Appendices . . . 91
1 Characteristics of the loads connected to the existing Barkantine's DHN . . . 91
2 Characteristics of the potential loads to be connected to the Barkantine's DHN . . . 92
3 Technologies selected by the optimisation program in the first scenario (model 1 and 2) . . . 101
4 Technologies selected by the optimisation program in the second scenario (model 1 and 2) . . . 101
5 Technologies selected by the third optimisation program for both scenarios . . . 101
6 Technologies selected by the optimisation program in the first scenario (models 2B, 2P and 2T) . . . 107
7 Technologies selected by the optimisation program in the second scenario (models 2B, 2P and 2T) . . . 107
8 Technologies selected by the optimisation program in the first scenario (models 3B, 3P and 3T) . . . 107
9 Technologies selected by the optimisation program in the second scenario (models 3B, 3P and 3T) . . . 108

List of Abbreviations

BB	Branch-and-Bound
CHP	Combined Heat and Power
DECC	Department of Energy and Climate Change
DH	District Heating
DHC	District Heating and Cooling
DHN	District Heating Network
DHS	District Heating System
DHW	Domestic Hot Water
DNO	Distribution Network Operator
DUKES	Digest of United Kingdom Energy Statistics
GAMS	General Algebraic Modeling System
GHG	Greenhouse Gas
GIS	Geographic Information System
GLA	Greater London Authority
IDE	Integrated Development Environment
LCA	Life Cycle Analysis
LHV	Lower Heating Value
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer NonLinear Programming
MIP	Mixed Integer Programming
NLP	NonLinear Program
OA	Outer Approximation
QGIS	Quantum Geographic Information System
RHI	Renewable Heat Incentive

Chapter 1

Introduction

Growing concern about climate change as well as the continuous increase of greenhouse gas emissions led nations to consider global warming and to assume the responsibility of limiting its effects. If renewable energies and recent technologies have widely been promoted as a way to tackle climate change issues, some well-established processes can also be part of the solution. In providing heat generated in a centralised location to a set of consumers, district heating (DH) helps improving the energy efficiency of urban areas, hence contributes to their sustainable development. District heating networks (DHN) have been used for decades in the Northern hemisphere, especially in Europe, North America and Japan. Originally using boilers as a main heat source, DHNs are today mainly based on combined heat and power (CHP) plants but can be used with a large variety of energy sources, adding flexibility to the system. DHNs have recently received political support from the European Union and the UK, and there is a global trend towards the acceleration of DH expansion.

If some British local authorities currently investigate the possibility of installing new district heating networks, several existing schemes already plan to expand. This is the case of the Barkantine district heating network, operated by EDF Energy in the Isle of Dogs, London.

1.1 Imperial College - EDF Energy partnership

EDF Energy is one of the UK's major energy companies and a big producer of low-carbon electricity. Providing electricity to more than 5.5 millions homes in the UK [1], EDF Energy owns and operates a large portfolio of power production plants including nuclear power plants, gas plants, coal plants, onshore and offshore wind farms [2]. EDF Energy has also a technical expertise in smart energy supply, microgeneration and storage, electric mobility, CHP optimisation and heat networks.

In this context, the EDF FlexiFund, a collaboration between the Imperial College London and EDF Energy, was launched in 2015. This partnership aims to develop short-term exploratory projects in areas of common interest to both the Imperial College and EDF Energy. Several projects led by the Imperial College Centre for Process Systems Engineering or the Imperial College Department of Chemical Engineering have already been funded by the EDF FlexiFund. Work under the partnership continues to be carried on, involving research in multi-disciplinary studies ranging from energy market regulations to transports or buildings.

1.2 Project: scope, purpose and focus

Developing or expanding a district heating network requires a good implementation strategy to deal with the economical and environmental impacts associated with DH. If building a new DHN involves a deep understanding of the networks physics and a good planning, design and operation strategy, expanding a network is even more challenging. Indeed, expanding a network requires to take into account the existing network specifications as well as to target a good expansion strategy with a proper time horizon. In fact, having a good investment and expansion schedule enables to generate an optimal profit while ensuring a reduction of Greenhouse Gas (GHG) emissions.

In such circumstances, the project will have to answer to the following questions:

- In the Barkantine area context, how can we model the marginal extension of an existing district heating network?
- Focusing on the energy centre design, is there an optimal expansion strategy to adopt in order to maximise the network's economical profit or decrease its environmental impact?
- In parallel to the capacity expansion, which operating strategy for the technologies selected can help achieving the same goals?
- What are the potential economical and environmental benefits of expanding the existing network compared to the current situation in the area?

Since DHN expansion has not been widely studied or experienced, the project will have to provide above all a systematic approach for district heating expansion, especially for the design of the energy centre. The Barkantine area will rather be a case study for the methodology developed.

1.3 Thesis organisation

After providing sufficient background about DH and DH expansion to the reader as well as an overview of the project (**Chapter 2**), the methodology used to estimate the heat demand and establish connection scenarios will be detailed (**Chapter 3**). **Chapter 4** will describe in depth the optimisation model developed to design and operate the energy centre along with the input data and assumptions used. The model variants will also be presented in this chapter. **Chapter 5** will focus on the network connection costs and pumping costs required for the extension, detailing the approach used to estimate them. The models results will then be presented and analysed in detail (**Chapter 6**). The connection and pumping costs associated with the spatial network expansion will also be analysed. The next chapter will provide a discussion of the results obtained as well as a discussion regarding several elements of the methodology (**Chapter 7**). The final chapter will conclude the thesis by summarising the project key findings and presenting opportunities for future work (**Chapter 8**).

Chapter 2

Background and literature review

2.1 Strategic importance of district heating

As explained by Frederiksen and Werner, the main idea of district heating is to provide an energy service based on moving heat from available sources to an immediate use by customers [3]. The main driving forces for DH are found in the synergies that result from the connection of the demand with locally available heat sources, especially with heat resources that would otherwise be wasted.

2.1.1 Benefits of district heating

District heating presents significant advantages. From an economic point of view, having a joint production process, a higher conversion efficiency and less maintenance helps decreasing the costs associated to heat production and addresses fuel poverty problems. For customers, this means lower investment costs for their heating equipment and a simple, continuous, reliable and direct heat delivery. Moreover, more space is available in buildings since domestic boilers are not needed any more. In addition, property and liability insurance costs decrease since district heating is safer than classical domestic boilers [3, 4]. DH is particularly well-suited for areas of mixed use with strong anchor clients [5].
Thus, a variety of energy sources can be used for DH. This increases the flexibility of the energy system, and decreases the dependency to primary energy and fossil fuels by displacing combustion of natural gas in domestic boilers [6]. The higher security of supply comes further with additional environmental benefits, since centralised processes have higher efficiencies and make carbon capture easier to accomplish. Furthermore, pollutants are not emitted in customers houses any more, since domestic boilers are removed from people's houses. In addition to these benefits, district heating, helping the deployment of CHP plants, has the potential to reduce the pressure on electrical network infrastructure and to offset additional electrical peaking plants.

Despite all these advantages, DH is often seen as a monopoly that captures customers in an energy system that is difficult to leave, although some efforts have been put on developing voluntary customer protection schemes like the Heat trust [7]. More regulation is also needed in terms of developer rights and financing costs [5]. On a technical point of view, district heating systems (DHS) failures intensify the risk of coordinated damages. These drawbacks can be a barrier to exploit DHN's advantages [3]. On the other hand, as buildings insulation becomes more efficient, domestic heating requirements are reduced, which decreases the DH competitiveness [8, 9].

2.1.2 Heat use in the UK and in the EU

District heating networks are well-known systems and have been used for decades, especially in the Northern hemisphere and in Europe. For example, early hot water systems were built in Saint Petersburg from the 1840s [4]. Indeed the total heat demand for residential and service sector buildings amounts to around 11.7 EJ per year in the EU27 [10]. The energy used for heating and cooling in buildings and industry accounts for approximately 50% of the EU's annual energy consumption. Furthermore, the amount of heat wasted by industrial processes could be sufficient to cover the EU's entire heating needs. Natural gas remains the largest primary heating and cooling source in Europe (46%) [3, 11]. Currently district heating represents 12 % of EU27 heat supply, with Sweden, Denmark and Finland being the leading countries (respectively 61%, 53% and 49% of their heat supply) [3].

In the UK, the total heat demand corresponds to 2.56 EJ per year and accounts for 48 % of the final energy consumption in the country. It even reaches 78 % of the final energy consumption if the transport sector is not considered [12, 13]. 58 % of this heat is consumed in the domestic sector (see also Figure 2.2). Heat demand's future evolution is difficult to forecast. Thus, depending on the average outdoor temperature evolution, on the buildings level of insulation and on the hot water demand evolution, various scenarios can be established. Depending on the circumstances and improvements (thermal efficiency, buildings insulation), heat demand could either increase or decrease. In any case, massive amounts of space heating and hot water will still be needed in the future.

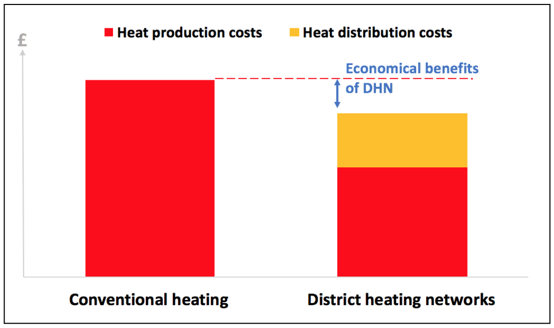


Figure 2.1 – Economical benefits of district heating networks (adapted from [3]).

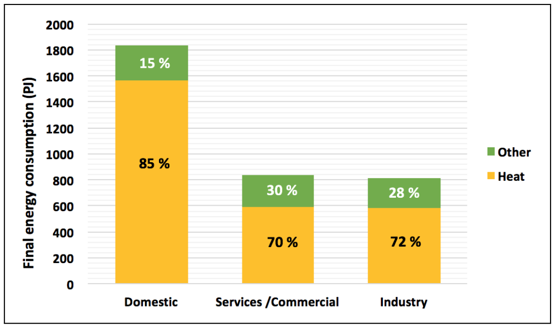


Figure 2.2 – Final energy consumption by sector and end use in the UK, 2013 (adapted from [12]).

There are currently 1765 DHNs in the UK. A majority of them was built before the 1990s and 55 % of them are located in London (mostly small networks, with less than 100 residential properties and/or less than 3 non-domestic users). As for Europe, gas is predominantly used as the primary fuel source in UK networks (see also Figure 2.4) [14].

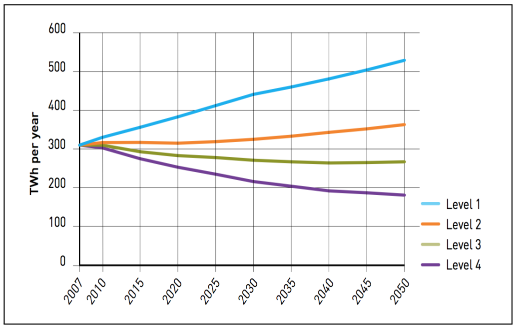


Figure 2.3 – Trajectories for total domestic heat demand under four levels of change (Level 1 corresponds to an increase of the internal average temperature + buildings thermal efficiency + hot water demand while level 4 considers a decrease of the internal average temperature + domestic hot water consumption, and an increase of buildings thermal efficiency) [15].

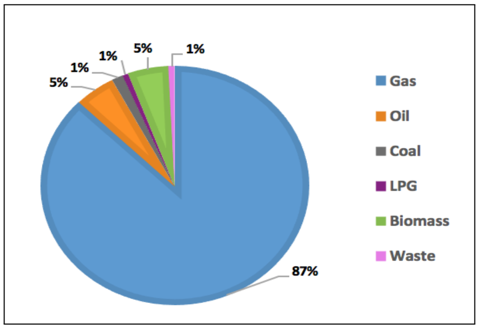


Figure 2.4 – Share of primary fuels used for district heating networks in the UK (adapted from [14], based on available data).

2.1.3 Strategic importance of district heating and future targets

District heating networks are already well established in the Northern hemisphere, and often based on old and well-known technologies like CHPs. Since global warming has been on the worldwide agenda for over 20 years and since many nations have set emission reduction targets, DH seems to be an appropriate solution.

Indeed, promoting district heating and cogeneration is part of the European Energy Efficiency directive, that gives some guidance to assess DH potential in Europe [16]. The Energy Roadmap 2050, document produced by the Aalborg and Halmstadt universities for the European Commission, highlights the potential of DH in the EU27. It identifies strategic heat synergy regions characterised by a large usable excess heat [10, 17]. A wide scale implementation of DH, where it is competitive, would help Europe reducing its greenhouse gases emissions to 80% below

1990 levels by 2050 and achieving its Energy Strategy target [18].

From a national perspective, UK has committed to reduce its emissions by at least 80% in 2050 from 1990 levels [19]. In this context, the Department of Energy and Climate Change (DECC) actively promotes DH, as part of its district heating strategy.This strategy encompasses building efficiency measures, development of DH and industrial transformations in order to avoid too much waste heat [13, 20, 21]. However, DHNs remain expensive: £150/MWh and £25-624/MWh, respectively for average annual network installation costs and average annual connection costs, and £1000/m for buried pipes installation [22]. To support DH, hence to promote a lower-carbon future, several mechanisms and financial schemes have been implemented to make district heating and the associated technologies cheaper to invest in:

- The Heat Networks Delivery Unit (HNDU), that was set up in 2013, provides support (grant funding and guidance) to local authorities to progress HN projects development stages [23]. 201 heat projects across 118 authorities are currently supported by the HNDU initiative.
- The non domestic Renewable Heat Incentive (RHI) helps offsetting the costs associated with the installation and operation of a renewable heating system (quarterly tariff payment for every kilowatt hour produced, for seven years) [24]. Technologies like biomass boilers, heat pumps or solar panels are for example subsidised.
- On a more technological aspect, Quality Assurance for Combined Heat and Power (CHPQA Standard) is a certification used to determine the eligibility of specific CHPs for financial schemes, like Renewable Obligations (RO). In addition, Feed-in Tariffs (FIT) promote the use of very small scale renewable electricity generation technologies, like micro-CHPs.

CHP plants are indeed essential for the economical viability of DHNs, since their electricity can be sold to the grid with variable prices. Furthermore, big CHPs can participate to different balancing mechanisms [25]:

- The STOR mechanism is used to retain spare generation capacity on stand-by during certain hours of the day. This spare capacity balances demand forecast errors, unexpected losses of thermal generation and variable wind generation. Generation providers can be either committed or flexible but must be able to deliver at least 3 MW of reserve.
- Fast reserve is used to control the frequency changes following sudden or unpredictable changes in demand or generation. Fast reserve providers (optional or firm service) operate quicker than STOR providers. Fast reserve requires at least 50 MW capacity.
- Frequency response is an automatic mechanism providing demand reduction or increased generation consecutive to a drop in system frequency. Frequency response involves different services provided by demand side participants and generation plants (Frequency control demand management, firm frequency response...).

In addition, CHP plants can be part of the Capacity Market mechanism. Introduced by the Electricity Market Reform in 2013, the Capacity Market has the purpose to deliver generation adequacy. Capacity providers, committed to deliver energy in times of system stress, receive a capacity payment revenue stream in return. If they fail to deliver, they expose themselves to penalties [25]. Depending on the CHP plant's power to heat ratio (see also 2.4), participating to these mechanisms ensures regular income, hence make DHNs more viable.

Finally, from a local perspective, London's response to climate change (2011) involves supporting the connection to existing heating and cooling networks, promoting site wide CHP networks, communal heating and cooling [26]. Indeed London aims achieving 60 % reduction of its emissions in 2025, based on 1990 levels, and 25 % decentralised energy production in 2025 [27]. The Greater London Authority (GLA) has moreover published in 2014 its London Heat Network Manual to provide some guidance to develop DHNs. It covers at the same time technical, economical and administrative aspects [6]. Thus, several London Boroughs have already successfully implemented DHNs. Some of them even plan to expand like Islington or Bunhill-Shoreditch [28–30]. Other boroughs plan to build decentralised energy networks and have already published masterplanning studies like Redbridge [31].

2.2 Overview of district heating networks

District heating networks are already well-established, based on proven technologies and have been used for decades in the Northern hemisphere. They have their own characteristics and even their own physics. A better understanding of these networks involves as well the concepts associated with heat demand and heat demand mapping. While the first generation of DHNs was using steam as heat carrier, later generation networks mostly use hot water [3, 4].

2.2.1 What is a District Heating Network ?

Although DHNs present multiple geometries, technologies and characteristics, they typically have two major components (see also Figure 2.5):

- One heat centre consisting of one or several heat sources that balance the heat demand and provide backup/peak supply.
- A spatial heat transmission and distribution network comprising:
  - A primary network that transports and distributes hot water from the heat generation plant to the substations (mostly customers substations).
  - Substations connecting the primary and the secondary network.
  - A secondary network transporting water to the end user (mainly located in buildings or houses).

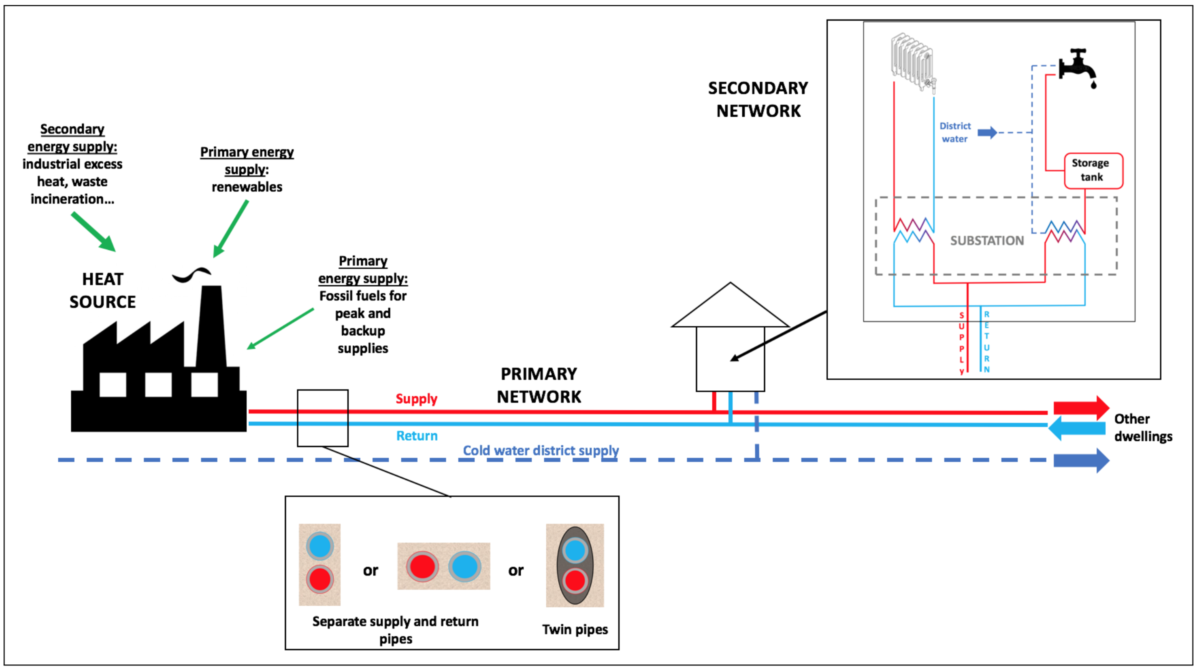


Figure 2.5 – Schematic representation of a district heating network with indirect space heating and hot water supply (adapted from [3, 6, 32, 33]).

More specifically, within the energy centre, there is a distinction within between primary and secondary heat sources [3, 8]:

- Secondary heat supply corresponds to the excess heat that can be injected into the network (CHP, waste incineration...).
- Primary heat supply is the heat specifically produced for district heating, like renewable heat (geothermal, solar heat, biomass...) or heat based on fossil fuels for peak and backup supply.

DHN's key component is the primary network that transports and distributes hot water. It has to be carefully designed to minimise the system's heat losses while ensuring a relatively low cost operation (see also 2.4 for a detailed explanation of the system design and operation trade-offs). The primary network comprises [3, 6]:

- Pipes: two pipes, a supply pipe and a return pipe, are usually buried in the ground. Some old networks were only using a supply pipe while other networks can use three pipes (an additional recirculation pipe) for low energy applications [33]. Their diameter may reach 1 m. Whereas rigid steel pipes are frequently used, flexible polymer pipes with smaller diameters are easier to install and less expensive [3]. Pipes design is mainly stress-based to avoid fatigue and rupture problems. Heat losses in the network can be partly reduced by pipes insulation. Polyurethane foams are commonly used for this purpose. Since there is no linear dependency between pipes diameter and the insulation jacket thickness, the insulation thickness (hence the losses) has to be balanced against pipes costs. Locating both pipes within a common circular insulation with an outer casing (twin pipes) can also decrease the losses. It facilitates heat transfers from the supply pipe to the return pipe, hence reuses heat losses from the supply pipe to warm the return water.

- Distribution pumps distribute heat through the network. These pumps are usually controlled for variable flow rates using variable speed drives. Since the network is unable to operate without them, several distribution pumps can be installed in parallel and run simultaneously. Back up pumping capacity is often installed.
- Pressurization pumps are used to maintain a sufficient amount of water within the system by controlling its pressure. They are also used to prevent water from boiling. They are often linked to expansion tanks allowing removal of excess water from the system.
- Valves are used for flow regulation and/or isolation.
- Joints (welded joints are often considered to be the most robust ones).
- A water treatment station is used to stabilise the pH and water's hardness. In purifying water (with reverse osmosis, ion exchanger units, thermal daerators...), risks of corrosion, bacteria or metering accuracy problems can be prevented. DH water is usually softened or demineralised water, with a pH of 9-10. Water quality is essential to maintain the design's lifespan of the heat network.
- A leakage and breakage monitoring control: Usually installed during the pipes' pre-insulation, leakages wires are connected to a control box (usually at the energy centre). They enable to detect any leakage when the circuit resistance is modified.
- Thermal storage (optional): storage tanks can be installed alongside the circuit. They may be used to balance quasi-instantaneously demand peaks.

A substation is a unit in which the temperature (and pressure) of the primary network is lowered. Substations usually separate the district heating side from the consumer side (house or building). They facilitate maintenance in the primary network, especially in case of disturbances. In addition, since their fabrication is mostly standardised, these equipments are less expensive. A distinction can be made between area substations and house/building/apartment substations. Multiplying the number of consecutive substations increases the level of security but lowers the heat transfer efficiency [3, 6, 32]. Key elements of substations are:

- Heat exchangers (mostly plate heat exchangers).
- Mixing equipment performing the temperature and pressure lowering.
- Control valves (mechanical or motorised) that prevent an unwanted continuous on-off behaviour. To decrease pressure losses, they may be replaced by inverter-controlled heat pumps. [34, 35].
- Control equipment (optional) to limit the heat power or mass flow rate.
- Hot water storage tanks.

Multiple layouts can be found for substations. An essential distinction has to be made between indirect connections (hydraulic separation between the primary and the secondary network) and direct connections (individual consumers separated from the primary network by a small heat interface unit). Within substations, space heating can be decoupled from hot water preparation (direct and/or indirect connection), the latter being prepared either instantaneously in heat exchangers or in storage tanks. Cascading of heat transfer in substations can also be used to improve the temperature performance [3, 4, 6, 32].

Finally, the secondary network transports hot water to the end user (radiators, tap water).

DHNs present typical layouts/network structures. At an early stage of development, tree network designs with a central heat plant are often found. With the network's development, additional peripheral heat plants/backup plants may appear and the network evolves towards an integrated network with a meshed structure [3]. Laajalehto et al. have investigated a new control system and a new network design called "Ring network". Without requiring major changes in the urban planning, the ring design makes the system easier to control and reliable, and reduces the total heat consumption [34, 35]. Indeed in case of a network failure, ring networks ensure a continuous heat supply since hot water has more than one way to reach customers houses [30].

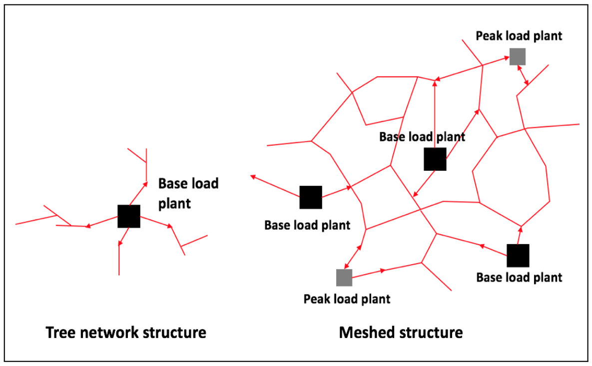


Figure 2.6 – Typical district heating network structures (adapted from [3]).

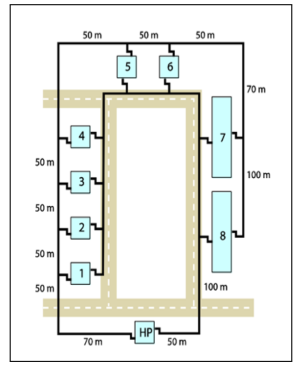


Figure 2.7 – Example of a ring network structure [34, 35].

One must consider that DHNs are an interesting option for dense urban areas with mixed customers, since transmission costs remain high [9, 36]. DHSs can be profitable in sparse areas if the heat density is greater than 2 GJ.m^{-1} and the annual heat demand is at least 50 GJ per house. These values remain however highly dependent on the country and on the policies implemented to support DH [37].

2.2.2 Heat demand and heat demand mapping

In order to be competitive, district heating costs need to remain lower than any other heat supply alternative for customers [9]. This is why, accurate heat demand estimation is essential to precisely evaluate the costs required by a DHN's installation. The aggregate heat load (load that will need to be met by the heat supply units) needs to be precisely determined [3]. For this reason, heat demand estimation is the first task to be completed in any DH project [38].
However, estimating the heat demand differs from estimating the electricity demand, since heat requirements vary throughout the year depending on the weather and the outdoor temperature (see also Figure 8) [3, 39]. Moreover, consumers habits and their heat requirements (desired temperature) affect the heat demand. Buildings quality of insulation influences the heat demand as well. Consequently, heat demand estimation depends on:

- Seasonal variations: Winter days are colder than Summer days, thus space heating requirements are higher in Winter.
- Weather variations: Solar gains, wind chill and transient heat demand resulting from the delay between an outdoor temperature change and the temperature change within the building affect the heat load composition, hence the heat demand (see also Figure 9).
- Daily variations: Heat demand is related to the quality of buildings insulation and to the desired indoor space temperature. In addition, buildings level of occupancy varies, depending on their activity, which influences the heat demand. For example, a residential building will have a higher demand in the morning and in the evening during weekdays (when the end-users are at home). A typical service sector building (public office) will have a high heat demand during weekdays, with a peak demand around the opening time in the morning. By contrast, a hospital will have a flatter demand and there will be almost no difference between the weekdays and the weekend, since the building's occupancy remains stable. This is why, it is possible to find typical heat demand patterns for specific building types.

All these variations and various levels of buildings insulation make the heat demand very specific for each building and time period. Consequently, a very good resolution is needed to estimate the heat demand with available data. Whereas a rough estimation of the electricity demand is always possible with annual figures, heat demand estimation requires a lot more data.

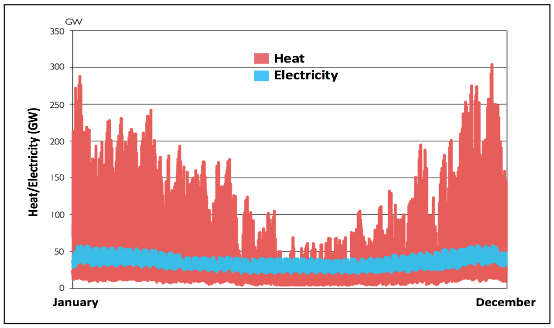


Figure 2.8 – Composition of heat and electricity demand variability across a year in the UK (domestic and commercial), 2010 [13].

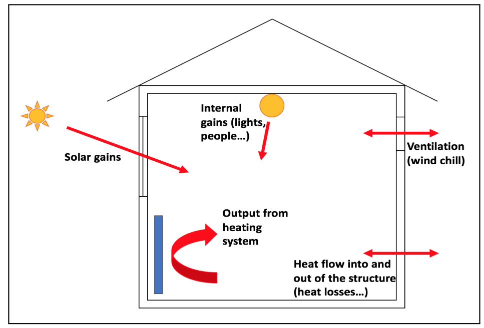


Figure 2.9 – Energy balance on a heated building (adapted from [3, 39]).

Estimating the heat demand as part of a DHN's installation requires to take into account the various buildings interactions. In this context, it is important to consider the buildings diversity factor (i.e. the synergies that results from customers not having their peak capacity demand at the same moment [3]). Having a high diversity factor is beneficial in a collective system because the peak capacity required (hence the investment costs associated) will be smaller. Diversity synergy effects are often quantified by the coincidence factor. The capacity factor (ratio between the average capacity demand and the maximum capacity demand) is another useful metric to shape the heat demand and size the heat sources capacity.

Heat load estimations can be obtained by extrapolating the existing heat load measurements (bills), which is very useful in case of existing buildings. However, these data are not always accessible (e.g. when the buildings are not built yet) and another method is needed to accurately evaluate the heat demand. The degree-day method is particularly powerful since it requires only a reduced number of inputs, which are easily accessible and have a high time resolution (outdoor temperature for a specific location, weather conditions...). Indeed, the method assumes that the incidental gains (solar gains, wind chill...) can be averaged out over time to give some representative indoor temperature that can be related to the heating system contribution [39]. The concept of degree-days is mostly reliable for long periods of time, large aggregated heat quantities and typical average buildings [3]. It is also possible to estimate the aggregated heat demand using pre-defined consumer archetypes. Knowing few parameters like a given building type, its floor area or its annual heat consumption is for example sufficient to deduce hourly heat consumption profiles with such archetypes [40].
The aggregated heat demand's estimation is specifically useful to establish load duration curves and size the heat unit plants (see also 2.4).

Since DHNs are spatially widespread, and since distribution costs dominate heat network costs, other metrics are needed to take into account the HN's geographic component. One of the metrics that has a high influence on the heat network costs is the linear heat density $\frac{Q_s}{L}$ (ratio of the annual heat delivered to the network length [3]). If this metric is really useful in case of an existing DHN, it is difficult to define in case of a network planned in a new area. In addition, Persson and Werner highlight the fact that this quantity can lead to a risk of overestimating the investment costs in case of low heat density areas [32, 41]. To better assess heat networks costs in areas of future deployment, they suggest to introduce new metrics: the effective width w (ratio of the available area and pipe network length), the specific heat demand q (estimations on total heat demand and total building space area) and the plot ratio e (total building space area share of total land area; has specific values for given zones like inner city area, parks...). They reformulate the linear heat density as $\frac{Q_s}{L} = w \times q \times e$. If the effective width formulation proves to be successful for high plot ratio areas, it needs however to be reformulated with corrective equations for low plot ratio areas.

Finally, with the development of geographic information systems (GIS), it is really helpful to visualise heat demands and possible networks locations on geographical maps. Indeed GIS-based analysis with a high spatial resolution are particularly relevant in case of studies assessing the heat demand / HN potential at a national and even international scale [42]. GIS-based methods are notably useful for heat mapping and heat supply planning based on public data registers. They have been particularly investigated in Danish studies [43, 44]. The London heat map is an example of heat mapping using an interactive GIS system [45].

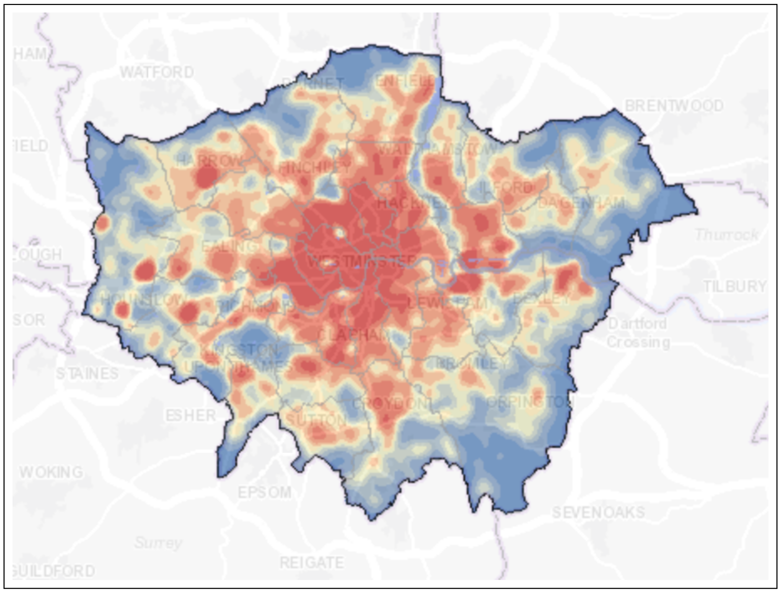


Figure 2.10 – An example of heat mapping using a GIS system: the London Heat Map [45].

GIS systems appear to be an indispensable tool for the development of 4^{th} generation DHNs [46]. Their utilisation is also highly valuable to study the potential expansion of existing DHNs (see also 4.1) [47, 48].

2.2.3 Heat production and storage

As explained in 2.2.1, primary and secondary heat sources can be used in a DHN. Indeed, a wide range of technologies can produce heat [8]. Because of its availability and its low cost, natural gas is a common fuel in thermal networks. CHP plants and geothermal sources / heat pumps are already widely used in the existing DHNs [3].

CHP plants can be used for district heating as well as to serve an industrial plant. These plants recuperate low grade heat and use it to provide high grade heat which is suitable for DHN (110-120°C). Indeed the DHS is a large heat sink for the cooling water in the CHP plant power production process. Connecting such a plant to a DHN can increase the CHP plant overall efficiency [32, 49]. Assessing the performance of a CHP plant is difficult since heat and power have not the same quality (exergy). This is why, various efficiency definitions can be found (overall efficiency, heat to power ratio, Fuel Energy Saving Ratio... [3]). For cogeneration plants, it is important to make a distinction between [32]:

- Topping cycles where exhaust gases can be directly used for process heating or district heating.
- Bottoming cycles where the exhaust heat has been recuperated to produce more electricity before being reused for heating purposes.

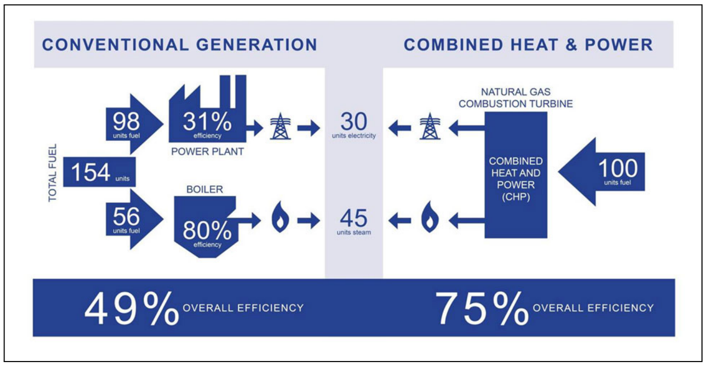


Figure 2.11 – Efficiency of a CHP plant compared to conventional heat and power generation [1].

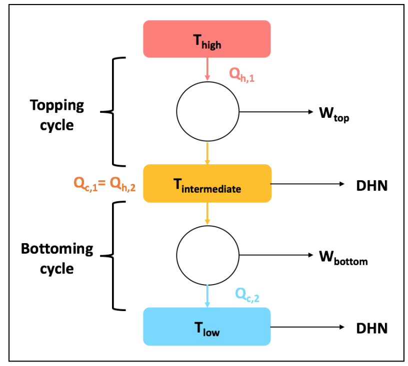


Figure 2.12 – An example from topping and bottoming cycles (adapted from [8]).

CHP technologies differ in:

- their prime mover (used to produce electricity): steam turbines, diesel engines, fuel cells, combustion engines, organic Rankine cycles... may be used. Most CHP plants use steam turbines as prime mover.
- their installed capacity.
- their fuel type (naural gas, biogas, biomethane, hydrogen, liquid fuels...).
- their electrical and their overall efficiency (for example, steam turbines will have an electrical efficiency of 7-20 % compared to 35-45 % for diesel engines [50]).
- their part load performance which indicates whether a CHP will have a good efficiency by producing small heat quantities (compared to their nominal heat output) or not. For example steam turbines will have poor part load performances whereas spark ignition engines will have a good part load performance [50].
- their working temperature.
- their heat to power ratio (0.1-0.5 for steam turbines, up to 2.13 for fuel cells [50]).

When CHP plants are only used for DH, the electricity produced can be sold with variable prices to the grid [3]. This is mostly the electricity sold that makes DH viable. Consequently, the operation of CHP plants is essential to the competitiveness of DHNs (see also 2.1.3).

Since heat pumps have the ability to integrate intermittent sources of electricity (especially in case of surplus electricity production), they are often included as part of future energy scenarios analyses like in Denmark [51] or in the UK [13, 20]. Heat pumps are used to move heat from a low-temperature location to a warmer location. They usually convert heat to a higher temperature heat through a closed process. A distinction can be made between compressor heat pumps (using electricity) and absorption heat pumps (using steam, hot water or flue gas)[52].
As explained in [53], ground sources and water sources centralised heat pumps are mainly used for district heating. While providing a large fraction of the heating, these heat pumps often operate with a lower source-sink temperature difference, which leads to an increased efficiency. Large heat pumps have a capacity that ranges from 100 kW to 1 MW [52, 53]. It is possible to connect several heat pumps in series, which can be beneficial in terms of flexibility and efficiency. A large variety of heat sources can be used to operate them, including low-temperature industrial excess heat, supermarkets, waste water, drinking and usage water, ground water, rivers, lakes or sea water [51]. Heat pumps may also differ by their refrigerant (ammonia, R134a, R407c... [40]). It is also possible to find gas driven heat pumps used for heating, cooling and hot water production [54]. Whereas gas engine heat pumps and gas absorption heat pumps are mature technologies and already in use in the commercial sector, adsorption heat pumps are still in development. The competitiveness of gas driven heat pumps will be highly dependent on the evolution of gas and electricity prices [54]. Despite these advantages, heat pumps in district heating schemes are associated with higher costs than the typical gas-based district heating schemes [53].

On a building scale, small-scale heat pumps can be used to increase the primary supply water temperature [3, 55]. Indeed, small-scale heat pumps alone can not always provide all the heating required, especially in Winter, but they can be complementary to the existing network.

1. Source: `https://facm.umn.edu/sites/facm.umn.edu/files/efficiency-graphic.jpg`

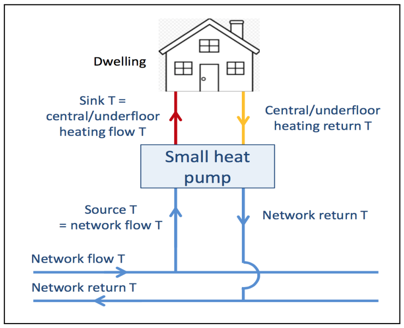


Figure 2.13 – Example of integration of small-scale heat pumps in a DHN [56].

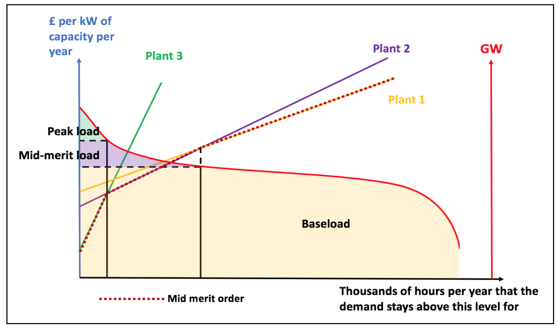


Figure 2.14 – Sizing of the heat source capacities (adapted from [3]).

In addition to CHP plants and heat pumps, other heat sources can be used within a DHN: excess heat from industrial plants, fuel-based or electric boilers and solid fuel combustion (which are often used as peak/backup capacity, since their efficiency reaches easily 90%), geothermal sources, waste-to-energy plants, PV panels, solar thermal technologies, urban wind [3, 4, 8].

Heat sources sizing relies on the establishment of the load duration curve, representing the annual aggregated heat demand in the descending order (see also part 2.3). Since heat sources have variable capacities and utilisation costs, the installations sizing needs to ensure that the selected heat sources will give the lowest system's costs. These sources need exactly to be operated for the number of hours for which they are the lowest-cost option. For this purpose, the mid-merit order curve and its intersection with the load duration curve can be used. It can thus be determined which plant is going to be used for the baseload, and which are the other plants that will be used for mid-merit and peak load (see also Figure 14 [3]).

Thermal storage can be used as a complementary option to heat production sources. As storage can be used to replicate instantaneously the peak demand on the supply side, thermal stores help decreasing the required heat production plant capacity [6]. In addition, they can allow these plants to run continuously (see also Figure 2.15). If the storage facility is well designed, benefits of storing heat overcome heat losses associated with the storage. However, thermal storage should be used preferably in case of low-carbon or low-cost heat production, which is more profitable [3]. Short-term storage (daily and rarely weekly) with atmospheric pressure or pressurised steel tanks is a well-established and commonly used technology, inter-seasonal heat storage being still in development [3, 57]. Thermal storage can be centralised or decentralised, more flexibility being given to a system using centralised storage [58]. To some extent, the network itself can provide some short-term storage capacity. Thermal storage appears to be an indispensable component of 4^{th} generation DHNs [46].

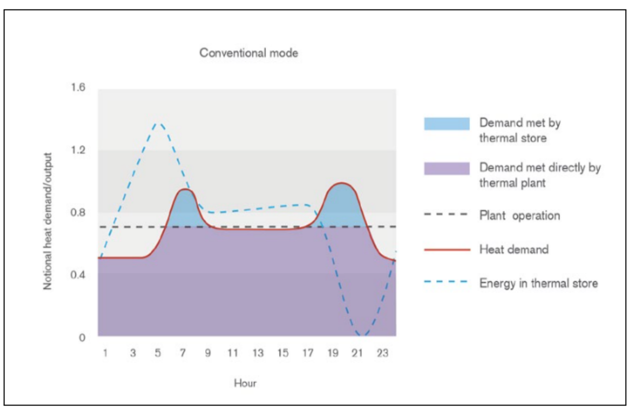


Figure 2.15 – Typical mode of operation of conventional thermal stores [6].

2.2.4 Design and operating parameters

As explained in the London Heat Network Manual, a properly designed DHN has to meet consumers demand at all times. It has to provide hot water with a sufficient temperature, minimum heat losses and a sufficient mass flow rate. The pressure has to be high enough to avoid water boiling. The operating parameters selection needs to allow the system to run for its designed lifespan [6]. More specifically, to make the system competitive, it is essential to minimise the costs, the energy requirements to operate the system, and the heat losses (typically 5–15 % of the total heat supply [3]). This can be done by optimising the network components design properties or by optimising the network operating parameters (temperature control, mass flow rate control...).

It is first possible to decrease annual heat losses by a proper design of the system. Since heat losses are proportional to the network's length, it is important to build DHNs in areas where the linear heat density remains high (thus heat losses will remain low regarding the quantity of heat supplied, see also 2.2.2 [41]). As the heat transfer coefficient decreases with the pipes diameter and the insulation thickness, it seems appropriate to build pipes with a larger diameter. However, investing in such measures needs to be balanced between selling costs of the lost heat and the pumping costs required to compensate pressure losses at a given diameter[3]. Pipes heat losses can be partly counterbalanced by the friction phenomenon. Smaller losses can also be achieved by specific pipes geometries (see also 2.2.1).

Above all, heat losses are proportional to the DH water temperature. Subsequently the network's supply and return temperatures should be as low as possible. Currently, a majority of DHNs are designed with a supply temperature of 80-110°C and a return temperature of 55°C while low temperature DHNs can operate with a supply temperature of 50°C and a return temperature of 25°C [59]. The implementation of a low-temperature DHN in Lystrup, Denmark, has for example reduced heat losses by 75% [60]. Indeed reducing DH water supply temperatures would allow a more economical utilisation of waste heat sources [6]. In addition, less expensive materials (plastic,...) could be used, which would lower the network investment costs [34, 35]. An increased temperature difference (ΔT) between the supply and return parts of the network can also be beneficial for the plants supplying heat into the system (fuel efficiency increased as more energy is transferred per unit volume of distributed circulation fluid) [32]. It has to be highlighted that the return temperature is sometimes ignored for the network design [4]. Nevertheless, the temperature is not the only parameter affecting the system's performance. Mass flow rate and pressure losses (which are related since $\Delta p = -k \times \dot{m}^2$, where k is a constant determined by the network geometrical and material properties) have to be taken into account as well. The modification of one of the network's parameters will affect the others [3]. Indeed a low supply temperature in the network results in large flow rates and consequently, higher pumping costs are required to compensate pressure losses [61]. Usually, a 20 kPa maximum pressure loss is allowed in the primary network [6].
It is consequently crucial to consider the interactions between the temperature, the pressure and the mass flow rate, the effects they can have on the whole system, and the trade-offs associated concerning networks costs.

Heat demand and load controls require an important system monitoring and can be managed by four independent control systems [3]:

- Heat demand control (manual opening taps and radiator thermostatic valves).
- Flow control (managed by the control valves in the substations).
- Differential pressure control (hence a mass flow rate control, provided by the distribution pumps).
- Supply temperature control (provided in the heat supply units).

On the heat supply side, grid control is mainly ensured by controlling the supply temperature and the differential pressure / mass flow rate. Depending on the the outdoor temperature, four major operating modes can be used, as can be seen in Table 2.1.

Outdoor temperature	Lowest temperature	Medium low temperature	Medium high temperature	Highest temperature
Supply temperature	Variable	Variable	Constant	Constant
Mass flow rate	Constant	Variable	Variable	Constant

Table 2.1 – Typical operating modes in a DHN (adapted from [3, 35].

In case of altered demand conditions, dynamic responses are necessary. It is always easier to change first the mass flow rate and then the temperature (delayed effects due to the network's inertia). However, mass flow rate and temperature variations are limited by the maximum pressure allowed in the network. Mass flow rate and supply temperature control can also be used in the secondary network [32].

Designing and operating a DHN are two separate things. As the outdoor temperature varies throughout the year and as new-built DHNs need to have sufficient capacity to enable the possible connection of future heat loads, there is a deliberate tendency to oversize networks. This decreases the overall system efficiency, on the primary network side [6, 61], as well as on the consumers side (radiators oversizing [62]).

Considering the system physical parameters, a review of the existing literature shows that some articles only deal with the design of specific parts of the network. For example, they consider pipes design [33], primary network design and layout [34, 63, 64] or consumers house insulation [59], whereas an integrated approach would be expected. Other articles deal with the operation of specific parts of the network and the selection of operating parameters (e.g. mass flow rate in the primary network [35] or control of the operating parameters in the secondary network [32, 62]). Few articles focus on the interdependencies between the different parts of the network, and their analysis remain partial. For example, Laajalehto et al. only focus on the primary network design and on mass flow rate control techniques [35], without taking into account the rest of the network. Pirouti et al. study various primary network designs and operations without considering interactions between the network and the heat source (assumed to be an "ideal" source) [61]. Li et al. examined at the same time the design and operating parameters of an integrated system based on a large scale coal-fired CHP plant [49]. The conclusions of their study show that taking into account the system as a whole has an influence on the results of the system's optimisation, which differs from component-centered optimisation.

2.3 Heat network modelling and optimisation

District heating networks are complex systems involving a lot of different technologies and multiple layouts. They have their own physics. In addition, they are subject to spatial constraints (urban geography) as well as physical limits and temporal constraints. All these characteristics make a single DHN unique and developing/expanding a network requires a considerable modelling and optimisation work. Indeed DHNs need to produce a low-cost heat and costs optimisations are mainly performed to study DH projects viability. In a global warming context, it can also be interesting to look for the DH alternatives with the lowest greenhouse gases (GHG) emissions. Although studying all the possibilities to build the network and look for the optimum case after enumeration could seem attractive, it would require a huge amount of time. This is not feasible in practice. In these circumstances, models are needed to deal with a colossal amount of data in a reasonable amount of time.

2.3.1 Classical algorithms: why are they relevant for district heating ?

As explained in [65], selecting a specific optimisation method depends on the number and type of variables, on the number and type of constraints and on the objective function.
In the case of DHNs, different types of variables can be used:

- Continuous variables can model heat demand, heat production, flow rates or heat sources capacity...
- Integer variables can model time periods, describe the number of generating units of a certain type...
- Binary variables typically model decisions. For example the existence of a plant at a given time or whether this plant is producing heat at a given time (1) or not (0) can be modelled by such variables...

In a lot of studies, the annual cost function is defined as the objective function to minimize [63, 64, 66, 67]. Some articles focus on the cost minimisation associated with specific parts of the network (e.g. the plant operation [68]). Sometimes, articles deal with multi-objective optimisations: costs and energy usage minimisation [61], costs and CO_2-emissions optimisation [69], maximisation of the system efficiency combined with the minimisation of both overall CO_2-emissions and total annual costs [70]. Objective functions can be classified into linear and nonlinear objective functions.

Although the objective function has to be minimised, the whole DHN's purpose is to deliver a sufficient amount of heat, considering the system's physical restrictions. This is why it is essential to take into account system's constraints. These constraints can be network related energy balances, network related capacity and consistency bounds, local energy systems balances, local energy systems capacity bounds, part load operation constraints and sometimes economic and legislation constraints [67]. Constraints can be linear or nonlinear.

When the objective function and the constraints are linear, linear programming can be used to solve the problem whereas nonlinear functions and/or nonlinear constraints will require nonlinear programming solutions [65]. Several approaches can be applied to optimise complex problems like those involving DHNs.

A Mixed Integer Programming MIP method can first be used to solve DHN problems. When the problem has continuous and integer variables, a single linear objective function and only linear equality or inequality constraints, a Mixed Integer Linear Programming (MILP) method can be selected. A Mixed Integer NonLinear Programming (MINLP) method will be applied for a nonlinear objective function and/or constraints. In such problems, binary variables can be modelled using either/or constraints and big constants ("big M approach") [65]. MILP and MINLP problems can be solved with the Branch-and-Bound method (BB).

Using a BB approach to solve a MILP problem begins by a relaxation of the 0 and 1 constraints (being allowed to take any value between 0 and 1) and by the resolution of the relaxed linear problem. If integer solutions can be found, their value is fixed for this level. If fractional values are found for the constraints, two subproblems are created ("branching step" creating two nodes: subproblems 0 and 1) and tested. The optimum is replaced if a best solution is found. If not, or if another fractional variable is found by relaxing the new subproblem, the steps are repeated and a new level is created. The BB approach allows not to test all the possible combinations since subproblems that leads to an optimum higher than the current one, to no solution or to a solution with only integers are not further investigated ("fathoming" [71]). It is common to fix a stopping condition in such programming methods.

Due to their ease of implementation, their good solution quality and computing times, MILP techniques have been applied in most research papers. But in recent years more attention has been paid to MINLP methods [72]. MINLP can be solved using a BB method as well. In this case, the problem is decomposed between a MILP and a NLP (NonLinear Program) problem. The relaxed subproblems at the nodes of the BB tree (continuous variables NLPs) are solved by a NLP method. It is also possible to solve MINLP problem by using an outer approximation (OA) approach. Each major iteration of the OA creates a MILP and a NLP subproblem, the NLP subproblem at major iteration k being formed by fixing the integer variables at some set of values and being optimised over the continuous variables.

If a global solution is always guaranteed for a MILP problem, one needs to ensure that each subproblem is convex in case of a NLP to make certain the convergence of the program (BB or OA) to a global solution [65].

Despite these advantages, computation times required to solve MIP problems often increase rapidly with the number of integer variables. With the growing model complexity, it can be interesting to switch from MIP to alternative methods that can deal with a larger amount of data in a shorter time. For such models, heuristic approach and meta-heuristic approaches can be applied.

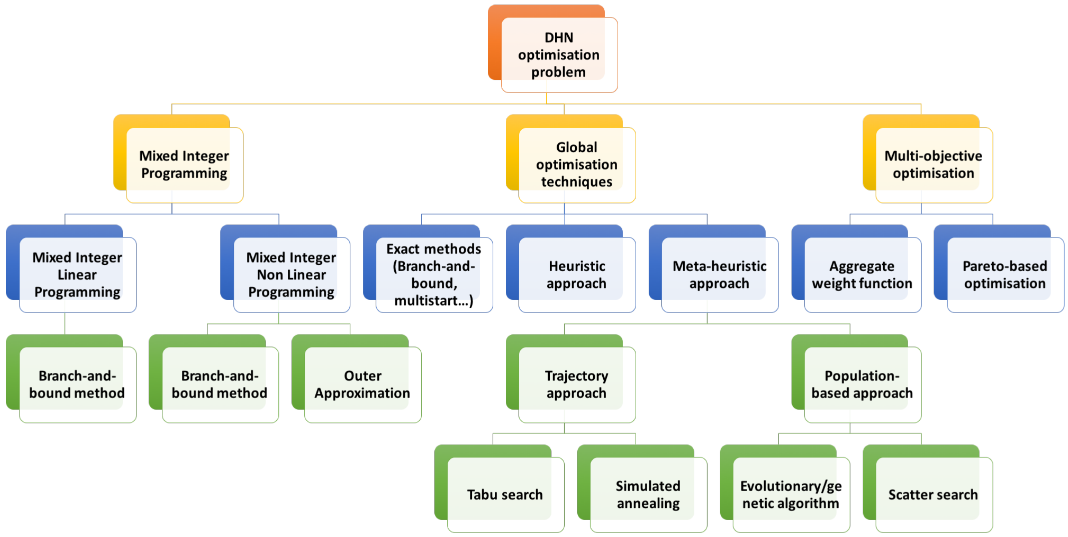


Figure 2.16 – Optimisation techniques that can be used to solve DHN problems [65, 71, 73, 74].

Heuristic approaches are neighbourhood-based methods exploring the neighbourhood of a current solution by an operation called move (for example a permutation). If a better solution is found, it becomes the current solution and new neighbourhoods are investigated. However, algorithms using a heuristic search are often limited by the fact that they are problem-specific. Moreover, for many important problems, the current solution ends trapped in non-optimal points, which are sometimes far from the global minimum [65]. To overcome this limitation, meta-heuristic approaches, based on heuristic methods and problem-independent, allow non-improving moves in the algorithm. Indeed, meta-heuristic search algorithms force the optimum search process to move beyond and look for new points without going backwards or revisiting points that have already been checked. To ensure that the procedure will terminate and to guarantee a result, a "maximum moves criterion" can be specified (otherwise it is possible to fix a maximum number of restarts without improvement).
There are two types of meta-heuristic approaches [73]:

- Trajectory meta-heuristic approaches that use a single solution during the search and return a single optimised solution. These methods are most of the times iterative procedures that have been improved to enable the program to move from local optima. For example the Tabu Search method uses a short-term memory list to avoid revisiting points while the simulated annealing approach allocates a moving probability to the neighbouring points [65, 74].
- Population-based meta-heuristic approaches that work with a set of solutions called population and also return a population of solutions. At the beginning of each iteration, the population is changed by replacing one or several individuals with new solutions, these solutions being created either by combining two individuals (crossover) or by changing an individual (mutation) [65]. While genetic and evolutionary algorithms massively use crossovers and randomizations to create new populations, scatter search uses deterministic principles and memory along with linear combinations to create them [73].

For problems involving a multi-objective optimisation, it is possible to use aggregate weight functions that combine all the objectives in a single mathematical function, each objective having a relative weight. However, with this approach, it can be difficult to adjust the weights of the objectives to minimise. In addition, as a single solution is returned, it is difficult to see the impact of each objective in the final solution [73]. It is also possible to use a Pareto-based multi-objective optimisation. This method establishes relationships between solutions according to the Pareto-dominance concept, by finding a set of non-dominated solutions.

Finally, to find an optimal solution in problems involving uncertain data (e.g. uncertainties about heat demand or future fuel costs), stochastic methods can be applied. By contrast to the previous deterministic approaches, stochastic programs generate feasible solutions over a range of predetermined scenarios and allow to better assess the risks. Among stochastic methods, multi-stage stochastic programming can be applied for planning problems and project phasing [75].

All these optimisation techniques are relevant for DHNs, since they can support the decision process in a multi-criterion environment. However, as for any optimisation process, a balance has to be found between the accuracy and the simplicity of the model [65].

2.3.2 Heat network modelling and optimisation

A lot of articles have already focused on DHNs modelling. A review of the existing literature shows that three major types of articles can be found [67, 76]:

- Some articles deal with technology selection and network/layout optimisation in order to find the best mix of technologies. These articles mostly focus on the equipments sizing and on the heat plant/distribution network's location ("Synthesis" articles).
- The second category of articles considers the network's essential parameters design: supply temperature selection, determination of pipes diameters minimising heat losses...("Design" articles)
- The last class of DHNs articles deal with network operation and the optimisation of several operating parameters (temperature, mass flow rate, etc.) in order to increase the system's efficiency or to decrease the costs. In these articles, the DH layout and the heat plants types and locations are almost always given ("Operation" articles).

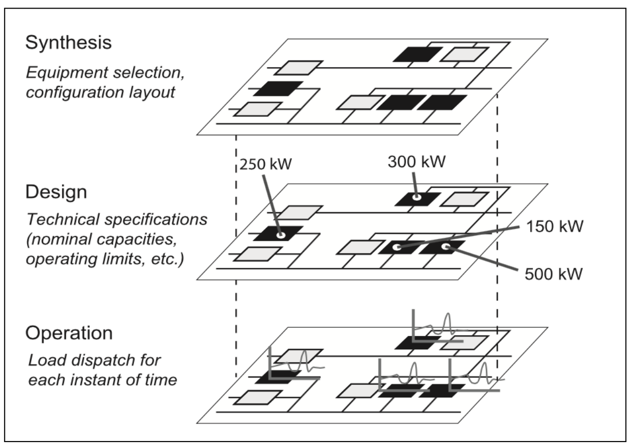


Figure 2.17 – Schematic representation of the DHNs modelling levels [76].

While Weber et al. deal with networks layouts and try to find the best mix of plants and their optimum location throughout the year with a MILP method [77], Abdollahia et al. use a multi-objective Pareto-based evolutionnary algorithm to size and select different parts of a CCHP plant, focusing on a specific part of the network [78]. Li and Svendsen apply a genetic algorithm to find a heat plant location that minimises heat losses [64].

By contrast to these "synthesis" driven articles, Haikarainen et al. use a MILP method to optimise pipes design, taking into account pressure and flow velocity constraints as well as storage requirements [63]. Xiang-li et al. implement a genetic algorithm to optimise the pipes design as well, considering an existing heat source (sewage water heat pump) and taking into account heat losses for their cost optimisation [79]. Dalla Rosa et al. focus on the supply temperature design that will enable an extensive use of renewable energy sources [80].

Several articles have noticed these distinction between "synthesis" and "design" articles in the literature and try to combine both aspects. For example, Chinese applies a MILP model to design and locate a decentralised district heating and cooling (DHC) system and the distribution network associated [67]. Weber et al. implement at the same time a genetic algorithm to choose and size energy conversion plants based on a list of available technologies, as well as a MILP optimisation model to configure a network having a predefined diameter and to size a single peak load boiler [69].

Operation articles deal with various parameters and concepts like temperature control or operation planning. For example, Li et al. have investigated the primary and secondary temperature effects on the energy efficiency, pumping power and heat losses, from the heat plant to the end-user [49]. They emphasise the importance of considering the whole system for the optimisation, as the results obtained for the system differ from those obtained for a component-centred optimisation. Gustafsson et al. focus on the secondary network and on the consumer substations, trying to find the best method to control the ΔT on the consumer side by varying the supply temperature and the mass flow rate in the primary network [32].Laajalehto et al. implement a mass flow rate control to optimise the supply and return temperature in a ring network [35] while Fang and Lahdelma optimise simultaneously the heat production at multiple heat plants with a genetic algorithm. They vary at the same time the mass flow rate and the supply temperature thanks to smart meters feedback [81]. Sakawaa et al. have studied a DHC plant's operational planning, applying genetic algorithms to determine integer variables, while the continuous variables are obtained by solving LP problems [68]. Gopalakrishnan and Kosanovic have extended their model to a multi-period cost optimisation of combined cycle district heating systems, using a MINLP methodology and a genetic algorithm solution [72].

Several articles highlight that the variety of operating conditions found in the network is not always reflected by the DHN design and they try to include operating considerations in their network design. For instance, Pirouti et al. focus on the operating parameters selection (temperature regimes and target pressure losses), in relation with four operating scenarios (see also Table 2.1) [61]. Nuytten et al. study the combined effect of a CHP system and various thermal storage facilities on the network's operation and flexibility [58].

One needs to emphasise that only few articles include thermal storage in their model. In these articles, daily thermal storage is predominantly considered and continuous time bands are used for their modelling [57]. While Wang et al. build a planning model to operate a DHN using a CHP plant based on renewable energy sources and including storage (MILP approach) [82], Giuntoli and Poli optimise the day-ahead electrical and thermal scheduling of virtual power plants. They model thermal storage and its dimensioning with a branch and bound MILP algorithm [83]. Obuleye et al. apply as well a MILP approach in their study, considering thermal storage and various heat technologies' part load performances. They examine system design aspects and highlight the importance of selecting appropriate time segments for results accuracy [84]. Focusing on the design of distributed energy systems (heat and electricity) under uncertainty, Zhou et al. use a two stage stochastic programming method, combining a genetic algorithm and a Monte Carlo method. If their study does not especially focuses on DHNs, their model take into account the thermal storage devices sizing and highlight the differences between stochastic and deterministic approaches [85]. Fazlollahi et al. have published a relatively complete study, covering storage, synthesis and design aspects, using a multi-objective Pareto-based evolutionary algorithm. They tested their model with a set of pre-selected scenarios to analyse the network operation [70].

In addition, almost all articles deal with simple linear or branched network layouts, quite far from reality. Only few articles focus on modelling techniques for meshed networks, using loops [86, 87]. Moreover, Lambert et al. have highlighted that classical approaches for DHN optimisation barely consider chronological constraints and time-dependent frameworks [88]. They emphasise the fact that "now-or-never" investment criteria are mostly used, whereas incremental approaches and investments schedules would be more suitable for real project phasing.

Finally, Voll et al. have noticed that DH modelling and optimisation articles always give an optimum solution that is specific to a model, which is itself not completely representative of the reality. Using integer-cut constraints, they have developed the near-optimum solution concept, a powerful concept that better fits the reality and is helpful for the decision process [76].

2.4 Extension of district heating networks

With the growing urban population density and since DHN are already well-established in some densely populated cities, it can be interesting to evaluate the potential expansion of existing district heating networks.

2.4.1 How to identify the areas that are suitable for the extension of the network?

First of all, it is essential to ensure that expanding an existing DHN to a specific area will be beneficial. This is why the areas that are suitable for expansions need to be carefully identified.

Methodologies used to identify the areas that have a sufficient heat demand and would be appropriate for DH extension have been widely studied in Denmark. Indeed the existing DHN in Denmark is relatively old and DH is considered at a national level in this country. Many Danish articles dealing with networks expansion use GIS-based methods and cost assessment, as a lot of heat data and heat maps are available in Denmark. For example, Nielsen and Möller have used a GIS-based model to assess heat production, heat distribution and heat transmission costs associated with DHN expansion. Their study is based on the heat demand at a national scale and on the associated metrics (see also 2.2.2) [43, 47]. Möller and Lund have developed a spatially explicit model to identify the areas that are currently using natural gas boilers and would be suitable for DH implementation. They investigated several scenarios with different shares of renewable energy sources [44]. It has been identified that DH could represent up to 55-57% of all heating in Denmark [89].
In the UK, Finney et al. have investigated the potential extension of DHNs in Sheffield, using a GIS-based model [48]. Again, the potential for expansion was identified using a cost assessment. Existing and emerging heat sources and sinks were first identified based on their heat production/demand and then linked to create "heat zones" suitable for expansion or for the creation of a new DHN.

Apart from the Danish case, it should be noticed that identifying suitable areas for DHN expansion has not been investigated a lot. In addition, the existing articles always focus on cost assessment based on heat demand/data and do not consider other criteria.

2.4.2 How to model their extension?

As seen previously in 3.4, a lot of modelling and optimisation articles dealing with DHN focus on simple networks layouts. Only a few papers dealing with more complex layouts, including loops or meshed grids, were found in the literature [35, 86]. Bordin et al. argue that most of the optimisation articles propose models that are far from the reality of existing networks [87]. Consequently, they developed a practical tool using a graph representation and taking into account physical and hydraulic operational conditions to study DHN's implementation and expansion. Their tool, that maximises the overall net profit, is already in use for DHN planning in Italy. It can easily be adapted to integrate loops and meshed networks. Applying a MILP approach, they determined which users could be connected to the network in the city of Emilia-Romagna, Northern Italy. However, their model does not consider design parameters like pipes diameter. In addition, pumping costs are not taken into account in their method and only a single heat source is considered.

Furthermore, strategic energy masterplans and company reports present interesting methodologies for network expansion. They often focus on marginal expansion of the existing networks. For instance, the London Boroughs of Redbridge and Bunhill-Shoreditch have commissioned consultancies to study possible extensions and connections of the existing DHNs within the area [29, 31]. Using public data like the London Heat Map and a spatial representation, a cost assessment was performed to evaluate which sub-areas would be economically viable for an expansion. The results are presented as a set of possible extensions from a cluster network but do not detail the investments or extension phasing. Other feasibility studies include a more detailed phasing of the extension. For example, Buro Happold Ltd has been commissioned by the London Borough of Islington to study the possible extension or connection of the existing DHNs within the area. Considering mostly two technologies (gas fired CHP and boilers), they sized the heat source, the thermal storage associated and determined an optimum network layout ("synthesis" cost-driven approach, see also 3.2) [28]. Taking into account various key drivers and scenarios, they obtain various extension planning strategies, which highlights the importance of considering an incremental approach.

Optimal heat sources sizing and phasing in the context of DHN extension has also been considered by Mojica Velazquez [90]. He developed an optimisation framework to find an optimum investment schedule, considering several heat technologies and implementing a nonlinear model (model predicting control formulation). Lambert et al. considered as well the DHN investments phasing. Applying first a classical method to optimally size the heat network, their multi-stage stochastic programming approach was then used to simulate the optimal marginal expansion of an existing DHN [88]. Their sequential decision-making approach could be further enriched to take into account production facilities, maintenance costs or hydraulics.

Apart from these articles and reports, DH expansion has not been investigated a lot in the literature.

Following this lack of literature on DH expansion, it can be interesting to look at capacity expansion and capacity planning problems in other industrial and scientific domains. Indeed, capacity planning is a well-known topic in the entrepreneurial branch [91]. Depending on the approach used to match the supply and the demand, a distinction can be made between three capacity expansion methods:

- a leading approach where the production capacity is increased a lot in advance, anticipating an increase of the demand. This strategy is very risky since one can never ensure that a demand increase will actually occur.
- a matching approach where the production capacity is incrementally increased as market conditions evolve. This approach is the hardest to apply.
- a lagging approach where the production capacity is increased following an increase of the demand. This strategy is also risky, as it can result in a loss of customers.

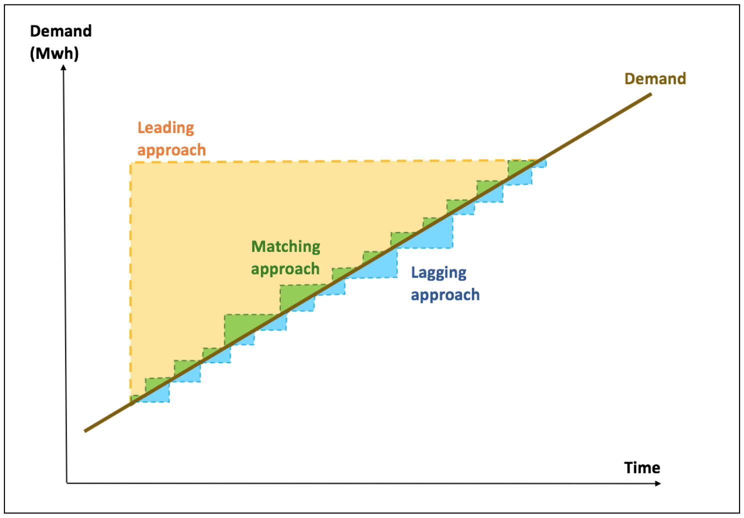


Figure 2.18 – Leading, matching and lagging approaches that may be used in capacity expansion problems [91].

Capacity expansion problems have also been investigated for power production. For example Saif et Almansoori studied the capacity expansion of a desalination and power supply chain, using the General Algebraic Modelling System (GAMS) software and considering various capacity expansion scenarios. Their optimisation model uses a multiperiod mixed integer linear programming approach [92]. Henggeler Antunes et al. also developed a multi-objective MILP approach to provide decision support in the evaluation of power generation capacity expansion policies. Considering expansion costs as well as environmental impacts, their model also takes into account demand side management aspects [91]. Tekiner et al. also focus on electricity generation expansion planning. They use a Monte Carlo simulation to generate various scenarios and a multi-period MILP program with a weighted objective function to solve their capacity expansion problem [93].

Overall, we can highlight a lack of literature dealing with the expansion of DHNs. Even if a very small number of articles detail the approach used, most of the documents dealing with network expansion are owned by private or consulting companies. They give few details on the modelling and optimisation approaches applied. However, capacity expansion problems have been studied in other domains, and especially for power generation expansion planning. The methodologies applied for power capacity expansion may be reused in DHNs expansion problems.

2.5 Conclusion - presentation of the existing network and area

As shown by the previous overview, district heating networks have been massively studied by communities, consultancies and the research community. Due to the complexity of DHS and their modelling, the existing literature often focuses on specific parts of DHNs, and rarely on the system as a whole. In addition, articles often consider simple networks layouts, which are quite far from the reality. Phasing and planning approaches that are relevant for investments schedules are often overlooked and the time frame is frequently neglected. Concerning the modelling and the optimisation of DHNs, the existing literature looks at the design, the operation, the layout and the sizing of the system but barely considers how they interact together. Moreover, there is a lack of literature dealing with the extension of existing district heating networks.

Therefore the study will have to provide a methodology to model, optimise and phase the marginal extension of an existing district heating network.

The model developed in the next chapters will be applied to a case study, the Barkantine area in the Isle of Dogs, London.

Indeed a DHN already exists in the Barkantine area. This network, which started running in 2001, supplies heat to 22 buildings, using 2.4 km of pipes (see also Appendix A). It runs with a supply temperature of 90 °C and a return temperature of 70 °C [94].

Figure 2.19 – Isle of dogs location (the Barkantine area is bordered in red, source: Google Maps).

Figure 2.20 – London Heat Map, zoom on the Isle of dogs area (the existing network is drawn in yellow, the energy centre being represented by the green point [45]).

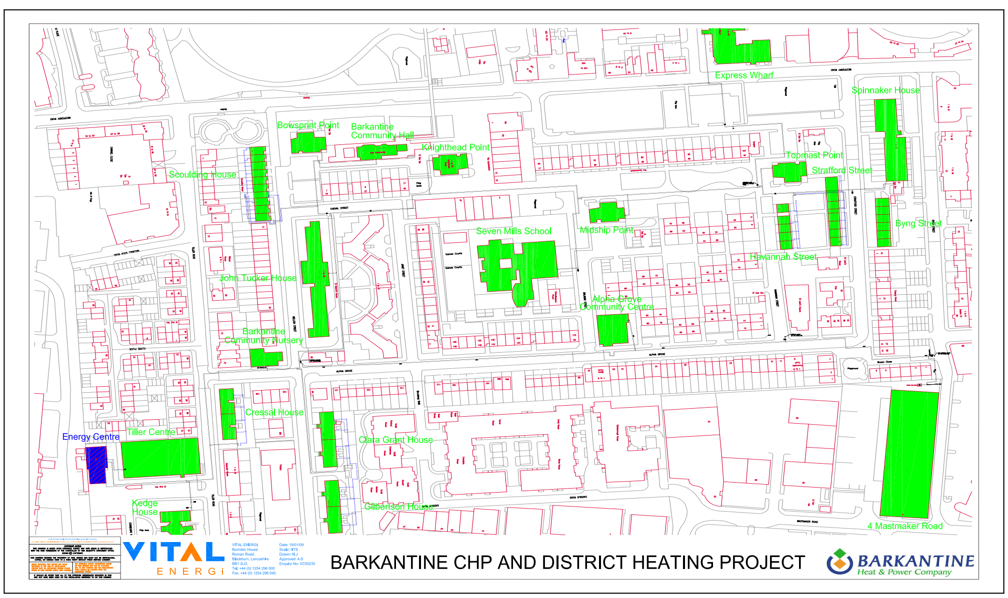


Figure 2.21 – Schematic representation of the existing Barkantine district heating network [95].

The energy centre, located in the south of the area already comprises the following heat and electricity production units [95]:

- A cogeneration engine with a capacity of 1 600 kW$_{th}$ (1 300 kW$_e$) used to produce both heat and electricity with natural gas.
- Two complement natural gas boilers with a capacity of 1 400 kW$_{th}$ each. Two other additional boilers with the same capacity are in back-up on site.
- Two thermal storage units with a capacity of 105 m^3 each, which can store up to 4.5 MWh.

Chapter 3

Heat demand analysis

As seen in 2.2, estimating accurately the heat demand is the key to size the heat capacity required in the energy centre [3, 30, 39]. Thus, an inaccurate heat demand estimation may lead to oversize the installations, hence to additional investment costs [32, 36]. Annual metered customers heat consumptions (made available on customers bills) may first be used. Such data are often recorded when the buildings considered are already connected to the network. However, few data is available on potential loads to be connected and a different methodology is required to estimate their heat demand. If EDF Energy provided the annual metered heat consumption for the existing DHN's buildings, a different method was applied to estimate the heat demand for the potential heat loads to connect.

For simplification purpose, no distinction was made between domestic hot water (DHW) requirements and heating requirements. The following methodology was built in order to create connection scenarios for the model:

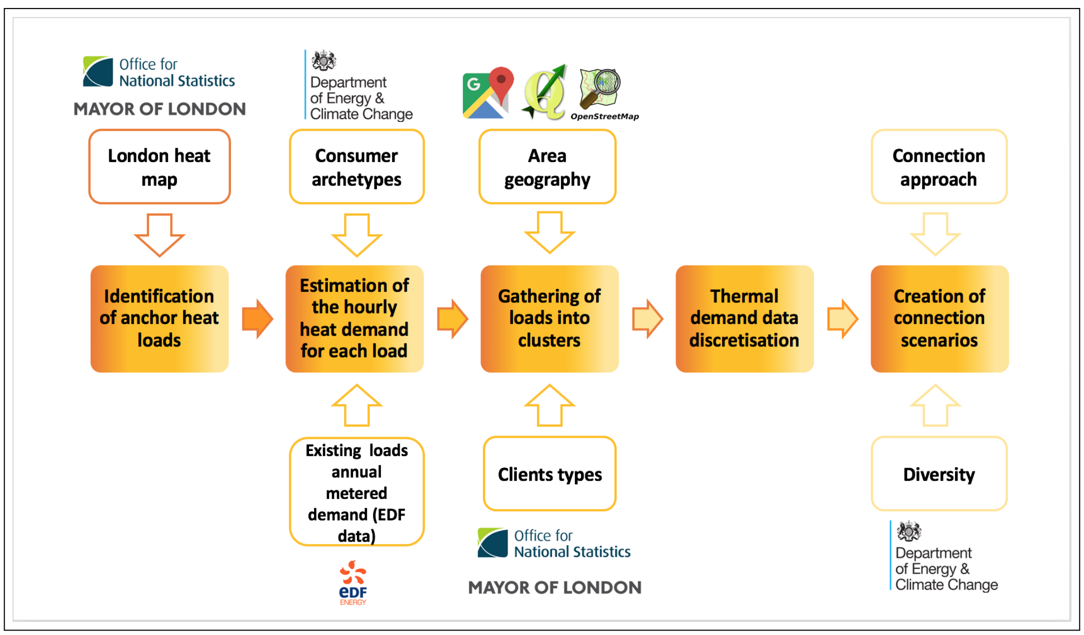


Figure 3.1 – Methodology and data sources used to estimate heat demand and build connection scenarios

An in-depth description of the steps involved in the methodology is provided in the next paragraphs.

3.1 Loads selection and clustering

3.1.1 Identification of anchor heat loads

Analysing the heat demand starts with the identification of existing (or future) anchor heat loads in the area. Since the project considers the marginal expansion of an existing DHN, the area located at the periphery of the existing Barkantine DHN was selected for the study. The London heat Map, which seeks to support heat mapping for London boroughs, was then used to identify anchor heat loads in the chosen area [45] (see also Appendix A).

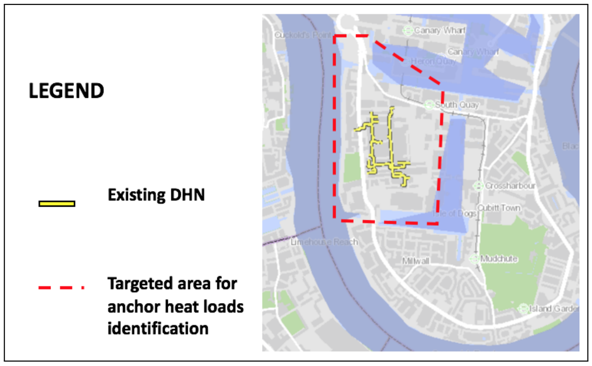


Figure 3.2 – Targeted area for the DHN's expansion problem [45].

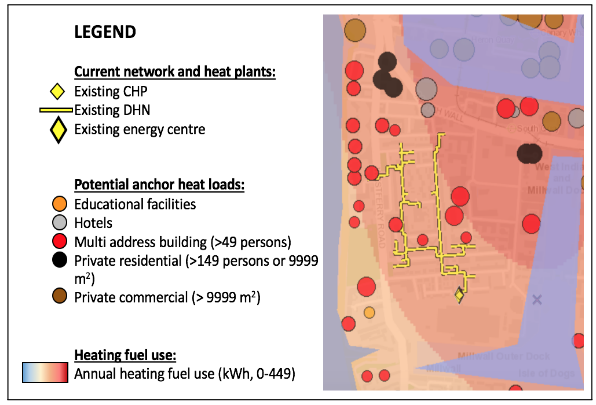


Figure 3.3 – Anchor heat loads identified in the area of interest [45].

As it may be seen on Figure 3.4, thirty-one buildings or construction areas were identified as potential heat loads to be connected.

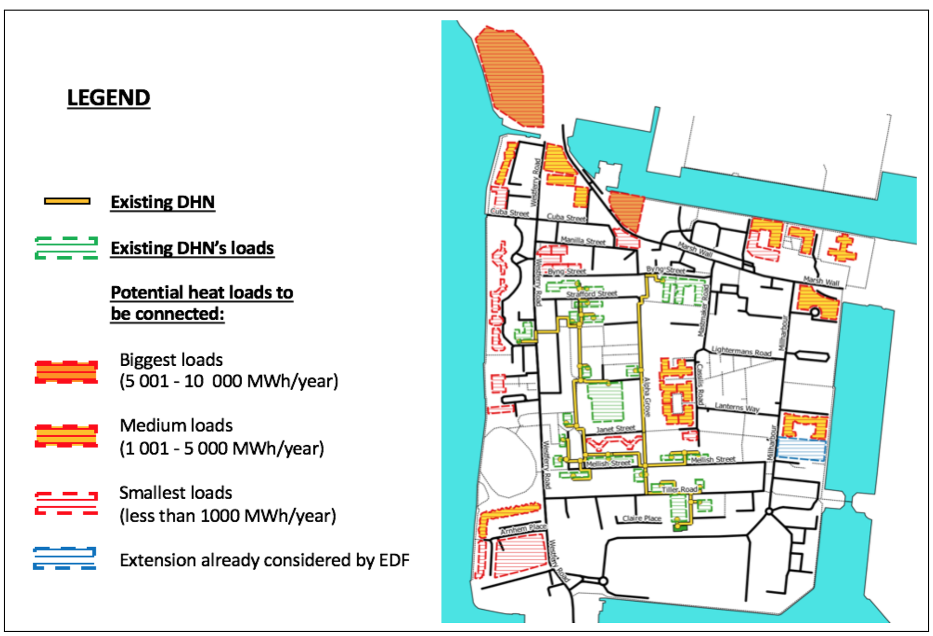


Figure 3.4 – Spatial representation of the potential loads to be connected using QGIS software

3.1.2 Heat demand estimation for each load

Following the identification of major heat loads in the vicinity and given EDF data for the existing DHN's loads, it was necessary to generate heat demand profiles with a good temporal resolution. Indeed, as heat demand varies throughout a day and throughout the year, a building's annual heat demand data does not show anything about its heat consumption pattern. This is why, heat demand profiles were generated for each building using pre-existing consumer archetypes. The model developed by Element Energy Ltd was selected for this purpose [40]. In this model, each archetype can be adjusted to specific buildings characteristics. For each potential load to be connected, the model was used to generate one hourly heat demand consumption profile throughout the year. The model inputs were adjusted to the average annual heat demand provided by the London Heat Map and to the buildings types, areas, and number of storeys. For the Millharbour, 45, the extension of which is already considered by EDF, the forecasted building's annual peak demand was used to adjust the model's inputs to the building [95].

It is important to emphasize that most of the buildings considered in the area are new or currently under construction, which was taken into account to generate the hourly demand profiles.

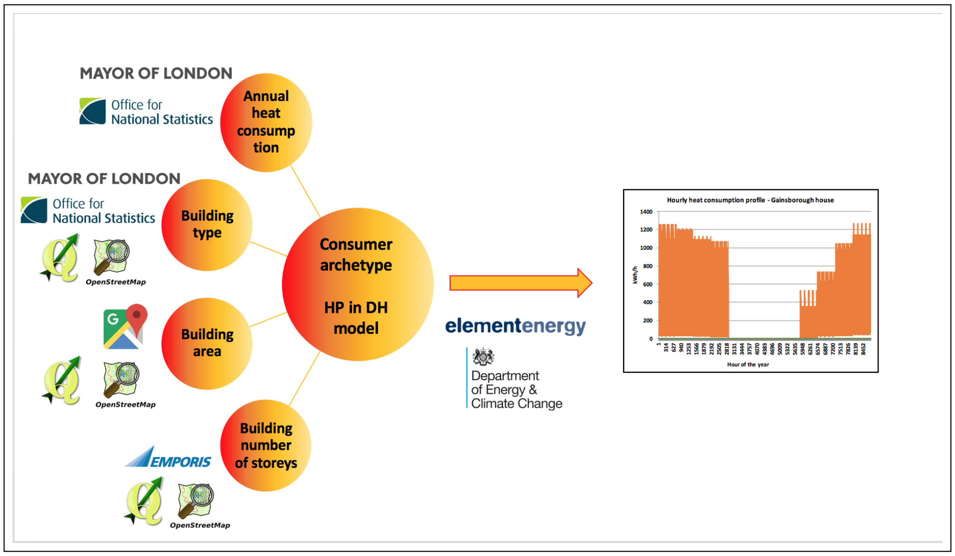


Figure 3.5 – Methodology used to generate hourly heat demand profiles: example of Gainsborough house

Applying the same method to the twenty-two existing loads and the thirty-one potential loads to connect, one yearly heat demand profile was generated for each load in the area.

3.1.3 Generation of clusters of interest

Although it would be possible to optimise the spatial expansion of the network, everything depends in reality on the willingness of stakeholders to connect. In such circumstances, loads can be gathered into small groups. Each group will then be connected to the network at a given time decided by stakeholders. Consequently, the twenty-three loads were divided into ten clusters of interest. Loads gathering into clusters were based on geographic considerations, the idea being to connect a cluster to the network with a main single transmission pipe and several distribution pipes.

The clusters repartition is given in the following table and figure (see also Appendix B for loads characteristics):

Cluster	Number of loads	Average annual heat demand (MWh/year)	Specific loads in the cluster
1	3	4 001.5	one school
2	3	3 501.5	/
3	1	250.5	/
4	5	12 252.5	one office building and one hotel
5	2	501	/
6	7	4 253.5	one fire station
7	2	8 251	two hotels (one is currently under construction)
8	5	12 752.5	one residential building currently under construction
9	1	7 500.5	the whole cluster is currently under construction (office and retail buildings)
10	2	6 385.5	one building considered by EDF for the DHN's expansion

Table 3.1 – Repartition of the loads of interest into clusters.

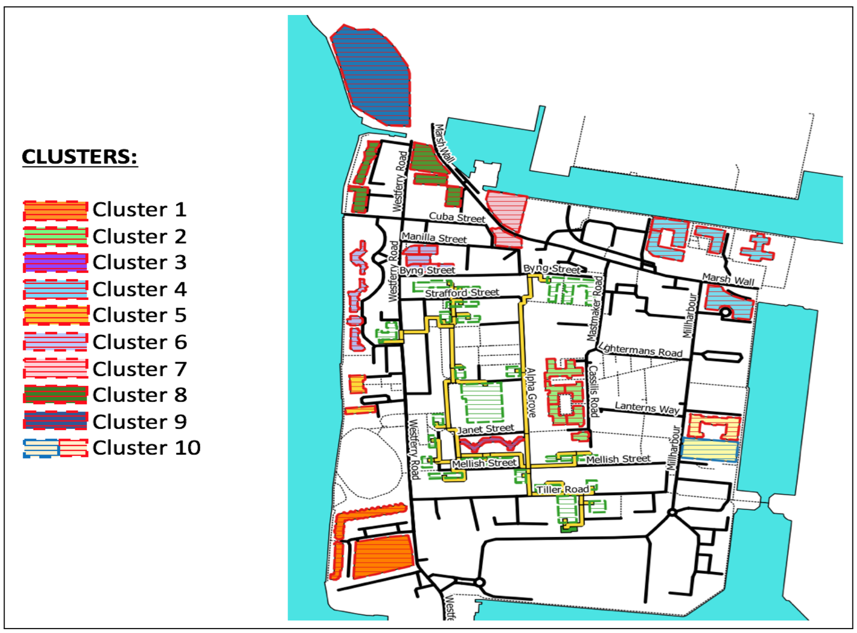


Figure 3.6 – Spatial representation of the clusters using QGIS software

As it may be observed in the previous table, clusters 4, 7 and 9 offer a mix of demands that makes them particularly interesting to connect to a DHN. It has indeed been seen in 2.2 that it is worth connecting areas presenting an important heat demand diversity to DHNs, which is the case for these clusters. Hotels, office buildings and retail buildings presenting different heat demand profiles compared to residential buildings, they may consume heat during summer, late spring and early autumn. Their connection may thus increase the energy centre capacity factor.

3.2 Thermal demand data discretisation

As explained in 2.4, thermal demand data discretisation is essential to ensure that the problem will be solvable in a reasonable amount of time. In general, the number of time bands selected for a DH problem has to take into account:

- the available heat data and their representativity of the problem.
- the time horizon chosen for the model.

- the problem size.

Depending on these parameters, the number of time bands selected for the problem varies.

A review of the existing literature shows that several articles consider a short time horizon (mainly one year) and use continuous demand data [44, 82]. Among the articles mentioning thermal demand data discretisation, some deal with a time horizon of one or two years and select a small number of time bands. For example, Haikarainen et al. consider a 12-period year for their MILP problem [63] whereas Weber et al. use six periods per day and three representative days per year to model the demand [77]. Cedillos Alvarado considers a higher time horizon but a smaller number of typical days (two seasons, weekdays and weekend) and half-hourly demand intervals [96]. Chinese, as well as Oluleye et al. include electricity tariffs variations in their model. They take into account heat demand variations and electricity tariffs evolution to generate proper time bands [67, 84]. Mojica Velasquez separates the year in two seasons and uses a weighted averaged hourly demand to estimate the peak and the base demand for each day type [90].

Since the data generated by the Element Energy Ltd were based on consumer archetypes, it turned out to be difficult to apply a thermal demand data discretisation method without highly modifying heat demand values. For example, breaking the year into four seasons, then normalising the demand using the average heat demand and the hourly standard deviation for each season, resulted in a loss of weekly and monthly demand specificity. Such an approach led to underestimating the demand.

It was finally decided to keep hourly demand data and two typical days per month (weekdays and weekends), which gives 576 time slices per year. As CHPs and boilers have a 15-years lifetime [77, 96] and since 10 clusters were built, it was decided to use a 12-year period, one cluster connecting to the network each year in July from year 2. 6912 time bands were eventually considered.

3.3 Elaboration and presentation of the scenarios

Following thermal demand data discretisation and the gathering of loads into clusters, connection scenarios were established. The analysis of the demand was exclusively used to build these scenarios, the connection rapidity and its amplitude varying from one scenario to another. As most of the buildings considered for the expansion are new or currently under construction, fuel poverty criteria were not relevant to choose which loads to connect first. GHG emissions reduction criteria were not considered either, although the GHG emissions reduction potential associated with each scenario will be studied in the model.

Given Barkantine's geography, several restrictions on clusters connection order were added:

- Cluster 8 has to connect before cluster 9 and after cluster 6.
- Cluster 9 has to connect after cluster 8 (and cluster 6).
- There are no constraints for clusters 1, 2, 3, 4, 5, 6, 7 and 10.

Finally three real connection scenarios were built for the model:

- A baseline scenario in which the existing DHN is not expanded, customers using domestic natural gas boilers for heating purposes.
- Scenario 1 considers an incremental connection of buildings, from small clusters (low heat demand) to big clusters (high demand). The heat demand evolution is slow at the beginning and then increases rapidly (see also Table 3.2).
- Scenario 2 also considers an the incremental connection of buildings, big loads (clusters with a high heat demand) being connected first. The heat demand increases rapidly at the beginning to almost reach a plateau after a few years (see also Table 3.2).

Year	Scenario 1		Scenario 2	
	Cluster connected	Total number of loads connected	Cluster connected	Total number of loads connected
1	/	22	/	22
2	3	23	3	23
3	5	25	4	28
4	1	22	7	22
5	2	31	6	37
6	10	33	8	42
7	7	35	9	43
8	6	42	10	45
9	8	47	1	48
10	9	48	2	51
11	4	53	5	53
12	/	53	/	53

Table 3.2 – Clusters connection order considered for scenarios 1 and 2.

As explained in 2.2, all customers do not reach their peak demand at the same moment. This diversity effect and the resulting synergies associated have to be taken into account to accurately shape the heat demand and properly size heat sources [3]. This is why it is essential to estimate the area diversity with a good precision to ensure a correct sizing of the energy centre.
The diversity curve used in the Energy Element Ltd model and its default coefficients were applied to the Barkantine area [40]:

$$D(x) = B + (1 - B) \times exp(-Ax) \tag{3.1}$$

where x is the number of loads considered, A=0.05 and B=0.2. D=1 means no diversity whereas D=0 means full diversity. The real heat demand is then given by:

$$Heat\ demand = \sum_{p \in loads} Heat\ demand_p \times D(x) \tag{3.2}$$

Taking into account diversity and no diversity effects, the following curves were obtained for each scenario:

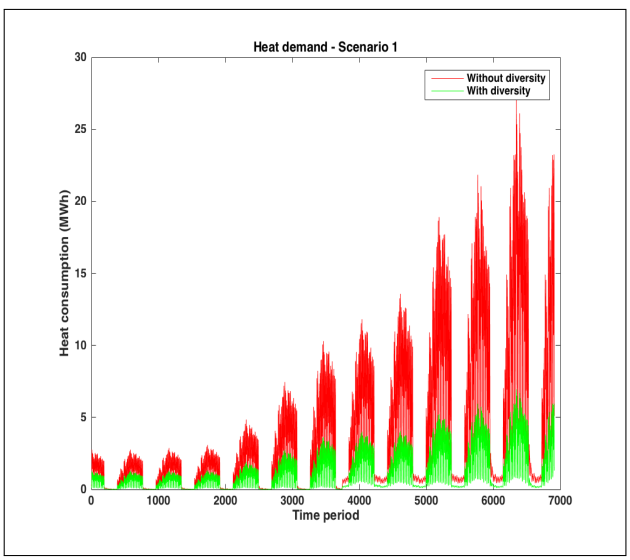


Figure 3.7 – Heat demand - Scenario 1, with and without diversity

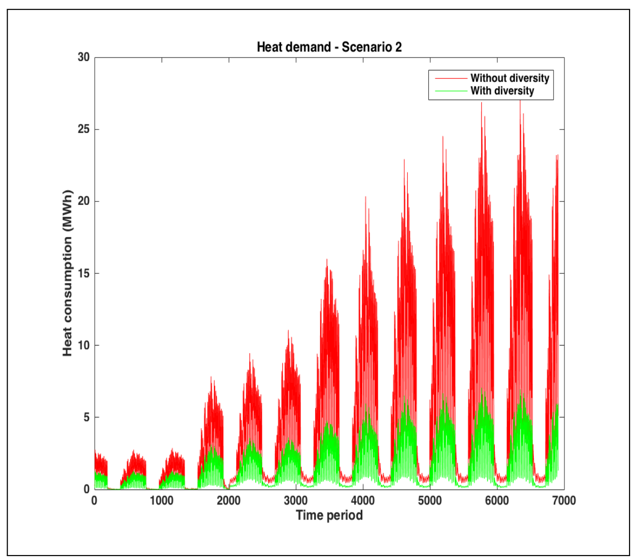


Figure 3.8 – Heat demand - Scenario 1, with and without diversity

All these demand scenarios will then be used as inputs for the energy center sizing model, as well as for estimating the spatial network's extension costs. In accordance with EDF Energy data, each scenario's heat demand was multiplied by 1.13 to take into account spatial network heat losses and ensure that heat supply meets customers demand [95].

For each scenario, the model developed in chapter 4 will have to find an optimal mix of technologies under given constraints (cost minimisation, GHG emissions minimisation, etc.).

Chapter 4

Design of the energy centre

As mentioned in part 2.3, it is essential to chose a modelling approach that will minimise the amount of time needed to solve the problem. For this purpose, a mixed-integer linear programming approach was developed, using discrete binary and continuous variables. As will be discussed further on, binary variables were used to represent whether a given technology is built or not at a given time and whether it is used to produce heat or not. The model was developed in the General Algebraic Modeling System (GAMS) Integrated Development Environment (IDE). GAMS is a high-level modeling system for optimisation and mathematical programming, using a language compiler and various integrated solvers (solving most of the problems types discussed in 2.3). The model and its variants were run through Imperial College's Linux Cluster, using GAMS version 24.2.3. The GAMS Cplex solver was chosen. This solver uses a branch and cut algorithm to solve a series of linear sub-problems.

The following figure illustrates the optimisation model structure detailed in the next sections.

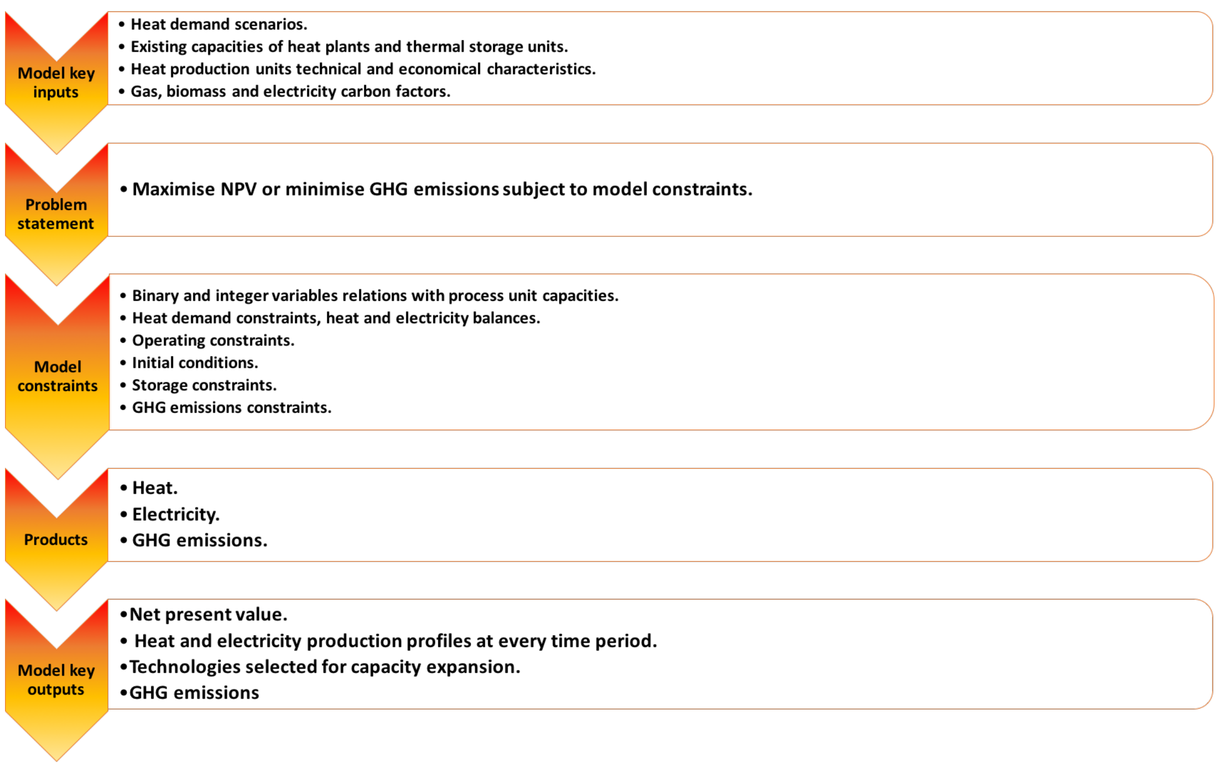


Figure 4.1 – Optimisation model structure (adapted from [92]).

4.1 General model: Mixed integer linear programming

As discussed beforehand, it was decided to use a MILP approach to allow the use of discrete and continuous variables. Four different types of inputs were used for the model:

- sets: used to model the dimensions on which parameters, variables or equations will depend.
- parameters: known inputs for the model (for example heat demand). They may depend on the sets or not (scalar values).
- variables: unknowns for which the model is solved.
- equations and constraints: they define the problem's structure, modelling energy conversions and transfer processes, heat and electricity balances, units sizing and operating levels. Among these equations, the objective function's result needs either to be maximised or minimised depending on the problem formulation.

A detailed description of the model is provided in the next sections. This model reuses part of the work done by Hakarainen et al. [63], part of the assumptions used by Weber and Shah [77], part of the work done by Corral Acero [97], part of the work done by Lambert et al. [30], as well as additional equations and assumptions.

4.1.1 Sets

The following sets were introduced to highlight the dependence of several parameters and variables on time, technologies and consumer types:

Index	**Description**
t	hourly interval
s	day type
y	year
p	technology
chp(p)	CHPs (subset of technologies)
hp(p)	heat pumps (subset of technologies)
boilerNG(p)	natural gas boilers (subset of technologies)
boilerbio(p)	biomass boilers (subset of technologies)
st(p) [2]	thermal energy storage units (subset of technologies)
consumers	consumer types

Table 4.1 – Sets used in the model.

Twelve years (y), twenty-four day types (s) per year and twenty-four hours (t) a day were considered, which gives 6912 time bands to investigate.
Since all technologies share common characteristics, it was decided to create the index p and to add technologies subsets in order to reflect technologies specifications in the model (e.g. boilers efficiency, heat pumps COP...).
As the area presents various types of customers, which may influence heat prices, the customers index was also introduced.

4.1.2 Parameters

Parameters are the model's inputs. They can be split into technical and economical data.

2. Only used in model 3

Parameter	Dependence	Description	Unit
length	s	Number of days of type s	/
elim	p	Capacity of plant type p	MW
K	p	Minimum allowed part load for technology p	%
a	p	Slope of the curve GasConsumption=f(part load) (CHPs only)	/
b	p	Intercept of the curve GasConsumption=f(part load) (CHPs only)	MWh
w	p	Slope of the curve ElectricalOutput=f(part load) (CHPs only)	/
z	p	Intercept of the curve ElectricalOutput=f(part load) (CHPs only)	MWh
u	p	Slope of the curve Area=f(size)	m^2/MW
v	p	Intercept of the curve Area=f(size)	m^2
boiler_NG_Eff	p (boilerNG(p))	efficiency of natural gas boilers	%
COP	p (hp(p))	coefficient of performance of heat pumps	/
max_num	/	Maximum number of plants allowed for a given technology	/
h_	/	Minimum number of consecutive working hours allowed for a given technology (heat pumps and CHPs only)	h
d	y, s, t	Aggregated heat demand at time period t	MWh
CF_NG [3]	/	Natural gas carbon factor	$t_{CO_{2eq}}$/MWh
CF_bio [3]	/	Biomass carbon factor	$t_{CO_{2eq}}$/MWh
CF_elec [3]	y, s, t	Dynamic electricity carbon factor	$t_{CO_{2eq}}$/MWh
B_disp [3]	/	Mean ratio electricity carbon factor/gas carbon factor for CHPs using the boiler displacement method	/
P_disp [3]	/	Mean ratio electricity carbon factor/gas carbon factor for CHPs using the power station displacement method	/
T_disp [3]	/	Mean ratio electricity carbon factor/gas carbon factor for CHPs using the DUKES method	/
Losses [4]	/	Thermal storage losses	%/h

Table 4.2 – Technical parameters used in the model.

Technical inputs include the aggregated heat demand calculated for each time band (see also chapter 3) as well as data related to technologies energy inputs and heat outputs. As it will be seen in 4.3.1, some technologies properties like CHPs electrical output or CHPs gas consumption were linearised to allow continuous part loads. For some technologies, additional working inputs were added: minimum number of consecutive working hours, maximum number of units allowed in the energy centre, minimum part load allowed. These parameters were added to ensure model consistency (e.g. a CHP will not be used for one hour because it will never be the case in the reality).

3. Not considered for model 1, see also 4.4.4
4. Taken into account in model 3 only

Parameter	Dependence	Description	Unit
C	p	Investment costs for technology p (CHPs only)	£
Var	p	Variable investment costs for technology p (other technologies)	£/MW
Mn	p	Maintenance cost for plant type p (CHPs only)	£/year
F	p	Maintenance factor for plant type p (other technologies)	% of investment costs
An [5]	p	Annuity factor for technology p	%
gasprice	y	Gas price at time period t	£/MWh
costEXPelec	y, s, t	Electricity export price at time period t	£/MWh
costIMPelec	y, s, t	Electricity import price at time period t	£/MWh
biomass_cost	/	Biomass cost	£/MWh$_{heat\ produced}$
RHI_bio	/	Non-domestic biomass boilers RHI subsidy	£/MWh$_{heat\ produced}$
RHI_HP	/	Non-domestic heat pumps RHI subsidy	£/MWh$_{heat\ produced}$
Consprop	consumers	Consumers proportion	%
Consprice	consumers	Heat price for a given type of consumers	£/MWh

Table 4.3 – Economic parameters used in the model.

Economic inputs involve technologies investment costs as well as maintenance costs. To ensure a fair comparison between technologies, capital investments were spread over each technology's projected lifetime into annualised payments using the annuity factor An. Although electricity import and export prices vary on a hourly basis, natural gas prices were assumed to remain constant over a year. Subsidies, biomass cost and heat prices were assumed to be constant.

4.1.3 Variables

Variables can be split into binary variables and continuous variables.

Variable	Dependence	Description	Unit
PEx	p, y	Unit p exists at year y	/
work	p, y, s, t	Unit p produces heat at time t	/

Table 4.4 – Binary variables used in the model.

Binary variables model the existence of a given heat production unit at a given year. They also indicate whether a plant is working at a given time or not.

5. An is given by $An = \dfrac{r \times (1+r)^N}{(1+r)^N - 1}$, N being the unit lifetime.

Variable type	Variable	Dependence	Description	Constraint	Unit
Heat production	size	p, y	Unit size at time t	positive	MW
	q	p, y, s, t	Heat produced by unit p at time t	positive	MWh
	q_in	p, y, s, t	Heat received by thermal store p at time t	positive	MWh
	L	p, y, s, t	Storage level in thermal store p at time t (thermal storage units only)	positive	MWh
	areareq [6]	y	Area occupied in the energy centre at year y	positive	m^2
Costs	CHP_HP_ElecCost	y, s, t	CHP/HP electricity import/export balance at time period t	/	£
	Cost	y	Annualised investment costs	positive	£
	OM_costs	y	Yearly operation and maintenance costs	positive	£
	Heat_income	y, s, t	Heat income at time t	positive	£
	Boiler_costs	y, s, t	Boiler operating costs at time t	positive	£
	Obj	/	overall cost function (see also below)	/	£
Electricity	HP_elec	p, y, s, t	Electricity consumed by heat pump p at time t	positive	MWh
	Elecbuy_grid	y, s, t	Electricity bought from the grid at time t	positive	MWh
	Elecsold_grid	y, s, t	Electricity sold to the grid at time t	positive	MWh
	Elecbuy_HP_grid	y, s, t	Electricity bought from the grid to run heat pumps at time t	positive	MWh
	ElecCHP_to_HP	y, s, t	Internal electricity used to run heat pumps at time t	positive	MWh
	ECHP	y, s, t	Electricity produced by CHPs at time t	positive	MWh
GHG emissions	CarbonB	y, s, t	GHG emissions at time t using the boiler displacement method	/	$t_{CO_{2eq}}$
	CarbonP	y, s, t	GHG emissions at time t using the power station displacement method	/	$t_{CO_{2eq}}$
	CarbonT	y, s, t	GHG emissions at time t using the DUKES displacement method	/	$t_{CO_{2eq}}$
	CarbontotB	/	Total GHG emissions calculated using the boiler displacement method	/	$t_{CO_{2eq}}$
	CarbontotP	/	Total GHG emissions calculated using the power station displacement method	/	$t_{CO_{2eq}}$
	CarbontotT	/	Total GHG emissions calculated using the DUKES displacement method	/	$t_{CO_{2eq}}$

Table 4.5 – Other variables used in the model.

The other variables used in the model are either continuous or continuous and positive. Forcing some variables to be positive is already a constraint. Most variables depend on y, s and t, which is logical since the energy demand needs to be satisfied following a hourly pattern. Annualised investment costs as well as operation and maintenance costs only depend on y. The remaining variables mainly consist of the sum of time-dependent variables and are principally used as indicators (see also 4.1.4).

4.1.4 Main equations and constraints

The equations define the mathematical structure of the problem and link the variables one to another and to the parameters. Expressed as constraints, they also restrict the number of possible solutions. As described below, many different equations were used in the model. Only the main equations and constraints will be presented in this section.

4.1.4.1 Technology sizing

As fixed capacities were considered, the following equation links technology sizing to their existence at a given time:

$$size_{p,y} = elim_p \times PEx_{p,y} \ \forall p, y \tag{4.1}$$

Once it is decided to build a plant, the variable PEx(p,y) is set equal to 1:

6. Only in versions 2 and 3

$$PEx_{p,y} \geqslant PEx_{p,y-1} \ \forall p, y > 1 \tag{4.2}$$

For each technology, a maximum number of units allowed in the energy centre is defined. For CHP units, this gives for example:

$$\sum_{p \in chp(p)} PEx_{p,y} \leqslant max\_number\_CHP \ \forall p \in chp(p), y \tag{4.3}$$

Finally, the technology size constraints the maximum heat produced at a given time:

$$q_{p,y,s,t} \leqslant size_{p,y} \ \forall p, y, s, t \tag{4.4}$$

4.1.4.2 Working constraints

Working constraints limit technologies operation and heat production. For example, non-existing plant cannot produce any heat:

$$work_{p,y,s,t} \leqslant PEx_{p,y} \ \forall p, y, s, t \tag{4.5}$$

$$q_{p,y,s,t} \leqslant M \times work_{p,y,s,t} \ \forall p, y, s, t \tag{4.6}$$

where M is an arbitrary large positive real number.

Heat production is also constrained by the minimum part load allowed for each technology. As it may be observed in the following equation, the active working level of a given technology is restrained but can take continuous values (see also 4.3.1):

$$q_{p,y,s,t} \leqslant size_{p,y} \times K_p - M \times (1 - work_{p,y,s,t}) \ \forall p, y, s, t \tag{4.7}$$

Finally, constraints on the minimum number of working hours per year or on the minimum number of consecutive working hours allowed were added for model consistency. For example, this gives for CHP technologies:

$$work_{p,y,s,t} \geqslant work_{p,y,s,t-1} - \sum_{z=t-2}^{t-h\_CHP} \frac{work_{p,y,s,z}}{h\_CHP - 1} \ \forall p \in chp(p), y, s, t \tag{4.8}$$

$$\sum_{s} \sum_{t} work_{p,y,s,t} \leqslant min\_time\_chp \times PE_{p,y} \ \forall p \in chp(p), y, s, t \tag{4.9}$$

Thus, all these equations shape the heat demand production for each time band and each technology.

4.1.4.3 Heat and electricity balance

Energy balance equations are divided into heat balance and electricity balance. The heat balance equation states that the heat demand has to be satisfied at each period, the surplus of heat produced being stored in thermal storage facilities:

$$\sum_{p} q_{p,y,s,t} = d_{y,s,t} + \sum_{p \in st(p)} q\_in_{p,y,s,t} \ \forall y, s, t \tag{4.10}$$

Electricity balance equations can be split into two major electricity balance equations and several constraints on electricity production. The electricity balance equation states that the amount of heat produced by CHPs and the electricity bought from the grid are either used to run heat pumps or sold to the grid:

$$Elecbuy\_grid_{y,s,t} + ECHP_{y,s,t} = \sum_{p \in hp(p)} HP\_elec_{p,y,s,t} + Elecsold\_grid_{y,s,t} \ \forall y, s, t \tag{4.11}$$

The other electricity balance equation states that the electricity used to run heat pumps can be either provided by the grid or by working CHPs:

$$ElecCHP\_to\_HP_{y,s,t} + Elecbuy\_grid\_HP_{y,s,t} = \sum_{p \in hp(p)} HP\_elec_{p,y,s,t} \ \forall y, s, t \tag{4.12}$$

The amount of electricity needed to run heat pumps depends on the quantity of heat they produce and on their COP:

$$HP\_elec_{p,y,s,t} = \frac{q_{p,y,s,t}}{COP} \ \forall p \in hp(p), y, s, t \tag{4.13}$$

The amount of electricity produced by CHPs is linked to their heat output by the following linear equation (see also 4.3.1):

$$ECHP_{y,s,t} = \sum_{p \in chp(p)} (\frac{q_{p,y,s,t}}{elim_p} \times w_p + z_p \times work_{p,y,s,t}) \ \forall y, s, t \tag{4.14}$$

The electricity bought from the grid and used to run heat pumps needs to be smaller than the total amount of electricity bought from the grid:

$$Elecbuy\_grid_{y,s,t} \geqslant Elecbuy\_grid\_HP_{y,s,t} \ \forall y, s, t \tag{4.15}$$

Finally the electricity produced by CHPs constraints the amount of electricity that can be sold to the grid, as well as the amount of electricity that can be used internally to run heat pumps:

$$Elecsold\_grid_{y,s,t} \leqslant ECHP_{y,s,t} \ \forall y, s, t \tag{4.16}$$

$$ElecCHP\_to\_HP_{y,s,t} \leqslant ECHP_{y,s,t} \ \forall y, s, t \tag{4.17}$$

4.1.4.4 Storage constraints

Thermal storage was modelled using a daily approach. Indeed, daily thermal storage is the most common form of thermal storage employed in DH schemes and is easier to model using day types. Consequently, it is assumed that thermal stores resume their initial state at the end of the day: the heat storage level is set to be equal to the storage level of the beginning of the day. This approach is similar to the constraints used by Hakarainen et al. and by Oluleye et al. in their respective models [63, 84]. The main equation used to model storage is the hourly heat balance, linking the thermal store level, heat inputs, heat outputs and hourly thermal losses:

$$(-q_{p,y,s,t} + q\_in_{p,y,s,t} + L_{p,y,s,t-1}) \times (1 - Losses) = L_{p,y,s,t} \ \forall p \in st(p), y, s, t > 1 \tag{4.18}$$

For the first hour of the day, no heat can be discharged from the thermal stores.

The thermal storage level is also constrained by the size of the thermal store:

$$L_{p,y,s,t} \leqslant size_{p,y} \ \forall p \in st(p), y, s, t \tag{4.19}$$

4.1.4.5 Costs calculations and resource use

The overall cost function Obj, detailed in 4.1.4.7, is obtained by combining different cost variables.
The annualised investment costs are calculated using fixed and variable investment costs as well as the annuity factor. Considering annualised investment costs allows to spread the investments over the technologies lifetime. It was chosen to adjust the annualised investment cost to the technologies lifetime instead of the project lifetime because all technologies have an expected lifetime longer than 12 years and will remain on-site after that period (see also 4.3.1).

$$Cost_y = \sum_p (C_p \times PEx_{p,y} + size_{p,y} \times Var_p) \times An_p \ \forall y \tag{4.20}$$

Annual operation and maintenance costs are calculated with the following equation:

$$OM\_costs_y = \sum_p PEx_{p,y} \times Mn_p + Var_p \times An_p \times size_{p,y} \times F_p \ \forall y \tag{4.21}$$

Resource use and prices have to be taken into account when calculating the amount of natural gas, electricity and biomass needed by the technologies considered. Since heat pumps and biomass boilers are subsidised through the non-domestic RHI scheme, resource equations also involve subsidies for these technologies:

$$Boiler\_costs_{y,s,t} = \sum_{p \in boilerNG(p)} \frac{q_{p,y,s,t} \times gasprice_y}{boiler\_NG\_Eff} + \sum_{p \in boilerbio(p)} q_{p,y,s,t} \times (biomass\_cost - RHI\_bio) \; \forall y, s, t \quad (4.22)$$

$$CHP\_HP\_ElecCost_{y,s,t} = \sum_{p \in chp(p)} (\frac{q_{p,y,s,t}}{elim_p} \; a_p + b_p \; work_{p,y,s,t} \; gasprice_y) + Elecbuy\_grid_{y,s,t} \; costIMP\_elec_{y,s,t} - Elecsold\_grid_{y,s,t} \; costEXPelec_{y,s,t} - \sum_{p \in hp(p)} q_{p,y,s,t} \; RHI\_HP \; \forall y, s, t \quad (4.23)$$

Finally, the heat produced in the energy centre is sold to customers, which is modelled by the following equation:

$$Heat\_income_{y,s,t} = d_{y,s,t} \times \sum_{consumers} Consprop_{consumers} \times Consprice\_consumers \quad (4.24)$$

The overall objective cost function is defined as the opposite of the net present value. It will be minimised in several model variants (see also 4.3):

$$Obj = \sum_y (\sum_s (\sum_t Boiler\_costs_{y,s,t} + CHP\_HP\_ElecCost_{y,s,t} - Heat\_income_{y,s,t}) \times length_s) + Cost_y + OM\_costs_y \quad (4.25)$$

As it can be seen in the previous equation, resource use variables as well as heat incomes have been multiplied by the number of day types to accurately balance investments and maintenance costs, which are considered over a year.

4.1.4.6 GHG emissions

As the considered technologies contribute differently to GHG emissions, it is possible to split the associated emissions between:

- those due to the on-site combustion of natural gas in boilers.
- those associated to the on-site combustion of biomass in boilers.
- the indirect GHG emissions associated with the external electricity use.
- GHG emissions due to working CHPs: as it will be seen in 4.4.4, it is necessary to separate heat and electricity outputs to properly allocate the total amount of fuel used by CHPs.

For the power station displacement method (see also 4.3.4), this gives the following equation:

$$CarbonP_{y,s,t} = (\sum_{p \in chp(p)} \frac{q_{p,y,s,t}}{elim_p} \times a_p + b_p \times work_{p,y,s,t} + \sum_{p \in boilerNG(p)} \frac{q_{p,y,s,t}}{boiler\_NG\_Eff}) \times CF\_NG + \sum_{p \in boilerbio(p)} q_{p,y,s,t} \times CF_{bio} + Elecbuy\_grid_{y,s,t} \times CF\_elec_{y,s,t} - Elecsold\_grid_{y,s,t} \times CF\_NG \times P\_disp; \quad (4.26)$$

Similar equations are obtained for the DUKES displacement method (CarbonT$_{y,s,t}$) and the boiler displacement method (CarbonB$_{y,s,t}$). It is interesting to observe that CHPs heat and electricity outputs have been separated in the previous equation. GHG emissions associated with CHPs heat output are taken into account in the first part of the equation using the natural gas carbon factor. On the contrary, GHG emissions associated with the electricity produced are calculated using the non dimensional P_disp factor. Only the electricity that is sold to the grid is considered in the last part of the equation, the electricity reused internally (mainly to run heat pumps) being not considered here.

4.1.4.7 Surface required to build the plants

In models 2 and 3, an additional variable, areareq_y, was added to give an estimation of the surface required to build the plants selected by the optimisation program. This required area is calculated using the following equation (see also 4.4.1):

$$areareq_y = \sum_p u_p \times size_{p,y} + v_p \times PEx_{p,y} \; \forall y \tag{4.27}$$

4.1.4.8 Initial conditions

As explained in 2.5, four units (two CHPs and two natural gas boilers) as well as two thermal stores are installed in the energy centre and supply heat to the existing network. This is why the binary variable $\text{PEx}_{p,y}$, associated with the existence of a technology at a given year, is set equal to 1 at year 1 for these units.

4.1.4.9 Objective functions

As it will be seen in part 4.3, the model variants consider either costs or GHG emissions as the objective function to minimise.

The overall objective cost function, which is the opposite of the net present value and will be minimised in several models, is defined by:

$$\begin{aligned} Obj = \sum_y (\sum_s (\sum_t Boiler\_costs_{y,s,t} + CHP\_HP\_ElecCost_{y,s,t} \\ - Heat\_income_{y,s,t}) \times length_s) + Cost_y + OM\_costs_y \end{aligned} \tag{4.28}$$

As it can be seen in the previous equation, variables modelling resource use as well as heat incomes have been multiplied by the number of day types to accurately balance investments and maintenance costs, which are considered over a year. If resource variables were not multiplied by the number of day types, the optimisation program would favour technologies with the lowest investment costs, since some costs benefits associated with more expensive technologies would be forgotten.

Concerning GHG emissions, three objective functions can be optimised depending on the method chosen to apportion fuel to heat and power for CHPs. These functions are obtained by adding hourly GHG emissions over the considered time horizon. As in the previous equation, daily GHG emissions were multiplied by the number of day types to obtain annual GHG emissions values:

$$CarbontotP = \sum_y (\sum_s (\sum_t CarbonP_{y,s,t}) \times length_s) \tag{4.29}$$

Similar equations are obtained for the DUKES displacement method (CarbontotT) and for the boiler displacement method (CarbontotB).

All these equations were used to build the various capacity expansion models presented in section 4.3.

4.2 Baseline scenario

In order to see the impact of expanding the existing district heating network in the Barkantine's area, a baseline scenario was built. This scenario considers a decentralised residential use of natural gas boilers within each building instead of the centralised scheme suggested by a DHN approach.

For each residential building considered in the expansion scheme, one domestic boiler was assumed to be installed per flat. For non residential buildings, one boiler was considered per building.

The following equations were used to evaluate the baseline costs for domestic customers. A discounted cash flow approach was used. Each building's peak demand was multiplied by 1.10 to reflect customer side oversizing tendencies [62]:

$$\begin{aligned} Domestic\ costs = \sum_{residential\ buildings} (&Installation\ costs + 1.10 \times Building\ peak\ demand \\ &\times Domestic\ boiler\ costs) \times Number\ of\ flats \times An \end{aligned} \tag{4.30}$$

$$Non\ domestic\ costs = \sum_{non\ residential\ buildings} Investment\ costs \times 1.10 \times Building\ peak\ demand \times An \tag{4.31}$$

The natural gas costs associated with these boilers for one year were estimated using the following equation:

$$Natural\ gas\ costs = \sum_{buildings} \frac{Annual\ heat\ demand \times Natural\ gas\ price}{Boilers\ efficiency} \tag{4.32}$$

The net present value for the baseline scenario was then obtained by adding all previous costs over twelve years. The evolution of natural gas prices forecasted by DECC was taken into account in this calculation.
Finally GHG emissions were determined using this equation:

$$GHG\ emissions = \sum_{12years} \sum_{buildings} \frac{Annual\ heat\ demand \times CF\_NG}{Boilers\ efficiency} \tag{4.33}$$

Where CF_NG is the natural gas carbon factor.

4.3 Model variations

Several model variants were implemented in order to see the impact of some characteristics and constraints on the final results.

As explained before, a **baseline scenario** where no additional load is connected to the network was built in order to evaluate the economical and environmental impact associated with the Barkantine network's expansion.

To evaluate the impact of using a computationally optimised approach, a **direct optimisation by hand** was also performed. In this heuristic strategy, the mix of plants installed in the energy centre was selected in advance. Two strategies were considered:

- a **leading capacity expansion approach**: big capacities are added at the beginning of the expansion project (mainly CHPs and boilers) and run in part load if necessary (see also 2.4).
- a **matching capacity expansion approach**: small capacity units are installed at the same rate as buildings connect to the DHN (see also 2.4).

To run these strategies, the second version of the model (see also below) was used. Units installation times were imposed to the model by setting the binary existence variable $\mathrm{PEx}_{p,y}$ equal to 1 when a new unit is built and equal to zero before. $\mathrm{PEx}_{p,y}$ was set equal to zero for the plants that will never be built in the heuristic scenarios. No lagging approach was considered in this heuristic approach, as the heat supply needs to meet consumers demand at all times.

Finally various computationally optimised versions were built based on the previous equations:

- **Version 1** optimises the costs associated with the network expansion without considering GHG emissions and subsidies.
- In the **Version 2** of the model, subsidies, GHG emissions and the indicative calculation of the area required are added. This model itself presents sub-variants:
  - **Version 2** optimises the costs associated with the network expansion.
  - **Version 2B** minimises GHG emissions using the boiler displacement method approach, without optimising any cost.

- **Version 2P** minimises as well GHG emissions using the power station displacement method approach. Again, costs minimisation is not considered in this model.
- **Version 2T** also minimises GHG emissions using the DUKES method approach, without any costs optimisation.

- In the third version (**Version 3**), thermal storage is modelled. As for the second model, four sub-variants (**Version3**, **Version3B**, **Version3P** and **Version3T**) were considered. Either costs or GHG emissions were minimised in these variants.

The following section details all the inputs and assumptions used in these models.

4.4 Input data and assumptions

Given the model sensibility to the input data, a lot of time was spent on gathering reasonable data or on generating them using justifiable trends or projections. All the inputs used in the various GAMS models are summarised below. They were all gathered in a single Excel spreadsheet and read by the software using GAMS Data Exchange files (GDX).

4.4.1 Technologies considered and subsidies

Although it is possible to use many heat sources for district heating (see also 2.2), the four following technologies were considered for the Barkantine DH extension scheme:

- CHP plants which are commonly used in DH schemes, as they produce both heat and power at the same time.
- Natural Gas boilers, which may be used as backup in DH schemes and offer more flexibility than CHPs, since they can work at almost any part load.
- Heat pumps, which may be an interesting technology to consider in the Barkantine area, as the electricity produced by CHPs can be reused to run them and since the Isle of Dogs is close to the Thames. Moreover, their use is subsidised through the non-domestic RHI scheme.
- Biomass boilers, which are also subsidised through the non-domestic RHI scheme.

Technical and economical characteristics are detailed for each technology in the next sections.

4.4.1.1 Combined heat and power plants

CHP plants are commonly used in DH schemes and two CHP units are already installed in the Barkantine's energy centre. For each CHP type, it was decided to include the same unit twice in the inputs. Considering several CHP units with the same capacity avoids oversizing risks since each capacity can be selected twice. Otherwise the model could be forced to select bigger capacities once all the small units have been chosen, which could oversize the energy centre.

Using CHPs technical characteristics, it was noticed that their power consumption as well as their electrical output evolve linearly with part load, as it can be seen on the next figures. Following these observations it was decided to consider continuous part loads instead of discrete part loads in the model.

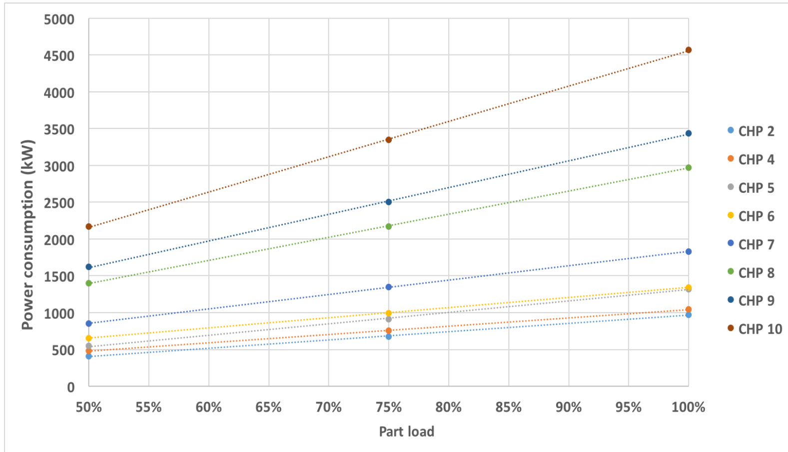


Figure 4.2 – CHPs power consumption as a function of their part load

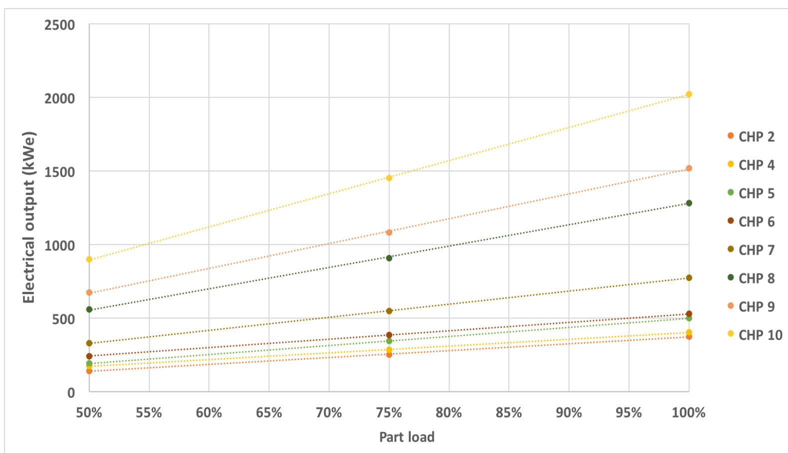


Figure 4.3 – CHPs electrical output as a function of their part load

According to the previous curves, a given CHP heat output (hence the corresponding part load) and the previous curves' slopes and intercepts will be sufficient to determine CHPs power consumption and electrical output. It is also possible to express the floor surface required to build CHP plants as a linear function of their full load heat output (see also Appendix C).

The following tables detail CHPs technical and economical parameters used in the model. An interest rate of 7 % was considered for all technologies, including CHPs [77].

Name	Theoretical capacity (MW)	Heat output (elim, MW)	Minimum part load (K, %)	Investment costs (C, £)	Annual maintenance costs (Mn, £/year)	Lifetime (years)
chp2a & chp2b	972	0.398	70	230 000	38 769	15
chp4a & chp4b	1 047	0.513	70	233 333	39 498	15
chp5a & chp5b	1 321	0.538	70	258 000	43 393	15
chp6a & chp6b	1 342	0.648	70	316 940	56 784	15
chp7a & chp7b	1 832	0.823	70	875 000	67 411	15
chp8a & chp8b	2 972	1.323	70	1 020 000	111 708	15
chp9a & chp9b	3 437	1.402	70	1 250 000	132 153	15
chp10a & chp10b	4 569	1.901	70	1 550 000	176 088	15

Table 4.6 – Hypothesis used to model CHPs I (costs are displayed in £$_{2016}$) [77, 97].

Name	Slope of the curve GasConsumption=f(part load) (a, /)	Intercept of the curve GasConsumption=f(part load) (b, MWh)	Slope of the curve ElectricalOutput=f(part load) (w, /)	Intercept of the curve ElectricalOutput=f(part load) (z, MWh)	Slope of the curve area=f(size) (u, m^2/MW)	Intercept of the curve area=f(size) (v, m^2)	Existence at year 1
chp2a & chp2b	1.130	-0.164	0.467	-0.094	23.16	25.06	yes (chp2a)
chp4a & chp4b	1.300	-0.201	0.542	-0.118	23.16	25.06	no
chp5a & chp5b	1.545	-0.233	0.616	-0.115	23.16	25.06	yes (chp5a)
chp6a & chp6b	1.374	-0.033	0.573	-0.043	23.16	25.06	no
chp7a & chp7b	1.958	-0.124	0.886	-0.112	23.16	25.06	no
chp8a & chp8b	3.148	-0.181	1.449	-0.170	23.16	25.06	no
chp9a & chp9b	3.635	-0.206	1.691	-0.176	23.16	25.06	no
chp10a & chp10b	4.798	-0.237	2.247	-0.226	23.16	25.06	no

Table 4.7 – Hypothesis used to model CHPs II [77, 97].

Moreover, it was decided to limit the number of CHPs built in the energy centre to 6 and to consider 4 consecutive working hours as a minimum for CHPs operation [77].

4.4.1.2 Natural gas boilers

Two natural gas boiler types were considered in the study:

- Domestic natural gas boilers for the baseline scenario.
- Non domestic natural gas boilers for the energy centre design as well as for big customers in the baseline scenario.

As the capacities (hence the costs associated) differ a lot, it was essential to make a distinction between domestic and non-domestic boilers to avoid overestimating non-domestic boilers costs.

Domestic boilers

Estimations of domestic boilers costs were based on existing and available technologies. Since there are five main domestic boilers providers on the market, and as installation and investments costs data may be easily found, boilers purchasing prices were averaged. A representative price per kW installed was obtained. Applying the same methodology to each provider gives very close costs per kW installed, prices differing of less than 1£/kW.

The following table gathers the hypothesis used to model domestic boilers:

Parameter	Value	Unit
Installation cost	1500-1800	£/boiler
Domestic boiler cost	40.8	£/kW
Efficiency (based on natural gas LHV)	89	%
Lifetime	15	Years

Table 4.8 – Hypothesis used to model domestic boilers (costs are displayed in $£_{2016}$) [98].

Non domestic boilers

Non domestic boilers were considered for the energy centre design as well as for big non-residential buildings in the baseline scenario. The following assumptions were used to model natural gas boilers:

Parameter	Value	Unit
Investment costs (Var)	121 000	£/MW
Maintenance cost (F)	18	%
Minimum part load allowed (K)	0.5	%
Efficiency	90	%
Lifetime	15	Years
Slope of the curve area=f(size) (u)	20	m^2/MW
Intercept of the curve area=f(size) (v)	7.61	m^2

Table 4.9 – Hypothesis used to model non domestic boilers (costs are displayed in $£_{2016}$) [77].

Compared to CHPs and heat pumps, natural gas boilers offer more flexibility. For this reason, no minimum number of consecutive working hours was considered for boilers. A maximum number of 4 boilers (natural gas and biomass boilers) was allowed in the energy centre.

Two boilers with 1.4 MW capacity each (referenced as boiler 1 and boiler 2) already exist at year 1. As for heat pumps, it was observed, while running the first models, that the optimisation program favours big boilers capacities. This why, 0.5, 1 and 1.5 MW capacities were selected for the model.

4.4.1.3 Heat pumps

Given the Thames proximity, it was decided to include heat pumps in the technologies portfolio. Three different heat sources were first considered:

- Water.
- Ground.
- Air.

Since the Barkantine's network supply temperature is 90 °C, ammonia was chosen as refrigerant [40]. It can be observed that for this sink's temperature, ammonia heat pumps COP evolves linearly with the heat source temperature.

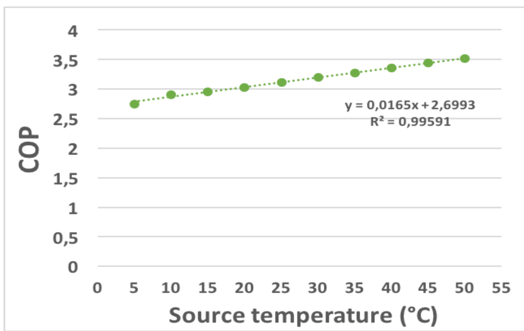


Figure 4.4 – Ammonia heat pumps coefficient of performance as a function of the source temperature for a sink's temperature of 90 °C [40].

The following table gathers all the assumptions used to model heat pumps:

Heat source	Water	Ground	Air
Heat source temperature [7] (°C)	10	12	5
Corresponding COP (using the previous linear curve)	2.864	2.897	2.782
Minimum part load allowed (K, %)	20		
Investment costs (Var, £/MW)	1 936 000		
Maintenance cost factor (F, %)	6		
Lifetime (years)	25		
Slope of the curve area=f(size) (u, m^2/MW)	32.37		
Intercept of the curve area=f(size) (v, m^2)	13.65		
Minimum number of consecutive working hours (h_HP, hours)	2		
RHI (£/MWh produced)	36.12 [8]		25.7

Table 4.10 – Hypothesis used to model heat pumps (costs are displayed in $£_{2016}$) [24, 53, 56, 77, 99].

7. Winter temperatures were mainly considered
8. Tier 1 and 2 considered

Running the first models, it was observed that the model was only building big heat pumps (1 or 2MW), when it was interesting to install one. To reduce the time needed to run the optimisation program, it was decided to restrict the number of heat pumps to 2, and to consider 1 and 2 MW capacities. Only water heat pumps were considered. In addition, the maximum number of heat pumps allowed in the DH scheme was set to 1.

4.4.1.4 Biomass boilers

As biomass boilers are commonly used in Scandinavian DH schemes [3, 89], and since they are subsidised through the non-domestic RHI scheme [24], it was decided to include biomass boilers in the study.

The following table gathers the hypothesis used to model biomass boilers:

Parameter	Value	Unit
Investment costs (Var)	133 250	£/MW
Maintenance cost factor (F)	16	%
Minimum part load allowed (K)	70	%
Lifetime	15	Years
Slope of the curve area=f(size) (u)	24.8	m^2/MW
Intercept of the curve area=f(size) (v)	22.2	m^2
RHI	20.6	£/MWh produced

Table 4.11 – Hypothesis used to model non domestic boilers (costs are displayed in $£_{2016}$) [24, 77].

No minimum number of consecutive working hours was considered for biomass boilers in the model. Compared to natural gas boilers, biomass boilers efficiency is reduced as their part load decreases and a minimum allowed part load of 70 % was considered in the model [3, 77].

4.4.2 Electricity prices and variations

Hourly electricity import and export prices were generated using the Electricity Tariffs model developed by Soler-Garcia and Acha from the Imperial College [100]. Based on existing or projected wholesale electricity prices, the model factors in all the additional charges for transmission and distribution of electricity as well as the associated losses. Although the model can be used to generate electricity tariffs for each distribution network operator in the UK, only the area of London (DNO 12) was considered. As explained in [101], a low voltage connection to the site's electrical distribution system was assumed. The following table gathers all the factors involved in the electricity cost breakdown. Although all these factors are included in the import electricity cost breakdown, only the TLM, the LLF and the DUoS commodity are taken into account to calculate the export electricity prices.

Factor	Description	Source
Comodity (electricity)	Cost of electricity purchased on the wholesale market.	DECC wholesale electricity price projections adjusted to the historic market index price (MIP) [102, 103].
BSUoS	Balancing Services Use of System charge, paid by generators and suppliers (flat tariff across all users) to recover the cost of a day to day operation of the transmission system.	Forecasts provided by the National Grid [104].
DUoS commodity and capacity	Distribution use of system charges covering the distribution networks operation and maintenance costs (fixed annually).	forecasted and published yearly by each DNO [105].
TNUoS (Triad charges)	Transmission Network Use of System charge for the use of the transmission network. The triad charges encourage users to cut load during peak periods.	Tariffs and forecasts are anually published by the National Grid [106].
RO	Renewables Obligation charge, spread across electricity consumers.	Charge is characteristic of the ROC buy-out price (determined by Ofgem) [107].
CCL	Climate Change Levy (environmental tax on electricity prices set by the government).	Rates fixed by the H&M Revenue and Customs [108].
FiT	Feed-in tariff charge paid by customers, enabling suppliers to recover their payments to generators involved in the FiT scheme.	Charge is characteristic of the ROC buy-out price (determined by Ofgem) [109].
AAHEDC	Assistance for Areas with High Electricity Distribution Costs, charge paid by all UK customers to enable distribution charges in the North of Scotland to be reduced.	Fixed annually by the National Grid [109, 110].
CfD	Contracts for Difference charges.	Scheme implemented by DECC [109].
CM	Capacity Market charges.	Scheme implemented by DECC [109].
TLM	Transmission Loss Multipliers used to allocate transmission losses to parties.	Historic data can be found on the ELEXON portal [102].
LLF	Line Loss factors multipliers used to adjust the metering system volumes to account for distribution networks losses.	Fixed annually and published by each DNO, accessible through the ELEXON portal [102].

Table 4.12 – Factors considered in the Electricity Tariffs Model.

Using this Tariff Model, hourly electricity prices were generated for each day type. Since half-hourly commodity prices were considered by the model, these prices were averaged to obtain hourly electricity tariffs and keep the same input structure as for the heat demand.
It has to be emphasized that the (projected) factors used to calculate the aggregated electricity tariffs are available until 2020 only. As the time horizon considered for the model is 12 years, wholesale electricity prices projections were adjusted to the DECC projections for the last 7 years. The electricity factors were kept constant, equal to their projections for the year 2019-2020.

Using the Electricity Tariffs model, the following curves were for example obtained for import electricity prices:

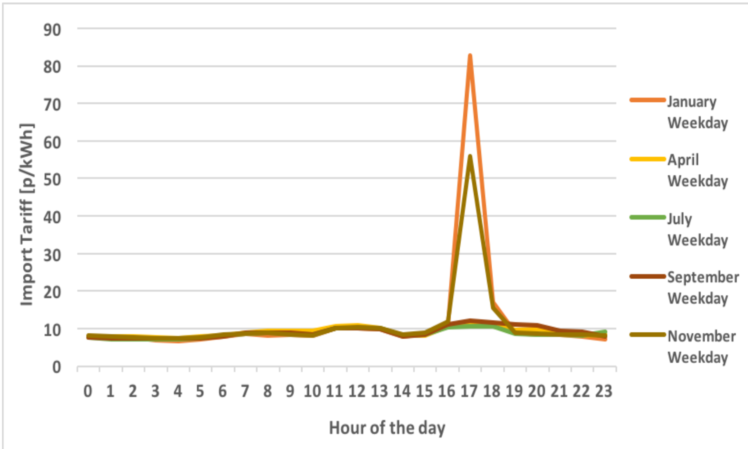


Figure 4.5 – Example of electricity import tariffs generated for weekdays using the Tariff Model [100].

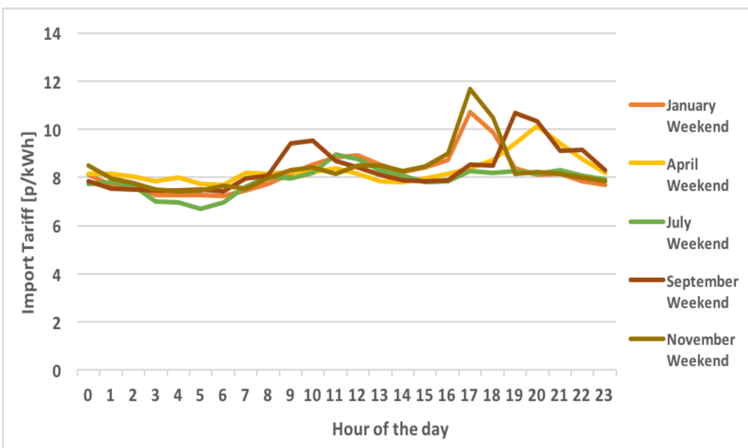


Figure 4.6 – Example of electricity import tariffs generated for weekends using the Tariff Model [100].

Due to the TNUoS charge, it can be seen that Winter weekdays electricity import prices can be particularly high.

4.4.3 Consumer types and heat prices

Heat prices were assumed to be static inputs. As heat prices vary with consumer categories, it was necessary to evaluate the share of the heat demand for each customer type. The London Borough of Redbridge Decentralised Energy Masterplanning Study heat prices were reused [31] for this purpose. Customer types and heat prices are gathered in the following table:

Customer type	Heat price (p/kWh)	Share of the heat demand
Public users	3.81	4 %
New medium commercial users	5.70	53 %
Existing customers	4.53	5 %
New residential customers	8.10	38 %

Table 4.13 – Heat prices and customers share of the demand considered (costs are displayed in £$_{2016}$) [31].

As it may be seen in the previous table, commercial users represent the biggest share of the heat demand in the area of interest.

4.4.4 Carbon factors

As discussed in 4.2, several model variants try to minimise GHG emissions using various allocation methods. This is why, considerable attention was given to GHG emissions data and to the way they can be modelled.

4.4.4.1 Fuel allocation to CHPs electricity output

The methodology used to allocate fuel to CHPs heat and electricity outputs varies from one model to another. Indeed, as explained in [111], three different methods can be used to properly allocate the fuel use to CHPs outputs.

The Boiler Displacement Method

The boiler displacement method assumes that the heat generated by a CHP displaces the heat raised by a boiler with an efficiency of 81% on a gross calorific value basis. To determine the GHG emissions, the method considers that the boiler uses the same fuel mix as the actual fuel mix used by the CHP .

Mathematically, the CHP electricity carbon factor can be calculated with the following equation:

$$CHP\ electricity\ factor = \frac{(Total\ fuel\ input - \frac{Qualifying\ heat\ output}{0.81}) \times Fuel\ mix\ emission\ factor}{Total\ power\ input} \tag{4.34}$$

The Power Station Displacement Method

The Power Station displacement method assumes that the electricity generated by a CHP displaces the electricity generated by a conventional power only plant with an agreed efficiency. The model considers an efficiency of 47,6 % (power generation efficiency of a gas fired power station on a GCV basis).

Mathematically, the CHP electricity carbon factor can be estimated according to the following equation:

$$CHP\ electricity\ factor = \frac{Fuel\ mix\ emission\ factor}{0.477} \tag{4.35}$$

The DUKES displacement Method

The DUKES displacement method (also called 1/3 : 2/3 displacement method) considers that twice as many units of fuel are necessary to provide one unit of electricity than to generate one unit of heat.

Under these assumptions, the electricity carbon factor is modelled by the following equation:

$$CHP\ electricity\ factor = \frac{2 \times gas\ consumption}{2 \times Electricity\ output + Heat\ output} \times Fuel\ mix\ emission\ factor \tag{4.36}$$

Reusing the methodology developed by Corral Acero in [97], CHP electricity factors were calculated for all the selected units and for different part loads. The values obtained were then divided by the fuel mix emission factor to obtain dimensionless values. These values were then averaged over all the CHPs considered to obtain one single coefficient, B_disp, P_disp or T_disp, depending on the method considered.

Displacement coefficient	Value (adim)
B_disp	1.12
P_disp	2.10
T_disp	1.61

Table 4.14 – Displacement coefficients used in the model.

Using one single displacement coefficient for each method considered reduces the number of inputs for the model. It is a reasonable assumption, since the coefficients obtained for each CHP are relatively close one to another.

4.4.4.2 Dynamic grid electricity carbon factors

Following the global electricity demand across the UK, the electricity carbon factor varies throughout the day and throughout seasons depending on the mix of plants used to produce this electricity. For example, when the electricity demand is low, the least polluting power plants can be privileged. On the contrary, when the electricity demand is high, more generating capacity is required and electricity sources with a higher carbon footprint may be used. Thus, the electricity carbon factor varies dynamically throughout the year and it was decided to include such variations in the model.

To generate this dynamic electricity carbon factor, two different data types were used:

- Forecasted electricity carbon footprints for the next twelve years.
  DECC reference projections [112] were used and adjusted to last year's carbon footprint by multiplying the expected value for the years to come by the ratio $\frac{carbon\ factor\ recorded\ in\ 2016}{carbon\ factor\ expected\ in\ 2016}$. The 2016 greenhouse gas reporting conversion factor was used to adjust the projected factors [113]. Applying this ratio to the expected electricity carbon factors ensures that these factors will not be underestimated. Indeed, when we compare last years real carbon factors to their expected values, projections seem a bit optimistic a posteriori.
- Hourly, weekly and monthly carbon factor variations between 2009 and 2015 recorded on earth.org.uk [114]. These variations were made dimensionless by dividing them by the average carbon factor recorded on earth.org.uk for each year. These dimensionless ratios were finally averaged over the 2009-2015 period (see Appendix D for more details).

Finally, dynamic carbon factors were generated for each hour, day type and year by multiplying the adjusted values and ratios together following this equation:

$$\begin{aligned} Dynamic\ carbon\ factor = Expected\ carbon\ factor\ (DECC) \times \frac{carbon\ factor\ recorded\ in\ 2016}{carbon\ factor\ expected\ in\ 2016} \\ \times Hourly\ ratio \times Weekly\ ratio \times Monthly\ ratio \end{aligned} \tag{4.37}$$

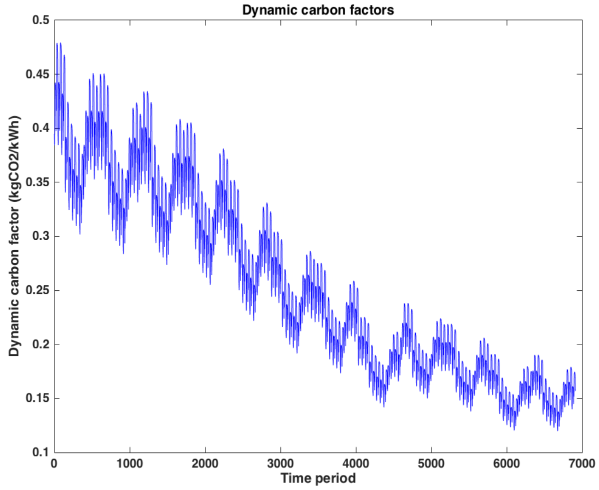


Figure 4.7 – Dynamic electricity carbon factors used in the model.

4.4.4.3 Other factors

The natural gas carbon factor considered was taken from DECC Updated energy and emissions projections, 0.18445 $t_{CO_{2eq}}$/MWh being assumed [103]. For biomass, 0.016 $t_{CO_{2eq}}$/MWh were considered [40].

4.4.5 Natural gas and biomass prices

As explained in 4.1.2, natural gas prices were assumed to vary on a yearly basis. Natural gas prices were based on DECC 2015 projections, the central price scenario being selected for the model [103].

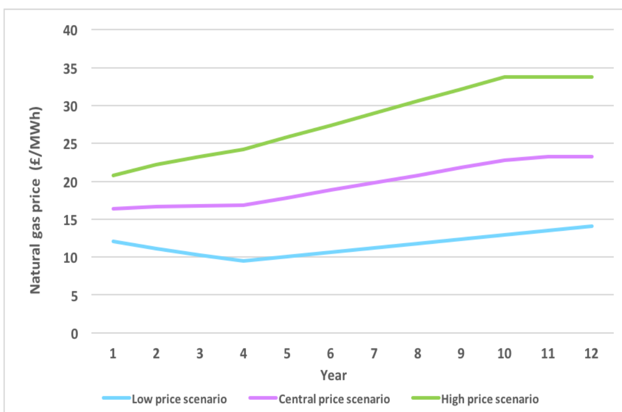


Figure 4.8 – Natural gas prices used for the model based on DECC projections [103].

The biomass cost was assumed to be constant in the model. The Element Energy Ltd model hypothesis were reused and a price of 31 £/MWh$_{produced}$ was assumed [40]. This price already takes into account biomass boilers efficiency.

4.4.6 Storage modelling

As the Barkantine's DH scheme uses thermal heat storage, it was decided to include thermal storage in the model. As explained in 2.2, daily thermal storage is the most common form of thermal storage used in DH schemes, hourly thermal storage being provided by the distribution network inertia, weekly, seasonal and inter-seasonal storage remaining uncommon [3, 57]. A quick review of the existing literature shows that most articles considering thermal energy storage use a continuous demand approach [82, 83, 97, 115, 116]. Using such an approach makes thermal storage modelling easier, since it is possible to consider continuous heat level variations instead of restricting the heat level with daily constraints. This last option was chosen by Hakarainen et al.: in their model, thermal stores heat content must stay constant over any day-night period [63]. The most useful approach found in the literature was the one developed by Oluleye et al. [84]. Indeed, they consider discrete time bands in their model and impose thermal stores to resume their initial state after a given number of time periods.

Following these observations and the necessity to model storage using day types, it was decided to model thermal storage using simple design considerations, as well as the existing thermal store capacities (2 thermal stores with a capacity of 4.5 MWh, called st1 and st2 in the model). The following table gathers all the parameters used to model storage:

Parameter	Value	Unit
Storage price factor	962	£/m^3
Storage price for capacity [9]	44 893	£/Mwh
Dimensionless storage maintenance factor	1	%
Insulation thickness	0.3	m
Insulation thermal conductivity	0.045 (fiberglass)	W.K^{-1}.m^{-1}
Ratio height:diameter	3:1	/
Height	Variable [10]	m
Diameter		m
R$_{int}$		m
R$_{ext}$		m
Internal temperature (T$_{int}$)	90	°C
External temperature (T$_{int}$)	15	°C
Slope of the curve area=f(size) (u)	0.09	m^2/MWh
Intercept of the curve area=f(size) (v)	0.4	m^2

Table 4.15 – Assumptions used to model storage (costs are displayed in £$_{2016}$) [3, 40, 95].

Storage losses were calculated using a simple thermal diffusion model detailed in Appendix E. These losses were estimated for various thermal store loads (from 1% to 100 %) and averaged to obtain a representative loss percentage per hour. Since the heat losses obtained with this approach were close from one load to another, averaging them was a reasonable assumption. An average heat loss of 0.106 %/hour was estimated with this approach. The following heat storage capacities were considered as input for the model: 0.5 MWh (st3 and st4), 1 MWh (st5), 2 MWh (st6) and 3 MWh (st7).

9. Knowing the capacities and volumes of the existing thermal stores, it was possible to determine the energy capacity volume factor (in kJ/m^3 associated). This value was then multiplied by the storage price factor to obtain a storage investment price per MWh.

10. Knowing the energy capacity volume factor, it is possible to determine the thermal store volume for a given capacity. Given the height:diameter ratio, the internal thermal store diameter is calculated using $V = \dfrac{3\pi D^3}{4}$.

Chapter 5

Pipes network extension

As explained previously (see also 2.2.1), the energy centre and the distribution network differ in their design and building approach. Indeed, building a spatial network is much more expensive than building an energy centre given the disturbance caused by pipes laying. For this reason, pipes need to be made of a robust material, since on-site repairing may be prohibitively expensive. Furthermore, one needs to find a good balance between the pipes insulation costs and the surplus of heat sold with such measures (see also 2.2.1 and 2.2.4). In addition, as the distribution network may have an expected lifetime of around 60 years [3], it has to be carefully designed in order to account for potential future expansions without being too oversized. Overall, many tradeoffs are faced while designing the pipes network and choosing the operating parameters associated.

The following section details the methodology used to estimate the connection and pumping costs required by the network extension.

Since predefined connection strategies were built for the study, pipes design and layout was not optimised. However representative investment and pumping costs were calculated for each scenario.

5.1 Investments required for the spatial network expansion

As it was agreed not to optimise the pipes layout, it was decided to build new transmission and distribution pipes along the routes, as it is commonly done in many district heating networks [3, 28–30].

The following methodology was then applied to determine pipes investment costs for each cluster:

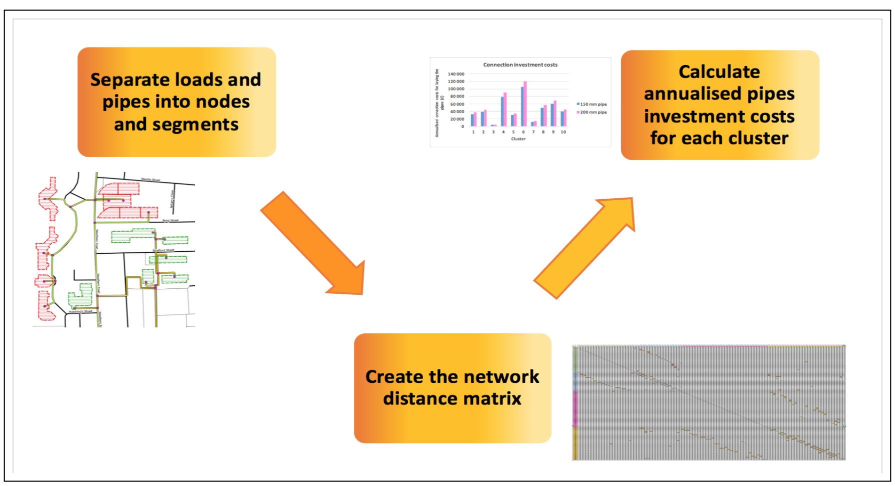


Figure 5.1 – Methodology applied to estimate spatial network investment costs.

First of all, it was necessary to separate loads and pipes into nodes and segments. Indeed, as an incremental expansion of the network is considered, it is necessary to estimate for each cluster the costs associated with its physical connection to the network. Nodes correspond to existing loads, potential loads to be connected, existing pipes network branchings and new pipes network branchings. The following pipes and nodes layout was obtained:

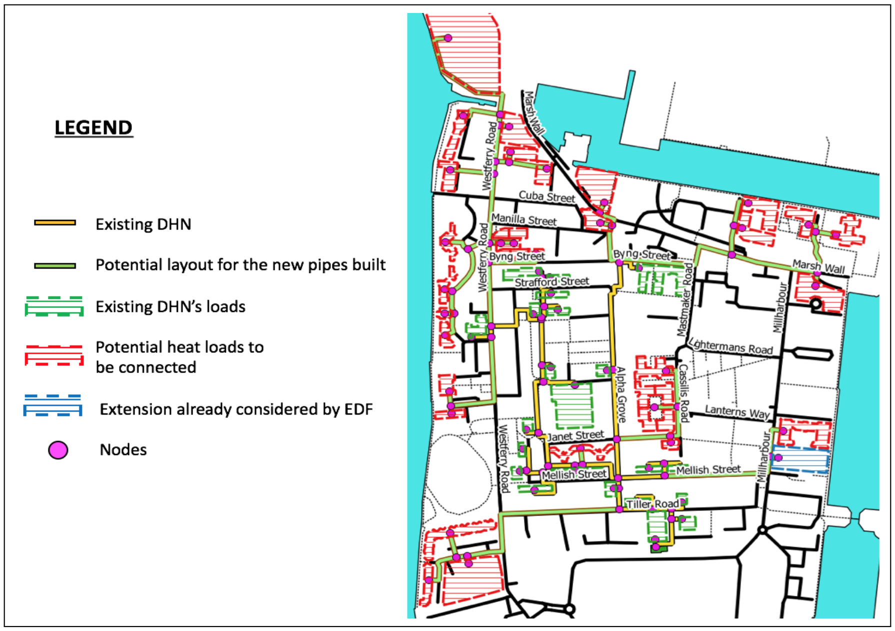


Figure 5.2 – Pipes and nodes layout (QGIS representation used).

For a given node, the distance between this node and its direct adjacent nodes was measured using the London heat map. 3,47 km of pipes need to be built in order to extend the network. If all the buildings considered for the expansion were connected to the existing scheme, the linear heat density associated with the extended network would be 43.06 GJ.m^{-1}.year^{-1}. According to DHN standards, such a high linear heat density should make the extension project profitable [3, 36].

All the distances for all the nodes were then gathered into a big distance/adjacency matrix. This matrix named D is a 102 x 102 symmetric matrix (see also Appendix F). Nodes were then gathered into clusters, one cluster comprising given buildings (see also Chapter 3) as well as the transmission and distribution pipes connecting these buildings to the network.

For each cluster, pipes connection costs were then estimated. It was assumed that pipes are built in a hard urban environment (which is almost always the case in London [30]). Costs of laying out transmission pipes were taken from the ARUP-DENet decentralised energy masterplanning prefeasibility tool [117]. It was observed that the cost of laying out transmission pipes for a hard urban environment evolves linearly with pipes diameter:

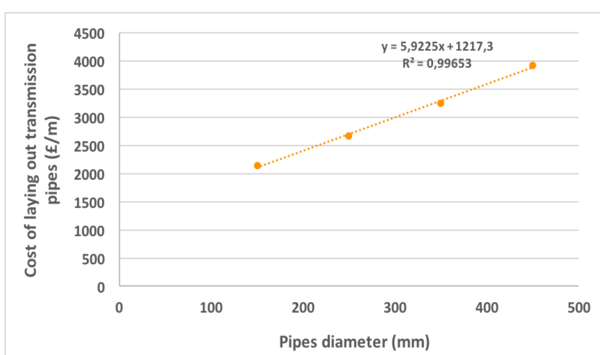


Figure 5.3 – Cost of laying out transmission pipes in a hard urban environment as a function of their diameter (costs are displayed in £$_{2016}$).

Pipes investment costs for a given diameter d were then evaluated for each cluster with the following equation and the trendline previously obtained:

$$Pipes\ investment\ costs = \frac{1}{2} \sum_{node\ i\ \in\ cluster} \sum_{j \neq i} D_{i,j} \times (5.9225d + 1217.3) \times An \tag{5.1}$$

Where An is the annuitizing factor associated with pipes (7 % interest rate and 60 years lifetime considered). Since D is a symmetric matrix, investment costs were divided by 2 to avoid them being taken into account twice.

5.2 Estimation of the pumping costs required

The pumping costs associated with the network extension were estimated for each cluster, reusing the hydraulic equations presented by Hakarainen et al. in their model [63].

For each segment, it was first necessary to determine the friction factor associated to the pipe. The Haaland equation approximation was used to estimate this friction factor for a given pipe diameter:

$$f_d = (1.8 \times \log(\frac{6.9}{Re} + (\frac{\frac{k}{d}}{3.7})^{1.11}))^{-2} \tag{5.2}$$

where d is the pipe's diameter, k the pipe's roughness and Re the Reynolds number associated (expressed as $Re = \frac{v_{max}\ d}{\nu}$, ν being the water kinematic viscosity at the considered temperature).
The pressure drop per unit length in a pipe of diameter d is then calculated with:

$$\Delta p_d = \frac{f_d\ \rho\ v_{max}^2}{2d} \tag{5.3}$$

where v_{max} is the upper velocity limit (depends on the pipe's diameter) and ρ the water density at the considered temperature.
The pumping requirements in a pipe of diameter d, located between nodes i and j, is finally given by:

$$Pump_{i,j,d} = \frac{\Delta p_{i,j,d}\ \pi\ d^2\ D_{i,j}\ v_{max}}{4\ \eta_{pump}} \tag{5.4}$$

where $D_{i,j}$ is the distance between nodes i and j and η_{pump} the pumping efficiency. The pumping requirements for one cluster, assuming a diameter d for pipes, are then given by:

$$Pumping\ requirements = \sum_{i\ \in\ cluster} \sum_{j \neq i} Pump_{i,j,d,90} + Pump_{i,j,d,70} \tag{5.5}$$

where $Pump_{i,j,d,90}$ is the pumping power required in the supply pipe and $Pump_{i,j,d,70}$ is the pumping power required in the return pipe.
Finally, the annual pumping costs for one cluster are given by:

$$Annual\ pumping\ costs = \sum_{s} \sum_{t} Pumping\ requirements \times Electricity\ cost_{s,t} \times length_s \tag{5.6}$$

Where s and t denote respectively day types and hour of the day considered (see also Chapter 4). The electricity tariffs for year 1, presented in 4.4.2, were reused.

The following parameters were used in the equations presented above:

Parameter	Value	Unit
Commercial or welded steel roughness	0.045	mm
Water density ρ_{90} at 90 °C	965.3	$kg.m^{-3}$
Water density at ρ_{70} 70 °C	977.8	$kg.m^{-3}$
Water kinematic viscosity ν_{90} at 90 °C	$0.326.10^{-6}$	$m^2.s^{-1}$
Water kinematic viscosity ν_{70} at 70 °C	$0.413.10^{-6}$	$m^2.s^{-1}$
Pumping efficiency η_{pump}	90	%
Upper velocity limit v_{max}	1.15-3.5 (depends on the pipe size)	$m.s^{-1}$

Table 5.1 – Assumptions used to estimate additional pumping costs required by the network expansion [63, 118–120].

Chapter 6

Results analysis

The model presented in the previous chapters was implemented using GAMS for the energy centre design. MATLAB and QGIS were used to calculate the network's spatial expansion costs.
The analysis provided in the next sections will detail the results obtained for the design of the energy centre and will present an estimation of the costs associated with the spatial expansion. Most curves used for the analysis are presented in the appendices.

6.1 Design of the energy centre

The energy centre design model was implemented and solved using GAMS. Depending on the complexity of the model, it takes between a few hours and eight days to run one model with the Imperial College cluster.
The following sections present a detailed analysis of the costs optimisation and GHG emissions minimisation performed while expanding the energy centre.

6.1.1 Costs optimisation

As explained in 4.3, costs were optimised in models 1, 2, 3 as well as in the heuristic models (leading and matching approaches).

6.1.1.1 General overview

The following figures present for each model the evolution of the heat production capacity as well as the evolution of the demand with time. The corresponding plants and capacities installed are provided in Appendix G.

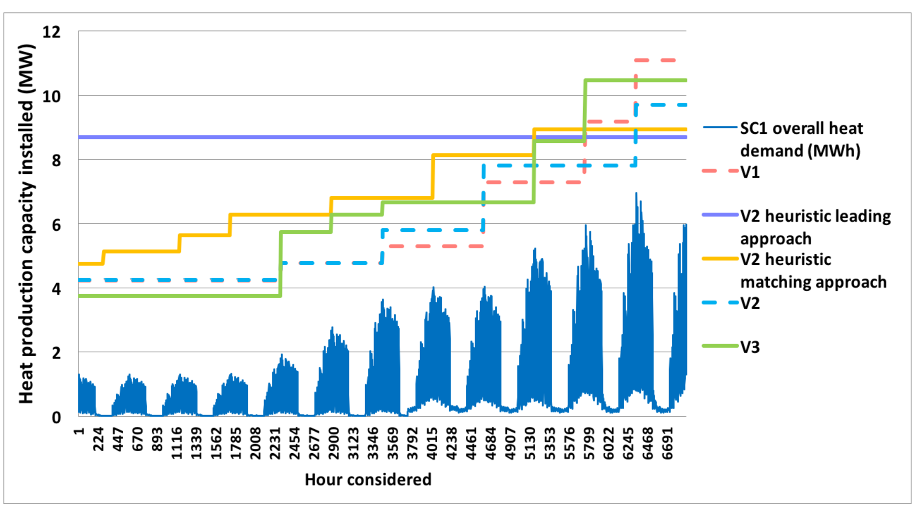


Figure 6.1 – Heat production capacity evolution for scenario 1 (storage is not taken into account as heat production capacity for model 3).

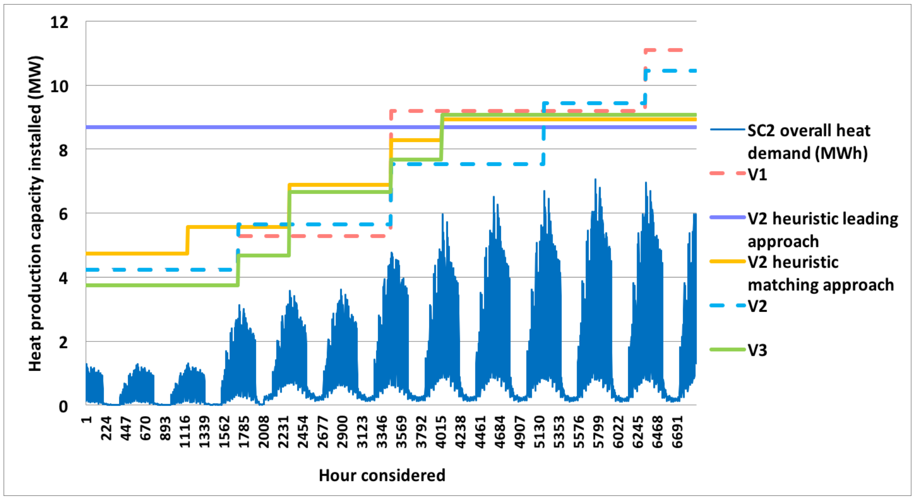


Figure 6.2 – Heat production capacity evolution for scenario 2 (storage is not taken into account as heat production capacity for model 3).

Finally, the following graph displays the net present value associated with each scenario and each model, which is the opposite of the objective function calculated in each model.

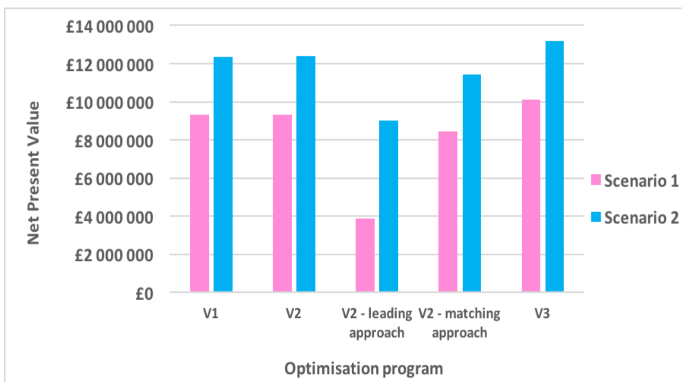


Figure 6.3 – Net Present Value obtained for each model and each scenario (costs are displayed in $£_{2016}$).

First of all, it is interesting to observe that the net present value is positive in each model, which means that the DH project is viable for both scenarios. For each model, the NPV associated with the second scenario is higher. Indeed, as big loads are connected first to the DH scheme in this scenario, more profit is consequently generated. Heat revenues occur earlier and more electricity is sold to the grid, as big CHPs are installed and used earlier in the energy centre.
In addition, it can be noticed that the NPV increases with the complexity of the model. Since heat revenues for a given scenario remain constant from one model to another, it means that the investment schedule and the associated revenues increase the profit as the model becomes more complex. The more complex the model is, better is the costs optimisation

Moreover, we can observe that the optimisation program tends to oversize the heat production capacity in the energy centre. As it can be seen on figures 6.1 and 6.2, heat capacities installed with the heuristic approach are smaller at year 12 than those obtained with models 1, 2 and 3. However, the NPV obtained with the heuristic strategies is smaller for both scenarios, which indicates that it should be beneficial to oversize the heat production capacity.

Comparing both heuristic strategies, it can then be observed that the matching strategy is more beneficial than the leading strategy. Indeed, as it will be seen in the next section, leading models invest at year 1 in some units without using them before a few years, which leads to higher investment and O&M costs. This is not the case in the matching approach (see also 6.1.1.2). Thus, benefits decrease in the leading case.

In the following sections, a detailed costs analysis is performed for each model. GHG emissions are also analysed. An estimation of the surface required in the energy centre for each scenario is finally provided.

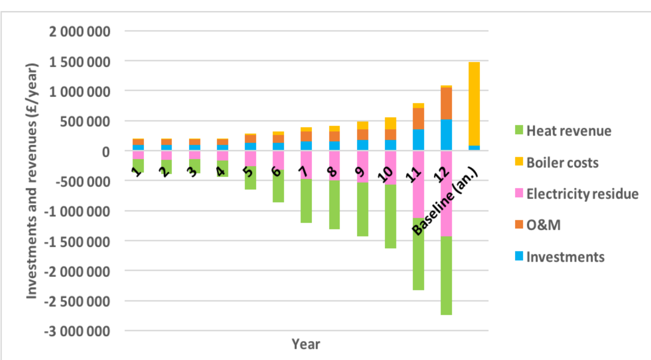
6.1.1.2 Detailed costs analysis

First version

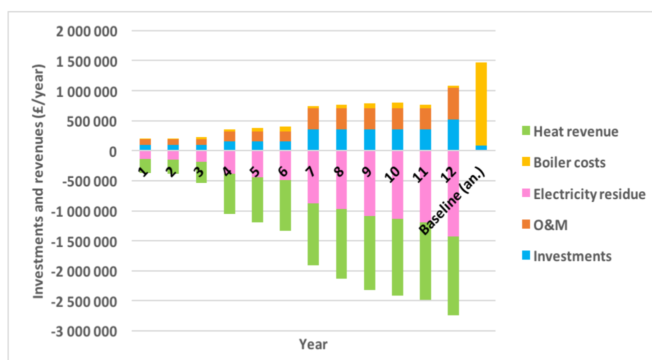
The first model performs a costs optimisation without considering GHG emissions, thermal storage or subsidies. Looking at the mix of plants selected for scenarios 1 and 2, the following observations can be made:

- Since big loads are connected first in the second scenario, there is a bigger capacity increase during the early years for scenario 2. Conversely, small capacity increases are observed in the first scenario during the early years and bigger capacity increases occur during the last years. For example, at year 7, two small CHPs have been installed in scenario 1 (1.04 MW in total) while two small CHPs (1.04 MW), one big CHP (1.9 MW) and one big biomass boiler (2 MW) have been added in the second scenario.
- For both scenarios, the program installs an additional boiler at year 1. Indeed, the model does not consider thermal storage and the missing operating flexibility is compensated by adding an additional boiler in both scenarios. As CHPs offer less flexibility than boilers (70 % minimal part load required for CHPs), the model logically invests in a small natural gas boiler.
- In both scenarios, a biomass boiler is installed. However one can observe that this boiler is exclusively used to cover the peak demand in winter in the middle years (7-10). When it becomes interesting enough to invest in a new big CHP, the model favours heat production with this big CHP instead of considering the biomass boiler. In fact, it is financially more interesting to sell the extra-electricity produced by CHPs to the grid than to use biomass boilers.
- The last capacity expansion occurs at year 12 in both scenarios. Although the last cluster connection takes place at year 11 in July, the peak demand effects associated with this connection appear at year 12, which requires a new capacity expansion.
- Neither of the scenarios consider heat pumps for the expansion. Consequently, all the electricity produced by CHPs is sold to the grid.

The yearly investment schedule for both scenarios is presented on the following graphs. On these graphs, the electricity residue corresponds to the yearly electricity balance (taking into account the electricity bought, sold as well as the gas purchased for CHPs). On each graph, the extreme right bar called Baseline (an.) corresponds to the annualised costs associated to the baseline scenario (see also 4.2). Positive values correspond to yearly investments and expenses while negative values denote revenues.



(a) Scenario 1.

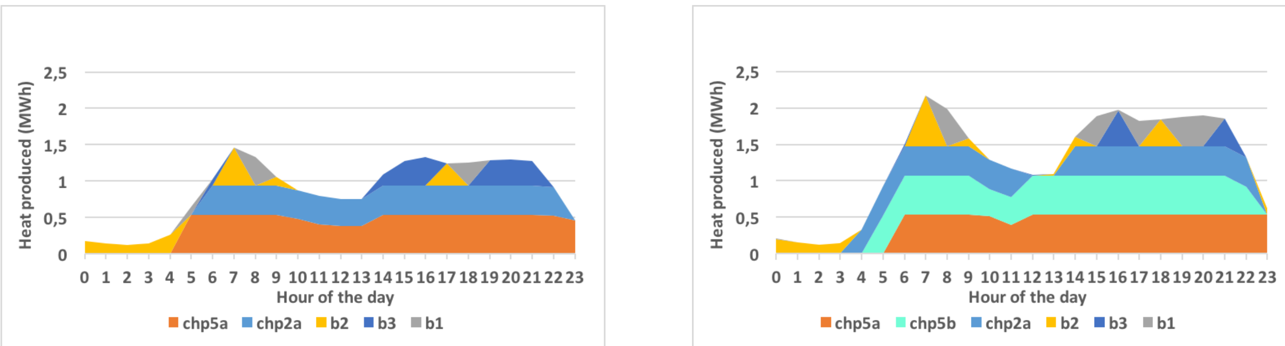


(b) Scenario 2.

Figure 6.4 – Yearly investment schedule - Scenarios 1 and 2, model 1 (costs are displayed in $£_{2016}$).

First, it is interesting to observe that yearly investments and expenses associated with the DH scheme are always smaller than the annual baseline scenario running costs. Although baseline investment costs are smaller than the DH scheme investment, a lot of money is spent on buying natural gas for domestic boilers. Gas is also purchased to run boilers and CHPs in the energy centre, but these costs are recovered by the electricity sold to the grid (negative electricity residue). In each scenario, it can be observed that the sum of heat revenue and the electricity residue is in absolute value greater than the energy centre expenses (annualised investments, O&M costs and boiler costs). This means that profit is generated. Finally, as big heat loads are connected earlier to the DH scheme in the second scenario, investments are made earlier and more money is spent for operation and maintenance in this scenario. However, these expenses are compensated by more heat and electricity sellings, which make scenario 2 more profitable than the first scenario.

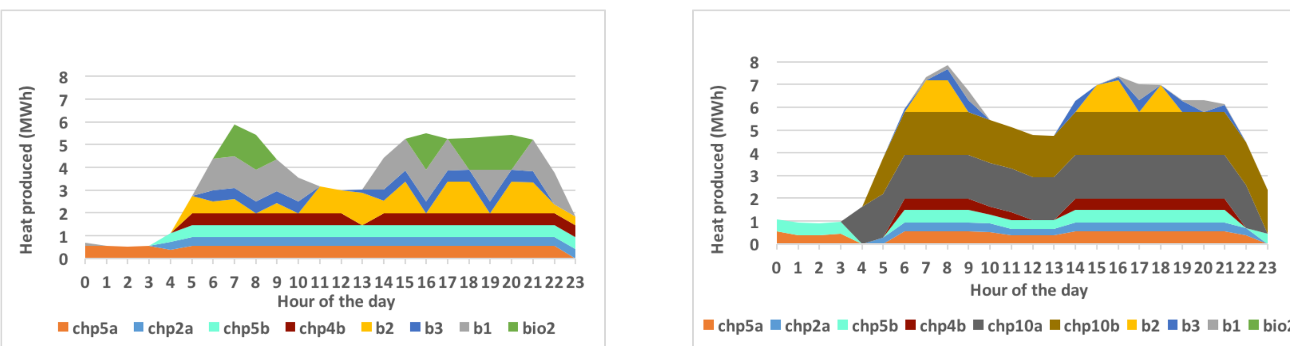
It is also interesting to have a closer look at the heat production patterns. The following figures show day 1 heat production profiles at year 2, 5, 10 and 12.



(a) Year 2.

(b) Year 5.

Figure 6.5 – Heat production profiles - Scenario 1, model 1, day 1, years 2 and 5.



(a) Year 10.

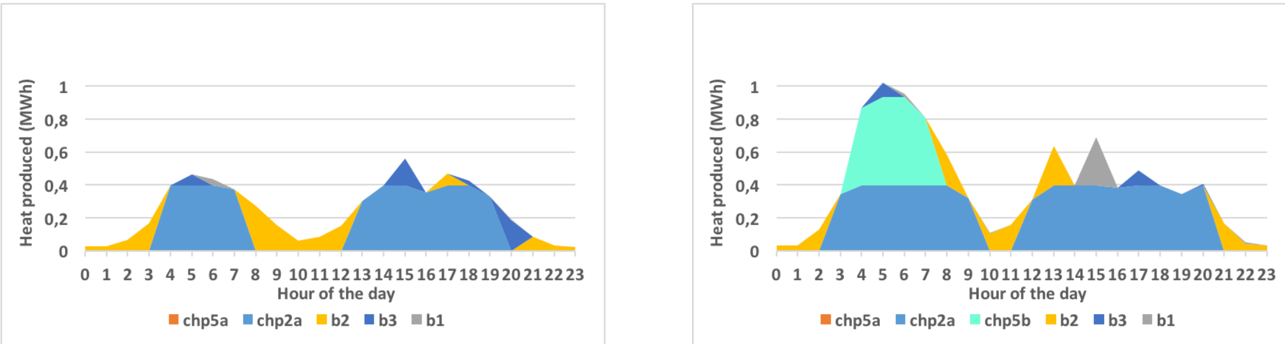
(b) Year 12.

Figure 6.6 – Heat production profiles - Scenario 1, model 1, day 1, years 10 and 12.

As it can be seen on the previous graph, there are two peak times in day 1: one around 7-8 AM in the morning and the second one around 4-7 PM in the evening. At year 2, we can observe that CHPs 5a and 2a are used as base capacity, boilers being used during the night and during peak times to provide extra-capacity. At year 5, a new CHP (chp5b) has been installed and is running most of the day. Boilers still provide heat during the night, but for a reduced number of hours. They also provide extra-capacity during peak times.
At year 10, a small CHP (chp4a) and a big biomass boiler (bio2) have been added. CHPs are now running all the day, the night's heat demand being supplied by a small CHP. Boilers (natural gas and biomass) are used during the day, especially during peak times. At year 12, two big CHPs have been installed. It is now interesting to observe that the heat demand is mainly supplied by these big CHPs, small CHPs being less used. Indeed, as it can be seen on figure 4.3, a big CHP used at part load will always produce more electricity than small CHPs used at full load, hence more profit will be generated. The extra-heat supply at peak times is provided by the natural gas boilers, the biomass boiler being unused.

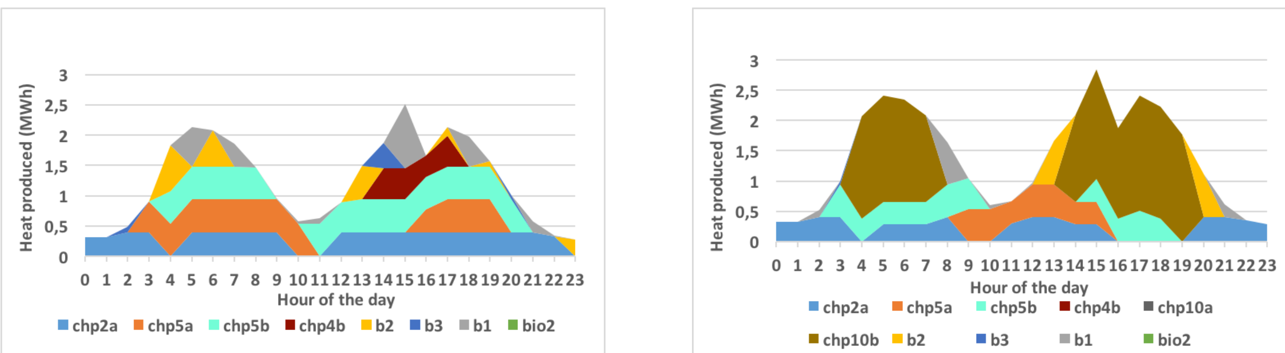
Similar observations can be made for the second scenario. As the bigger loads are connected earlier in this scenario, one big CHPs is installed earlier (year 7) and used as base capacity, generating more profit with the electricity sold (see also Appendix H).

The following heat production profiles are obtained for the first scenario at day 18, which is a September weekday:



(a) Year 2. (b) Year 5.

Figure 6.7 – Heat production profiles - Scenario 1, model 1, day 18, years 2 and 5.



(a) Year 10. (b) Year 12.

Figure 6.8 – Heat production profiles - Scenario 1, model 1, day 18, years 10 and 12.

As it can be observed on the previous figures, there are still two peak periods in day 18. The model tries at most to supply heat with CHPs, playing with CHPs allowed part loads and natural gas boilers flexibility. Using CHPs at most enables to sell the electricity produced and helps maximising the NPV. Similar heat production patterns are observed for the second scenario (see also Appendix H).

In conclusion, the first optimisation model shows that:

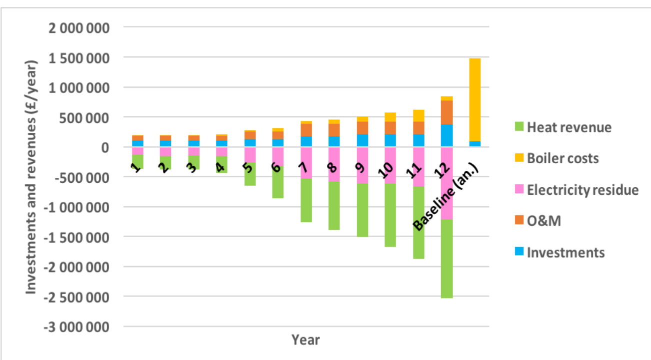
- CHPs usage is maximised in both scenarios in order to sell the electricity they produce to the grid, natural gas boilers providing complementary heat during peak times or when the demand is too low to make it worth using a CHP.
- Both scenarios install a big biomass boiler and use it temporarily during the middle years.

Second version

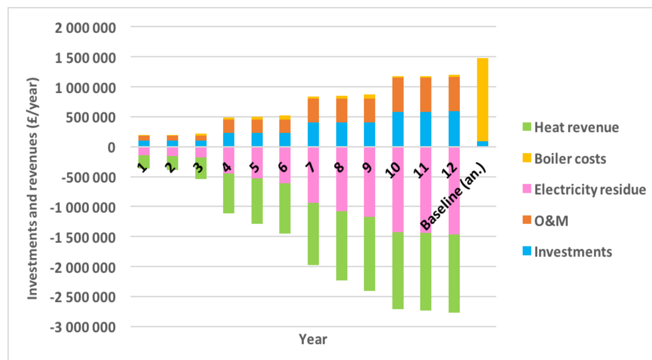
The second model variant includes additional parameters and equations like the estimation of GHG emissions, subsidies associated with some technologies or an estimation of the surface required to install the units selected by the optimisation program. Observing the mix of plants selected by the optimisation program, the following remarks can be made:

- As for the first model, big capacity increases occur earlier in the second scenario than in the first scenario. The second scenario is still more profitable than the first scenario, a higher NPV being obtained.
- The model never installs heat pumps in the energy centre despite RHI subsidies.
- As for the first model, the second optimisation program installs one biomass boiler in each scenario. Although the biomass boiler was not used a lot in the first model, it is now interesting to observe (see also the graphs below) that biomass boilers are much more used than in the previous model, due to RHI subsidies (especially during Winter). Consequently, daily heat production patterns are modified.
- Overall, the model favours biomass boilers usage in Winter. Natural gas boilers, which are more flexible than biomass boilers, are preferably used in summer.
- As it is financially more interesting to install biomass boilers, less capacity is installed than in the first model and the capacities installed are more used than in the previous model.

Looking at the investment schedule for both scenarios, the following histograms are obtained:



(a) Scenario 1.

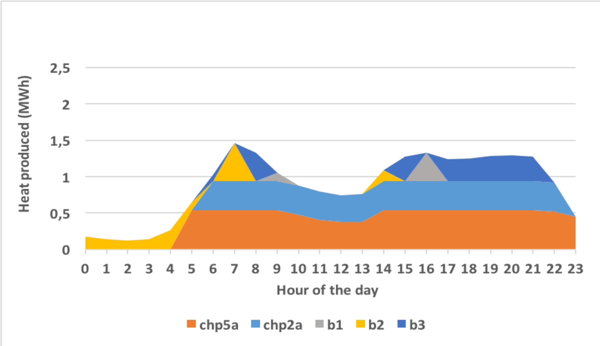


(b) Scenario 2.

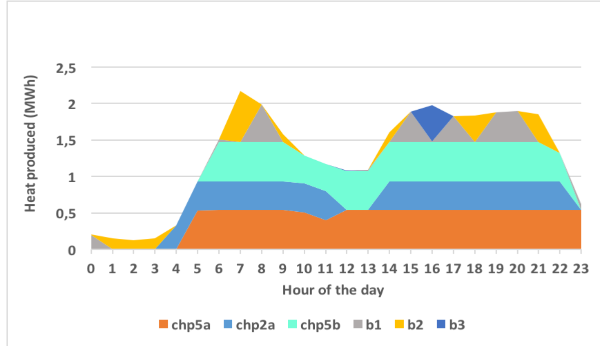
Figure 6.9 – Yearly investment schedule - Scenarios 1 and 2, model 2 (costs are displayed in £$_{2016}$).

As it can be observed on Figures 6.9a and 6.9b, the DH scheme is still more interesting to invest in than the baseline scenario. As for the first model, DH expenses are smaller than the sum of the electricity residue and the heat revenue in absolute value, which makes DH profitable. In this second model, it can be observed that more investments are made for the second scenario, which was not the case in the first model. It is interesting to notice that the yearly electricity residue is smaller for both scenarios in model 2. Indeed, as boilers (and especially biomass boilers) are much more used in the second model, less electricity is produced by CHPs and the associated revenue decreases. Simultaneously, less capacity is installed in both scenarios (compared to model 1), which lowers the investment costs. The overall cost balance remains positive and the net present value associated with the second model is eventually higher than the first model's NPV for both scenarios.

The following heat production profiles are obtained for day 1, scenario 1:

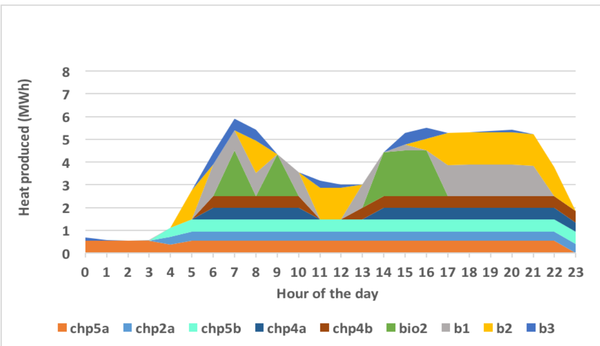


(a) Year 2.

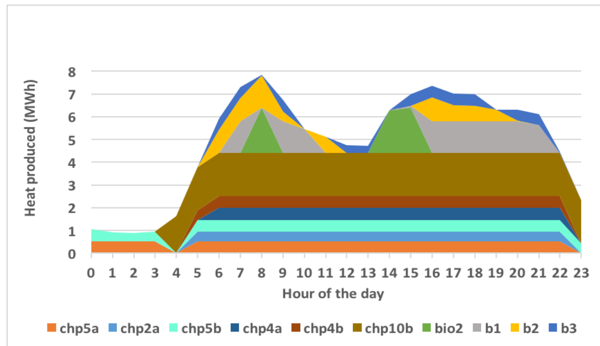


(b) Year 5.

Figure 6.10 – Heat production profiles - Scenario 1, model 2, day 1, years 2 and 5.



(a) Year 10.



(b) Year 12.

Figure 6.11 – Heat production profiles - Scenario 1, model 2, day 1, years 10 and 12.

As it can be seen on the previous figures, the heat production profiles obtained for day 1 at years 2 and 5, are similar for the first and the second model. The model always tries to use CHPs as base capacity in order to maximise the amount of electricity sold to the grid. Two major differences can be noticed by comparing the heat production profiles at year 10 and 12:

- The biomass boiler is by far more used in the second model than in the first model. Consequently, natural gas boilers produce less heat.
- Only one big CHP is installed at the end of the time horizon, whereas the previous model had installed two big CHPs. Consequently natural gas boilers are more used in the late years than in the first model. The biomass boiler is also still in use at year 12.

For the second model, it is interesting to observe that a different capacity expansion strategy is used compared to model 1. Whereas in scenario 1 heat production patterns differ between models 1 and 2, heat production units are modified between models 1 and 2 for the second scenario.

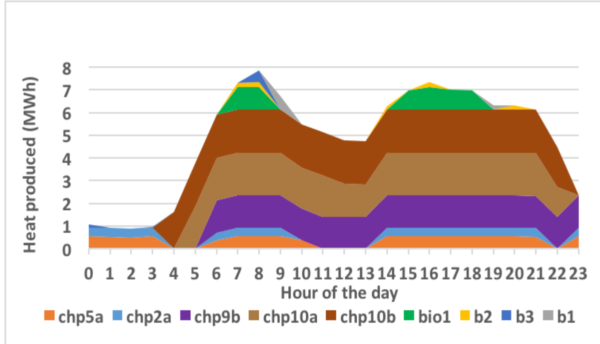


Figure 6.12 – Heat production profile - Scenario 2, model 2, day 1, year 12.

Whereas two big CHPs and one big biomass boiler were installed in the first model, three big CHPs and one medium-sized biomass boiler are now installed by the second program in scenario 2. If this medium-sized biomass boiler is smaller, it offers more flexibility than the big biomass boiler and it is slightly more used than the big boiler in the previous model (61 MWh produced in 24 day types by the small biomass boiler against 45.9 MWh produced by the bigger boiler). The model still tends to invest in big CHPs for scenario 2, as these units have a large power production capacity, which generates more income (see also Appendix I for the the remaining heat production patterns for scenario 2).

The heat production patterns obtained for the first scenario at day 18 are provided in Appendix I. As for the previous model, the optimisation program tries to maximise the use of CHPs at day 18 in order to sell the electricity produced to the grid. One can notice that the biomass boiler is more used during peak times at year 10 than in the first model. Similar trends are observed in the second scenario, although the biomass boiler is less used than in the first scenario.

In conclusion, the second model demonstrates that the capacity expansion approach differs from the first to the second scenario:

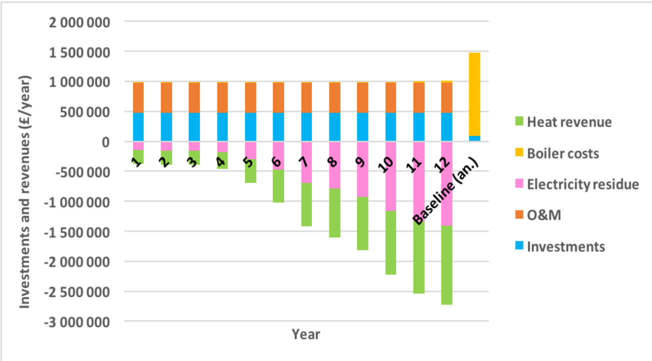
- In the first scenario, subsidies change the heat production patterns: the biomass boiler is used a lot more than in the first model. Thus, subsidies have a big influence on this scenario.
- In the second model, a smaller boiler is installed and used slightly more than in the first model. However, connecting big loads to the DHs first makes it economically too interesting to invest in big CHPs to sell the electricity produced. Subsidies have a small influence on the capacity expansion approach.

In both scenarios, heat pumps are not sufficiently subsidised to be considered as an economically viable heat producing option. Neither of the scenarios invest in them.

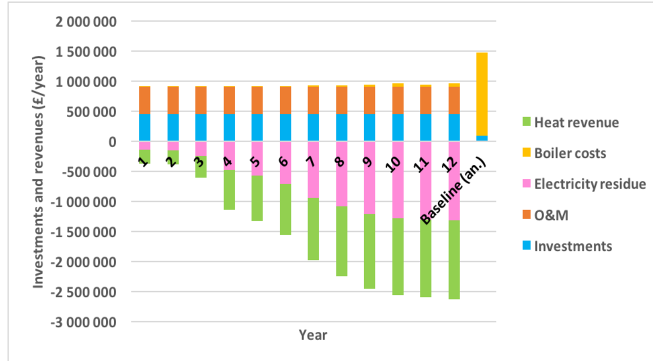
Heuristic models

Both heuristic strategies were run using the GAMS optimisation program developed in the second model. Instead of letting the model decide which units to select and when to install them, a capacity expansion strategy was decided in advance by hand and imposed to the model as constraints. Given the mix of plants selected, the model only optimises the hourly heat and electricity production strategy to maximise the NPV.

In the leading approach, the capacity expansion is anticipated and big heat production units are installed at the beginning of the project. The following investments schedules were obtained for scenarios 1 and 2 using a leading approach:



(a) Scenario 1.

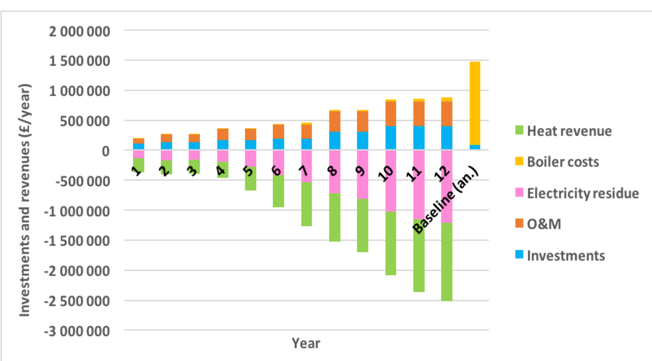


(b) Scenario 2.

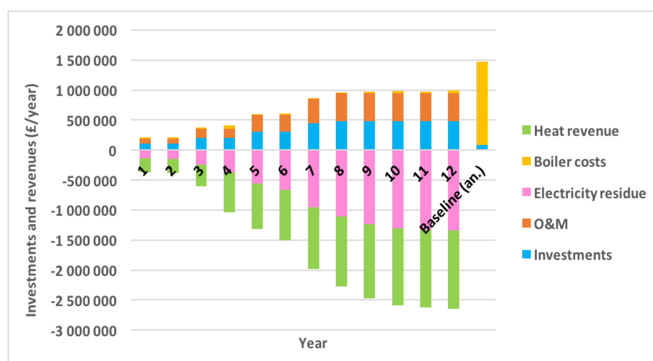
Figure 6.13 – Yearly investment schedule - Scenarios 1 and 2, model 2 heuristic, leading approach (costs are displayed in $£_{2016}$).

As it can be observed on the above graphs, using a leading approach makes the annualised investment costs as well as the O&M costs almost constant throughout the years. Again, the annualised expenses associated with the baseline scenario are higher than those associated with the DH schemes for both scenarios: the DH scheme remains financially more interesting than the baseline solution. However, it can be observed that in the early years of each project, the expenses are greater than the revenue generated with heat and electricity sellings. In fact, although all capacities are installed at year 1, some of them are not used before a few years (lack of flexibility for big CHPs, high operating costs...). Consequently, money is spent to maintain these units but they are not generating any revenue. As clusters connect to the network, it can be observed that more revenue is generated through heat and electricity sellings, making each scenario profitable after a few years. If scenario 2 has a positive costs balance at year 4, one needs to wait until year 6 to make profit in the first scenario. Finally, the NPV is positive in both scenarios and higher for scenario 2 than for the first scenario.

In the matching approach, new units are progressively installed in the energy centre as clusters connect to the DHN. The following investments schedules were obtained for both scenarios with a matching approach:



(a) Scenario 1.



(b) Scenario 2.

Figure 6.14 – Yearly investment schedule - Scenarios 1 and 2, model 2 heuristic, matching approach (costs are displayed in $£_{2016}$).

As it can be observed on the previous graphs, the investments and O&M costs associated with each scenario increase as additional capacity is installed in the energy centre. Simultaneously, the electrical residue and the heat revenues increase in absolute value, which means that profit is made. Compared to the leading approach, the matching approach enables the DH scheme to be profitable from year 1. Indeed, as soon as a new heat producing unit is installed in the energy centre, it starts being used and generates revenues. Consequently, the NPV is higher for both scenarios with the matching approach. As for the leading approach, expenses are lower in the DH scheme than in the baseline scenario. Finally, the NPV is higher for the second scenario than for the first scenario, as for the leading approach.

In conclusion, the leading and the matching strategies are economically viable for both scenarios and more interesting to invest in than the baseline scenario. However, if the capacity installed in both strategies and scenarios is smaller than the capacities installed by the optimisation program (first and second model), one can observe that more profit is generated by the optimisation program. Indeed the optimisation program tends to install and operate bigger CHPs, which will produce more electricity and generate more revenues at a given part load than smaller CHPs. Thus, oversizing a bit the heat production capacity and anticipating the connections is more profitable than installing capacities that fit the peak demand. Following this observation, it is better to use an optimisation approach than to use a heuristic / by-hand strategy if we want to maximise the DH expansion profit.

Third version

In the third optimisation program, thermal storage is modelled, two thermal stores being initially installed in the energy centre.
Observing the mix of plants chosen by the optimisation program, the following remarks can be made:

- In both scenarios, it can be observed that the heat production capacity increases between the second and the third model. If less heat production capacity is installed in the second scenario compared to the first scenario, the thermal storage capacity installed is the same in both scenarios. Overall, thermal stores are installed earlier in the second scenario, since the heat demand increases a lot during the first years in this scenario.
- As for the second model, neither of the scenarios installs heat pumps in the energy centre despite RHI subsidies.
- As it will be seen in details below, the heat production strategy has changed with the introduction of thermal stores. First of all, more heat is produced than what is needed at a given time, as this heat can be stored. In addition, the model tends to use CHPs continuously in order to sell the electricity produced to the grid, the surplus of heat being stored or sent to the network. To a certain extent, thermal stores are more used to enable CHPs to sell electricity continuously than to store the heat produced.
- Following the previous remark, the existing natural gas boilers are less used in this model than in the previous models: thermal stores displace the heat produced by natural gas boilers. These boilers remain sporadically used but no regular usage pattern emerges from the results.
- In both scenarios, the model prefers investing in biomass boilers than in natural gas boilers, heat pumps or additional CHPs. Most of the times, it also prefers using these biomass boilers instead of the existing natural gas boilers, which shows the influence of RHI subsidies on the mix of plants chosen. This trend was not so clearly observed in the previous model, especially for the second scenario.

The following investments schedules were obtained for scenarios 1 and 2 in the third model:

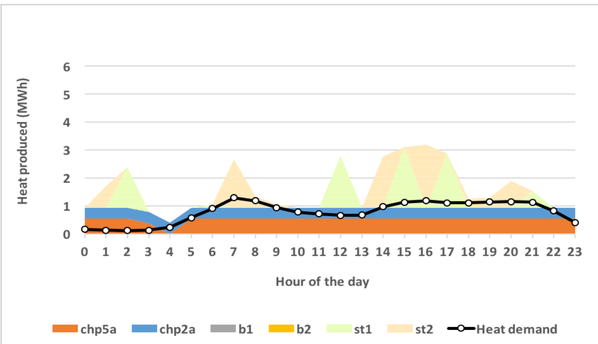
(a) Scenario 1.

(b) Scenario 2.

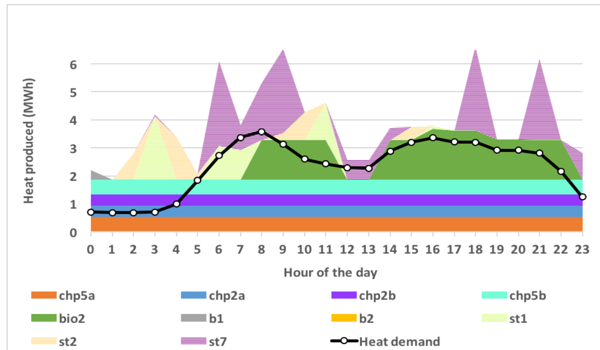
Figure 6.15 – Yearly investment schedule - Scenarios 1 and 2, model 3 (costs are displayed in £$_{2016}$).

As it can be observed on Figures 6.15a and 6.15b, both scenarios are financially more interesting to invest in than the baseline scenario. Furthermore, more profit is generated in both scenarios compared to the previous programs. £2.5m profit was made at year 12 in the previous model whereas both scenarios reach now £3m profit at year 12. If less investments are made in the first scenario compared to the previous models, the second scenario sees its investments increase. This is mainly due to the fact that this scenario now invests in big biomass boilers, which are more expensive than the natural gas boilers installed in the previous models. Finally, as for the previous models, the second scenario generates its profit quicker than the first scenario. The NPV associated with this scenario is higher than in the first scenario.

The following heat production profiles were obtained in the second scenario for Day 1. As the amount of heat produced is now bigger than the heat demand, an additional curve representing the hourly heat demand was added on each graph:

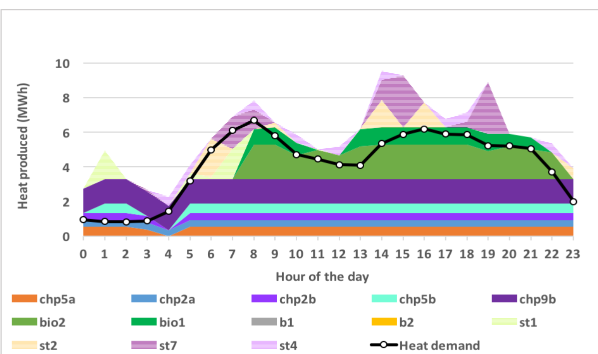


(a) Year 2.

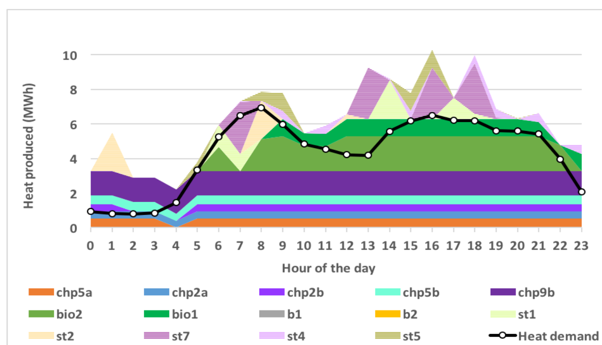


(b) Year 5.

Figure 6.16 – Heat production profiles - Scenario 2, model 3, day 1, years 2 and 5.



(a) Year 10.



(b) Year 12.

Figure 6.17 – Heat production profiles - Scenario 2, model 3, day 1, years 10 and 12.

As it can be seen on the previous graphs, the heat production is higher than the heat demand. The difference between the heat produced and the heat demand is particularly significant during the night and overall, heat profiles are flattened compared to the second model. On each graph, it can be observed that the model tries to maximise the use of CHPs in order to sell the electricity they produce to the grid. Consequently, CHPs provide the base heat capacity at all times whereas biomass boilers are mainly used during the day and for peak times, especially in Winter. It is interesting to notice that natural gas boilers are almost not used in this model. Concerning thermal stores, their usage pattern evolves with time. If they are mainly used during peak times to supply heat in the early years, it can be seen that they are less used to supply heat during late years. During the morning peak (5AM-9AM) they still deliver heat to the network. During the afternoon peak, all the required heat could be produced by the CHPs and biomass boilers without using thermal stores. However, as it is the time of the day where the electricity

price is high, it is financially more interesting to use thermal stores as extra-loads in order to make all the CHPs run at full load. This is achieved by transferring heat from CHPs to thermal stores and by transferring heat between the thermal stores themselves. Consequently, the amount of electricity sold to the grid is maximised.
Similar trends can be observed for the first scenario. Compared to Scenario 2, thermal stores are more used to supply heat to the network during late years in this scenario (see also Appendix J).

Heat profiles obtained for day 18 are provided in Appendix J. For this day, it can still be observed that the optimisation programs tries to maximise CHPs usage. It is interesting to notice that in the third model, thermal stores have replaced boilers when CHPs are not used in September. These stores are charged at the beginning of the day by CHPs and biomass boilers and discharged throughout the day, especially during peak times. As thermal stores are more flexible than CHPs and less expensive to operate than natural gas and biomass boilers, the program favours their usage during summer and mid-season, natural gas boilers remaining sporadically used. Similar trends are observed for the first model (see also Appendix J).

In conclusion, major differences are introduced by the third model compared to the previous models developed:

- The model favours the use of CHPs to maximise the electricity production, thermal stores being used to help these units running continuously.
- Thermal stores displace the use of natural gas boilers, especially during summer and mid-seasons.
- The third model installs and uses a lot biomass boilers, which are subsidised.
- Heat production patterns change with time: if thermal stores are initially used to supply heat to the network, they are progressively used as extra-loads to make CHPs produce more electricity, thus to generate more profit by selling it to the grid. To a certain extent, the optimisation purpose changes: the model tries to maximise the electricity production, heat becoming a by-product cheaper to sell.

6.1.1.3 GHG emissions

The following graph presents the GHG emissions obtained in each of the scenarios analysed in the previous section.

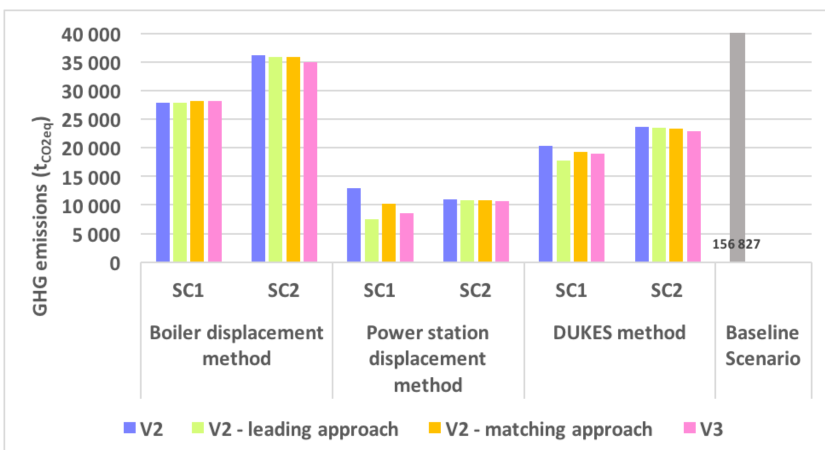


Figure 6.18 – GHG emissions associated with each model and scenario (The scale used for the baseline scenario has been modified and the baseline value is shown on the graph).

As it can be observed on the above graph, the highest GHG emissions are obtained for both scenarios with the boiler displacement method, the lowest emissions being obtained with the power station displacement method. This reflects the value obtained for the coefficients B_disp, P_disp and T_disp obtained in 4.4.4. Moreover, all scenarios and model variants produce less GHG emissions than the baseline scenario, which highlights the environmental benefit of DHNs. In addition, the second scenario has higher GHG emissions than the first scenario in all the models studied. This is mainly due to the fact that heat production is required earlier in the second scenario, since big loads are connected earlier to the DHN.

Looking in details at the scenarios, it can be observed that the trends observed between one model and another remain the same from one displacement method to another.

In the first scenario, GHG emissions decrease from the second model to the leading approach, increase again in the matching approach and decrease in the third model.
Comparing the first and the second model, it has been seen previously that natural gas boilers are used a lot in the second model, which should tend to increase GHG emissions. However, this effect is counterbalanced by an important use of biomass boilers as well as by the emissions displaced by the electricity production. Overall, GHG emissions decrease from the first model to the second model.
In the leading approach, natural gas boilers are less used than in the second model. Moreover, the electricity produced by CHPs still displaces GHG emissions: the emissions slightly decrease in this model. In the matching approach, GHG emissions increase a bit, natural gas boilers being more used in this model (779.2 MWh produced against 522.9 MWh, using only 24 day types per year) and GHG emissions being less displaced by CHPs.
In the third model, natural gas boilers are almost not used any more and one could expect an important GHG emissions reduction. However, as it has been seen previously, CHPs usage is maximised in order to sell the electricity produced to the grid and more heat is produced than needed. Despite a growing use of biomass boilers, GHG emissions are not reduced a lot in this model.

In the second scenario, it can be observed that GHG emissions are reduced from one model to another. In the second model, natural gas boilers are still used a lot (1249 MWh considering 24 day types per year) while in the leading and matching approaches, their use is reduced (respectively 905.6 and 877.2 MWh). Moreover, more electricity is produced by CHPs in these heuristic models, which displaces GHG emissions.
The small difference observed between the second model and the heuristic approaches can be explained by the presence of one biomass boiler in the energy centre in the second model. This biomass boiler counterbalances GHG emissions from natural gas boilers and helps decreasing the use of CHPs, hence the emissions.
Finally, in the third model, natural gas boilers are not used any more and biomass boilers are used a lot. However, as CHPs are used a lot more in this model and produce heat along with electricity, GHG emissions are only slightly reduced.

In conclusion, the three displacement methods applied give different results. However, the trends observed between the models remain the same from one allocation method to another. Overall the second scenario is associated with higher GHG emissions than the first scenario, which can be explained by the cluster connection strategy. A proper Life Cycle Analysis (LCA) would be required for a more detailed GHG emissions analysis.

6.1.1.4 Surface required in each scenario

From model 2, one equation was used to roughly estimate the area required to install the mix of plants selected by the optimisation program. The following graph presents the surface required in the energy centre for each model.

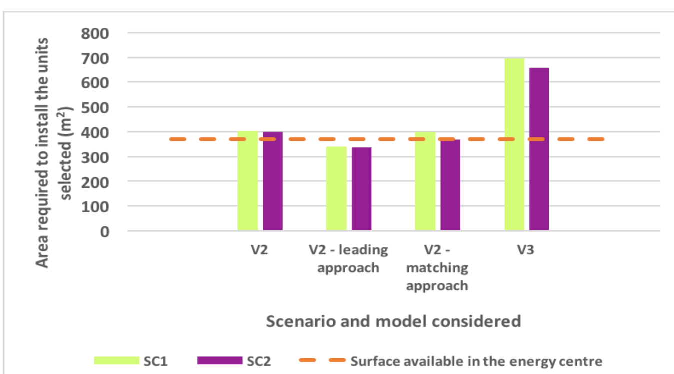


Figure 6.19 – Surface required to install the technologies selected in each scenario.

As it can be observed on the above graph, the leading approach (V2) is the only model for which the area required is smaller than the energy centre surface. For all other models, the area needed is bigger than the available surface. Consequently, one should carefully consider extending the existing energy centre building or even build a new one.

6.1.1.5 Conclusion: costs optimisation - main differences and outcomes

The following table gathers the main differences observed between the models as well as their main outcomes:

Optimisation program version	Main modelling characteristics	Main outcomes - Scenario 1	Main outcomes - Scenario 2
Version 1	• Costs optimisation. • Day types. • Heat and electricity production.	• low NPV and slow revenues. • CHPs usage maximised. • One biomass boiler installed but not used a lot.	• Higher NPV and quicker revenues. • CHPs usage maximised. • One biomass boiler installed but not used a lot.
Version 2	• GHG emissions. • Surface required.	• Higher NPV than model 1. • CHPs usage maximised. • Heat profiles modified by subsidies: biomass boiler used a lot more. • Lower GHG emissions than scenario 2. • Surface required larger than the available surface.	• Higher NPV than model 1. • Heat profiles not particularly affected by subsidies: CHPs usage is maximised. • Higher GHG emissions than scenario 1. • Surface required larger than the available surface.
Version 2H - leading approach	• Mix of technologies manually selected.	• Lower NPV than model 1 and 2 (generates profit from year 6). • CHPs usage maximised. • Some technologies installed at year 1 are not used during the early years. • Lower GHG emissions than model 2 • Surface required smaller than the available surface.	• Lower NPV than model 1 and 2 (generates profit from year 4). • CHPs usage maximised. • Some technologies installed at year 1 are not used during the early years. • Lower GHG emissions than model 2 • Surface required smaller than the available surface.
Version 2H - matching approach	• Mix of technologies manually selected.	• Higher NPV than the leading approach (generates profit from year 1) but lower than models 1 and 2. • CHPs usage maximised. • Lower GHG emissions than the leading approach. • Surface required larger than the available surface.	• Higher NPV than the leading approach (generates profit from year 1) but lower than models 1 and 2. • CHPs usage maximised. • Lower GHG emissions than the leading approach. • Surface required larger than the available surface.
Version 3	• Thermal storage.	• Higher NPV and revenues than models 1 and 2. • CHPs usage maximised by thermal stores: more electricity is sold to the grid. • Heat profiles modified by thermal stores: more heat is produced than needed. • Natural gas boilers almost not used any more. • Influence of subsidies: one big boiler installed and used a lot. • Lower GHG emissions than scenario 2. • Surface required larger than the available surface.	• Higher NPV and revenues than models 1 and 2. • CHPs usage maximised by thermal stores: more electricity is sold to the grid. • Heat profiles modified by thermal stores: more heat is produced than needed. • Natural gas boilers almost not used any more. • Influence of subsidies: two big boilers installed and used a lot. • Higher GHG emissions than scenario 1. • Surface required larger than the available surface.

Table 6.1 – Costs optimisation: summary of the main outcomes.

6.1.2 GHG emissions optimisation

As explained in 4.3, GHG emissions were considered from the second model, and minimised in models 2B, 2P and 2T as well as in models 3B, 3T and 3P.

6.1.2.1 General overview

The following figures present for each model the evolution of the heat production capacity as well as the evolution of the demand with time. The corresponding plants and capacities installed are provided in Appendix K.

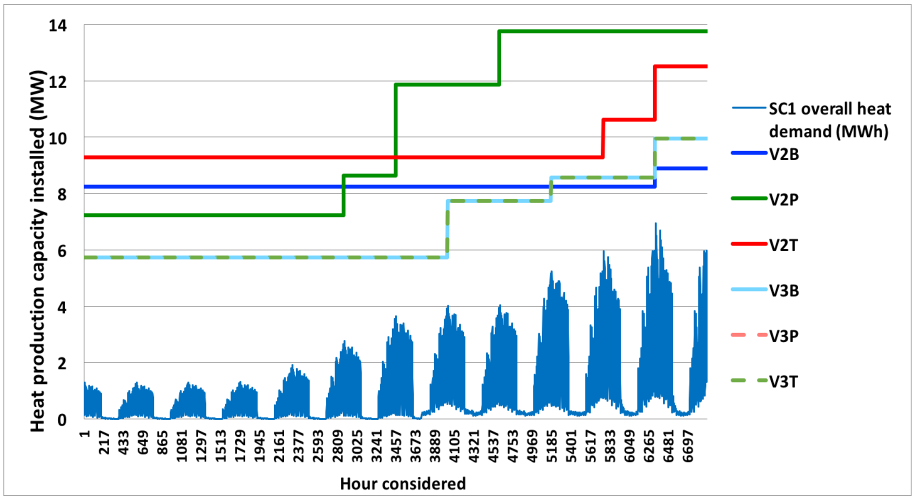


Figure 6.20 – Heat production capacity evolution for scenario 1 (storage is not taken into account as heat production capacity for models 3B, 3P and 3T).

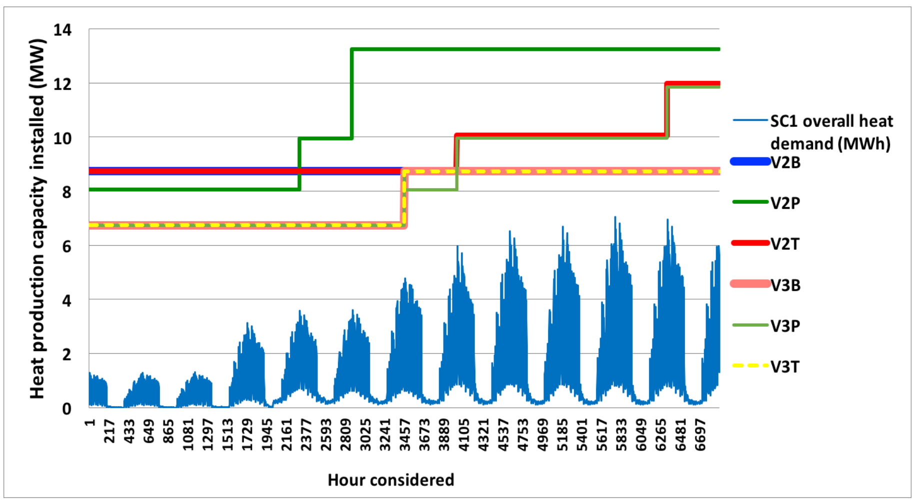


Figure 6.21 – Heat production capacity evolution for scenario 2 (storage is not taken into account as heat production capacity for model 3B, 3P and 3T).

The following graphs displays the GHG emissions obtained in for each scenario, each model minimising the global GHG emissions calculated according to a given methodology (boiler displacement method, power station displacement method, DUKES method):

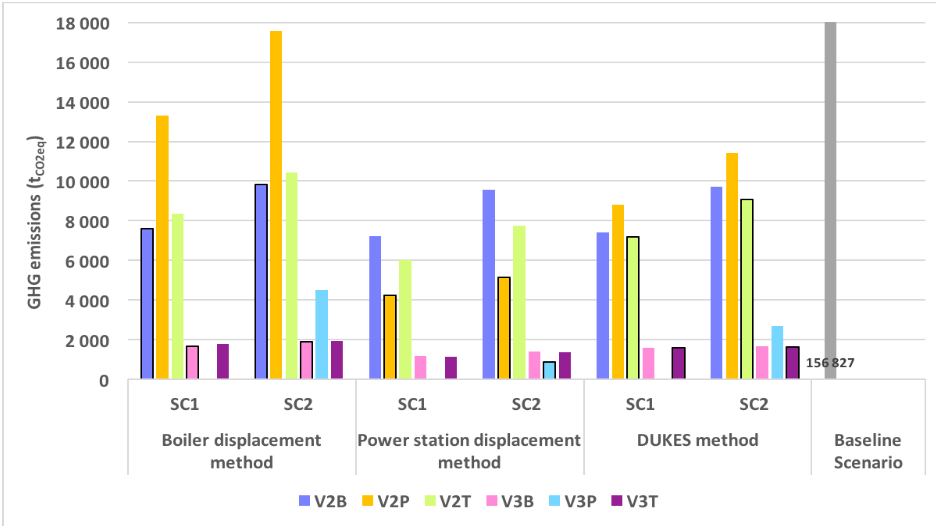


Figure 6.22 – GHG emissions obtained in each model (For each model, the value minimised the objective function is framed in black).

First of all, it is interesting to observe that the capacity expansion is anticipated a lot in each model. Indeed, as the optimisation minimises GHG emissions in each scenario, it tends to install low-emissions technologies (biomass boilers, heat pumps) from the beginning of the project and uses them instead of the existing technologies. As a consequence, it can be noticed that almost all the models install a heat pump (except in scenario 2, model 3P) and use it mostly as base capacity (see also 6.1.2.2). If the second model installs a heat pump at year 1 in each version, one needs to wait year 7 or 8 in the third model to see a heat pump installed in the energy centre. In fact, as CHPs are less used in the GHG emissions optimisation models, most of the electricity used to run heat pumps is bought from the grid. Since the second model does not consider thermal storage, minimising GHG emissions implies using heat pumps from the beginning. In the third model, thermal storage avoids using heat pumps in the early years, when the electricity carbon factor is still high. They start being installed at year 7/8, when the electricity carbon factor has already decreased a lot. Consequently, GHG emissions are lower in the third model than in the second model.
Moreover, it is interesting to observe that the base heat production capacity changes between both optimisation approaches (see also 6.1.2.2). While CHPs were used as base capacity in the costs optimisation models, biomass boilers and heat pumps are now used to supply the base demand.
Comparing the above graph with GHG emissions obtained in the costs optimisation models, we can observe that the boiler displacement method still leads to the highest GHG emissions. The DUKES method gives smaller GHG emissions and the power station displacement method has the lowest emissions.
As for costs optimisation problems, more GHG emissions are obtained in the second scenario, as large clusters connect earlier to the network in this scenario.

Looking more in details at the mix of plants selected in each model, it can be observed that model 2B almost never installs additional CHPs. Indeed, as the electricity produced by CHPs does not displace a lot of GHG emissions with this approach, the model prefers using less emitting technologies like biomass boilers or heat pumps. Consequently, less capacity is installed in the energy centre in this model (and this for both scenarios), which leads to the highest NPV for both scenarios (see also 6.1.2.3). Less surface is also required in the energy centre (see 6.1.2.4).
Compared to the boiler displacement method, it can be observed that additional CHPs are installed by the DUKES method. Indeed, more GHG emissions are displaced by selling CHPs electricity to the grid with this approach. Consequently, the DUKES optimisation program tends to install more CHPs and to use them more. This trend, which was almost not observed with the boiler displacement method, even becomes more visible if the power station displacement method is used. Indeed, this approach installs a lot of CHPs in the energy centre and uses them a lot, which displaces on site more GHG emissions. Although the DUKES method and the power station displacement method lead to lower emissions than the boiler displacement method, the production capacity required in these models is higher, which lowers the NPV and requires more space in the energy centre.

All the trends described above are particularly observed in the second model. In the third model, thermal storage decreases the number of CHPs installed. Indeed both models 3B and 3T select the same mix of plants and the number of CHPs installed in the energy centre is reduced. This indicates that the DUKES approach tries to select low emissions technologies first before displacing GHG emissions with electricity.
The approach is completely different in model 3P. Indeed, in the second scenario, the model installs big CHPs in the energy centre and uses them a lot. No heat pump is installed in this model. Despite these observations, this scenario still has the lowest GHG emissions. In the first scenario, the optimisation program even leads to a minimum of zero. In fact, it has been previously observed that GHG emissions associated with the first scenario are lower than those associated with the second scenario. As the optimisation program considers a positive objective function and as the allocation method used displaces a lot of emissions, the optimum must probably be negative for the first scenario. Too many emissions are displaced by the electricity produced. As a result, the model returns a value of zero. This shows the limits of the power displacement method to select an optimum mix of plants under the given constraints.

The third optimisation model leads to the smallest GHG emissions. It also clearly demonstrates that two optimisation approaches, the boiler displacement method and the DUKES method, lead to a sustainable way to expand the energy centre. The power station displacement method, which seemed to be the most promising given the low GHG emissions obtained, will displace the emissions produced by the DH scheme on-site. However, the environmental effect associated will be worse than if the other approaches are used, as the displaced emissions still exist. Moreover, the profit is much smaller in this case than in the costs optimisation model, without significant environmental benefits.

In the following sections, a detailed GHG analysis is performed for the DUKES optimisation model. Costs are also analysed. An estimation of the surface required for each scenario in the energy centre is finally provided.

6.1.2.2 Detailed GHG emissions analysis

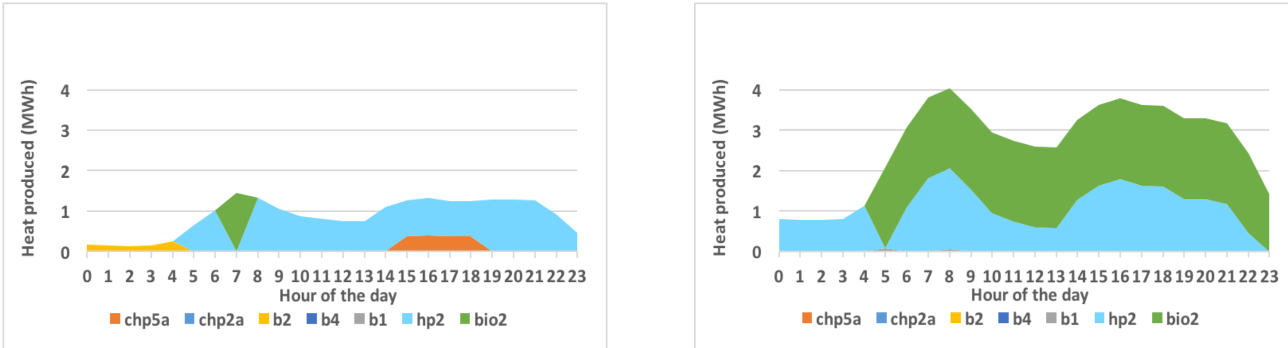
The following sections detail the heat and emissions profiles obtained using the DUKES optimisation approach. This approach was selected because it shares common characteristics with the power station displacement method (version 2) and the Boiler displacement method (version 3). As for the costs optimisation models, days 1 and 18 as well as years 2, 5, 10 and 12 were selected for the analysis.

Second model - DUKES method

The second model - DUKES approach performs a GHG emissions minimisation following the DUKES allocation method, and reusing the equations and constraints developed in the second model. Looking at the mix of plants selected by the optimisation program in both scenarios, the following remarks can be made:

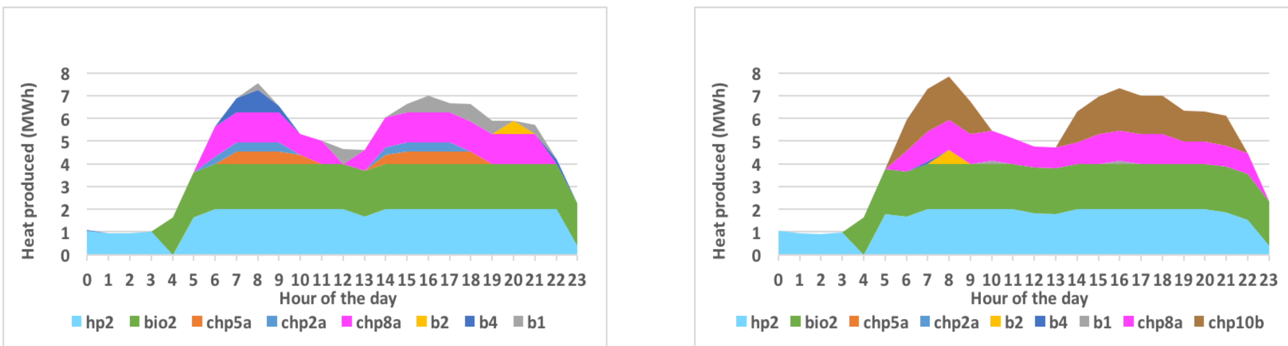
- Both scenarios anticipate a lot the capacity expansion. As GHG emissions are minimised, the model almost does not take into account the existing units. Indeed, these units have a worse environmental impact than the other technologies the model can select (biomass boilers...). In a sense, the energy centre is completely re-designed by the model at year 1, which has a negative effect on the profit generated (see also below).
- Each scenario installs one heat pump and one biomass boiler at year 1, and uses them as base capacity during the following years.
- In the first scenario, one small natural gas boiler and two small additional CHPs are installed at year 1 while a big natural gas boiler is selected in the second scenario. Both scenarios also install two big CHPs at the end of the project (years 8 to 12). The natural gas boilers installed in both scenarios are mainly used in summer and mid-seasons because they offer more flexibility than the other units installed. They are particularly used in the early years and then progressively replaced by CHPs.
- Both scenarios always try to maximise the use of heat pumps and biomass boilers. Depending on the demand, the optimisation program will always select the CHP that will maximise the GHG emissions displacement by selling electricity to the grid. This is notably visible in the first scenario. Indeed, the optimisation program invests in very different CHP capacities. By doing this, the model is always able to displace part of the GHG emissions using the appropriate CHP.

The following heat production profiles were obtained for the second scenario, day 1, using the DUKES approach:



(a) Year 2. (b) Year 5.

Figure 6.23 – Heat production profiles - Scenario 2, model 2T, day 1, years 2 and 5.



(a) Year 10. (b) Year 12.

Figure 6.24 – Heat production profiles - Scenario 2, model 2T, day 1, years 10 and 12.

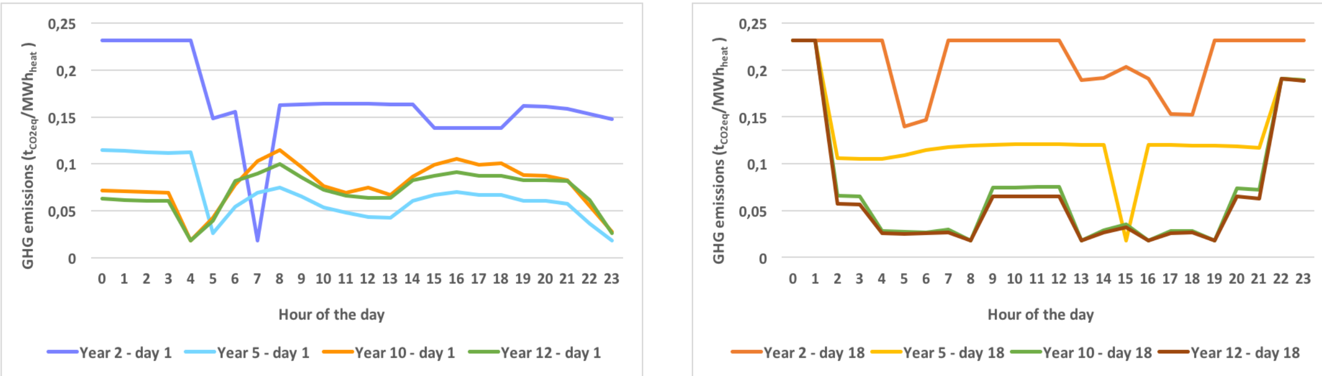
As it can be observed on the previous graphs, the heat pump and the biomass boiler are always used to supply the base demand, the existing capacities (Chp2a, chp5a, b1 and b2) being barely employed. In the early years, the model favours the heat pump use, as the heat pump has a greater flexibility than the biomass boiler. At year 5, it can be observed that all the heat is produced by the heat pump and the biomass boiler, the latter being less flexible and used only when the demand is sufficiently high. At year 10 and 12, the model starts using CHPs during the day, especially at peak demand times. Natural gas boilers complement small CHPs at year 10. At year 12, small CHPs are replaced by big CHPs in order to displace more GHG emissions. Small CHPs are still used during mid-seasons.

In the first scenario, the same trend can be observed (see also Appendix L). Since additional CHPs are installed at year 1 in this scenario, the biomass boiler and the heat pump are less used and CHPs usage occurs earlier (from year 2). As a result, more GHG emissions are displaced in this scenario than in the second one. Moreover, as connections to the DHN are slower in this model, less heat is produced in total, which also contributes to decrease GHG emissions (see Appendix L).

Heat production patterns obtained for the second scenario at day 18 are presented in Appendix L. As it can be observed on these profiles, CHPs, natural gas boilers and the heat pump are used to supply heat at year 2. As the demand increases, they are progressively replaced by the biomass boiler and the heat pump, the latter offering more flexibility. The biomass boiler is mainly used during peak times. Natural gas boilers are still used during the night, when the demand is very low.
A similar trend can be observed in the first scenario. Since the heat demand increases slower in this scenario, CHPs and natural gas boilers are still used at year 5 to supply heat. At year 10, the demand is high enough to favour the use of the biomass boiler and the heat pump. CHPs usage had been replaced by these technologies in mid-season

(see also Appendix L).

It is also interesting to have a look at daily GHG emissions profiles. The following graphs present the average carbon factor per MWh of heat produced in the second scenario.



(a) Day 1. (b) Day 18.

Figure 6.25 – Daily GHG emissions profiles - Scenario 2, model 2T.

As it can be observed on the graphs presented above, the average carbon footprint per MWh of heat produced decreases with time. For both days 1 and 18, the highest carbon footprint is obtained for year 2, when the electricity carbon factor is still high (heat pump) and when natural gas boilers and CHPs are still used (day 18). At year 5, when the model starts using the biomass boiler, it can be seen that GHG emissions have already been reduced a lot. The electricity carbon factor reduction contributes to the decrease observed. At year 10 and 12, CHPs start being used at day 1 and a small increase of GHG emissions is observed, despite what is displaced by CHPs. The emissions slightly decrease at year 12 for day 1. GHG emissions keep on decreasing at year 10 and 12 for day 18.

In conclusion, the DUKES optimisation approach applied in model 2 shows that:

- Low emitting technologies, GHG emissions displacement and technologies flexibility strongly influence the mix of plants selected by the optimisation program as well as the operating patterns.
- In both scenarios, one heat pump and one biomass boiler are installed in the energy centre, CHPs being later installed and used to displace GHG emissions. Due to technologies flexibility, CHPs and natural gas boilers tend to be used a lot in mid-season and summer in the early years.
- As the heat demand increases, the GHG emissions per MWh of heat produced progressively decrease with time.

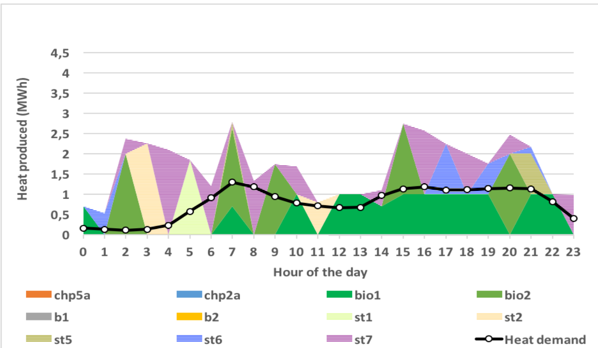
Third model - DUKES method

The third model - DUKES approach - also performs a GHG emissions minimisation. This version reuses the model developed in the third version, in which thermal storage was modelled. After observing the mix of plants selected by the optimisation program in both scenarios, the following observations can be made:

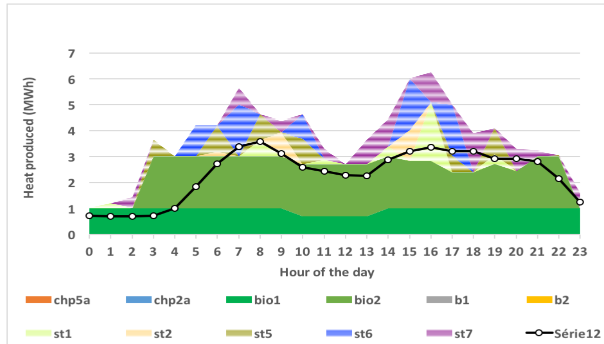
- The capacity expansion is still anticipated by the optimisation program, many additional units being installed in the energy centre at year 1. Additional thermal storage capacity is also installed at year 1 in the energy centre. In both scenarios, the thermal storage capacity installed is similar to what was installed in the third model.
- The heat production capacity decreases from model 2T to model 3T. Both scenarios install a biomass boiler (bio2) at year 1 and a heat pump at year 7/8, when the electricity carbon factor has already decreased a lot. If the second scenario installs an additional biomass boiler at year 1, two additional CHPs are installed in the first scenario at year 10 and 12. This shows that the first scenario is still influenced by the displacement method chosen.

- It is also interesting to observe that the model stops using several units that were originally installed in the energy centre. For example, natural gas boilers are not used any more in any of the scenarios (see also below). They are replaced by the complementary use of biomass boilers and thermal stores in both scenarios.
- Thanks to thermal storage, GHG emissions decrease a lot from model 2T to model 3T in both scenarios.

The following heat production profiles were obtained in the second scenario for day 1. As for the third model, the amount of heat produced in model 3T is bigger than the heat demand. An additional curve representing the hourly heat demand was consequently added on each graph:

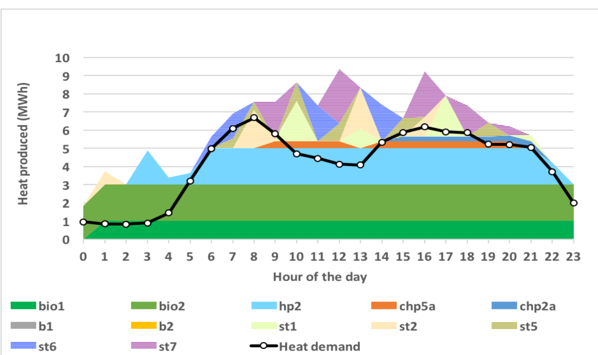


(a) Year 2.

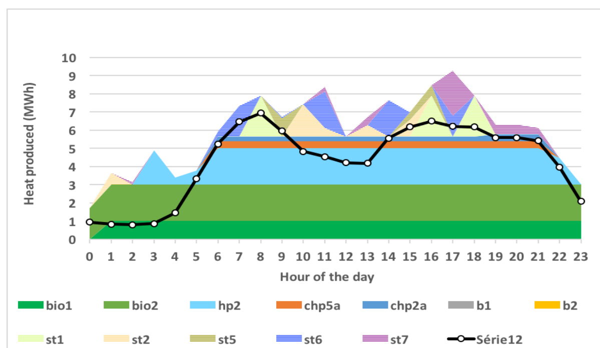


(b) Year 5.

Figure 6.26 – Heat production profiles - Scenario 2, model 3T, day 1, years 2 and 5.



(a) Year 10.



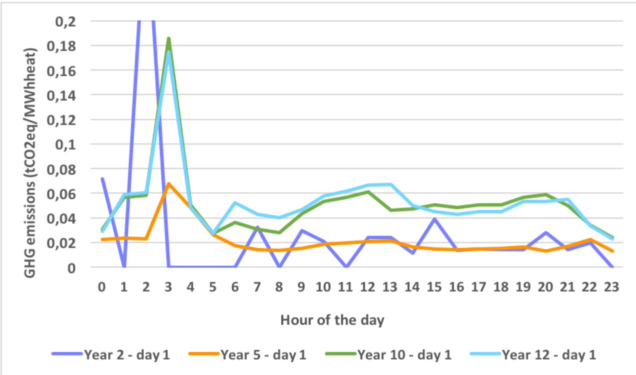
(b) Year 12.

Figure 6.27 – Heat production profiles - Scenario 2, model 3T, day 1, years 10 and 12.

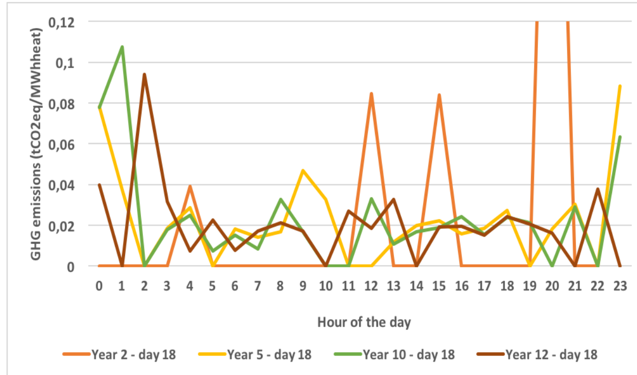
Observing the previous graphs, it is interesting to notice that thermal stores are more used as thermal stores than as extra loads, as it was the case in the third model. Indeed, thermal stores are particularly used during peak times, summer and mid-season in model 3T. As in the third model, more heat is produced that what is needed, thermal stores delivering heat to the network or exchanging heat between one another to minimise losses. During the early years (2 and 5), it can be seen that the base capacity is provided by biomass boilers and thermal stores. At years 10 and 12, the heat pump is also used as base capacity to supply heat to the network and extra capacity is provided by CHPs. It can be observed that biomass boilers are now used continuously during the day. The surplus of heat produced by these units during the night is stored to be delivered to the network during peak times.
Similar trends are observed in the first model (see also Appendix M). As only one boiler is installed in the first scenario, CHPs start being used earlier.

The daily heat profiles obtained for day 18 in the second scenario are presented in Appendix M. As it can be seen on these profiles, biomass boilers and thermal stores are exclusively used during mid-seasons to supply heat to the DH scheme, the other technologies being almost not used. In the first scenario, biomass boilers and thermal stores are also exclusively used (see Appendix M).

Finally, the following curves displays the GHG emissions obtained per MWh of heat produced.



(a) Day 1.



(b) Day 18.

Figure 6.28 – Daily GHG emissions profiles - Scenario 2, model 3T.

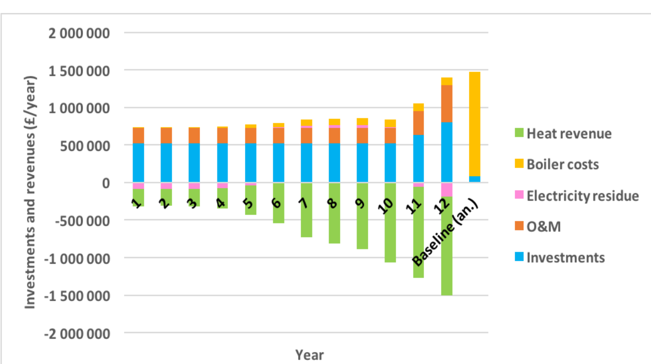
As it can be seen on the graphs presented above, the emissions are already very low from year 1. These emissions are higher at the beginning of the day, when heat is produced to charge thermal stores. Including thermal storage in the third model makes it really difficult to see an evolution trend emerge, especially for day 18. For the first day, one can notice a small increase of GHG emissions from year 2 to year 12. Although the technologies selected by the model are low-emitting technologies, the increase of the demand and the necessity to use CHPs from year 10 make the emissions slightly increase. For day 18, no clear evolution pattern emerges.

In conclusion, major differences are introduced by the third model compared to the second model:

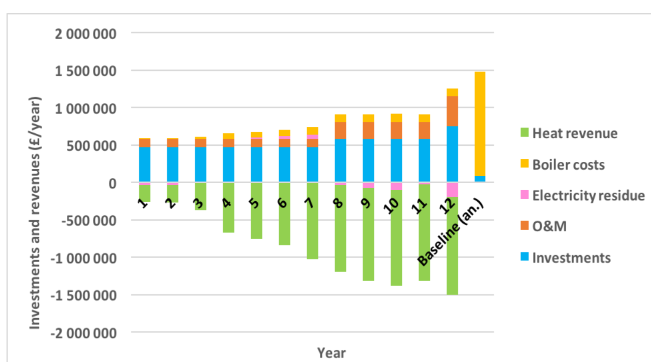
- Thermal storage decreases the capacity installed compared to the second model. It also avoids using some polluting units already installed in the energy centre, like natural gas boilers.
- Overall, GHG emissions decrease in the third model compared to the second model. There is no clear evolution pattern, the emissions per MWh of heat produced being already low at the beginning of the project.
- Finally, the first scenario is more influenced by the displacement method chosen, the model installing one biomass boiler and several CHPs whereas it could install two biomass boilers.

6.1.2.3 Costs associated with the models

The following graphs present the investment schedules obtained for models 2T and 3T:



(a) Scenario 1.



(b) Scenario 2.

Figure 6.29 – Yearly investment schedule - Scenarios 1 and 2, model 2T (costs are displayed in $£_{2016}$).

(a) Scenario 1.

(b) Scenario 2.

Figure 6.30 – Yearly investment schedule - Scenarios 1 and 2, model 3T (costs are displayed in £$_{2016}$).

First of all, it can be observed that the expenses associated with each model and scenario are much closer to those associated with the baseline scenario, compared to the costs optimisation models. Indeed, the investments are much higher in these models, since the optimisation program invests in expensive technologies like heat pumps. The investment costs associated with the second model are higher. Indeed, a higher heat producing capacity is installed in the energy centre in model 2T, where no thermal storage is considered.
Then, it can be seen that the electricity residue is much smaller in absolute value than it was in the costs optimisation scenarios. Moreover, this residue can be positive, which means that more electricity is bought to the grid (to run heat pumps) than sold to the grid.
It can also be noticed that none of the scenarios has a positive costs balance at year 1. As for the heuristic strategies (see also 6.1.1), a positive costs balance will occur earlier for the second scenario than for the first scenario:

- Model 2T: scenario 1 has a positive costs balance at year 9 whereas scenario 2 achieves it at year 4.
- Model 3T: scenario 1 has a positive costs balance at year 5 whereas scenario 2 achieves it at year 3.

Despite a positive revenue balance at year 9, one can observe that the total costs balance is negative in the first scenario, model 2T, the expenses being higher than the revenues generated. One needs to highlight the influence of thermal storage on the investments schedule: models in which thermal storage is considered generate profit earlier.

Given the high expenses and the low electricity revenues generated by each model, it becomes clear that the main revenue will be generated by selling heat. Consequently, the income will be maximised if large amounts of heat start being sold early, i.e. if big loads connect earlier. This is why, designing the energy centre following a GHG minimisation approach tends to favour the second scenario because it generates more profit. Indeed, as it can be observed in Figure 6.31, the NPV associated with the second scenario for a given model is always positive and higher than the NPV associated with the first scenario.

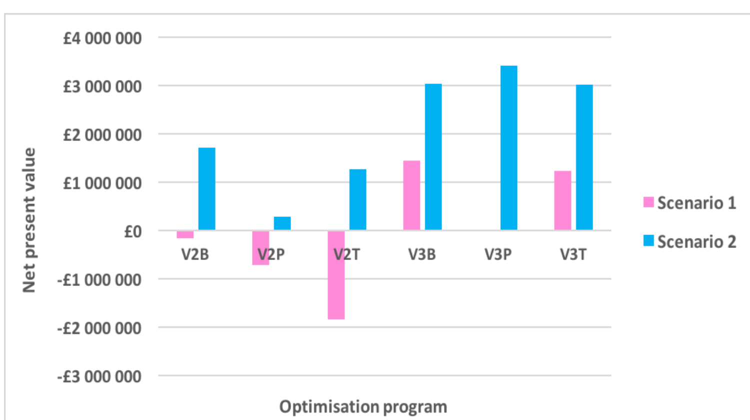


Figure 6.31 – Net Present Value obtained for each model and each scenario (costs are displayed in £$_{2016}$).

Looking closer at the previous graph, it is interesting to see that the first scenario is never financially viable if thermal storage is not considered (model 2). Depending on the capacities installed and depending on the electricity sold to the grid, the NPV will vary in this model, but it will never be positive. For example, model 2P has higher investments and O&M costs than model 2B. Although model 2P sells more electricity than model 2B, the electricity residue associated will be counterbalanced by high investment and O&M costs, which leads to a smaller NPV.

On the contrary, the second scenario will always be financially viable. It is interesting to observe that model 2P is the least interesting to invest in whereas model 3P has the highest NPV. Indeed, in model 3P, less capacity is installed. Moreover, as the model does not select any heat pump, the electricity residue will be positive, all the electricity produced by CHPs being sold to the grid. This is not the case for model 2P, where big CHPs and one heat pump were installed, which leads to high investment costs and to a low electricity residue.

In conclusion, the second scenario is more interesting to invest in, since it has a higher NPV and generates profit earlier than the first scenario. However, this scenario has higher GHG emissions than the first scenario.

6.1.2.4 Surface required in each scenario

The following graph presents the surface required in the energy centre for each model.

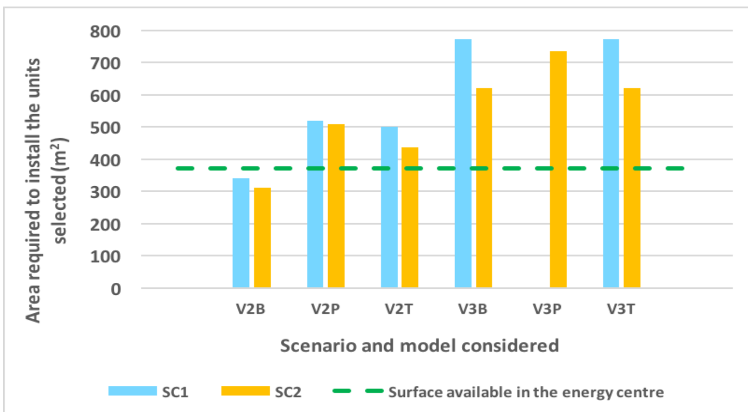


Figure 6.32 – GHG emissions obtained in each model (For each model, the value minimised the objective function is framed in black).

It can be observed that model 2B in the only model for which the area required is smaller than the area available in the energy centre. This is mainly because this model installs less heat producing capacity than the other models. For all other models, and especially for models including storage, the surface required to install the mix of plants selected by the optimisation program is too large. Consequently, one should carefully consider building a new energy centre or expanding the existing one if a GHG emissions optimisation approach is used for the design of the energy centre.

6.1.2.5 Conclusion: GHG emissions minimisation - main differences and outcomes

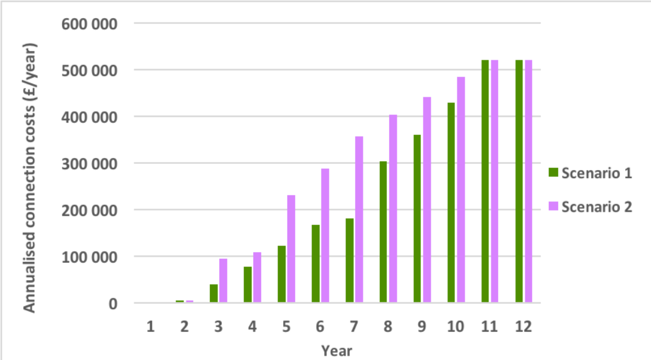
The following table gathers the main differences observed between the models as well as their main outcomes:

Optimisation program version	Main modelling characteristics	Main outcomes - Scenario 1	Main outcomes - Scenario 2
Version 2B	• GHG emissions optimisation. • Boiler displacement method.	• Not financially viable. • Biomass boiler and heat pump used as base capacity. Natural gas boilers and CHPs used during peak times. • Highest emissions on site. Very few emissions displaced by the electricity sold to the grid. • GHG emissions per MWh of heat produced decrease with time. • Surface required smaller than the available surface.	• Financially viable. • Biomass boiler and heat pump used as base capacity. Natural gas boilers and CHPs used during peak times. • Highest emissions on site. Very few emissions displaced by the electricity sold to the grid. • Higher GHG emissions than scenario 1. GHG emissions per MWh of heat produced decrease with time. • Surface required smaller than the available surface.
Version 2P	• GHG emissions optimisation. • Power station displacement method.	• Not financially viable. • Biomass boiler and heat pump used as base capacity. Big CHPs are quickly installed and used by the model. • Smallest emissions on site because most of the emissions are displaced by the electricity sold to the grid. • Unsustainable approach. • Surface required larger than the available surface.	• Financially viable. • Biomass boiler and heat pump used as base capacity. Big CHPs are quickly installed and used by the model. • Higher GHG emissions than scenario 1. • Smallest emissions on site because most of the emissions are displaced by the electricity sold to the grid. • Unsustainable approach. • Surface required larger than the available surface.
Version 2T	• GHG emissions optimisation. • DUKES displacement method.	• Not financially viable. • Biomass boiler and heat pump used as base capacity. CHPs installed and used in the last years by the model. • Medium emissions on site: low-emitting technologies and part of the emissions displaced by the electricity sold to the grid. • GHG emissions per MWh of heat produced decrease with time. • Surface required larger than the available surface.	• Financially viable. • Biomass boiler and heat pump used as base capacity. CHPs installed and used in the last years by the model. • Medium emissions on site: low-emitting technologies and part of the emissions displaced by the electricity sold to the grid. • Higher GHG emissions than scenario 1. GHG emissions per MWh of heat produced decrease with time. • Surface required larger than the available surface.
Version 3B	• GHG emissions optimisation. • Boiler displacement method. • Thermal storage modelling.	• Financially viable. • Thermal storage decreases the capacity installed. • Smaller GHG emissions than in model 2 due to thermal storage. Low emissions from year 1. • Operating strategy still influenced by the emissions displaced. • Surface required larger than the available surface.	• Financially viable. Higher NPV and revenues than model 2. Higher NPV than scenario 1. • Thermal storage decreases the capacity installed. • Smaller GHG emissions than in model 2 due to thermal storage. Low emissions from year 1. • Biomass boiler and heat pump : supply the base demand. • Surface required larger than the available surface.
Version 3P	• GHG emissions optimisation. • Power station displacement method. • Thermal storage modelling.	/	• Financially viable. Higher NPV and revenues than model 2. • Thermal storage decreases the capacity installed and the GHG emissions. • A lot of electricity sold to the grid: highest NPV and a lot of GHG emissions displaced. • Unsustainable approach. • Surface required larger than the available surface.
Version 3T	• GHG emissions optimisation. • DUKES displacement method. • Thermal storage modelling.	• Financially viable. • Thermal storage decreases the capacity installed. • Smaller GHG emissions than in model 2 due to thermal storage. Low emissions from year 1. • Operating strategy still influenced by the emissions displaced. • Heat production profiles slightly differ from model 3B. • Surface required larger than the available surface.	• Financially viable. Higher NPV and revenues than model 2. Higher NPV than scenario 1. • Thermal storage decreases the capacity installed. • Smaller GHG emissions than in model 2 due to thermal storage. Low emissions from year 1. • Biomass boiler and heat pump : supply the base demand. • Heat production profiles slightly differ from model 3B. • Surface required larger than the available surface.

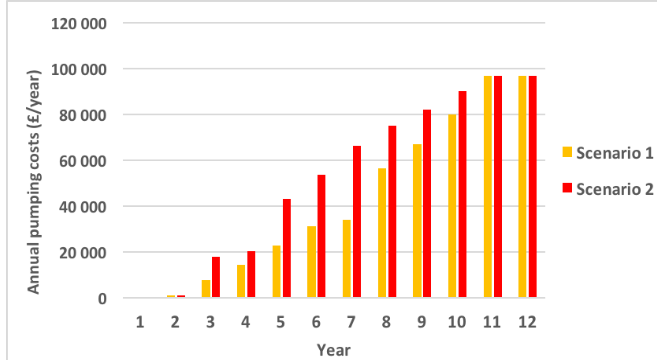
Table 6.2 – GHG emissions minimisation: summary of the main outcomes.

6.2 Network expansion

After studying the energy centre expansion, it is now interesting to investigate the effects of spatially expanding the network on the whole scheme.
The following graphs present the additional investment and pumping costs required by the DHN expansion for each scenario. Pipes with a diameter of 150 mm were chosen, as most of the pipes already existing in Barkantine have a diameter of 150 mm [95]. The costs associated with other pipes diameter are provided in Appendix N.



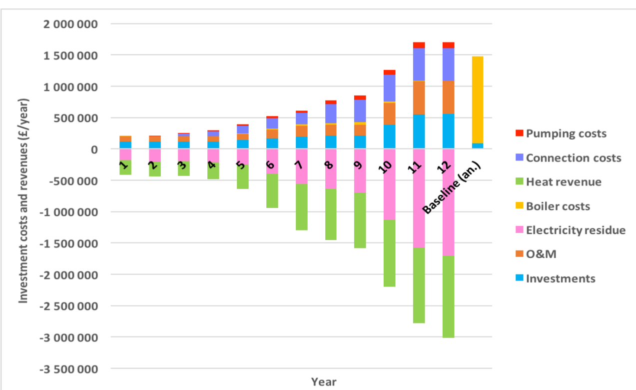
(a) Annualised connection costs.



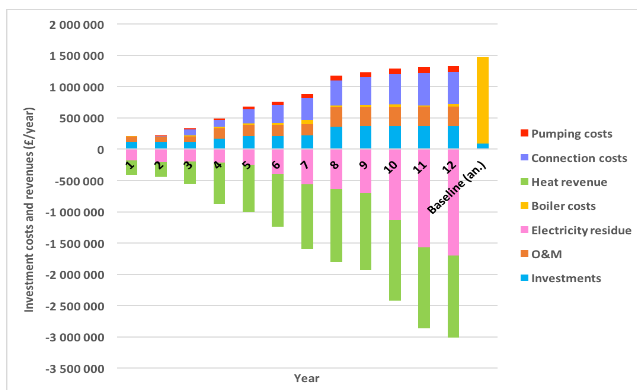
(b) Annual pumping costs required.

Figure 6.33 – Investments required for the DHN spatial extension (150 mm pipes, costs are displayed in £$_{2016}$).

As it can be observed on the previous graphs, higher spatial expansion costs are associated with the second scenario. Indeed, in the second scenario, big clusters (clusters 4, 6, 8 and 9) connect earlier. This leads to an early increase of the connection and pumping costs, these clusters being far from the energy centre and having a high heat demand. On the contrary, small loads are connected first to the DH scheme in the first scenario: the increase of connection and pumping costs occurs later and slower in this scenario. However, as it has been seen in 6.1.1, more revenue is generated by the second scenario (see model 3): big CHPs are installed early and more electricity is sold to the grid compared to the first scenario. In addition, this scenario has bigger heat revenues since big loads connect earlier: customers start paying for heat earlier. Following these observations, it is interesting to study the spatial expansion effects on both scenarios investment schedules:



(a) Scenario 1.

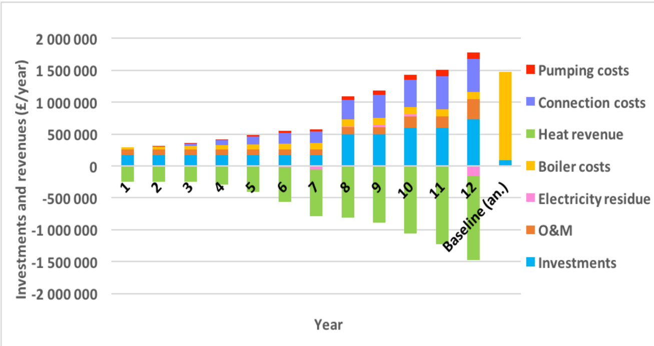


(b) Scenario 2.

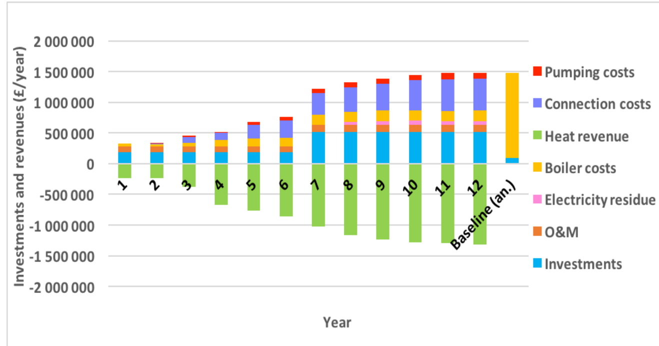
Figure 6.34 – Yearly investment schedule including spatial expansion - Scenarios 1 and 2, model 3 (costs are displayed in £$_{2016}$).

Both scenarios are financially viable, despite the additional investment costs required for the spatial expansion. At each year, the cost balance is positive and profit is generated from year 1 in both scenarios. It is now interesting to observe that the expenses required by the first scenario are bigger than those required by the baseline scenario, which is not the case for the second scenario. Indeed, more investment and O&M costs are required for the first scenario, as it has been seen in 6.1.1. Thus, it is still more interesting to invest in the second scenario than in the first one when spatial expansion costs are considered. Finally, one should keep in mind that it is the electricity sold to the grid in both scenarios that makes them financially viable, thermal stores being used as extra-loads in these scenarios.

It is also interesting to observe the spatial network expansion effects on a model minimising GHG emissions. The following graphs show the influence of the DH spatial expansion on model 3T results:



(a) Scenario 1.



(b) Scenario 2.

Figure 6.35 – Yearly investment schedule including spatial expansion - Scenarios 1 and 2, model 3T (costs are displayed in $£_{2016}$).

As it can be observed on the above graphs, the expenses required by the first scenario at year 12 are greater than those required by the baseline scenario. The expenses associated with the second scenario and those associated with the baseline scenario have the same order of magnitude. Furthermore, it can be noticed that the costs balance is negative almost each year for both scenarios. As the model mainly invests in low-emitting technologies and does not sell enough electricity to the grid, the electricity revenues are too low. Consequently, none of the scenarios is viable if a GHG emissions minimisation is used to design the energy centre.

In conclusion, including spatial expansion costs in the model shows that a costs optimisation has to be performed to design the energy centre in order to make the DHN expansion financially viable. Thermal stores largely contribute to the scheme's viability, enabling to maximise the electricity sold to the grid. Under these conditions, the second scenario has the highest revenues.

Chapter 7

Discussion

The previous analysis has revealed the difficulties of properly modelling DHN expansion. In the next sections, the results obtained will be discussed. A methodology discussion will also be provided at the end of the chapter.

7.1 Results discussion

7.1.1 Energy centre design

The results obtained in the previous chapter bring into light the influence of modelling hypothesis and design strategies on the mix of plants finally selected. Depending on the aspects taken into account and on the objective function selected to perform the optimisation, the results vary a lot from one model to another.

For example, costs optimisations have proven that increasing the complexity of the model leads to higher revenues and decreases the overall GHG emissions. More specifically, these models have shown that anticipating the capacity expansion as well as oversizing the heat production capacity can be beneficial. In comparison, the heuristic matching approach performed for the second model led to a smaller NPV, although the heat production capacity installed in the energy centre was smaller. In addition, the influence of the technologies already installed in the energy centre has to be emphasized. If the model reuses them when a cost optimisation is performed, they are almost never used when the model tries to minimise GHG emissions. Consequently, if the energy centre was designed from scratch, without any existing technology and knowing the connection scenario, the model would certainly invest in different technologies and a higher profit would be obtained.
In addition, costs optimisation models have shown that despite subsidies, it is more interesting to invest in CHPs and to sell the electricity they produce to the grid. In both scenarios, the model tends to invest first in CHPs, biomass boilers being installed later. Furthermore, the effect of subsidies depends on the connection strategy, a slow increase of the demand in the early years stimulating the installation of biomass boilers (scenario 1). Including thermal stores in the model also enhances the utilisation of biomass boilers. Heat pumps remain too expensive to make it worth investing in. Despite subsidies, the optimisation program never selects a heat pump when a costs optimisation is performed.
Moreover, the importance of thermal stores for the financial viability of DH schemes has been demonstrated by the third model. Although heat production profiles are overall flattened by the installation of thermal stores, the model tends to use them as extra-loads to maximise the amount of electricity produced by CHPs while storing the surplus of heat produced. If this operating strategy has a significant impact on the revenues generated, the GHG emissions associated with the third model are only slightly reduced in comparison with the second model. Finally, one needs to highlight the importance of using an optimisation program to design the energy centre. Although both heuristic approaches optimised the energy centre operation, the mix of plants manually selected in both strategies led to a smaller NPV for all scenarios.

GHG emissions modelling has also proven to be a major challenge for designing the energy centre while ensuring low emissions on-site. Indeed, it has been seen that the allocation method chosen for CHPs strongly influences the mix of plants selected by the program and their operating strategy. For instance, the power station displacement method led to the smallest GHG emissions on-site by displacing the emissions produced thanks to the electricity sold to the grid. Thus, the model selected a lot of CHPs to displace a lot of emissions while using a lot of gas, which has an unacceptably bad environmental impact. Such an approach is unsustainable. Consequently, it is crucial to choose an appropriate method to apportion CHPs fuel to heat and electricity when GHG emissions are minimised. Choosing a wrong method will have a bad environmental impact without particularly generating high revenues. GHG emissions minimisation lead actually to smaller NPVs than costs optimisation approaches. In these circumstances, the boiler displacement method, which allocates the smallest portion of GHG emissions to the electricity produced, seems to provide the least biased results. In all scenarios, biomass boilers and heat pumps are used as base capacity. The model naturally invests in biomass boilers, as it only considers on-site emissions. One should not forget that the whole biomass supply chain may have a bad environmental impact, which was not taken into account in the model. The model also chose heat pumps, the technology becoming particularly interesting from year 7/8, when the electricity carbon factor has already decreased a lot. In any case, a proper LCA would be required for a more detailed GHG emissions analysis.

Finally, it has been observed that the strategy chosen for connecting the clusters strongly influences the mix of plants selected as well as the energy centre operating strategy. In the costs optimisation models, it has been seen that the second scenario, in which big clusters are connected earlier, generates higher and quicker revenues than the first scenario. In addition, lower investment costs are required for the second scenario, especially when thermal storage is modelled (version 3).
When GHG emissions are minimised, it has been observed that the connection strategy chosen affects the financial viability of the project (models 2B, 2P and 2T) since a low NPV is obtained in each scenario.

Consequently, the energy centre design tends to favour the second scenario when a costs optimisation is performed, although this scenario has higher GHG emissions than the first scenario. When GHG emissions are minimised, the first scenario should be chosen only if thermal stores are included in the DH scheme. Nevertheless, the NPV associated with this scenario remains lower than in the second scenario.

7.1.2 Spatial network expansion

As it has been seen in the previous chapter, spatial network expansion costs also have a strong influence on the results obtained. They absolutely need to be included in DH extension models. Although network connection and pumping costs were not optimised in the model developed, their estimation already enable to draw interesting conclusions. First of all, it has been seen that when a costs optimisation including thermal storage is performed, both scenarios are viable. In both cases, the network generates a sufficiently high profit through electricity and heat sellings to cover the expenses required by the spatial expansion.
Although designing the energy centre following a GHG emissions minimisation principle proved to be financially viable if thermal storage was considered, none of the scenarios is viable any more if spatial expansion costs are included in the model.

Taking into account spatial expansion costs in the model tends to favour the second scenario even more, since the revenues generated by this connection strategy are greater than those obtained with the first scenario.

Finally, one should keep in mind that a single pipe diameter was chosen for the analysis. In the reality, pipes with different diameters will be built if the network is extended. Indeed, smaller diameters may be chosen, especially for distribution pipes which connect buildings to the network (32 to 65 mm in general [95]). Consequently, one should expect a decrease of the connection and pumping costs required for both scenarios in the reality. This would make both scenarios even more interesting to invest in while designing the DHN following a costs optimisation approach.

7.2 Methodology discussion

The model developed and applied to the Barkantine case study provided interesting results, satisfying either profit maximisation or GHG emissions minimisation objectives. Nonetheless, certain considerations and relevant aspects of the methodology applied in this project will now be discussed.

7.2.1 Analysis of the demand

The analysis of the demand developed in the third chapter was built in order to generate data that would then serve as inputs for the model. This methodology was mainly based on open access data like heat maps. Consumer archetypes and pre-defined profiles were also used to build connection scenarios. A large amount of time was spent on generating these demand curves. It can be emphasize that annual heat demand consumption for each potential building to be connected was averaged, which could lead to underestimate or overestimate some buildings heat consumptions.

Another aspect to highlight is the approach used to estimate buildings diversity. Indeed, diversity curves used in the Elements Energy Ltd - DECC model were used to shape the real heat demand in each scenario. However, the results presented previously, especially in the third model, show that new capacity is never added before year 4, whereas new loads already connect to the network at years 2 and 3. This could mean that the approach used to estimate diversity underestimates a bit the real heat demand or that the existing units installed in the energy centre are slightly oversized. Attention should be paid in future work to consider other diversity curves for buildings heat demand estimation, like Danish or Swedish curves [30].

Despite these remarks, the author is convinced that the heat demand curves obtained with this approach provide realistic even though approximated inputs for the model developed.

7.2.2 Time modelling strategy

Hourly intervals were considered in the model for heat demand estimations as well as to calculate electricity prices. It could be argued that heat demand and electricity and prices vary constantly on a second to second scale. The author believes that even if this granularity may not be completely exact, it enables to obtain representative inputs and serves for the purpose of the study.

Moreover, as the analysis of the demand performed generated 24 day types profiles, and given that a twelve years horizon was chosen for the project, it was necessary to use a discrete time representation to make the model solvable in a reasonable amount of time. More precision would be achieved using a day to day basis. However, one should not forget that data and assumptions used to model heat demand and electricity prices are themselves based on historic data and projections, which will certainly differ from next years reality.
Furthermore, it has been seen previously that using day types has an influence on the models results, especially for the first hours of the day for which constraints had to be adapted (minimum number of working hours, storage constraints...). Adopting a continuous time representation would avoid some of these problems but would come along with a significant increase of the computing time required to run the model.

Despite the previous observations, the author is convinced that the day types approach procured a useful and clear approximation for the study, while computationally solving the problem in a reasonable time. We acknowledge that there is an area of opportunity for future work with a higher level of temporal granularity.

7.2.3 Technology portfolio

The model developed for the Barkantine project investigates the possible installation of five different technologies in the energy centre: CHPs, natural gas boilers, biomass boilers, heat pumps with various heat sources and thermal storage devices. The model could obviously be completed to include additional technologies (biomass CHPs, other heat pumps...), but this would increase the time needed to solve the program.

In addition, eight medium-size to big CHP units were selected as inputs for the model. These CHPs were chosen because they were in line with the demand curves obtained (see also chapters 3 and 4) and they were able to supply the required heat under the different optimisations. Selecting more CHPs, especially smaller units, would certainly allow a better match between heat production and heat demand and provide an even better flexibility.
Moreover, it has been observed that heat pumps were not likely to be installed in the models performing a costs optimisation. It has to be highlighted that heat pumps remain a technology which is not well known and for which the investments and operating costs are still high. As their costs will decrease in the future, heat pumps could become a more viable option for DH.

Concerning the whole system flexibility, several constraints were added to ensure that the heat production process selected by the energy centre would reflect the reality. Minimum part loads and constraints on the number of working hours were for example added, following what had been done in the literature. It may be argued that some minimum part load constraints limit the system flexibility and force the optimisation program to look for alternative production processes when minimum part load constraints are not satisfied. However decreasing the minimum part load threshold would result in a loss of system efficiency. The author believes that the chosen approach ensures that the model reflects the reality while ensuring a good system efficiency, but also acknowledges that the values selected for the parameters discussed above could be modified.

Finally, it has been seen in the fourth chapter that for several technologies, some discrete technical parameters had been linearised. In some cases, it had been deliberately chosen to use linear curves where other trendlines would have better fitted the industrial data sets provided. One could argue that using linear curves decreases the model precision. However, in most cases, linear approximations appeared to be very close to the reality (CHPs electricity production, pipes installation costs, heat pumps COP...). In addition, using non linear curves would have required to use another solving strategy like an MINLP approach, which would enormously increase the program computing time.

7.2.4 Spatial network expansion

Since it was decided to mainly focus on the design of the energy centre, clusters were built and the spatial network expansion was not computationally optimised. As it has been seen in the previous section, this leads undoubtedly to an overestimation of the investments and pumping costs required. Pre-defined pipes sizes were selected, which will not be the case in the reality. Pumping costs which directly depends on the water flow rate (i.e. on the heat demand) should also be smaller in the reality. Future work should pay attention to the interdependences between units operation and spatial network optimisation. In fact these interdependences affect the whole network heat and electricity balances. For example, the electricity produced by CHPs could be reused to pump water through the network.

Chapter 8

Conclusion

The purpose of the project was to address EDF Energy questions regarding the expansion of their existing district heating network in the Barkantine area. More specifically, the project aimed to suggest a methodology for DH expansion studies, focusing on the energy centre design. The methodology developed to analyse the heat demand helped identifying key clusters for DH expansion. The analysis was also used to build various connection strategies to be tested with an optimisation approach. Then, the optimisation model developed with GAMS helped selecting the best mix of plants for the energy centre under given constraints (costs or GHG emissions). The model also optimised the operating strategy for the selected units. The optimisation program became progressively more complex in order to include elements that could influence the final results, like thermal storage. It was observed that building a good optimisation program is crucial, as some methods or hypothesis may lead to biased results. The model developed for the energy centre design demonstrated the necessity of using an optimisation program, better results being obtained in this case than with a manual selection of plants (heuristic approach). For the approach completeness, the costs associated with the spatial expansion (connection and pumping costs) were also included in the study.

The methodology developed in this project could be reused in other DH schemes to study DHN expansion feasibility.

8.1 Summary of the key findings

The optimisation approach developed demonstrated that planning strategies are essential for DHN expansion. The results obtained from the model proved that for each optimisation strategy, one connection scenario is better than the other scenario:

- If a costs optimisation is performed, the second scenario, in which big clusters are connected early to the DHN, should be chosen. Thermal stores should necessarily be installed in the energy centre to make the DH expansion viable. Indeed, the second scenario is financially viable thanks to heat and electricity sellings, these revenues being generated earlier as the heat demand increases quicker.
- If a GHG emissions minimisation approach is chosen, the first scenario should be selected along with thermal storage, since this scenario leads to the lowest GHG emissions, independently of the allocation method chosen for CHPs. However, none of the scenarios considered in the project are financially viable under a GHG emissions minimisation strategy. Consequently, additional subsidy mechanisms would be required to make it worth designing the energy centre following a GHG emissions minimisation principle.

For both optimisation approaches, the mix of plants selected requires an increase of the energy centre surface by building a second energy centre or making the existing one bigger.

Finally, the model proved that it can be financially and environmentally interesting to expand the Barkantine DHN, in comparison with the current situation.

8.2 Further work

The results provided by the optimisation model already give some insights about how to extend an existing district heating network. If the methodology developed already achieves good profit for DHN expansion, while having a limited impact on the environment, there is still room for improvement and further work. Three main areas of opportunity for future work were identified:

- Optimise the spatial network expansion along with the energy centre design.
- Combine the scenarios studied into one single optimisation problem using a stochastic approach.
- Perform a sensitivity analysis including demand variations, electricity and natural gas prices variations.

8.2.1 Optimisation of the spatial network expansion

As it was decided to focus on the energy centre during the project, spatial network extension costs and pumping costs were roughly estimated using the cluster approach and the pre-defined scenarios. Since the demand of each building has already been estimated and as the network's layout has been designed, it would be interesting to optimise at the same time the energy centre design, the network pipes design and the loads connections. Consequently, the connection costs and the costs associated with the energy centre expansion would be optimised at the same time.

Implementing such a model would not be too difficult, since loads and pipes have already been associated to nodes and segments. This model could still be implemented with a MILP approach using GAMS. This new model could possibly make new connection scenarios for the Barkantine area emerge.

8.2.2 Combination of the scenarios using a stochastic approach

Combining both scenarios into a single optimisation problem could also contribute to improve the model. For instance, this could be done with a stochastic approach. The two scenarios developed could be equally likely considered and combined into one optimisation problem using a two stages stochastic program. The approach could then be validated by using one unknown scenario within the envelope of the two previous scenarios. Using such a mathematical formulation would require additional constraints, like non-anticipativity constraints.

Implementing such a model would be already possible for the energy centre design model. Pipes design and spatial connection aspects could be added later.

8.2.3 Sensitivity analysis

Finally, it could be interesting to perform a sensitivity analysis to see the influence of some parameters on the final results. The following parameters could be included in the sensitivity analysis:

- Electricity and gas prices variations: the model developed considered DECC reference prices for gas and electricity. Low and high prices scenarios could be for example included.
- Heat demand: a low demand and a high demand scenario based on the existing heat maps could for example be implemented.

Performing a sensitivity analysis could be done with the existing MIP model by changing the inputs depending on the parameter modified. A stochastic model based on the existing model could also be used: each variation could be associated with a new scenario, the stochastic program combining these scenarios in the end.

Bibliography

[1] ukpower.co.uk. The Big Six Energy Companies, 2016. `https://www.ukpower.co.uk/the-big-six-energy-companies` Accessed 25^{th} January 2016.

[2] Department for Business, Energy Industrial Strategy. Digest of United Kingdom Energy Statistics - Chapter 5: Electricity, 2016. `https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/540933/Chapter_5_web.pdf` Accessed 8^{th} August 2016.

[3] S. Frederiksen and S. Werner. *District Heating and Cooling.* Studentlitteratur AB, First edition, 2013.

[4] American Society of Heating, Refrigerating and Air-Conditioning Engineers. *District Heating Guide.* ASHRAE, Atlanta, GA, 2013.

[5] Dr Keith MacLean. Heat decarbonisation - the options. Decarbonising Heat Conference - IGEM, 2013.

[6] Greater London Authority. London Heat Network Manual. 2014.

[7] Jonathan Graham. Why district heating and why it works - the association for decentralised energy. Decarbonising Heat Conference - IGEM, 2013.

[8] B. Rezaie and M. A. Rosen. District Heating and Cooling: Review of Technology and Potential Enhancements. *Applied Energy*, 93:2–10, 2012.

[9] U. Persson and S. Werner. Heat distribution and the future competitiveness of district heating. *Applied Energy*, 88(3):568–576, 2011.

[10] U. Persson, B. Möller, and S. Werner. Heat roadmap europe: Identifying strategic heat synergy regions. *Energy Policy*, 74:663–681, 2014.

[11] European Commission Fact Sheet. Towards a smart, efficient and sustainable heating and cooling sector, February 2016.

[12] Department of Energy and Climate Change. Estimates of heat use in the United Kingdom in 2013, September 2014.

[13] Department of Energy and Climate Change. The Future of Heating: A strategic framework for low carbon heat in the UK, March 2012.

[14] Department of Energy and Climate Change. Summary evidence on District Heating Networks in the UK, July 2013.

[15] HM Government. 2050 Pathways Analysis, July 2010.

[16] European Commission. Article 14: Promotion of efficiency in heating and cooling, 2013.

[17] D. Connolly, B. Vad Mathiesen, P. Alberg Østergaard, B. Möller, S. Nielsen, H. Lund, T. Trier, U. Persson, D. Nilsson, and S. Werner. Heat Roadmap Europe 2050, First pre-study for EU27, 2012.

[18] European Commission. Roadmap 2050: A practical guide to a prosperous, low-carbon Europe, 2010.

[19] UK government. Climate Change Act - Chapter 27, 2007.

[20] Department of Energy and Climate Change. The Future of Heating: Meeting the challenge (Executive Summary), March 2013.

[21] UK Trade and Investment and Department of Energy and Climate Change. Investing in the UK's heat infrastructure: Heat networks, November 2015.

[22] Department of Energy and Climate Change. Assessment of the Costs, Performance, and Characteristics of Heat UK Networks, 2015.

[23] Department of Energy and Climate Change. Heat Networks Delivery Unit, 2015.

[24] OFGEM. Non Domestic Renewable Heat Incentive (RHI), 2016. `https://www.ofgem.gov.uk/environmental-programmes/non-domestic-renewable-heat-incentive-rhi` Accessed 23^{rd} January 2016.

[25] Pöyry and UK Power Networks. Electricity storage in gb: Sns4.13 – interim report on the regulatory and legal framework, 2014.

[26] Greater London Authority. The London Plan, Chapter 5: London's response to climate change , 2011.

[27] Greater London Authority. Delivering London's Energy Future: The Mayor's Climate Change Mitigation and Energy Strategy, 2011.

[28] Buro Happold Ltd. Islington Borough Energy Mapping: Phase 3 - Development of a Strategic Masterplan Vision, 2014.

[29] Ove Arup Partners Ltd. Bunhill - Shoreditch District Heating Schemes - Feasibility for further expansion, 2013.

[30] Huw Blackwell. July 22, 2016.

[31] Ramboll. London Borough of Redbridge Decentralised Energy Masterplanning Study, 2012.

[32] J. Gustafsson, J. Delsing, and J. Van Deventer. Improved district heating substation efficiency with a new control strategy. *Applied Energy*, 87(6):1996–2004, 2010.

[33] A. Dalla Rosa, H. Li, and S. Svendsen. Method for optimal design of pipes for low-energy district heating, with focus on heat losses. *Energy*, 36(5):2407–2418, 2011.

[34] M. Kuosa, K. Kontu, T. Mäkilä, M. Lampinen, and R. Lahdelma. Static study of traditional and ring networks and the use of mass flow control in district heating applications. *Applied Thermal Engineering*, 54(2):450–459, 2013.

[35] T. Laajalehto, M. Kuosa, T. Mäkilä, M. Lampinen, and R. Lahdelma. Energy efficiency improvements utilising mass flow control and a ring topology in a district heating network. *Applied Thermal Engineering*, 69(1–2):86–95, 2014.

[36] U. Persson. The future competitiveness of district heating - 35^{th} Euroheat and Power Congress, Paris May 9^{th} and 10^{th}. 2011.

[37] C. Reidhav and S. Werner. Profitability of sparse district heating. *Applied Energy*, 85(9):867–877, 2008.

[38] M. King and R. Shaw. Community energy, planning, development and delivery, 2010.

[39] The Chartered Institution of Building Services Engineers. *Degree-days: theory and application*. CIBSE Publications, 2006.

[40] Element Energy Ltd. Heat pumps in district heating - DECC v62, 2015.

[41] U. Persson and S. Werner. Effective Width - The Relative Demand for District Heating Pipe Lengths in City Areas - The 12^{th} International Symposium on District Heating and Cooling. September 5^{th} to September 7^{th}, Tallinn, Estonia 2010.

[42] H. C. Gils, J. Cofala, F. Wagner, and W. Schöpp. GIS-based assessment of the district heating potential in the USA. *Energy*, 58:318–329, 2013.

[43] S. Nielsen. A geographic method for high resolution spatial heat planning. *Energy*, 67:351–362, 2014.

[44] B. Möller and H. Lund. Conversion of individual natural gas to district heating: Geographical studies of supply costs and consequences for the danish energy system. *Applied Energy*, 87(6):1846–1857, 2010.

[45] Mayor of London. London heat Map, 2013. `http://www.londonheatmap.org.uk/Content/HeatMap.aspx` Accessed 13^{th} August 2016.

[46] H. Lund, S. Werner, R. Wiltshire, S. Svendsen, J. E. Thorsen, F. Hvelplund, and B. Vad Mathiesen. 4th generation district heating (4gdh): Integrating smart thermal grids into future sustainable energy systems. *Energy*, 68:1–11, 2014.

[47] S. Nielsen and B. Möller. GIS based analysis of future district heating potential in Denmark. *Energy*, 57:458–468, 2013.

[48] K.N. Finney, V.N. Sharifi, J. Swithenbank, A. Nolan, S. White, and S. Ogden. Developments to an existing city-wide district energy network – Part I: Identification of potential expansions using heat mapping. *Energy Conversion and Management*, 62:165–175, 2012.

[49] P. Li, N. Nord, I. Ståle Ertesvåg, Z. Ge, Z. Yang, and Y. Yang. Integrated multiscale simulation of combined heat and power based district heating system. *Energy Conversion and Management*, 106:337–354, 2015.

[50] D.W. Wu and R.Z. Wang. Combined Cooling, Heating and Power: A review. *Progress in Energy and Combustion Science*, 32:459–495, 2006.

[51] R. Lund and U. Persson. Mapping of potential heat sources for heat pumps for district heating in Denmark. *Energy*, page 1–10, 2016 - in press.

[52] Energinet.dk and Energi Styrelsen. Technology Data for Energy Plants - Generation of Electricity and District Heating, Energy Storage and Energy Carrier Generation and Conversion, 2012.

[53] Department of Energy and Climate Change. Heat pumps in district heating, 2016.

[54] Department of Energy and Climate Change. RHI Evidence Report: Gas Driven Heat Pumps, 2014.

[55] D. Laukaa, J. Guscaa, and D. Blumbergaa. Heat pumps integration trends in district heating networks of the baltic states. *Procedia computer science*, 52:835–842, 2015.

[56] Element Energy Ltd. Heat pumps in district heating - DECC - Model user guide (draft), 2015.

[57] S. Gadd S., Werner. *Advances in Thermal Energy Storage Systems - Methods and applications*. Woodhead Publishing, 2014.

[58] T. Nuytten, B. Claessens, K. Paredis, J. Van Bael, and D. Six. Flexibility of a combined heat and power system with thermal energy storage for district heating. *Applied Energy*, 104:583–591, 2013.

[59] M. Brand and S. Svendsen. Renewable-based low-temperature district heating for existing buildings in various stages of refurbishment. *Energy*, 62:311–319, 2013.

[60] C. Christiansen, A. Rosa, M. Brand, P.K. Olsen, and J.E. Thorsen. Results and experiences from a 2 year study with measurements on a new low-temperature district heating system for low-energy buildings, - Proceedings of 13^{th} international symposium on district heating and cooling, September 3^{rd} and 4^{th}, Copenhagen, Denmark. 2013.

[61] M. Pirouti, A. Bagdanavicius, J. Ekanayake, J. Wu, and N. Jenkins. Energy consumption and economic analyses of a district heating network. *Energy*, 57:149–159, 2013.

[62] P. Lauenburg and J. Wollerstrand. Adaptive control of radiator systems for a lowest possible district heating return temperature. *Energy and Buildings*, 72:132–140, 2014.

[63] C. Haikarainen, F. Pettersson, and H. Saxén. A MILP Model for Distributed Energy System Optimization. *Chemical Engineering Transactions*, 35:295–300, 2013.

[64] H. Li and S. Svendsen. District heating network design and configuration optimization with genetic algorithm. *Journal of Sustainable Development of Energy, Water and Environment Systems*, 1(4):291–303, 2013.

[65] T.F. Edgar and D.M. Himmelblau. *Optimization of chemical processes*. McGraw-Hill, New York ; London, 1988.

[66] P. Voll, M. Jennings, M. Hennen, N. Shah, and A. Bardow. The optimum is not enough: A near-optimal solution paradigm for energy systems synthesis. *Energy*, 82:446–456, 2015.

[67] D. Chinese. Optimal size and layout planning for district heating and cooling networks with distributed generation options. *International Journal of Energy Sector Management*, 2(3):385–419, 2008.

[68] M. Sakawa, K. Kato, S. Ushiro, and M. Inaoka. Operation planning of district heating and cooling plants using genetic algorithms for mixed integer programming. *Applied Soft Computing*, 1(2):139–150, 2001.

[69] C. Weber, F. Maréchal, and D. Favrat. Network synthesis for district heating with multiple heat plants - International Conference Energy-Environment CIEM 2005, Bucharest, Romania, 20-21 October. 2005.

[70] S. Fazlollahi, G. Becker, A. Ashouri, and F. Maréchal. Multi-objective, multi-period optimization of district energy systems: IV - A case study. *Energy*, 84:365–381, 2015.

[71] Solving Integer Programming with Branch-and-Bound Technique. `http://www.columbia.edu/~cs2035/courses/ieor4600.S07/bb-lecb.pdf` Accessed 29^{th} February 2016.

[72] H. Gopalakrishnan and D. Kosanovic. Economic optimization of combined cycle district heating systems. *Sustainable Energy Technologies and Assessments*, 7:91–100, 2014.

[73] R. Banos, F. Manzano-Agugliaro, F. G. Montoya, A. Gila, A. Alcayde, and J. Gómez. Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, 15:1753–1766, 2011.

[74] M. Singh Kamboj and J. Sengupta. Comparative Analysis of Simulated Annealing and Tabu Search Channel Allocation Algorithms. *International Journal of Computer Theory and Engineering*, 1:588–591, 2011.

[75] J. R. Birge and F. Louveaux. *Introduction to Stochastic Programming, Second Edition*. Springer Editions, 2011.

[76] P. Voll, M. Jennings, M. Hennen, N. Shah, and A. Bardow. The optimum is not enough: A near-optimal solution paradigm for energy systems synthesis. *Energy*, 82:446–456, 2015.

[77] C. Weber and N. Shah. Optimisation based design of a district energy system for an eco-town in the united kingdom. *Energy*, 36(2):1292–1308, 2011.

[78] G. Abdollahi and M. Meratizaman. Multi-objective approach in thermoenvironomic optimization of a small-scale distributed cchp system with risk analysis. *Energy and Buildings*, 43(11):3144–3153, 2011.

[79] X. Li, L. Duanmu, and H. Shu. Optimal design of district heating and cooling pipe network of seawater-source heat pump. *Energy and Buildings*, 42(1):100–104, 2010.

[80] A. Dalla Rosa, R. Boulter, K. Church, and S. Svendsen. District heating (DH) network design and operation toward a system-wide methodology for optimizing renewable energy solutions (SMORES) in Canada: A case study. *Energy*, 45(1):960–974, 2012.

[81] T. Fang and R. Lahdelma. Genetic optimization of multi-plant heat production in district heating networks. *Applied Energy*, 159:610–619, 2015.

[82] H. Wang, W. Yin, E. Abdollahi, R. Lahdelma, and W. Jiao. Modelling and optimization of CHP based district heating system with renewable energy production and energy storage. *Applied Energy*, 159:401–421, 2015.

[83] M. Giuntoli and D. Poli. Optimized Thermal and Electrical Scheduling of a Large Scale Virtual Power Plant in the Presence of Energy Storages. *IEEE Transactions on Smart Grid*, 4(2):942–955, 2013.

[84] G. Oluleye, L. Vasquez, R. Smith, and M. Jobson. A multi-period mixed integer linear program for design of residential distributed energy centres with thermal demand data discretisation. *Sustainable production and consumption*, 5:16–28, 2016.

[85] Z. Zhou, J. Zhang, P. Liu, Z. Li, M. C. Georgiadis, and Pistikopoulos E. N. A two-stage stochastic programming model for the optimal design of distributed energy systems. *Applied Energy*, 103:135–144, 2013.

[86] M. Vesterlund and J. Dahl. A method for the simulation and optimization of district heating systems with meshed networks. *Energy Conversion and Management*, 89:555–567, 2015.

[87] C. Bordin, A. Gordini, and B. Vigo. An optimization approach for district heating strategic network design. *European Journal of Operational Research*, 252:296–307, 2016.

[88] R. S. C. Lambert, S. Maier, J. W. Polak, and N. Shah. Optimal phasing of district heating network investments using multi-stage stochastic programming. *International Journal of Sustainable Energy Planning and Management*, 9:57–74, 2016 - accepted paper.

[89] M. Münster, P.E. Morthorst, H.V. Larsen, L. Bregnbæk, J. Werling, H.H. Lindboe, and H. Ravn. The role of district heating in the future Danish energy system. *Energy*, 48(1):47–55, 2012.

[90] J. L. Mojica Velazquez. A Dynamic Optimization Framework with Model Predictive Control Elements for Long Term Planning of Capacity Investments in a District Energy System. *All Theses and Dissertations*, Paper 3886, 2013.

[91] gaebler.com Resources for entrepreneurs. Capacity Planning Strategies, 2016. `http://www.gaebler.com/Capacity-Planning-Strategies.htm` Accessed 4^{th} August 2016.

[92] Y. Saif and A. Almansoori. A capacity expansion planning model for integrated water desalination and power supply chain problem. *Energy Conversion and Management*, 122:462–476, 2016.

[93] H. Tekiner, D. W. Coit, and F. A. Felder. Multi-period multi-objective electricity generation expansion planning problem with monte-carlo simulation. *Electric Power Systems Research*, 80:1394–1405, 2010.

[94] Ramboll. The London Borough of Tower Hamlets London Heat Map Study, 2011. `http://www.towerhamlets.gov.uk/Documents/Planning-and-building-control/Strategic-Planning/Local-Plan/Evidence-base/LBTH-Heat-Map-Study-Final.pdf` Accessed 23^{rd} January 2016.

[95] Vuillermoz, A. and Pourre, A. Modelling of the Barkantine District Heating Network with Dymola: current state and '45 Mill Harbour' connection, EDF RD UK Centre Internal report. 2015.

[96] Cedillos Alvaro, D.,. Investment strategy for the decarbonisation of supermarket buildings in the UK. 2015.

[97] Corral Acero, J. Optimization, design and hourly operation schedule of a centralized district energy centre and sensitivity analysis assessment based on an East London case study. 2016.

[98] Boiler prices, 2016. `http://www.boilersprices.co.uk` Accessed 4^{th} August 2016.

[99] Thames Anglers' Conservancy. Angling Data view, 2016. `http://www.rivertac.org/adv/` Accessed 12^{th} June 2016.

[100] Soler-Garcia, A. UK real time pricing Energy models. 2016.

[101] Department of Energy and Climate Change. CHP - A detailed guide for CHP developers - Part 2, 2008.

[102] ELEXON. Market index price, 2016. `https://www.elexonportal.co.uk/news/latest?cachebust=qgxs0fo5vj`.

[103] Department of Energy and Climate Change. Updated energy and emissions projections - Appendix M, 2015. `https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/501292/eepReport2015_160205.pdf` Accessed 29^{th} June 2016.

[104] National Grid. Balancing Services Use of System Charges. Industry Information: Balancing Services Use of System Charges., 2016. `http://www2.nationalgrid.com/bsuos/` Accessed 29^{th} June 2016.

[105] UK Power Networks. London Power Networks - Use of system charges, 2015. `http://www.ukpowernetworks.co.uk/internet/en/about-us/duos/` Accessed 29^{th} June 2016.

[106] National Grid. TNUoS Tariff Forecasts and Condition 5, 2016. http://www2.nationalgrid.com/UK/Industry-information/System-charges/Electricity-transmission/Approval-conditions/Condition-5/ Accessed 29^{th} June 2016.

[107] Ofgem. Renewable Obligations - Energy suppliers, 2016. https://www.ofgem.gov.uk/environmental-programmes/ro/energy-suppliers Accessed 29^{th} June 2016.

[108] HM Revenue & Customs. Guidance - Climate Change Levy rates, 2016. https://www.gov.uk/government/publications/rates-and-allowances-climate-change-levy/climate-change-levy-rates Accessed 29^{th} June 2016.

[109] Energy Solutions. Electricity forecast figures for RE, FiT, CFD, CMC and AAHEDC, 2016. http://www.energybrokers.co.uk/news/electricity/forecast-figures-for-ro-fit-cfd-cmc-and-aahedc Accessed 29^{th} June 2016.

[110] National Grid. Assistance for Areas with High Electricity Distribution Costs, 2016. http://www2.nationalgrid.com/UK/Industry-information/System-charges/Electricity-transmission/Assistance-for-areas-with-high-distribution-costs/ Accessed 29^{th} June 2016.

[111] Department for Environment, Food Rural Affairs. 2014 Government GHG Conversion Factors for Company Reporting: Methodology Paper for Emission Factors, 2014. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/519244/Emission_Factor_Methodology_Paper_-_2014.pdf Accessed 11^{th} June 2016.

[112] Department of Energy and Climate Change. Valuation of energy use and greenhouse gas (GHG) emissions, 2015. https://www.gov.uk/government/publications/valuation-of-energy-use-and-greenhouse-gas-emissions-for-appraisal Accessed 16^{th} June 2016.

[113] Department of Energy and Climate Change. Greenhouse gas reporting - Conversion factors 2016, 2016. https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2016 Accessed 16^{th} June 2016.

[114] Earth.org.uk, 2016. http://www.earth.org.uk/note-on-UK-grid-CO2-intensity-variations.html Accessed 16^{th} June 2016.

[115] S. A. Kyriakis and L. P. Younger. Towards the increased utilisation of geothermal energy in a district heating network through the use of a heat storage. *Applied Thermal Engineering*, 94:99–110, 2016.

[116] A. Bachmaier, S. Narmsara, J-B. Eggers, and S. Herkel. Spatial distribution of thermal energy storage systems in urban areas connected to district heating for grid balancing. *Energy Procedia*, 73:3–11, 2015.

[117] ARUP, DENet. Decentralised Energy Networks Masterplanning Prefeasibility, 2011. http://www.arup.com/projects/denet Accessed 5^{th} June 2016.

[118] Pipeflow. Pipe Roughness, 2016. http://www.pipeflow.com/pipe-pressure-drop-calculations/pipe-roughness Accessed 5^{th} June 2016.

[119] The Engineering toolbox. Water - Dynamic and Kinematic Viscosity, 2016. http://www.engineeringtoolbox.com/water-dynamic-kinematic-viscosity-d_596.html Accessed 5^{th} June 2016.

[120] The Engineering toolbox. Water - Density and Specific Weight, 2016. http://www.engineeringtoolbox.com/water-density-specific-weight-d_595.html Accessed 5^{th} June 2016.

[121] Office for National Statistics. Tower Hamlets - neighbourhood statistics. http://neighbourhood.statistics.gov.uk/dissemination/LeadDatasetList.do?a=7&b=6275287&c=E14+8HH&d=13&g=6338123&i=1001x1003&m=0&r=0&s=1469896771781&enc=1&domainId=7 Accessed 20^{th} May 2016.

[122] Emporis.com, 2016. http://www.emporis.com/search/canary\%2520wharf\%2520london Accessed 20^{th} May 2016.

[123] Skyscrapernews.com, 2016. http://www.skyscrapernews.com/buildings.php?id=1521 Accessed 4^{th} August 2016.

[124] Royal Mail. Postcode Finder – Find an Address, 2016. http://www.royalmail.com/find-a-postcode Accessed 4^{th} August 2016.

[125] Bosch Commercial and Industrial Heating Combined heat and power modules, 2016. http://www.bosch-industrial.co.uk/files/Bosch_CHP_brochure_C01_14_WEB_UK.pdf Accessed 21^{st} June 2016.

[126] Clarke Energy, 2014. https://www.clarke-energy.com/gas-engines/type-2-gas-engine/ Accessed 21^{st} June 2016.

[127] Siemens gas turbine portfolio, 2016. http://www.energy.siemens.com/hq/pool/hq/power-generation/gas-turbines/downloads/gas-turbines-siemens.pdf Accessed 21^{st} June 2016.

[128] Evinox CHP, 2016. http://www.evinoxenergy.co.uk/Sites/Evinox/library/files/CHP\%20Data\%20Sheet\%202551128B.pdf Accessed 21^{st} June 2016.

[129] AB&Co, 2016. http://www.ttboilers.dk/Damp.htm#TypeDJ Accessed 21^{st} June 2016.

[130] Industrial Specifications Cochran, 2013. https://cochran.co.uk/Downloads/Industrial\%20Specifications\%20Booklet\%20Dec\%202013.pdf Accessed 21^{st} June 2016.

Appendices

A Buildings connected to the existing district heating network

Twenty-two buildings are currently connected to the Barkantine DHN. The annual heat demand for each building as well as the number of storeys in each building was provided by EDF Energy. The buildings characteristics are gathered in the following table:

Name	**Node**	**Type**	**Annual heat demand (MWh/year)**	**Ground floor area (m^2)**	**Number of storeys**
Tiller Leisure Centre	2	Leisure centre	737.8	1338	1
Kedge House	3	apartments	233.0	540	9
Cressal House	4	apartments	68.2	410	3
Barkantine Community Nursery	5	nursery	47.5	228	1
Clara Grant House	6	apartments	68.2	420	3
Gilbertson House	7	apartments	68.2	340	3
John Tucker House	8	apartments	456	970	3
Scoulding House	9	apartments	96.6	570	3
Bowsprit Point	10	apartments	466.0	400	20
Barkantine Hall	11	community centre	47.0	738	1
Knighthead Point	12	apartments	466.0	900	20
Seven Mills Primary School	13	school	129.7	1630	1
Midship Point	14	apartments	466.0	350	20
Express Wharf	15	apartments	448.2	980	5
Topmast Point	16	apartments	466.0	370	20
St Lukes Parish Hall	17	apartments	113.7	370	2
St Lukes Vicrage	18	apartments	96.6	500	2
Spinnaker House	19	apartments	238.7	760	5
Low rise Byng Street	20	apartments	102.3	430	2
Alpha Grove Community Centre	21	community centre	56.7	277	1
Phoenix Heights	22	apartments	1846.1	3610	22
Hammond House	23	apartments	383.2	340	4

Table 1 – Characteristics of the loads connected to the existing Barkantine's DHN.

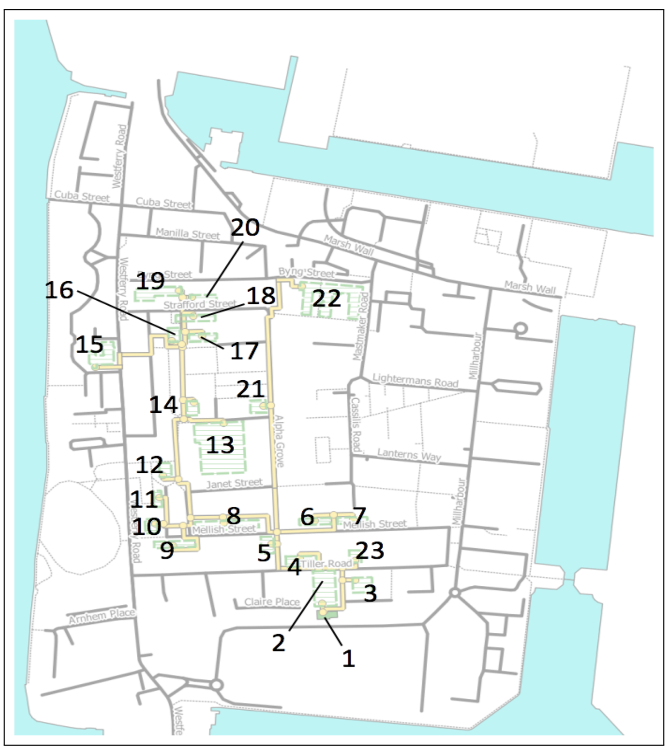


Figure 1 – Loads connected to the existing network (QGIS representation used, node 1 denotes the energy centre)

B Potential heat loads to be connected to the Barkantine district heating network

Thirty-one buildings or construction areas were identified as potential heat loads to be connected. The characteristics of each load were obtained using the following resources:

- Buildings types were obtained using the London heat map, data from the office of National Statistics and QGIS - Open Street Map data [45, 121].
- Annual heat consumptions were obtained with the London heat map and with data from the office of National Statistics[45, 121].
- Buildings areas were obtained using Google Maps and QGIS - Open Street Map data.
- Buildings number of storeys were obtained using QGIS - Open Street Map data and Emporis information [122].

These buindings characteristics are gathered in the following table:

Name	Cluster	Node	Type	Annual heat demand (MWh/year)	Ground floor area (m^2)	Number of storeys	Number of flats
Arnhem Wharf	1	44	apartments	501 - 1 000	1 230	8	62
Arnhem Wharf Primary School	1	42	school	1 - 500	2 620	2	/
New Atlas Wharf	1	43	apartments	1 001 - 5 000	1 600	11	86
Gainsborough House	2	47	apartments	1 001 - 5 000	1 660	11	99
Lowry, Moore, Turner and Constable House (4 buildings)	2	46	apartments	1 001-5 000	4 210	8	266
Stanliff House	2	45	apartments	1 - 500	1 230	8	56
St Hubert's House	3	48	apartments	1 - 500	460	4	57
Discovery Dock Apartments East	4	51	apartments	1 001 - 5 000	1 290	24	192
Discovery Dock Apartments West	4	50	apartments	1 001 - 5 000	1 910	15	60
Marsh Wall, 189	4	52	offices	1 001 - 5 000	1 730	18	/
Pan Peninsula	4	53	apartments	1 001 - 5 000	3 760	48 (east tower) and 39 (west tower)	762
Hilton London Canary Wharf	4	49	hotel	1 - 500	1 650	15	/
Garden Block-Ocean Wharf	5	55	apartments	1 - 500	930	12	57
Block A-Ocean Wharf	5	54	apartments	1 - 500	700	12	94
Millwall Fire Station	6	56	fire station	1 - 500	220	1	/
Pierpoint Building	6	59	apartments	501 - 1 000	1 070	10	69
Byng Street, 13	6	58	apartments	1-500	390	4	16
Manilla Street, 6 and 4 and Byng Street 9 and Marlin apartments (4 buildings)	6	57	apartments	501 - 1 000	2 400	8	119
Naxos Building	6	62	apartments	501 - 1 000	1 120	12	72
Seacon Tower	6	61	apartments	501 - 1 000	440	22	99
Vanguard building	6	60	apartments	501 - 1 000	1 160	10	97
Novotel	7	64	hotel (construction)	501 - 1 000	760	39	/
International hotel	7	65	hotel	5 001 - 10 000	1 690	13	/
Anchorage Points	8	67	apartments	501 - 1 000	1 180	10	79
Cascades Tower	8	68	apartments	1 001 - 5 000	1 340	20	171
Landmark West Tower	8	69	apartments	1 001 - 5 000	860	30	276
Landmark East Tower	8	66	apartments	1 001 - 5 000	710	44	274
Westferry and Marsh Wall construction area	8	70	apartments (construction)	1 001 - 5 000	3 300	78	822
Westferry roundabout construction (Riverside South, 3 buildings)	9	71	offices and retail (construction)	5 001 - 10 000	3 300	37, 45 and 13	/
Millharbour, 41	10	73	apartments	1 001 - 5 000	2 460	15	352
Millharbour, 45 (expansion considered by EDF)	10	72	apartments	1,5 MW_{peak} estimated	2 620	22	393

Table 2 – Characteristics of the potential loads to be connected to the Barkantine's DHN [45, 95, 121–124].

The correlation between nodes and buildings is given on the following figure:

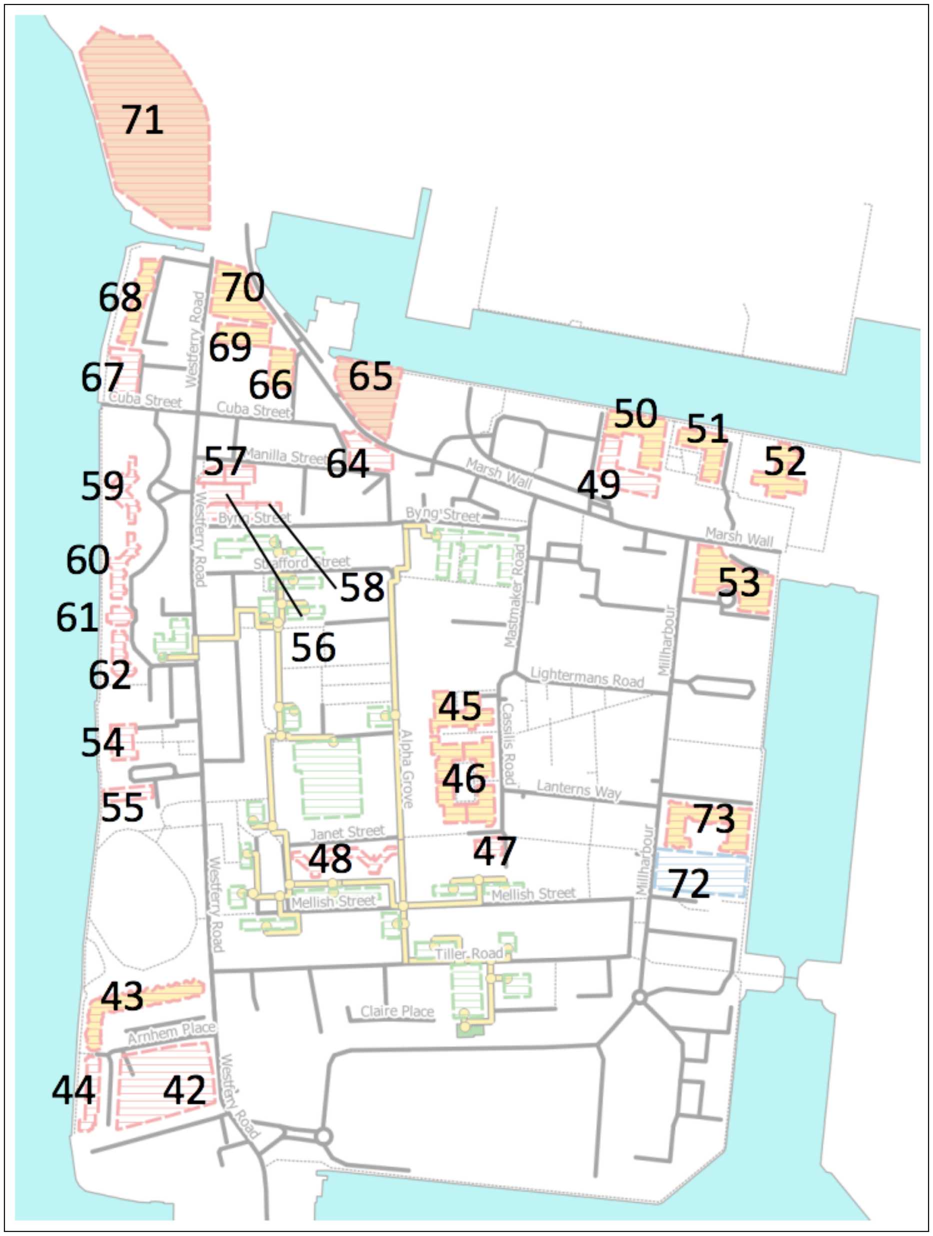


Figure 2 – Potential nodes to be connected to the network (QGIS representation used)

C Methodology used to estimate the surface required by each technology

The model developed for the study uses one equation to estimate the surface required by all the technologies built in the energy centre. The following methodology based on the work done in [97] was used to determine coefficients u and v.

For each technology, the full load heat output as well as the physical dimensions were gathered using industrial brochures. The floor surface required by each technology was then calculated and the curve 'area as a function of the heat output' was drawn. Using this methodology, it appears that it is possible to find a linear correlation between both parameters, which gives coefficients u and v for each technology.

The following curves were for example obtained for CHPs and biomass boilers:

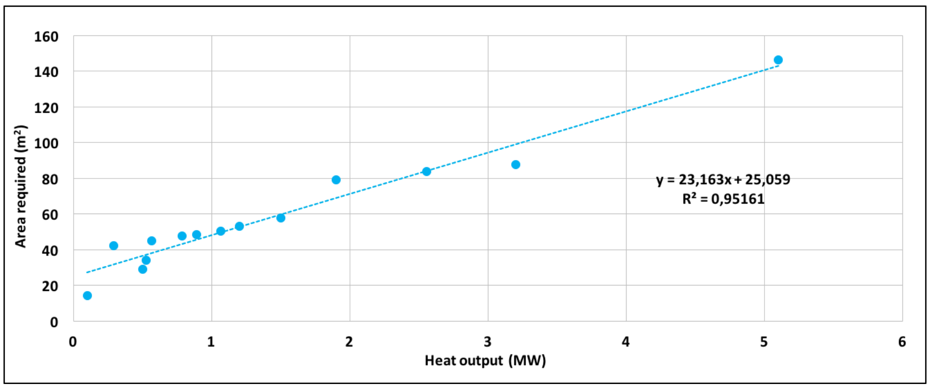


Figure 3 – Evolution of the floor area required by CHPs as a function of their heat output [125–128].

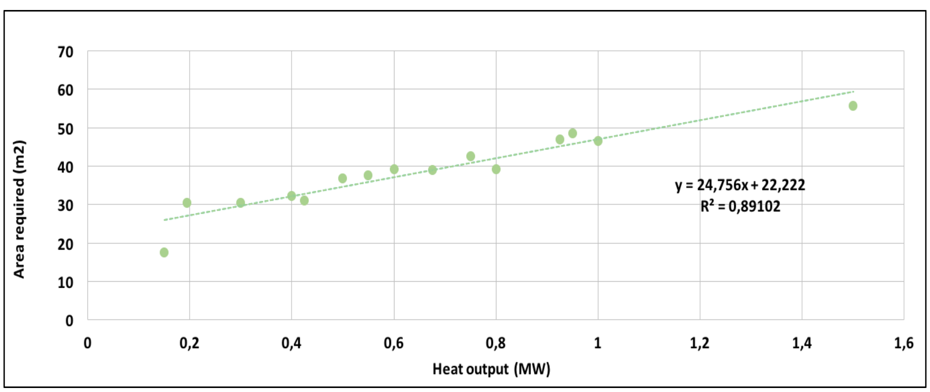


Figure 4 – Evolution of the floor area required by biomass boilers as a function of their heat output [129, 130].

Similar curves were obtained for heat pumps and natural gas boilers.

Thermal heat storage area was estimated reusing the cylinder volume definition, assuming that thermal stores are placed vertically in the energy centre, and considering various storage capacities (see also 4.4.6 and Appendix E). The following curve was obtained:

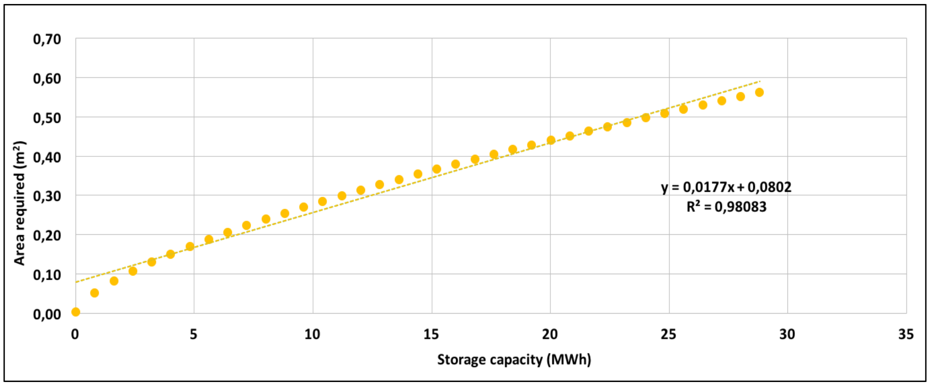


Figure 5 – Evolution of the floor area required by thermal stores as a function of their heat output.

Although it could be argued that some trendlines could be improved to better fit the reality (e.g. polynomial regressions), one should not forget that the GAMS model has to remain linear. Furthermore, as the area required in the energy centre is an indicative parameter and is not restricted by any constraint, using linearised curves to obtain an order of magnitude of the area required is a reasonable assumption.

D Generation of dynamic carbon factors

Dynamic electricity carbon factor were generated using DECC reference projections [112]. Indeed in DECC's Valuation of energy use and greenhouse gas emissions reports, past and future expected electricity carbon factors are recorded. The future carbon factors were adjusted to the 2016 carbon factor, published in the 2016 greenhouse gas reporting conversion factors report [113]. This adjustment was made by multiplying the forecasted carbon factors by the ratio $\frac{carbon\ factor\ recorded\ in\ 2016}{carbon\ factor\ expected\ in\ 2016}$.

The following curve was first obtained:

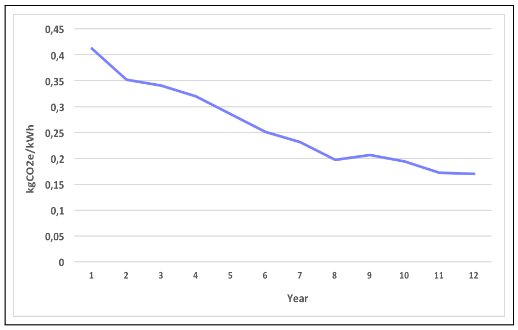


Figure 6 – Projected electricity carbon factors adjusted to 2016 (2016 is considered as year 1) .

Then the hourly, weekly and monthly variations recorded on Earth.org.uk for the period 2009-2015 were made dimensionless by dividing them by the average carbon factor recorded for each year. Thus 24 hourly ratios, 2 weekly ratios and 12 monthly ratios were obtained for each year. These values were then averaged between one another to obtain single ratios instead of yearly ratios. The following curves gather the hourly, weekly and monthly ratios calculated:

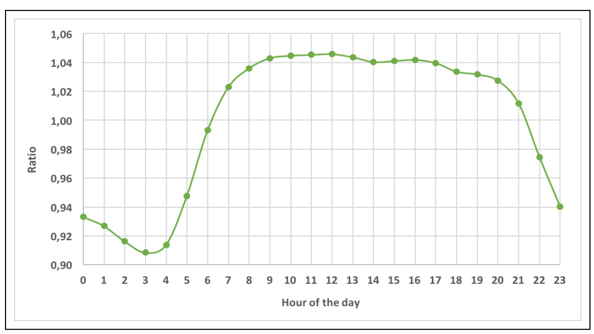


Figure 7 – Hourly ratios used to calculate electricity carbon factors averaged over the period 2009-2015.

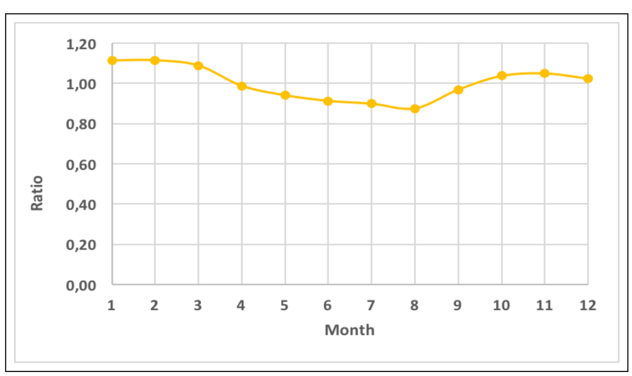


Figure 8 – Monthly ratios used to calculate electricity carbon factors averaged over the period 2009-2015

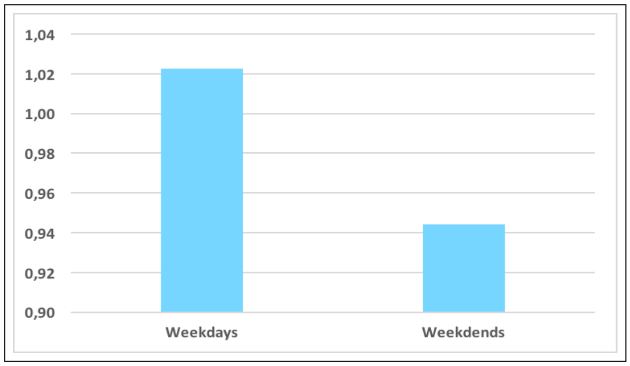


Figure 9 – Weekly ratios used to calculate electricity carbon factors averaged over the period 2009-2015.

Multiplying all these curves together, it is possible to generate dynamic carbon factors for each time band:

$$Dynamic\ carbon\ factor = Expected\ carbon\ factor\ (DECC) \times \frac{carbon\ factor\ recorded\ in\ 2016}{carbon\ factor\ expected\ in\ 2016} \times Hourly\ ratio \times Weekly\ ratio \times Monthly\ ratio \quad (1)$$

The following curve presents the dynamic carbon factors generated using the previous method and used as inputs in the model:

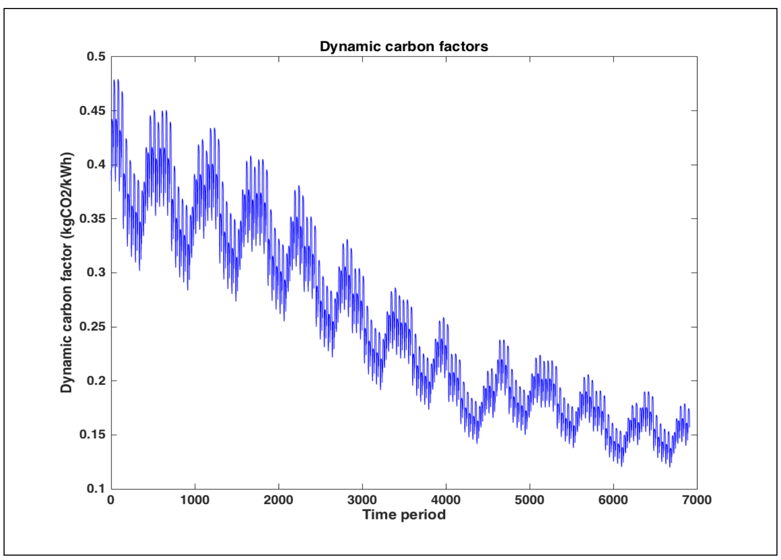


Figure 10 – Dynamic electricity carbon factors used in the model.

E Estimation of thermal storage losses

Thermal storage losses were estimating using a classical thermal diffusion model. Cylindrical thermal stores were considered.

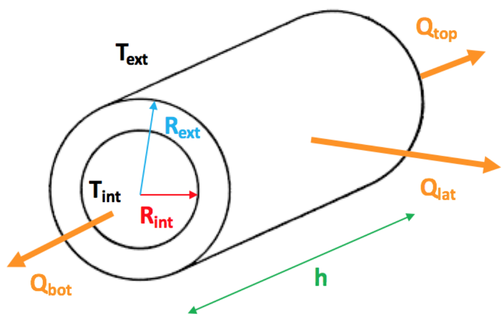


Figure 11 – Schematic representation of parameters used to estimate thermal storage heat losses.

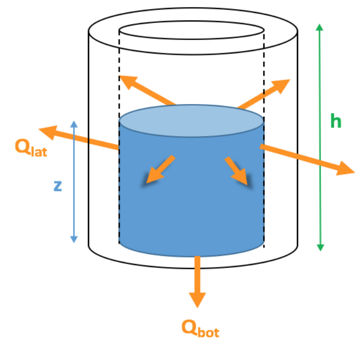


Figure 12 – Schematic representation of partial thermal storage losses.

Applying the first principle and neglecting convection and thermal radiations, we obtain:

$$div\vec{j}_Q + \mu c_v \frac{\partial T}{\partial t} = 0 \tag{2}$$

Where c_v is the cylinder's thermal capacity and μ the cylinder's material density.

According to Fourier's law, $\vec{j}_Q = -\lambda \overrightarrow{grad} T$, where λ is the cylinder's thermal conductivity. By combining the two previous equations, we obtain a classical heat equation :

$$\frac{\partial T}{\partial t} = D_{th} \Delta T \tag{3}$$

Assuming stationary conditions and using cylindrical coordinates, we can assume that the cylinder temperature field only depends on r which gives:

$$\Delta T = \frac{d^2T}{dr^2} + \frac{1}{r}\frac{dT}{dr} \tag{4}$$

Integrating twice and using the boundary conditions T_{ext} and T_{int} , we obtain the temperature field in the cylinder:

$$T(r) = \frac{T_{ext} - T_{int}}{ln(\frac{R_{ext}}{R_{int}})} ln(\frac{r}{R_{int}}) + T_{int} \tag{5}$$

The lateral heat flow is then obtained by integrating the thermal flux density vector over the cylinder's surface:

$$\Phi_{lat} = \int_S \vec{j}_Q.\vec{n} dS = \lambda 2\pi h \frac{T_{int} - T_{ext}}{ln(\frac{R_{ext}}{R_{int}})} = \frac{1}{R_{th,lat}}(T_{int} - T_{ext}) \tag{6}$$

Applying the same methodology at the cylinder's top and bottom, we obtain

$$\Phi_{top} = \Phi_{bot} = \frac{\lambda \pi R_{int}^2}{R_{ext} - R_{int}}(T_{int} - T_{ext}) = \frac{1}{R_{th,top}}(T_{int} - T_{ext}) \tag{7}$$

Knowing Φ_{lat}, Φ_{top} and Φ_{bot}, it is finally possible to estimate hourly heat losses:

$$Hourly\ heat\ losses = Q_{lat} + Q_{top} + Q_{bot} = \int_{one\ hour} (\Phi_{lat} + \Phi_{top} + \Phi_{bot})\ dt \tag{8}$$

When the thermal store is partially loaded, heat losses are calculated using Φ_{bot} and Φ_{lat}(z) instead of Φ_{lat}(h). Φ_{top} is not taken into account except when the thermal store is fully loaded.

$$Hourly\ heat\ losses = Q_{lat}(z) + Q_{bot} = \int_{one\ hour} (\Phi_{lat}(z) + \Phi_{bot})\ dt \tag{9}$$

F Adjacency matrix built to estimate pipes investment and pumping costs

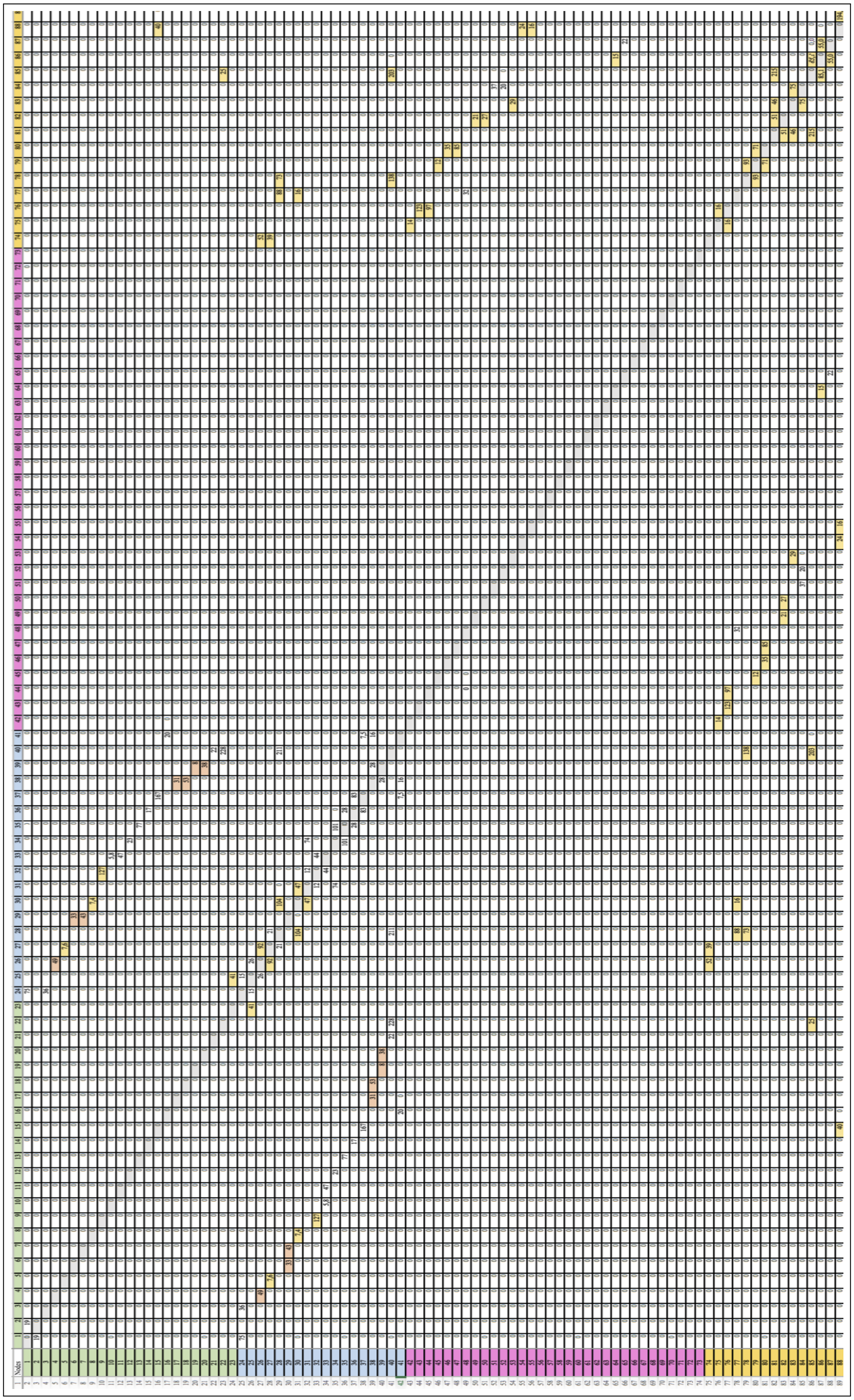


Figure 13 – Adjacency matrix built to estimate pipes investment and pumping costs (partial extract, distances are expressed in m) .

G Heat production and storage capacities selected in models 1, 2, 3 and in the heuristic models

Year	Version 1		Version 2		Version 2H - Leading approach		Version 2H - Matching approach	
	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)
Year 1	Chp2a, chp5a, b1, b2, b3	4.24	Chp2a, chp5a, b1, b2, b3	4.24	Chp2a, chp5a, b1, b2, chp6a, chp10a, chp10a, b3	8.69	Chp2a, chp5a, b1, b2, b4	4.74
Year 2	/	4.24	/	4.24	/	8.69	chp2b	5.13
Year 3	/	4.24	/	4.24	/	8.69	b3	5.63
Year 4	/	4.24	/	4.24	/	8.69	chp6a	6.28
Year 5	chp5b	4.77	chp5b	4.77	/	8.69	/	6.28
Year 6	/	4.77	/	4.77	/	8.69	chp4b	6.80
Year 7	chp4b	5.29	chp4a, chp4b	5.80	/	8.69	/	6.80
Year 8	/	5.29	/	5.80	/	8.69	chp8a	8.12
Year 9	bio2	7.29	bio2	7.8	/	8.69	/	8.12
Year 10	/	7.29	/	7.8	/	8.69	chp7a	8.94
Year 11	chp10b	9.19	/	7.8	/	8.69	/	8.94
Year 12	chp10a	11.09	chp10b	9.7	/	8.69	/	8.94

Table 3 – Technologies selected by the optimisation program in the first scenario (model 1 and 2).

Year	Version 1		Version 2		Version 2H - Leading approach		Version 2H - Matching approach	
	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)
Year 1	Chp2a, chp5a, b1, b2, b3	4.24	Chp2a, chp5a, b1, b2, b3	4.24	Chp2a, chp5a, b1, b2, b4, chp6a, chp9a, chp10a	8.69	Chp2a, chp5a, b1, b2, b4	4.74
Year 2	/	4.24	/	4.24	/	8.69	/	4.74
Year 3	/	4.24	/	4.24	/	8.69	chp7a	5.56
Year 4	chp4a, chp5b	5.29	chp9b	5.64	/	8.69	/	5.56
Year 5	/	5.29	/	5.64	/	8.69	chp8a	6.88
Year 6	/	5.29	/	5.64	/	8.69	/	6.88
Year 7	chp10b, bio2	9.19	chp10a	7.54	/	8.69	chp9a	8.26
Year 8	/	9.19	/	7.54	/	8.69	chp6a	8.93
Year 9	/	9.19	/	7.54	/	8.69	/	8.93
Year 10	/	9.19	chp10b	9.44	/	8.69	/	8.93
Year 11	/	9.19	/	9.44	/	8.69	/	8.93
Year 12	chp10a	11.09	bio1	10.44	/	8.69	/	8.93

Table 4 – Technologies selected by the optimisation program in the second scenario (model 1 and 2).

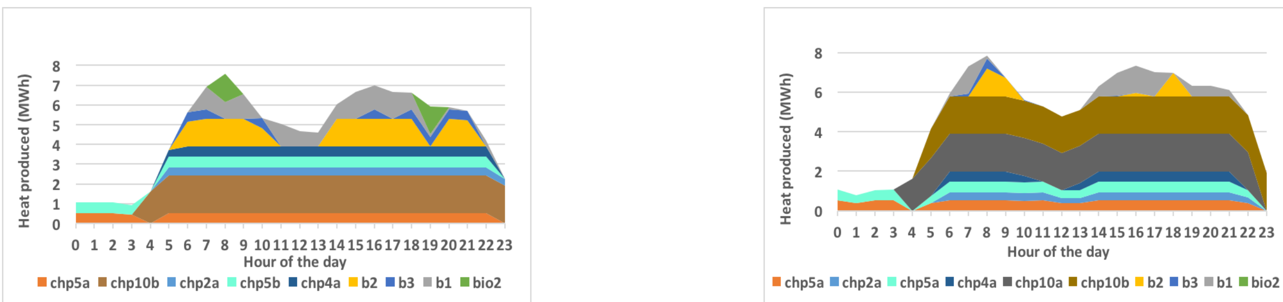
Year	Version 3 - SC1			Version 3 - SC2		
	Units selected	Total heat production capacity (MW)	Total heat storage capacity (MWh)	Units selected	Total heat production capacity (MW)	Total heat storage capacity (MWh)
Year 1	Chp2a, chp5a, b1, b2, st1, st2	3.74	4.5	Chp2a, chp5a, b1, b2, st1, st2	3.74	4.5
Year 2	/	3.74	4.5	/	3.74	4.5
Year 3	/	3.74	4.5	/	3.74	4.5
Year 4	/	3.74	4.5	chp2b, chp5b	4.67	4.5
Year 5	bio2	5.74	4.5	bio2, st7	6.67	7.5
Year 6	chp5b	6.27	4.5	/	6.67	7.5
Year 7	chp2b	6.67	4.5	bio1	7.67	7.5
Year 8	st7	6.67	7.5	chp9b	9.07	7.5
Year 9	st4	8.57	8	st4	9.07	8
Year 10	chp10a	8.57	8	/	9.07	8
Year 11	chp10b	10.47	8	st5	9.07	9
Year 12	st5	10.47	9	/	9.07	9

Table 5 – Technologies selected by the third optimisation program for both scenarios.

H Heat production profiles obtained for Scenario 2 - Model 1

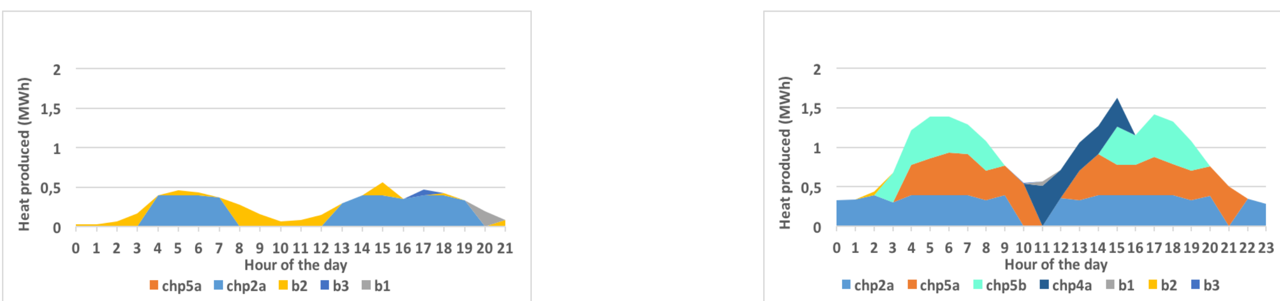
(a) Year 2. (b) Year 5.

Figure 14 – Heat production profiles - **Scenario 2**, model 1, day 1, years 2 and 5.



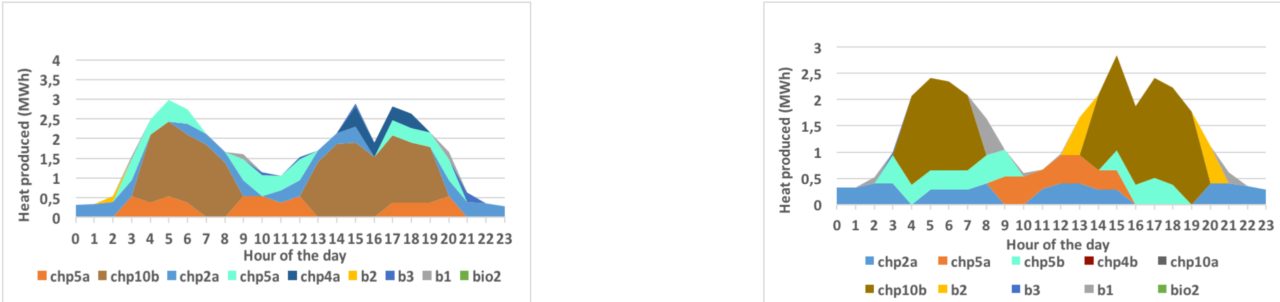
(a) Year 10. (b) Year 12.

Figure 15 – Heat production profiles - **Scenario 2**, model 1, day 1, years 10 and 12.



(a) Year 2. (b) Year 5.

Figure 16 – Heat production profiles - **Scenario 2**, model 1, day 18, years 2 and 5.



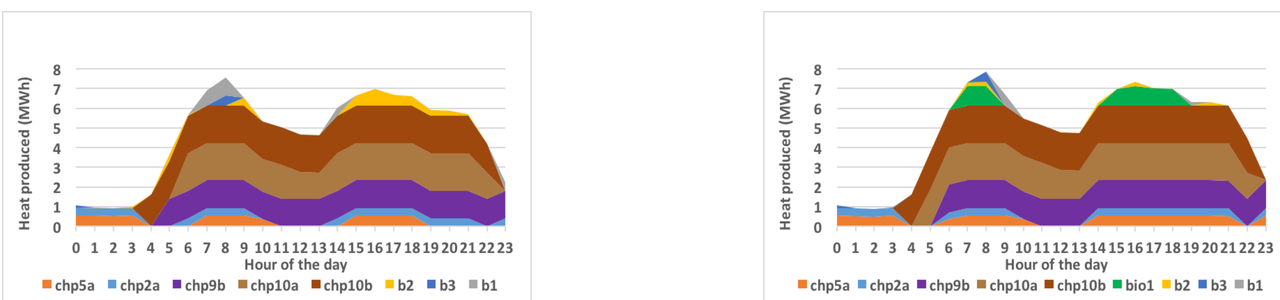
(a) Year 10. (b) Year 12.

Figure 17 – Heat production profiles - **Scenario 2**, model 1, day 18, years 10 and 12.

I Heat production profiles obtained in the second model

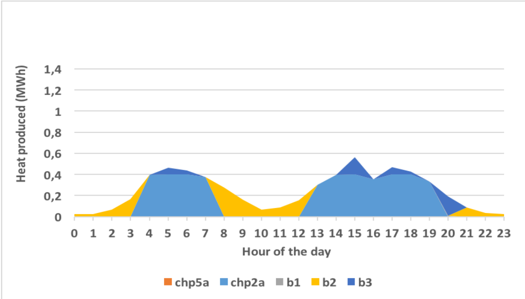
(a) Year 2. (b) Year 5.

Figure 18 – Heat production profiles - **Scenario 2**, model 2, day 1, years 2 and 5.

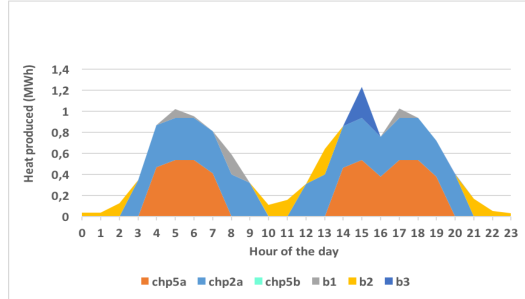


(a) Year 10. (b) Year 12.

Figure 19 – Heat production profiles - **Scenario 2**, model 2, day 1, years 10 and 12.

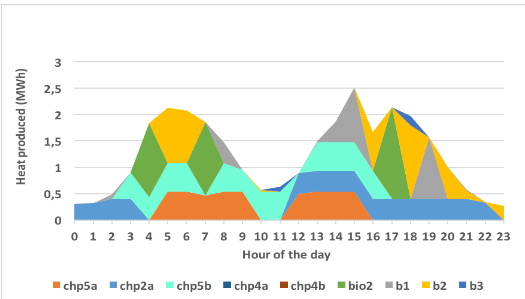


(a) Year 2.

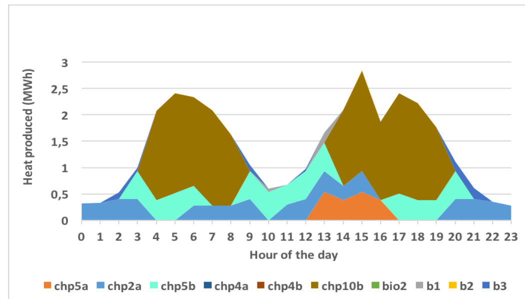


(b) Year 5.

Figure 20 – Heat production profiles - **Scenario 1**, model 2, day 18, years 2 and 5.

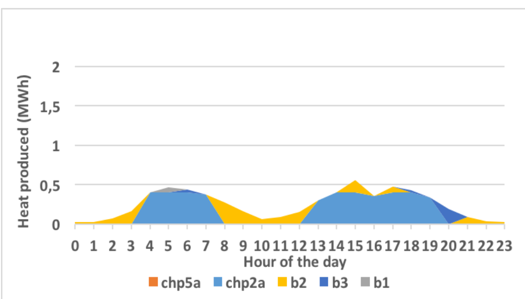


(a) Year 10.

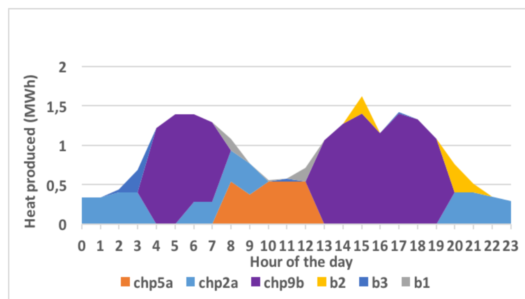


(b) Year 12.

Figure 21 – Heat production profiles - **Scenario 1**, model 2, day 18, years 10 and 12.

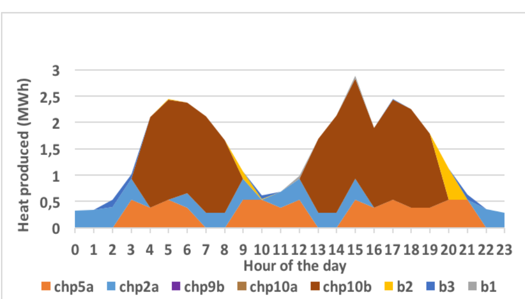


(a) Year 2.

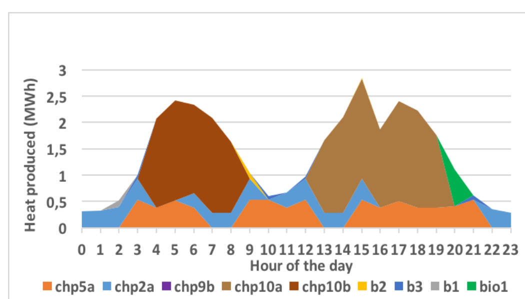


(b) Year 5.

Figure 22 – Heat production profiles - **Scenario 2**, model 2, day 18, years 2 and 5.



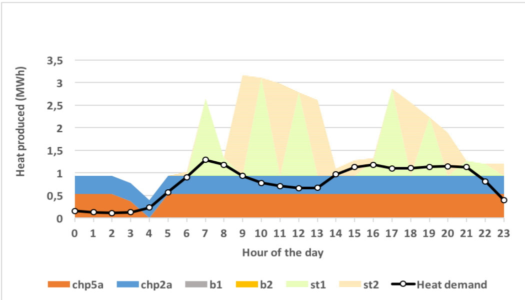
(a) Year 10.



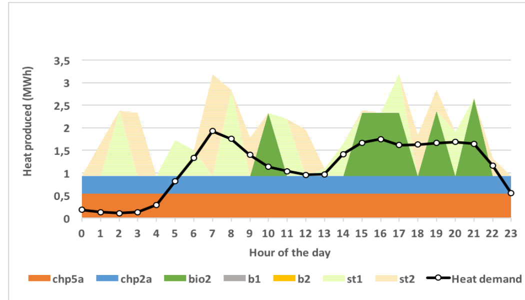
(b) Year 12.

Figure 23 – Heat production profiles - **Scenario 2**, model 2, day 18, years 10 and 12.

J Heat production profiles obtained in the third model

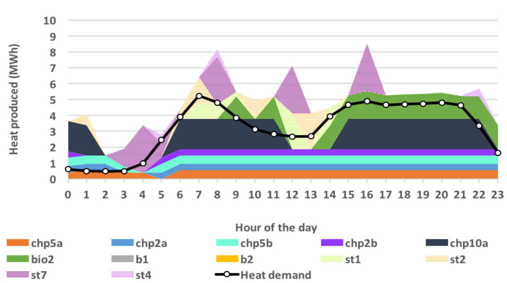


(a) Year 2.

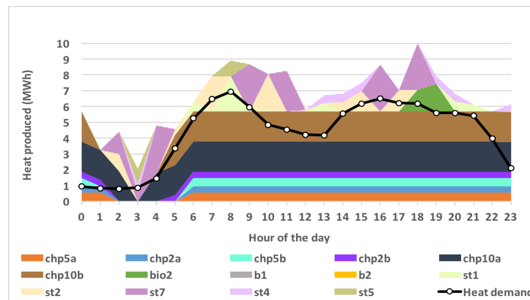


(b) Year 5.

Figure 24 – Heat production profiles - **Scenario 1**, model 3, day 1, years 2 and 5.

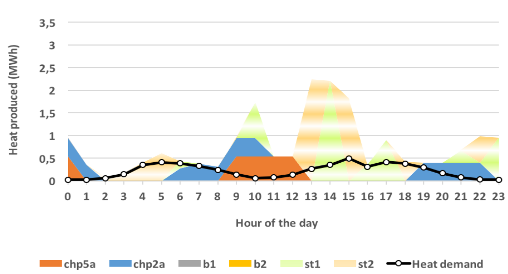


(a) Year 10.

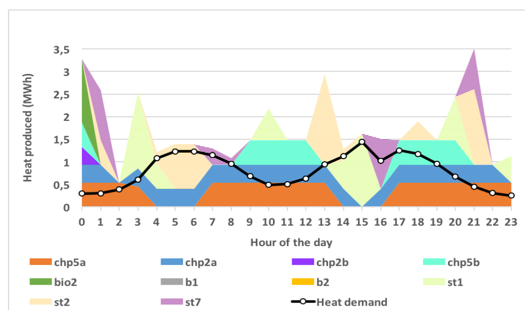


(b) Year 12.

Figure 25 – Heat production profiles - **Scenario 1**, model 3, day 1, years 10 and 12.

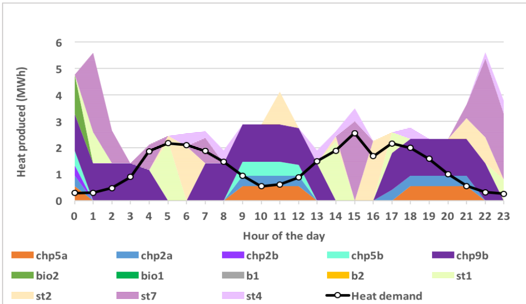


(a) Year 2.

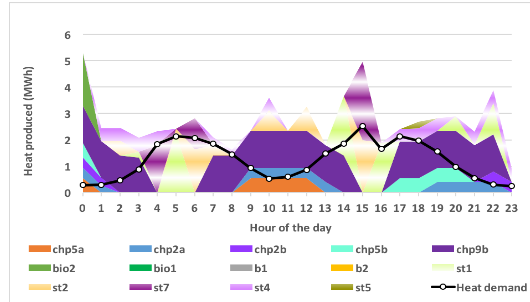


(b) Year 5.

Figure 26 – Heat production profiles - **Scenario 2**, model 3, day 18, years 2 and 5.

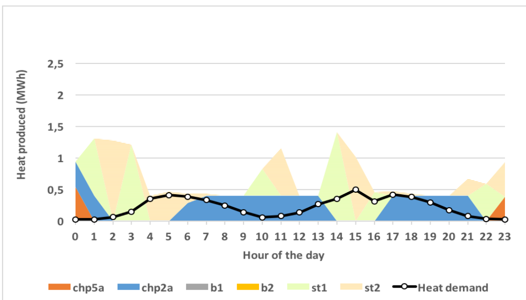


(a) Year 10.

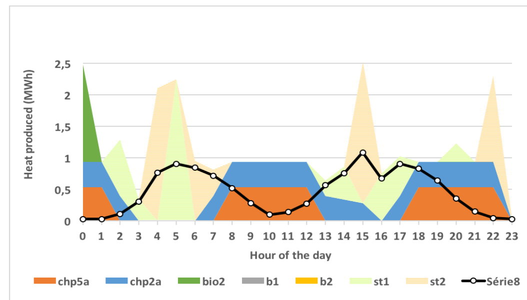


(b) Year 12.

Figure 27 – Heat production profiles - **Scenario 2**, model 3, day 18, years 10 and 12.

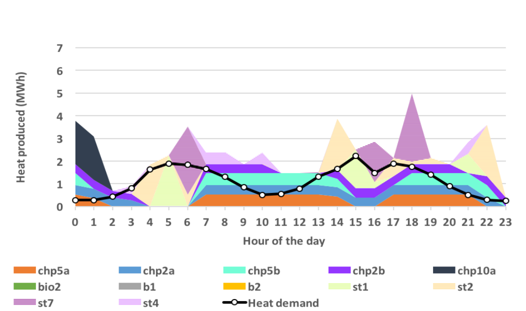


(a) Year 2.

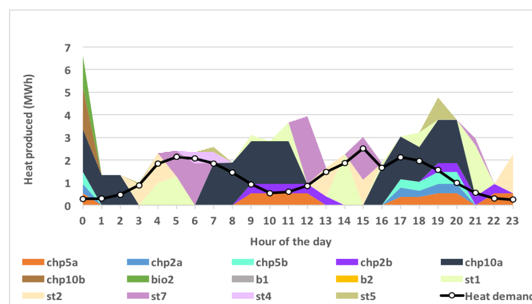


(b) Year 5.

Figure 28 – Heat production profiles - **Scenario 1**, model 3, day 18, years 2 and 5.



(a) Year 10.



(b) Year 12.

Figure 29 – Heat production profiles - **Scenario 1**, model 3, day 18, years 10 and 12.

K Heat production and storage capacities selected in models 2B, 2T, 2P, 3B, 3P and 3T

Year	Version 2B		Version 2P		Version 2T	
	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)
Year 1	Chp2a, chp5a, b1, b2, b3, bio2, hp2	8.24	Chp2a, chp5a, b1, b2, b3, bio2, hp1	7.24	Chp2a, chp5a, b1, b2, b3, bio2, hp2, chp2b, chp6b	9.28
Year 2	/	8.24	/	7.24	/	9.28
Year 3	/	8.24	/	7.24	/	9.28
Year 4	/	8.24	/	7.24	/	9.28
Year 5	/	8.24	/	7.24	/	9.28
Year 6	/	8.24	Chp9b	8.64	/	9.28
Year 7	/	8.24	Chp8a, chp10b	11.86	/	9.28
Year 8	/	8.24	/	11.86	/	9.28
Year 9	/	8.24	Chp10a	13.76	/	9.28
Year 10	/	8.24	/	13.76	Chp8a	10.61
Year 11	/	8.24	/	13.76	/	10.61
Year 12	Chp6a	8.88	/	13.76	Chp10a	12.51

Table 6 – Technologies selected by the optimisation program in the first scenario (models 2B, 2P and 2T).

Year	Version 2B		Version 2P		Version 2T	
	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)	Units selected	Total heat production capacity (MW)
Year 1	Chp2a, chp5a, b1, b2, b4, bio2, hp2	8.74	Chp2a, chp5a, b1, b2, b3, bio2, hp2, chp7b	8.06	Chp2a, chp5a, b1, b2, b4, bio2, hp2	8.74
Year 2	/	8.74	/	8.06	/	8.74
Year 3	/	8.74	/	8.06	/	8.74
Year 4	/	8.74	/	8.06	/	8.74
Year 5	/	8.74	chp10b	9.96	/	8.74
Year 6	/	8.74	chp9a, chp10a	13.26	/	8.74
Year 7	/	8.74	/	13.26	/	8.74
Year 8	/	8.74	/	13.26	chp8a	10.06
Year 9	/	8.74	/	13.26	/	10.06
Year 10	/	8.74	/	13.26	/	10.06
Year 11	/	8.74	/	13.26	/	10.06
Year 12	/	8.74	/	13.26	chp10b	11.96

Table 7 – Technologies selected by the optimisation program in the second scenario (models 2B, 2P and 2T).

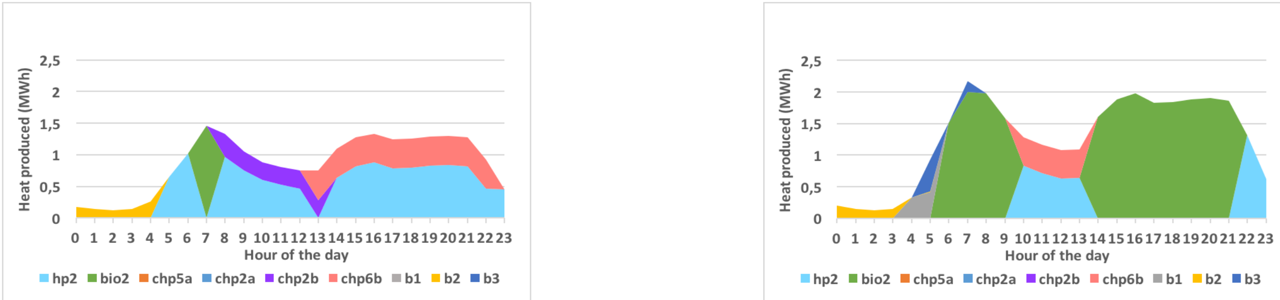
Year	Version 3B			Version 3P			Version 3T		
	Units selected	Total heat production capacity (MW)	Total heat storage capacity (MWh)	Units selected	Total heat production capacity (MW)	Total heat storage capacity (MWh)	Units selected	Total heat production capacity (MW)	Total heat storage capacity (MWh)
Year 1	Chp2a, chp5a, b1, b2, bio2, st1, st2, st4, st5, st7	5.74	9	/	/	/	Chp2a, chp5a, b1, b2, bio2, st1, st2, st4, st5, st7	5.74	9
Year 2	/	5.74	9	/	/	/	/	5.74	9
Year 3	/	5.74	9	/	/	/	/	5.74	9
Year 4	/	5.74	9	/	/	/	/	5.74	9
Year 5	/	5.74	9	/	/	/	/	5.74	9
Year 6	/	5.74	9	/	/	/	/	5.74	9
Year 7	/	5.74	9	/	/	/	/	5.74	9
Year 8	hp2	7.74	9	/	/	/	hp2	7.74	9
Year 9	/	7.74	9	/	/	/	/	7.74	9
Year 10	chp7a	8.56	9	/	/	/	chp7a	8.56	9
Year 11	/	8.56	9	/	/	/	/	8.56	9
Year 12	chp9b	9.96	9	/	/	/	chp9b	9.96	9

Table 8 – Technologies selected by the optimisation program in the first scenario (models 3B, 3P and 3T).

Year	**Version 3B**			**Version 3P**			**Version 3T**		
	Units selected	**Total heat production capacity (MW)**	**Total heat storage capacity (MWh)**	**Units selected**	**Total heat production capacity (MW)**	**Total heat storage capacity (MWh)**	**Units selected**	**Total heat production capacity (MW)**	**Total heat storage capacity (MWh)**
Year 1	Chp2a, chp5a, bio1, bio2, b1, b2, st1, st2, st5, st6, st7	6.74	10.5	Chp2a, chp5a, b1, b2, bio1, bio2, st1, st2, st5, st6, st7	6.74	10.5	Chp2a, chp5a, bio1, bio2, b1, b2, st1, st2, st5, st6, st7	6.74	10.5
Year 2	/	6.74	10.5	/	6.74	10.5	/	6.74	10.5
Year 3	/	6.74	10.5	/	6.74	10.5	/	6.74	10.5
Year 4	/	6.74	10.5	/	6.74	10.5	/	6.74	10.5
Year 5	/	6.74	10.5	/	6.74	10.5	/	6.74	10.5
Year 6	/	6.74	10.5	/	6.74	10.5	/	6.74	10.5
Year 7	hp2	8.74	10.5	chp8a	8.06	10.5	hp2	8.74	10.5
Year 8	/	8.74	10.5	chp10a	9.96	10.5	/	8.74	10.5
Year 9	/	8.74	10.5	/	9.96	10.5	/	8.74	10.5
Year 10	/	8.74	10.5	/	9.96	10.5	/	8.74	10.5
Year 11	/	8.74	10.5	/	9.96	10.5	/	8.74	10.5
Year 12	/	8.74	10.5	chp10b	11.86	10.5	/	8.74	10.5

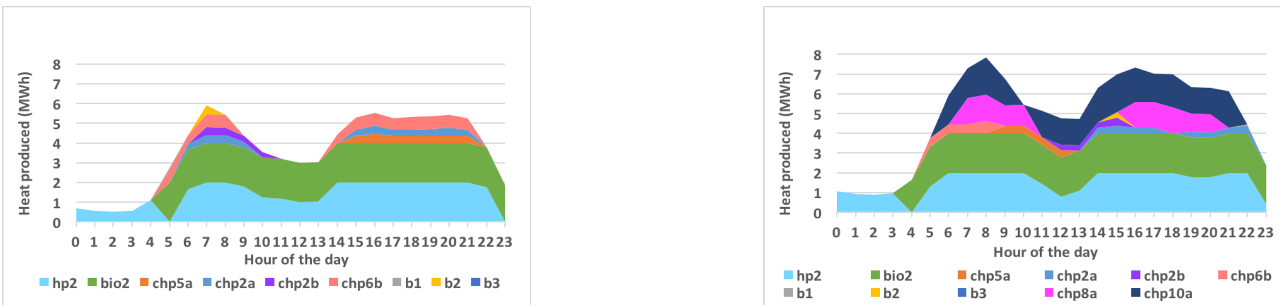
Table 9 – Technologies selected by the optimisation program in the second scenario (models 3B, 3P and 3T).

L Heat production profiles obtained in model 2T



(a) Year 2. (b) Year 5.

Figure 30 – Heat production profiles - **Scenario 1**, model 2T, day 1, years 2 and 5.

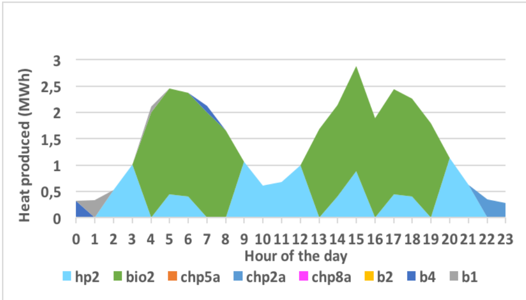


(a) Year 10. (b) Year 12.

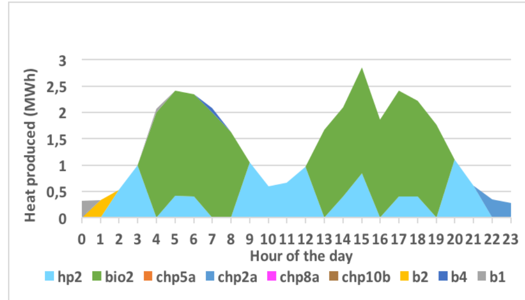
Figure 31 – Heat production profiles - **Scenario 1**, model 2T, day 1, years 10 and 12.

(a) Year 2. (b) Year 5.

Figure 32 – Heat production profiles - **Scenario 2**, model 2T, day 18, years 2 and 5.

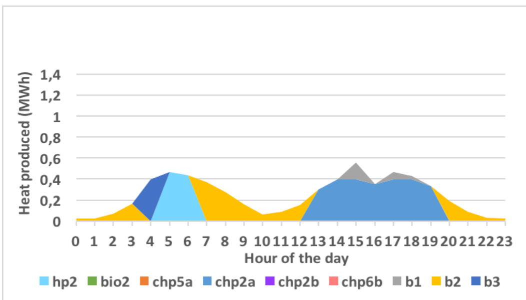


(a) Year 10.

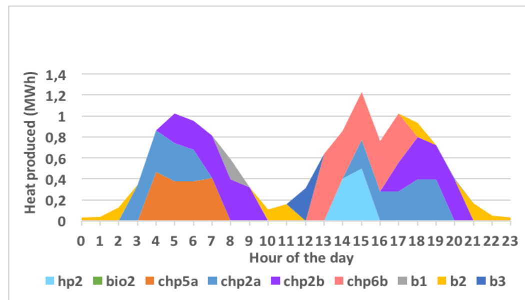


(b) Year 12.

Figure 33 – Heat production profiles - **Scenario 2**, model 2T, day 18, years 10 and 12.

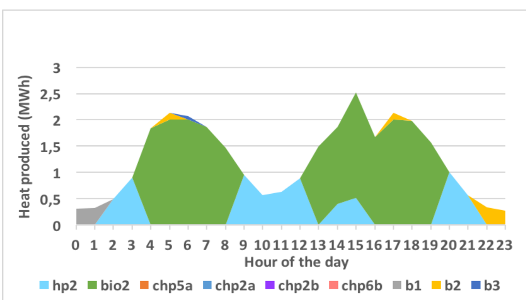


(a) Year 2.

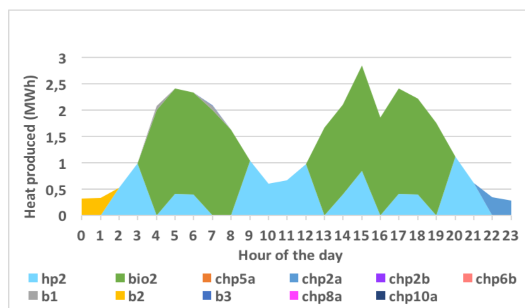


(b) Year 5.

Figure 34 – Heat production profiles - **Scenario 1**, model 2T, day 18, years 2 and 5.



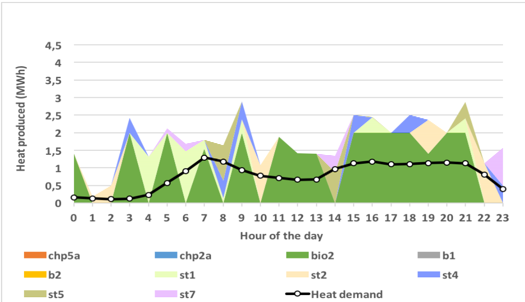
(a) Year 10.



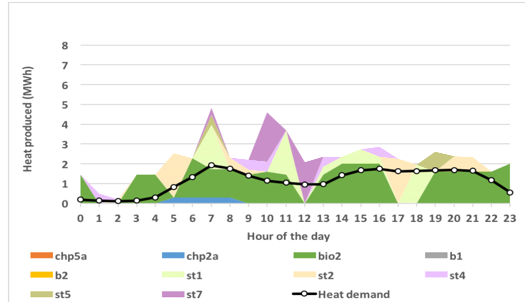
(b) Year 12.

Figure 35 – Heat production profiles - **Scenario 1**, model 2T, day 18, years 10 and 12.

M Heat production profiles for scenario 1, model 3T

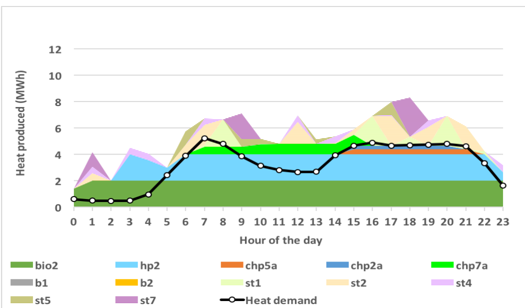


(a) Year 2.

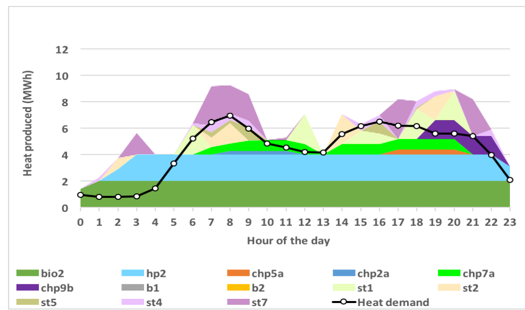


(b) Year 5.

Figure 36 – Heat production profiles - **Scenario 1**, model 3T, day 1, years 2 and 5.

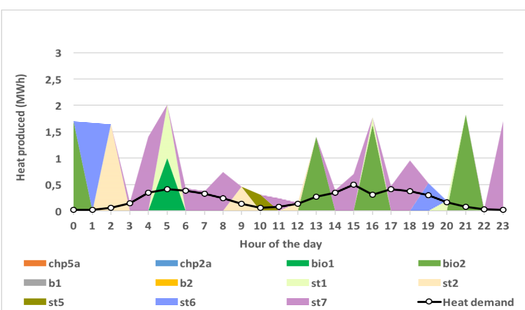


(a) Year 10.

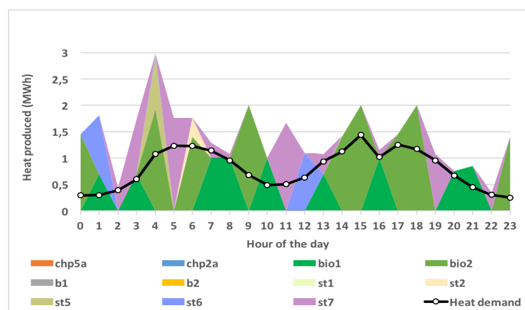


(b) Year 12.

Figure 37 – Heat production profiles - **Scenario 1**, model 3T, day 1, years 10 and 12.

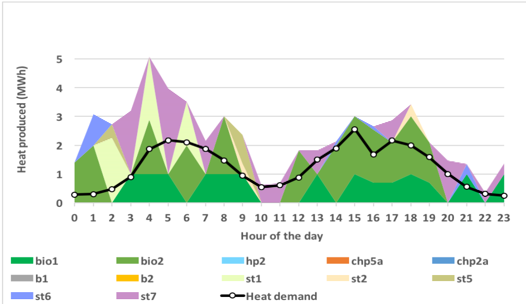


(a) Year 2.

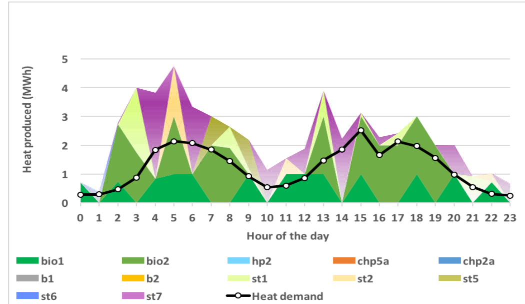


(b) Year 5.

Figure 38 – Heat production profiles - **Scenario 2**, model 3T, day 18, years 2 and 5.

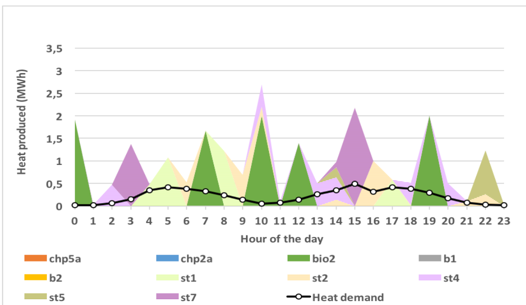


(a) Year 10.

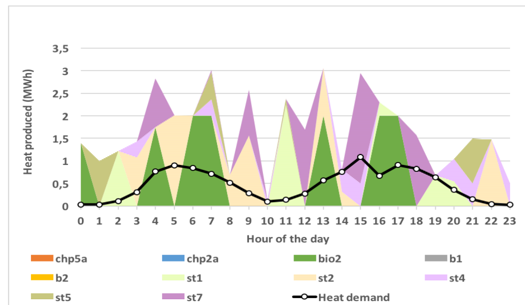


(b) Year 12.

Figure 39 – Heat production profiles - **Scenario 2**, model 3T, day 18, years 10 and 12.

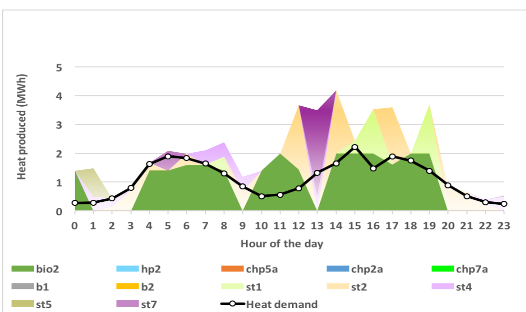


(a) Year 2.

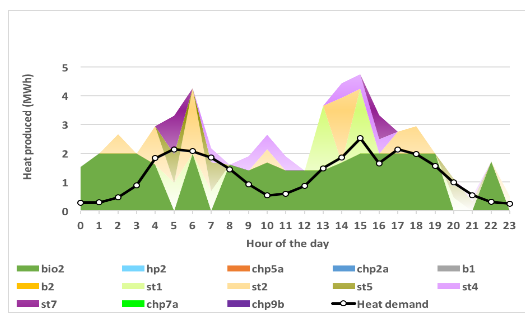


(b) Year 5.

Figure 40 – Heat production profiles - **Scenario 1**, model 3T, day 18, years 2 and 5.



(a) Year 10.



(b) Year 12.

Figure 41 – Heat production profiles - **Scenario 1**, model 3T, day 18, years 10 and 12.

N Costs associated with the network expansion

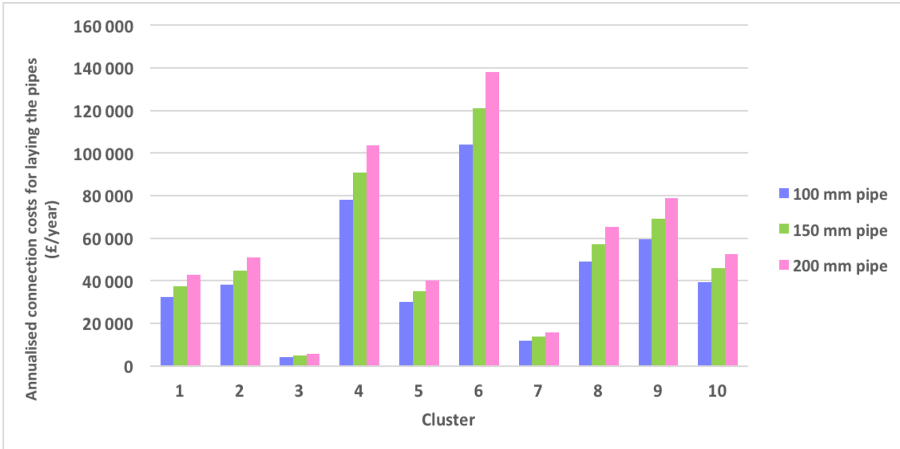


Figure 42 – Annualised connection costs per cluster for various pipes diameters (costs are displayed in £$_{2016}$).

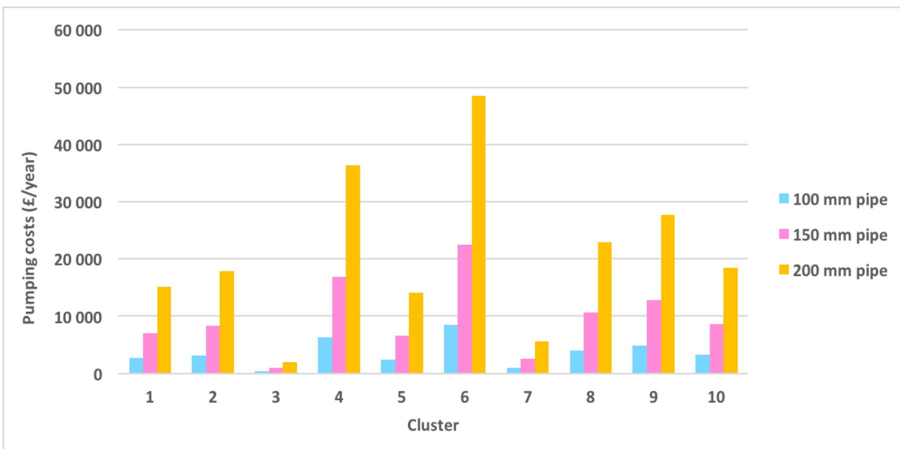


Figure 43 – Annual pumping costs required per cluster for various pipes diameters (costs are displayed in £$_{2016}$).