SAXION UNIVERSITY OF APPLIED SCIENCES

WARMING UP

Reviewing optimization methods for design and operational control of district heating and cooling networks

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Abstract

Conventional district heating systems are operated with relatively high supply temperatures from a central heat source which may contain a heat buffer for peak heat supply. The control system aims at keeping pressure and temperature between minimum and maximum bounds and in relation to this, the pumps and heat source are controlled. The control system is based on feedback control principles in which set points are used and control actions are triggered by deviations from set points. Due to the requirements of higher efficiency, lower supply temperatures and the integration of multiple, renewable sources and decentral buffers, finding optimal control schemes to achieve the lowest possible operational costs becomes difficult if not impossible with conventional control methods. Set points have to be defined in time by using the "smartness" of operators who oversee the operation. However, there are optimization methods available which can support or overtake this complex task from humans. For the development of an optimal control system, the highest priority should be given to operational cost minimization which can be achieved by aiming for lowest possible supply temperatures, preventing peak heat demands and optimal production scheduling of central or decentral heat sources and buffers. In this report, different classes of optimization problems are identified and suitable control methods are investigated from literature. Also, by combining past and recent insights, guidelines are given for development of a model predictive controller for district heating networks and future work is identified.

1. Introduction

District heating is one of the promising ways in the Netherlands to integrate renewable energy sources for heating buildings. Design and control of conventional high temperature district heating systems is well known and the basic design and control principles are also used for modern, low temperature systems. However, the introduction of multiple central or decentral heat sources, decentral heat storage, peak shaving strategies and optimal temperatures in relation to available heat sources, appears to challenge conventional design and control practices.

The Warming Up project aims to develop methods, frameworks and software which enables optimal design and control of modern district heating systems which have a better performance and allow for a better integration of renewables than conventional systems. The project consists of several project themes of which theme 1 deals with this development. For this theme the projects starts with investigations such as an inventory of stakeholder requirements and a literature review on optimization methods as a starting point for the developments. The purpose of this report is to review literature in order to find recent insights and methods which can be used for optimal design and control methods of district heating systems. The report has a focus on control methods but investigations on modelling of district heating networks are also relevant for the design of networks.

The problem statement for this investigation is: *what relevant methods and experiences are found in literature for optimal design and control of district heating systems?*

The problem statement is investigated by the following research questions:

1. how is a conventional district heating system designed and which control methods and targets are used? *chapter 2.*
2. what is "optimal" control of a district heating system and which goals are achieved? *chapter 3.*
3. which control optimization goals have the highest priority and through which physical mechanisms (control variables) are these goals achieved? *chapter 4.*
4. what is a suitable, general optimization framework for district heating systems? *chapter 5*.
5. which costs should be included into the optimization objective? *chapter 5.*
6. how can we group or structure the different optimization problems for design and operational control of district heating networks? *chapter 5*.
7. which methods are commonly used to solve energy system and district heating system optimization problems? *chapter 5*.
8. what is the general architecture of model predictive control for energy systems? *chapter 6*.
9. which simulation modelling methods are used for making model predictions? *chapter 6.*
10. how can heuristics support efficient solving of optimization problems? *chapter 6.*
11. what is multi-agent modelling and why is it an important method for optimal control of district heating systems? *chapter 6*.
12. what is price based control and why is it relevant for optimal control of district heating systems? *chapter 6.*
13. what relevant experiences with optimal control of energy systems are out there and what can we learn from them for the development of an optimal controller for district heating systems? *chapter 6.*
14. what are the most important challenges for developing an optimal control method for district heating systems? *chapter 6*.

The report is structured according to these research questions and Chapters indicated. The report ends with conclusions and future work in Chapter 7.

2. Conventional district heating design and control

A District Heating system (DHS) consists of one or more heat production units, a primary distribution network and secondary distribution network, see Figure 1.

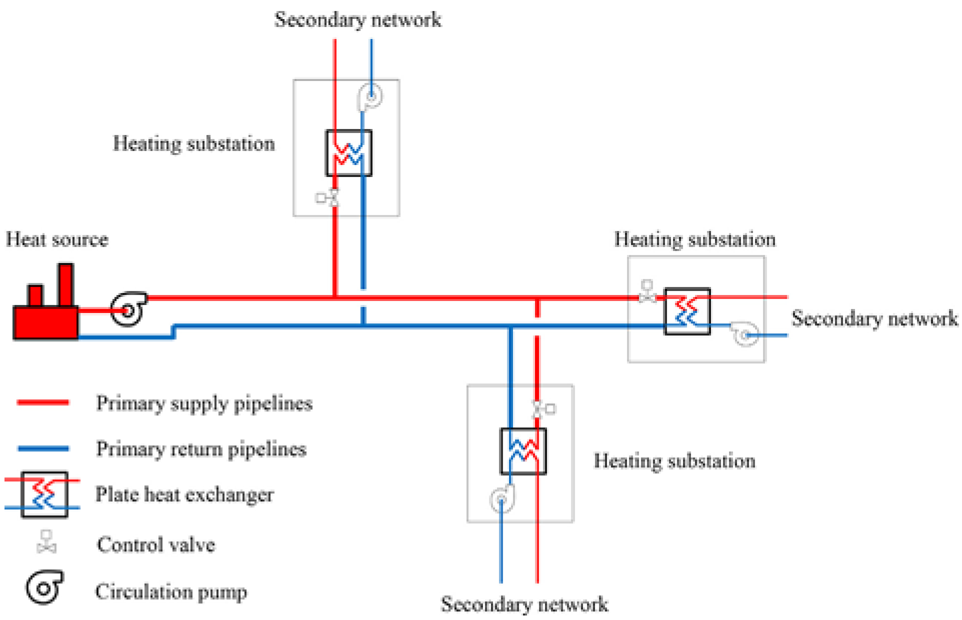

Figure 1: schematic overview of a District Heating system [1]

The secondary network may be a house or building heating system. The heating substation connects the home or building to the primary network. In larger networks, the network may be split into a primary network which supplies several secondary networks to which houses and buildings are connected. A heating substation between the primary and secondary network is then usually a building within a neighborhood. Each house or building has its own substation or connection to the secondary network. In such larger networks, the primary network usually has a higher temperature and water pressure than the secondary network, but there are exceptions to this, e.g. the backbone solution of Hengelo where the primary network is a low temperature, waste heat network and the secondary networks are high temperature networks. The substations contain a heat pump to raise the temperature.

Several control “layers” are present in any DHS:

- **Control of the heat sources**. The control is done by monitoring of the heating load of the DHS which is determined from the flow and both the approach and return temperatures. The control of the heat sources includes control of the frequency controlled pumps.
- **Hydraulic control of the primary and secondary network**. When the heating load increases, the pressure difference between the approach and return line increases and this should be compensated to maintain hydraulic pressure and flow balance. The control is done by differential pressure controllers between the approach and return line. The pump frequency control is an integrated part of the pressure control: more heating load results in wider opening of the differential pressure control valves and higher pump frequencies.

- **Control of the substations**. If the substation is the connection of a house or building, then the flow and pressure are controlled by a building thermostat which is connected to the substation. This opens or closes the main valve of water from the DHS which controls the heat input towards the building heating system. If there is a demand for domestic hot water, then the flow from the DHS is controlled by a second valve which controls flow towards a heat exchanger which is usually part of the substation. If the substation is an intermediate station between a primary and secondary network then the controller at the substation controls the flow and pressure of the secondary network in a similar way as the controller of the heat sources for the primary network.
- **Building temperature control**. Behind the substation, the temperature within a building may involve a single thermostat for the entire building, but also a more complex system of individual thermostats for each room in a building which control the valve to each radiator.

A conventional control system for DHS is operated in such a way that the system stays within certain bounds or operational goals (refer to Figure 2):

- **Central maximum supply temperature control**. The supply temperature is controlled to a certain setpoint value which may be weather dependent (higher at lower ambient temperatures).
- **Local minimum supply temperature control**. The DHS has to guarantee that the building at the coldest spot of the network (usually the building at the end of the network) receives sufficient heat with a certain minimum temperature.
- **Central and local maximum pressure control**. The pressure in any part of a DHS should not exceed a certain maximum pressure. This can be an issue in a DHS in areas with large height differences.
- **Central and local minimum pressure difference control**. The pressure difference in any part of the DHS between supply and return pipes should not be lower than a certain safe minimum value above the water vapour pressure. This control aspect is more problematic for larger networks and high heating loads.

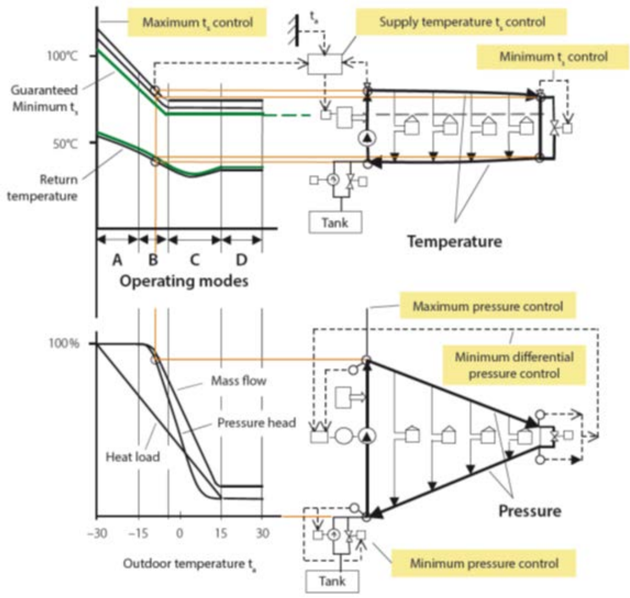

Figure 2: Operational modes for DHS control systems [2]

3. Possible goals for an optimal District Heating controller

Conventional control methods for a DHS are proven to reach operational robustness. However, the resulting performance of a DHS is not always optimal and may be improved further. In this chapter we explore targets to improve the performance of a DHS and some specific challenges which are hard to match with conventional control methods.

Based on an inventory involving multiple stakeholders coming from Dutch district heating companies, the following important performance aspects were determined which are difficult to accomplish by conventional control methods and therefore require other control methods:

a. **Reduce network heat loss by lower supply temperatures**. It is still common in many DHS to supply a constant high temperature throughout the year, e.g. 80°C. However, at times of low heating loads, the supply temperature could be much lower and this would decrease heat losses to the environment. This is often not done due to the risk of pipe fatigue resulting from heat stress and due to the more complex control in relation to ambient temperatures which requires additional monitoring and changes in the control system. Theoretically, a DHS could be operated with supply temperatures as low as 55°C which is the lowest possible temperature for safe domestic hot water supply. When even lower temperatures are considered, additional heating is required at each house or building for domestic hot water. Low supply temperatures are beneficial for efficient operation of renewable heat sources (e.g. solar thermal energy, heat pumps), see Figure 3.

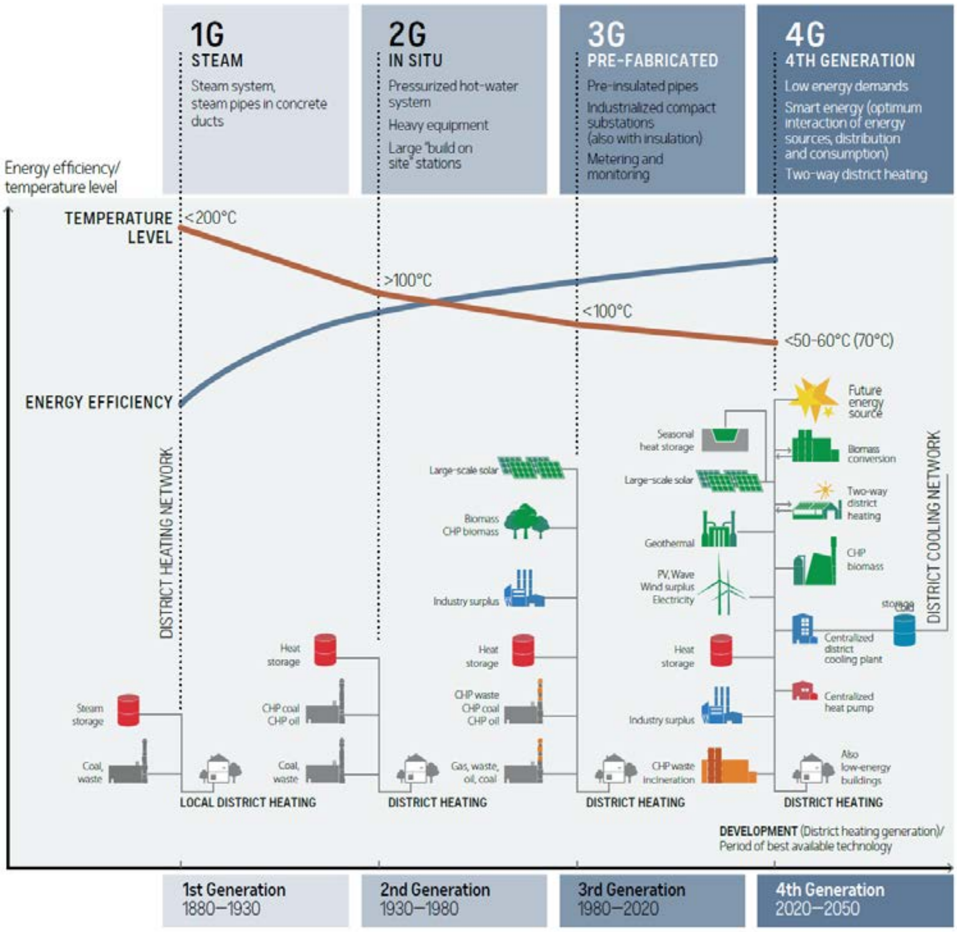

Figure 3: DHS generations [5]

b. **Reduce network heat loss by lower return temperatures**. Besides lowering the supply temperature, it is equally important to reach lower return temperatures. This is beneficial for the efficient operation of renewable heat sources. However, lower return temperatures are achieved by optimising the flow in the DHS and by improving building heating systems. Both are complex tasks to achieve and require additional monitoring and building system changes.
c. **Reduce pump losses by increasing the difference between supply and return temperatures**. In order to supply as much heat as possible with a minimum required pumping energy, the difference between supply and return temperatures should be as large as possible.
d. **Allow for distributed or sectional DHS control**. In a conventional DHS, temperature and flow are controlled for the entire network. It may be beneficial to make partitions within a DHS and to apply distributed control to each partition. If there is no heat demand in one partition, the flow may be controlled to a low value or even stopped within the entire partition, while the rest of the DHS maintains a certain flow. This control strategy may save a lot of pumping energy and heating energy.
e. **Prevent heat demand peaks**. If peak loads can be avoided, high pumping losses can be avoided and sustainable heat sources can be used more efficiently. A side effect of lower peak loads is that the pipe diameters of a heat network can be smaller. Avoiding peak demand is also called “peak shaving” or “demandside management”. Both terms come from electrical smart grid literature and involve influencing the demand at the house level.
f. **Optimize deployment of sustainable heat sources and heat storage**. The control is situated at the heat sources and is aimed at operation with the lowest possible costs and the highest possible efficiency. In Figure 4, operation of multiple heat sources in a DHS is shown for a case study.

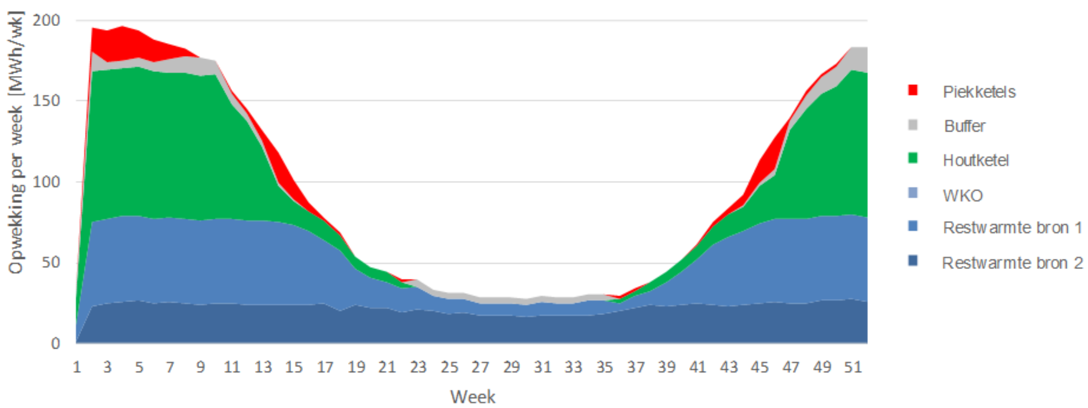

Figure 4: operation of multiple heat sources in a DHS [3].

g. **Facilitate system integration of a DHS**. This involves sector coupling e.g. by power to heat and may involve using the DHS as load balancing electricity consumer for an electricity grid with multiple sustainable sources. A modelling scheme for such a system is shown in Figure 5. In this, an electricity grid is shown with sustainable sources on the left, as well as heat sources connected to a DHS with demand on the right.

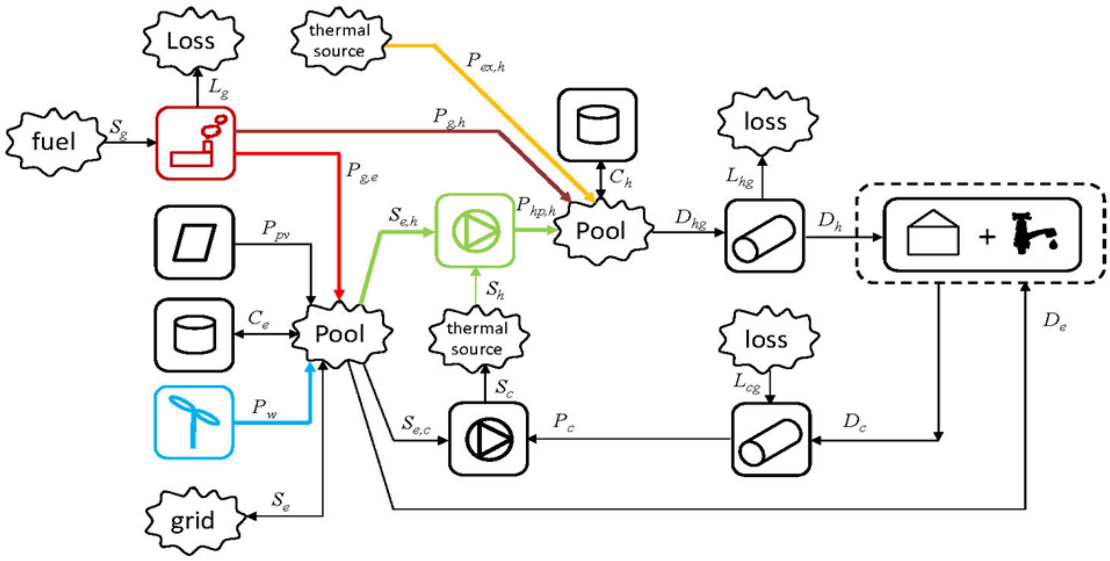

Figure 5: modelling scheme smart energy grid [6]

h. **Facilitate multiple decentral heat sources in one DHS**. Figure 6 shows a DHS with two heat sources placed far from each other within the primary network. The flow direction in each section of the primary network may depend on different states of operation of the heat sources and pumps within the network are controlled accordingly.

The concept of Figure 6 may be taken further towards full scale Third Part Access (TPA), which is characterized as follows:

- multiple sustainable centralized and decentralized sources,
- buildings can be operated either as heat source or sink in different time domains,
- bi-directional energy flows are possible and require appropriate heat metering techniques.

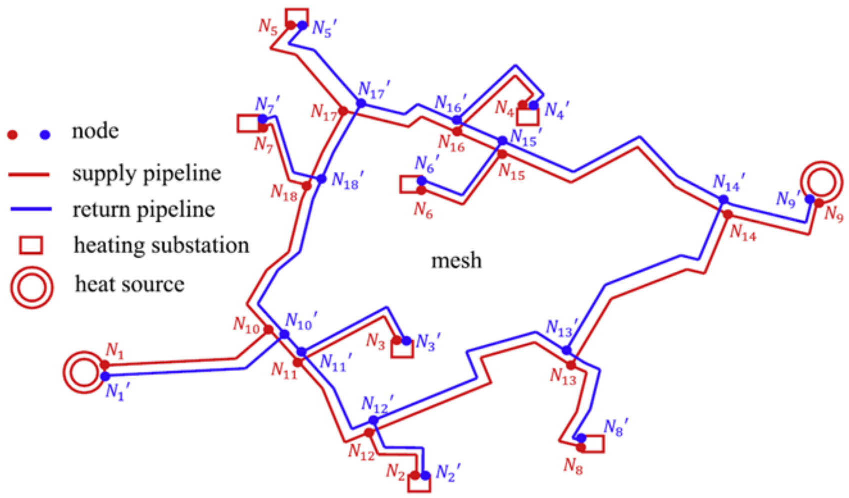

Figure 6: DHS with two decentral heat sources [4].

4. Prioritization of goals for the development of an optimal controller

In the previous chapter we developed a "wish list" of goals for optimal control of a DHS. Based on this, we develop a table in this chapter which evaluates the options on potential application, control goals and methods to achieve this. We conclude with opinions found in literature about the ranking that is made in the table.

In Table 1, the goals presented in Chapter 3 are given a number and the author estimated the potential and priority for application within optimal control methods. In the last column, the priority for each option is estimated based on the potential (high to low) and expected benefits (high to low) due to more optimal operation of the DHS.

To find more evidence about the prioritization shown in Table 1, stakeholders can be interviewed or evidence can be found in literature. In other parts of the project, the interviews with stakeholders are taken care of. We now provide further evidence found in literature. In [7] the following challenges for a future DHS are identified:

- Supply low temperature district heating to existing buildings, table nr. 1, 5.
- A DHS with low grid losses, nr. 1, 5.
- Integration of renewable heat sources and low temperature sources, nr. 5, 6, 8.
- Integrate a DHS as part of smart energy systems (sector coupling, power to heat), nr. 7.
- Suitable planning, cost and motivation structures in relation to operation and strategic investments (all options)

In [8] the following operational challenges for a DHS are addressed:

- Reducing heat loss costs and pumping costs, table nr. 1, 2, 3.
- Operational strategy and Priority scheduling of multiple renewable heat sources within a DHS network, nr. 5, 6, 8.
- Control strategies based on accurate load and heat supply predictions, nr. 1, 5, 6, 8.
- Integrate a DHS as part of smart energy systems (sector coupling, power to heat, distributed heat sources), nr. 7, 8.

From this literature survey, an additional objective for optimization during the design phase of a DHS network is identified as: *determine the optimal topology of a DHS*. The optimum is determined by minimum investment costs and lowest grid losses (heat and pumping losses).

Nr.	Overall target	Mechanism	Efficiency measure (Chapter 3)	Control goals	Potential for optimal control methods	Applicability priority
1	Minimize operational costs	Reduction of network heat losses resulting in reduction of required heat.	Lower supply temperatures	**Minimize** supply temperatures in relation to heating loads.	High. There are many examples in literature where MPC with a first order model or neural network model is used to predict loads in relation to weather forecasts and optimal supply temperatures are determined in relation to the predicted loads, taking a time constant for the network into account.	**High**
2			Lower return temperatures	**Minimize** return temperatures.	Low. This is achieved by: (a) network flow control which involves pump control and substation valve control: flow should be restricted as much as possible. This is already the purpose of conventional control. (b) optimization of building installations: radiator flow optimization, larger heat exchange surfaces. On the network side, this cannot be influenced.	Low
3		Reduce required pumping energy by reducing flow due to largest possible temperature difference.	Increasing the difference between supply and return temperatures	**Minimize** pumping energy.	Medium. Pump frequencies are conventionally often controlled by pressure difference. It is more optimal to control the flow based on temperature difference, taking a safe minimum pressure difference as constraint. However, the return temperature depends also on the substations and building installations.	Low
4		Create most optimal flow and temperature conditions for parts of the network. This may reduce network heat losses and required pumping energy. Choose optimal co-operation of heat sources.	Splitting a larger DHS into seperately controllable zones.	**Minimize** supply and return temperatures, **Minimize** pumping energy, **Minimize** heat production, **Minimize** costs of heat sources (central or distributed)	High. Control of zones (or secondary networks) within a larger DH network needs to be done at the substation level where the zone is connected to the primary network. For each zone, the primary network is the main heat source. The substation may also include an additional (distributed) heat source for the zone specifically, e.g. a heat pump and thermal storage. There is an interaction between the load within the zone and the control of the central and distributed heat source. Flow and temperature of each zone may be controlled in an optimal way, similar as mentioned under item 1 to 3.	Low
5		Avoid deployment of peak boilers (fossil fuel consumption), reduce peak capacity of heat sources and network.	Preventing heat demand peaks	**Minimize** peak heating load, **Optimize** control of thermal storage.	High. Minimizing peak heating load requires demandside management or load shifting at consumer level. Building thermal inertia or consumer thermal storage may provide flexibility. Optimal control of thermal storage is possible at heat source or may involve several distributed thermal storages.	**High**
6		Avoid using fossil fuel, optimize costs and (contractual) availability of multiple heat sources, optimize use of thermal storage.	Optimal control of central sustainable heat sources and thermal storages.	**Minimize** costs of heat sources and thermal storages.	High. Controlling multiple heat sources and thermal storage have a relation with thermal load predictions of the network. This is a straightforward MPC problem for simple networks with a central heat source location. However, if multiple heat sources are distributed and multiple flow directions are possible within the network, this is much more complex (refer to 8).	**High**
7		Make use of low energy tariffs (electricity) within a smart energy system (power to heat).	System integration of a DHS	**Minize** costs of heat sources and thermal storages.	High. A DHS may be use for peak shaving and solving congestion problems of electricity grids. The optimization problem is however complex as it involves multiple cost data and predictions, besides load predictions. Control of the DHS heat sources should be included into smart grid control of the integrated energy system.	Medium
8		Avoid using fossil fuel, optimize costs and (contractual) availability of multiple heat sources, optimize use of thermal storage.	Optimal control of multiple distributed sus-tainable heat sources and thermal storages.	**Minimize** costs of heat sources and thermal storages.	High. Controlling multiple heat sources and thermal storage have a relation with thermal load predictions of the network. This is a straightforward MPC problem for simple networks with a central heat source location (refer to 6). However, in case of TPA, multiple heat sources are distributed and multiple flow directions are possible within the network, this is much more complex.	**High**

Table 1: overview of optimization goals for DHS

5. Introduction into optimization methods for an optimal controller

In the previous Chapter we explore goals and estimated applicability of more optimal control of a DHS. In this Chapter we investigate common methods used from literature to achieve this. We also develop a classification for the different design and control optimization problems.

To develop a set of mathematical rules for optimization, it is not obvious that we can work with just a single **objective** function to steer the different goals in the right objective. In energy optimization, it is common to use cost functions as objective. Cost functions may contain CAPEX for the investments involved (including peak generation capacity in relation to demand) and OPEX (including costs for operating different heat sources, heat losses in relation to temperature and pumping energy costs). In most DHS optimization problems, the framework shown in Figure 7 is applied.

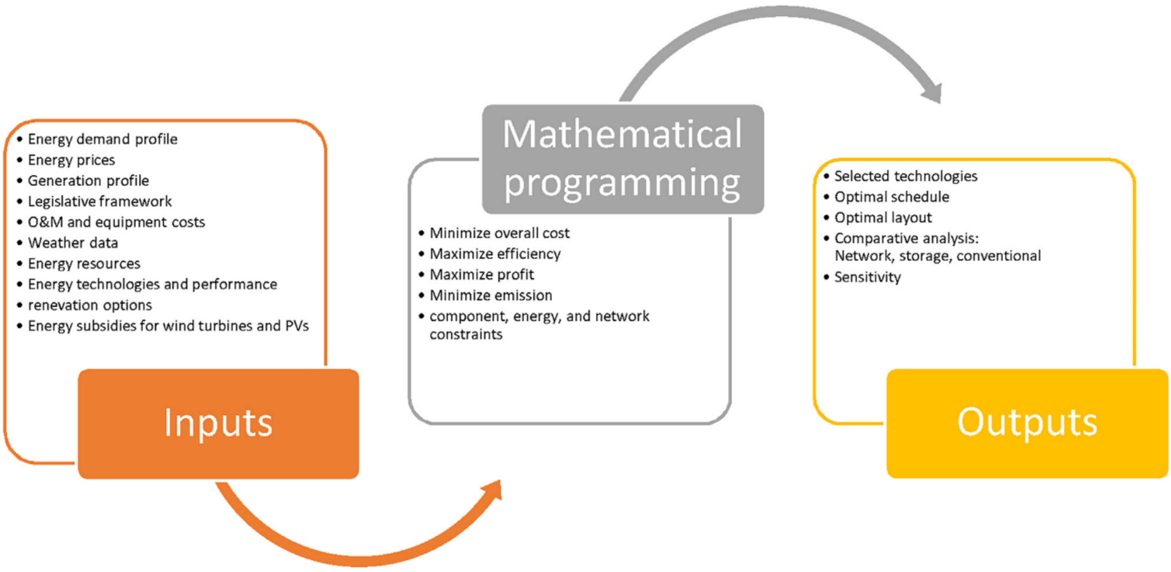

Figure 7: Framework for district level optimization [9]

Possible cost functions are shown in the *middle block*. Total cost of operation is usually part of the objective, the cost ingredients are shown in Figure 8.

It often requires some “art” to develop an objective function which is able to steer towards other goals, e.g. increase sustainability. This can be achieved for instance by including a penalty on CO_2 emissions from fossil fuel heat sources. In general, the relative importance of objective terms within an objective (cost) function may be scaled with a weighing factor. However, the more we use such scaling methods, the less the objective will have a practical significance. The functions are then just used to steer the system towards a desired operation. If an objective is to signify real costs or profits of a DHS, then no scaling or weighing factors are used for cost or profit terms and the outcome may be such that e.g. fossil fuel heat sources will be used more than desired, due to their low operational costs and the present day low penalties on CO_2 emissions. In Table 2, an overview is given of objective functions used in recent studies on optimization of DHS.

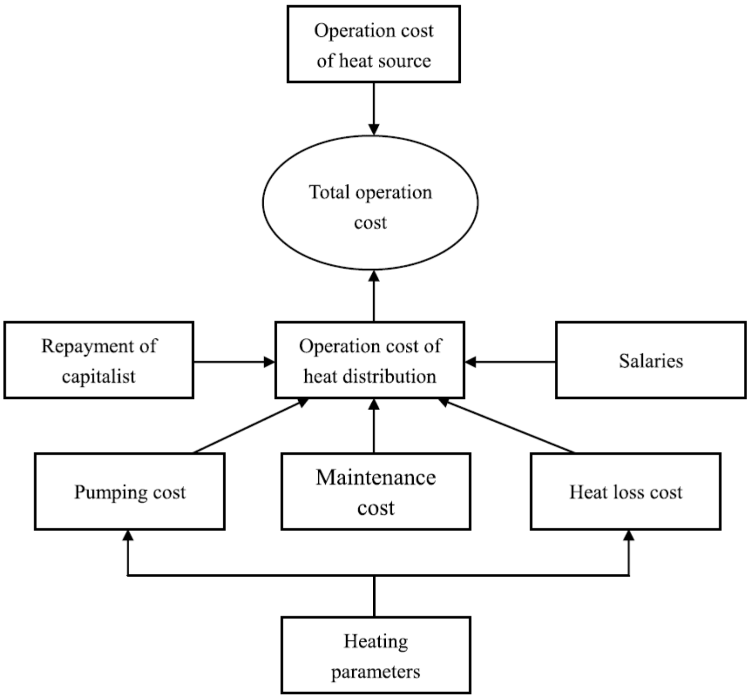

Figure 8: total operation cost of a DHS [13]

The output of optimization studies which are based on the framework of Figure 7 are shown in the *right block*. To understand the difficulty of solving optimization problems, it helps to define "classes" of problems. The first class is defined by energy balance equations of the DHS and aims at determining capacity and optimal scheduling in time of the heat sources, thermal storages, supply and return temperatures and mass flow rates of primary and secondary circuits. An example is given in [13]. The second class is defined by topographic relations and aims at determining the optimal layout of a network, which is a spatial optimization problem and therefore an entirely different class than the first class. An example is given in [4].

It is difficult to optimize both output classes within one optimization problem, especially for complicated networks. This is because of the need for elaborate **constraints** for each class:

- For the first class, to govern the relation between heat demand and heat production by multiple sources, and to govern charging and discharging of energy storage, logic control rules and boundaries are required as constraints.
- For the second class, to govern flow paths within a network, logic relations need to be defined in order to rule out impossible network layouts and flow directions. An overview of the possible types of constraints in energy optimization is given in Figure 9.

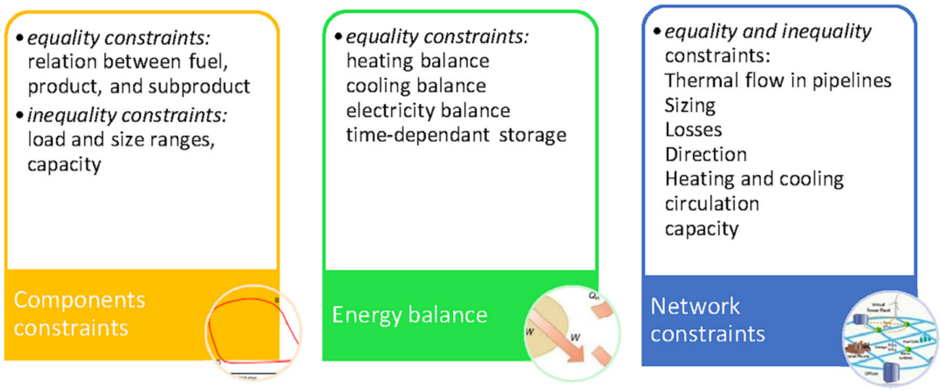

Figure 9: classification of constraints in district energy optimization problems [9]

During mathematical optimization, a system of equations is repeatedly solved, changing the variables which need to be optimized in a computational efficient way and storing the best solutions for the objective function until the solution does not improve anymore. The more "logic" relations (constraints) that are predefined between states for the inputs, variables and outputs, the less variables that need to be considered during the optimization and the faster the problem will be solved. The more variables a problem contains, the more difficult it is to solve. It is therefore more difficult to solve multiple class problems within one optimization problem. It can be concluded that each class of problems should be solved on its own.

The first class can be used during the design phase to estimate asset capacities, but also for operational control, e.g. to control heat sources, buffering and network states. It could also include distributed flexibility options within the network, e.g. demand response actions at the customer level in order to minimize peak heat demand. As this introduces far more variables to solve, we signify this as a <u>third class</u> of DHS optimization problems. An example is given in [14] which uses multi-agents at building level to control the heat supply to each building. This class will quickly involve large numbers of variables in time to solve and this may dramatically increase the time to solve the problem. Computational efficiency measures like "moving time horizon" are required to solve the problem within acceptable time.

The second class is often used during the design phase to determine the optimal routing and sizing of pipes within the network. It is also used for operational control of flow direction within more complex networks which have a ring structure and include multiple heat sources along the network (Third Party Access), refer to Figure 6. The purpose is then to control the distributed heat sources and flow directions within the network in time. This kind of complex operational network control can be seen as a class on its own and we introduce this as the <u>fourth class</u> of DHS optimization problems. An example is given in [15]. The paper shows the difficult problem of controlling local flow and temperature of DH networks when a large number of prosumers are involved.

To summarize, we introduce the following classes of optimization problems in relation to DHS:

<u>First class – energy balance of tree structured networks:</u>
- Design phase: capacities of heat sources and energy storages (static, dynamic)
- Operational phase: scheduling in time of heat sources, i.e. centralized heat sources or distributed heat sources (dynamic)

- Operational phase: scheduling of charging and discharging in central or distributed energy storages (dynamic)
- Operational phase: scheduling of primary and secondary mass flows, supply and return temperatures (dynamic)

Second class – optimal network layout:
- Design phase: network pipe diameters and section lengths (static)
- Design phase: optimal network layout (static)

Third class – operational control and demandside management of tree structured networks:
- Operational phase: scheduling of flexible loads at customer level (dynamic)
- Operational phase: peak or load shifting flexibility options along the network or at customer level (dynamic)

Fourth class – operational control of flow and distributed prosumers in complex networks:
- Design phase: capacities of heat sources and energy storages (static, dynamic)
- Operational phase: scheduling in time of distributed heat sources and energy storages (dynamic)
- Operational phase: scheduling of pipe section flow directions in time (dynamic)
- Operational phase: scheduling of primary and secondary mass flows, supply and return temperatures (dynamic)

Table 2 shows that the most commonly used optimization method is linear programming, in most cases of Mixed Integer type (MILP). It is common practice to formulate objective functions and constraints as linear relations, although this violates practical non-linear behaviour. However, solving non-linear, dynamic optimization problems with multiple control variables is computationally very difficult. Succesful methods include mixed Monte Carlo with Pareto front analysis or ant-colony analysis, although both methods require much computational time which is problematic for the purpose of online, operational control.

Study	Optimization type	Method/ Algorithm	Objective(s)	DH type	Solver
Superstructures					
Mehleri et al.	Single-objective	MILP	Total annualized cost of micro-grid	Centralized	GAMS CPLEX
Wu et al. [33]	Multi-objective	MILP	Both economic and environmental aspects	Decentralized	Not mentioned
Li et al.	Single-objective Multi-objective	MILP	Annual cost and carbon dioxide emission	Decentralized	MATLAB Gurobi
Bordin et al. [46]	Single-objective	MILP	Selection of new users	Centralized	Opti-TLR CPLEX
Ameri et al. [47]	Single-objective	MILP	Costs savings and reduction in CO_2 emissions	Decentralized	CPLEX AIMMS
Rivarolo et al. [48]	Single-objective	NLP	Sum of annual variable costs	Centralized	W-ECoMP
Buoro et al. [35]	Single-objective	MILP	Annual investment, operating and maintenance costs	Combined	Xpress
Karschin and Geldermann [49]	Single-objective	MILP	Cost-efficient heating network	Centralized	Xpress
Operation and planning					
Vesterlund et al. [50]	Single-objective	MILP	operating costs for heat production	Centralized	CPLEX
Wang et al.	Single-objective	LP	costs of the net acquisition for heat and power in deregulated power market	Centralized	LP2
Carpaneto et al.	Single-objective	MILP	dispatching strategy for the different power sources	Centralized	MATLAB
Wang et al.	Single-objective	Newton's method	total mass flow rate total thermal conductance	Centralized	Not mentioned
Khir and Haouari [54]	Single-objective	MINLP/MILP	capital and operating costs	Centralized	CPLEX
Zhou et al. [55]	Single-objective	MILP/MINP	annual capital, operation and maintenance cost of CCHP	Centralized	GAMS CPLEX
Powell et al. [56]	Single-objective	MILP/MINLP	system operating costs (fuel and grid)	Centralized	MATLAB BONMIN
Jie et al. [57]	Single-objective	NLP	pumping cost and heat loss cost	Centralized	MATLAB
Jiang et al. [58]	Single-objective	GSO	Energy consumption	Centralized	MATLAB
Ren et al. [59]	Single-objective	MILP	CO_2 emission and running cost	Centralized	Not mentioned
Fang et al. [21]	Single-objective	Genetics Algorithm	sum of fuel and pumping cost	Centralized	MATLAB C++
Kim et al. [60]	Single-objective	MILP	overall operation costs	Integration of Centralized systems	CPLEX
Distributed integration					
Sartor et al.	Single-objective	NLP	cost per unit of thermal energy used	Centralized	Not mentioned
Wang et al.	Single-objective	LP	overall net acquisition cost for energy	Centralized	LP2 EnergyPro
Ondeck et al.	Single-objective	MILP	profit of CHP plant by selling electricity	Centralized	GAMS CPLEX
Falke et al.	Multi-objective	Kruskal and Genetics Algorithms	costs of power and heat supply and CO_2 emission equivalents	Decentralized	Not mentioned
Weber and Shah [41]	Single-objective	MILP	Total annual costs including investment and operating	Centralized	GAMS CPLEX
Sameti et al. [42]	Multi-objective	NLP	total exergetic efficiency and the net power	Decentralized	MATLAB
Maatallah et al. [27]	Single-objective	Hybrid optimization	Total net present cost	Centralized	HOMER
Amutha et al. [26]	Single-objective	Hybrid optimization	Total net present cost	Centralized	HOMER
Subsystem building blocks					
Jie et al.	Single-objective	Calculus-based	pipe investment cost	Centralized & Decentralized	Not used
Wang et al.	Single-objective	Genetics Algorithm	Calibration	Centralized	MATLAB
Barberis et al. [23]	Single-objective	Genetics Algorithm	Annual variable cost	Centralized	W-ECoMP
Zeng et al. [24]	Single-objective	Genetics Algorithm	investment, depreciation, maintenance, heat loss, and operational cost of circulating pumps	Centralized	Not mentioned
Diangelakis et al. [63]	Single-objective	control vector parameterization (CVP) algorithm	Operation cost	Centralized & Decentralized	gPROMS gOPT
Xiang-l et al. [22]	Single-objective	Genetics Algorithm	Annualized price of distribution network	Centralized	Not mentioned

Table 2: summary of optimization methods in some recent studies [9]

6. Review of Model Predictive Control for district heating systems

Optimal control of energy systems is studied and developed for more than 30 years. Applications are widespread in the smart grid domain and include control of multi-energy generation, energy storage and demand response. In this chapter we investigate the application of Model Predictive Control (MPC) in energy networks. The general MPC framework is shown in Figure 10 and this applies both for network design problems (class 1 and 3) and for operational control problems (class 2 and 4).

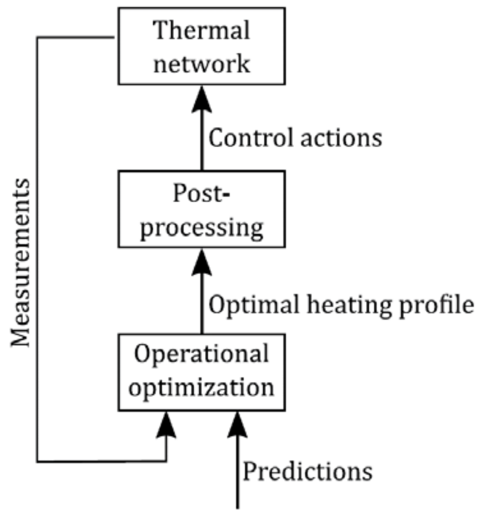

Figure 10: framework of model predictive control for DHS [16]

The bottom block contains the optimization method which uses a system model to generate predictions. The system model uses measurements and estimated control actions as input. By repeating the calculations, the objective function is optimized and optimal values for the control variables are found as output and this is postprocessed into control actions for the thermal network.

6.1 Overview of simulation modelling methods

In the previous Chapter we discussed problem classes and optimization methods, in this Section we investigate more closely the role of the predictive model. From system modelling theory, we distinguish three types of modelling methods [17]:

1. <u>System Dynamics modelling</u>
   This describes a system with mathematical equations, often in the form of differential equations that describe system state changes in time. A system model also contains feedback loops between inputs and outputs. The mathematical set of equations represents physical behaviour of the system. A white box model contains equations and parameters which are based on a physical model of the system. A good white box model correlates (nearly) exact with experimental data. On the other side, a black box model contains equations and parameters which are simply chosen to best represent experimental data, without considering a physical model of the system. Model parameters are optimized to match experimental data and parameters often need to be updated with recent data. In energy system optimization, linear ARMAX models and neural network models are often used.
   In between, a grey box model consists of mathematical equations and parameters similar as white box models but the equations are based on a simplified physical model of a more

complex system. Model parameters are dealt with in a similar way as black box model: they are optimized to match experimental data. The optimization of parameters can be done with several techniques: for models with a few parameters, least square difference minimization is sufficient. For models with many parameters, a machine learning algorithm is more succesful. System dynamics modelling is the most applied method for DHS system simulation for design and control purposes. However, it has its limitations when we consider decentralized or distributed control problems as the system model then becomes very complex and computationally expensive due to the relations between all of the nodes within the system model.

2. Discrete Event modelling
   This method is developed to simulate events and processes, e.g. a factory which contains multiple production processes and for which we want to evaluate optimal process routes, waiting times and schedules for delivery of material and labour intensity. Typically, a model contains processes which are connected to other process or pools and a process is a discrete event with a starting time and duration. A DHS can be modelled with this approach but this is somewhat artificial because in a DHS system, duration of for instance heat production events is not fixed but determined by demand. Hence, a discrete event model of a DHS cannot function without system dynamics models.
3. Agent Based modelling
   Application of agent based modelling started around the year 2000 and is therefore quite a new approach. It is made possible by increased CPU-power and object oriented programming tools. The use of agent based modelling for DHS becomes obvious when we consider Figure 11 which illustrates the difference between centralized, decentralized and distrubuted control problems.

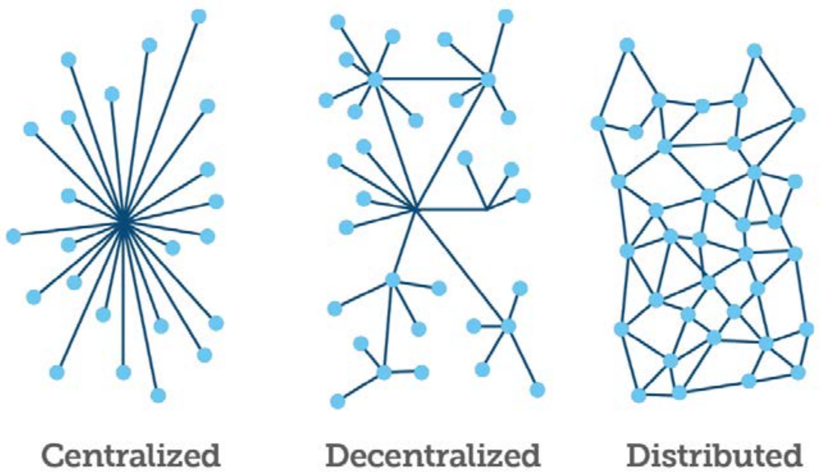

Figure 11: network classes for energy systems

A simple DHS contains a central heat source from which the network expands in a tree structure. The nodes at each branch represent aggregated demand for the branch. This type of system is relatively easy to model with a system dynamics model, e.g. by equations for the heat source, energy loss equations for the network and aggregated demand equations for the nodes.
However, a decentralized DHS contains more branches and may also contain decentralized heat storages and heat sources. In that case there are many relations possible between the

nodes. When system dynamics modelling is used, the system of equations and all the relations become complex to manage by the modeller. Also, during the design phase, when the design changes, the whole model needs to be changed as well, which is tedious work. In an agent based model, a system component is an object or an agent, for instance a heat source, a demand node, a household, a buffer. If necessary, pipe sections can also be modelled as agents. Each agent is part of a certain object class and may contain any kind of relation with other agents or may even contain a system dynamic model which e.g. describes heat demand. It may also be a bidding agent which is able to place bids on an energy market. This is explained later in this Section under price based control. The versatility of agents and the computational resemblance with objects, enables implementation of agents in a graphical modelling environment, for instance an overlay of a GIS map of a DHS. This makes if far easier to rebuild the model when the design of the DHS is changed.
The same arguments apply for distributed networks. Such a network structure is not common in DHS. But if we consider a district with many households and a DHS which is operated by price based control, the transactions and communication between households resembles a distributed network, but this is an entirely different flow than the flow of heat. For these kind of transactions, blockchain is a novel administrative system and this may be coupled to the DHS control system.

6.2 Supporting heuristics to solve MPC problems

Heuristics may be used either to limit the search space for solving the optimization problem in the form of cleverly constructed constraints, or to find faster routes for the optimization in the form of preselected solutions, or to limit the amount of required optimization problems within a time interval because we have some knowledge about optimality of the solution space. An example of the latter is a heuristic method called EDF (Earliest Deadline First) and this illustrates the power of using heuristics.
In [10] a group of decentral heat pumps and a single power source are scheduled in time by using EDF and results are compared with MILP (Mixed Integer Linear Programming). The heat pumps may also signify home district heating substations and the power source may be a heat source.
It was seen on the MILP solution that it is very hard to limit the amount of state changes of the heat pumps and the central power source in time. A lot of additional constraints are necessary to avoid frequent state changes and this has negative consequences for computational time. The EDF algorithm does a far better job by keeping the present state of each heat pump and the power source as long as possible, until a minimum or maximum boundary is violated and then the optimization problem is solved again. The result is that there are far less state changes (which is favorable for service life of equipment) but also less optimization problems in time to solve. So this also significantly reduces computational time. It is demonstrated that by making an adequate choice for the lower and upper boundaries, the quality of results, e.g. experienced thermal comfort of the households may be similar as the MILP solution.
Although heuristics can lead to a much reduced computational time for solving an optimization problem, the difficulty is that a heuristic approach is developed for a specific problem and it is difficult (if not impossible) to generally formulate heuristics which can work for a variety of problems. As a consequence, MILP is more often used as a general method but in relation to reduction of complexity and scale of the problem to keep computational time within limits.

6.3 Application of multi-agent system modelling for MPC of a DHS

District heating systems are physically distributed. Sensor data is collected via a distributed system. A relevant question is whether computation and control in relation to optimized control should be central or distributed.
When data is collected on a consumer/prosumer level and when we want to control on a consumer/prosumer level, then this requires a distributed type of control system and optimization method. We then need to predict demand patterns for each household and this requires not only large computational power when done on a central level, but also a lot of data exchange. This is not practical from a computational, data science and data security perspective.
As explained in Section 6.1 agent based modelling is the method of choice for decentral or distributed MPC problems. Further arguments for application of agent based modelling as part of MPC for a DHS are given in [11].

A suitable modelling representation is shown in Figure 12.

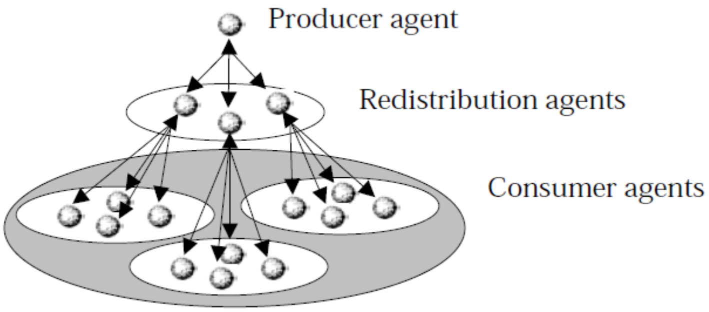

Figure 12: Multi-agent System model for a DHS [11]

Consumer agents

Within the model, agents must coordinate their activities with each other to satisfy group goals. It is difficult to identify group goals due to two types of conflicts. (1) Consumer agents want to maximize the comfort of the consumers by using as much heat from the network as the consumers demand. On the other hand, the producer agents want to produce as little heat as possible to reduce costs. In [11] this is solved by the following group goal: produce as little heat as possible while maintaining sufficient level of customer satisfaction.
(2) Another conflict exists between consumer agents when there is a shortage of heat in a part of the network. In this situation each consumer agent wants to satisfy their consumer´s demand, which is impossible. The solution given in [11] is the following group goal: when there is a shortage, the available heat should be shared fairly between the consumers. Satisfaction of these group goals could be achieved by either competition or cooperation. The architecture of consumer agents is shown in Figure 13.

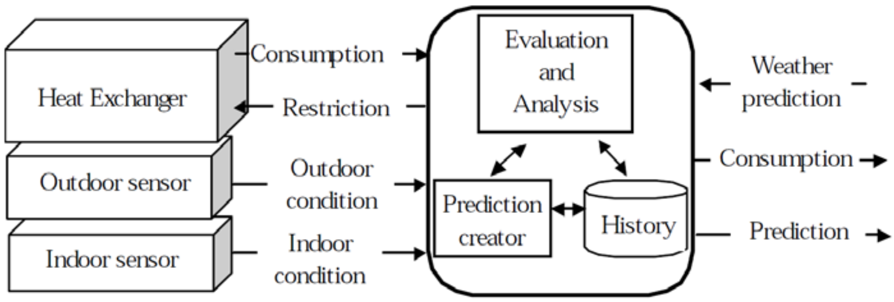

Figure 13: consumer agent architecture and interaction with environment [11]

Redistribution agents
These agents are responsible for a cluster of consumer agents. Their role is to be mediator between producer and consumer agents and to be decision maker [11]. Decisions concern restrictions upon consumer agents and maintaining an overall acceptable consumption rate, which is determined by predictions made by the consumer agents. The redistribution agents collect predictions and monitor the total consumption of a cluster of consumer agents.

Producer agent
This agent receives demand predictions from the redistribution agents and is responsible for the interaction with the control system of the heat production plant. The agent also monitors the actual consumption of consumer agents. This may be used to calculate the returning temperature, so that the producer knows in advance the temperature of the water to heat. The agent can also impose restrictions for consumers to reduce the cost of producing heat to cover for short temporary heating needs.

In Figure 14 a framework for an MPC control system with an agent based model is shown. This shows the relation between the control system (left) which has a similar schematic as Figure 10, and evaluation criteria (right). This framework was developed for a biogas system involving multiple biogas producers and users of biogas, but the framework is more widely applicable, also for a DHS.

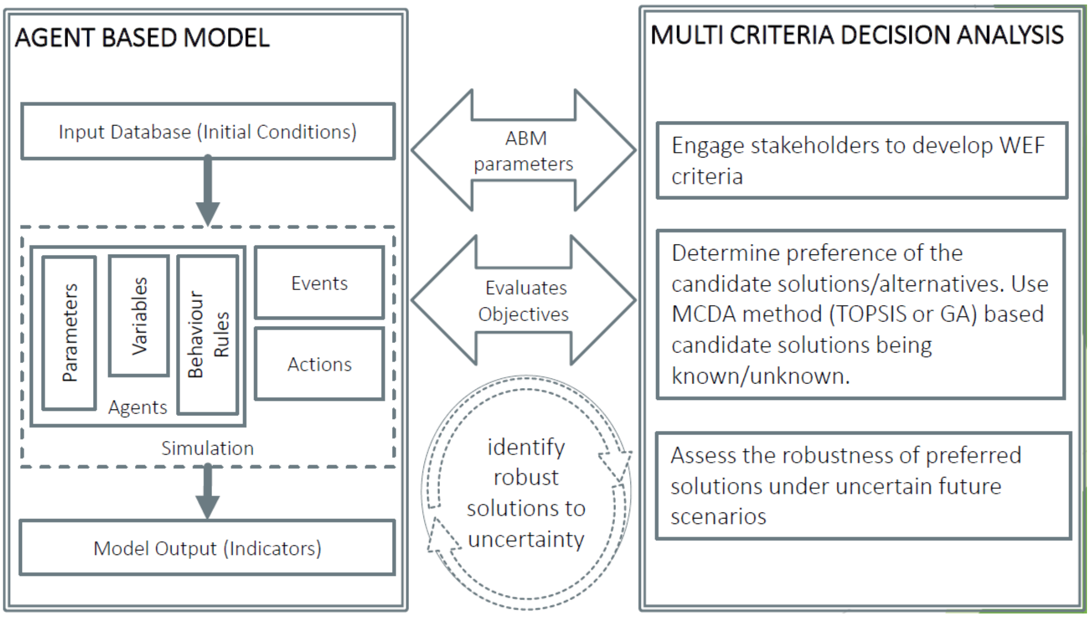

Figure 14: framework for a multi-agent system support tool [12]

6.4. Price based control
The method of price based control is part of the demand side management domain. This includes strategies to optimize consumption patterns and to use the potential of buffers and distributed generation. Demandside management methodologies commonly optimize on a device level (consumption, production, buffering). This introduces many constraints and thus complexity. Decisions for each device are taken in a hierarchical way to maintain scalability. The complexity can be reduced by using generic functions which express preferability of different options for the device. These functions are called utility functions, bidding functions or cost functions [18]. Cost functions

reduce the complexity of the optimization problem to a cost optimization problem with a limited number of constraints. The outcome of such an optimization problem is an energy price, which in combination with the cost function of the devices specifies the resulting dispatch for each device. For this method to work, some form of market organisation needs to be in place. It is common to organize an auction and to develop a multi-agent system model. Within the auction strategy, production agents offer and consumer agents place bids for the energy price, based on their cost function. The bids are aggregated and the market authority agent determines a market clearing price. The market clearing price may be steered towards a desired optimum which has to be learned (and be predictable) in time. Figure 15 demonstrates how the market clearing price is determined by aggregated production costs and the aggregated bids (price that consumers are willing to pay) in relation to the amount of energy.

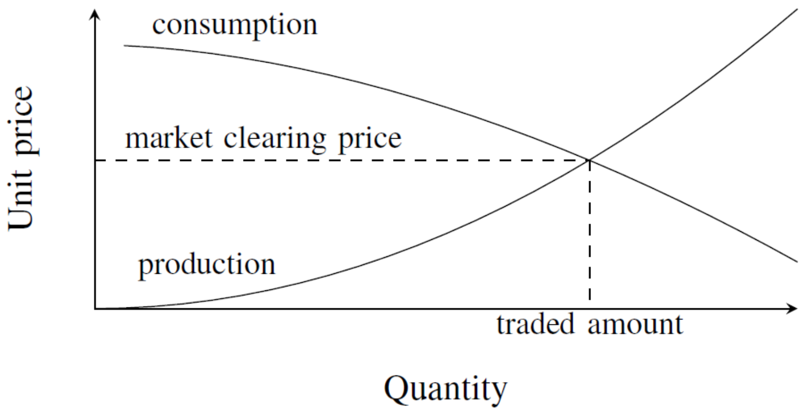

Figure 15: price function for an auction based strategy [18]

A well known concept which uses multi-agent system modelling and an auction based strategy is Powermatcher [19]. Each device is represented by an intelligent agent that trades on behalf of the consumer or producer. In this concept, a buffer can take the identity of consumer or producer. Data messages needed for the trading don't contain specific, local information which protects the privacy of the local consumer. Powermatcher is validated in practice and is a proven method for real time demandside management. It is interesting to consider application of this concept to a DHS. Dutch research organisation TNO is working on a similar concept in that field called Heatmatcher [20]. In a similar fashion, Vito in Belgium is working on a smart heat controller as part of the Storm project [26].

6.5. Novel optimal control strategies

In [24] a multi-agent system model of a heating network is part of a "cooperative multi-agent system (MAS) hierarchical model predictive control (HMPC) implementation." The approach is summarized as follows (quote): "The centralized model predictive control (CMPC) problem is formulated as a deterministic, multi-agent system, mixed-integer quadratic programming (MIQP) optimization problem and is subsequently distributed based on the Optimal Exchange Problem formulation using the alternating direction method of multipliers (ADMM). Hybrid system modelling theory is applied to model the agents' subsystems and a simplified heat energy exchange model with constant time delay is assumed. The latter was chosen as decoupled thermal and hydraulic equations proved to be non-linear in the valve positions and mass flow, iterative due to the friction factor and the Reynolds number, and dependent on a variable spatial sampling to accurately track the thermal propagation through the network." The method developed contains a simplified network modelling approach based on energy exchange between the agents to avoid non-linear equations when flow and temperatures would be used. By using simplified assumptions, the heat loss of the network is part of the modelling. The optimization problem involves minimizing the energy imbalance error for each consumer agent. As future work it is recommended to implement efficient solutions to deal with predictive modelling inaccuracies and to implement a lower level grid operation optimization problem to actually control valve and pump setpoints. Also application of a heuristic method is recommended to enable implementation on low cost computers in practice.

In [11] a similar concept as Powermatcher (multi-agent based modelling and an auction based strategy) is proposed for decentralized control of production, buffering and consumption in a DHS. However, an auction based strategy like Powermatcher aims at reaching an equilibrium at a certain moment in time and it repeats that process at a next time interval. This is a much different strategy than MPC, which uses predictions of future states to determine the best possible solution for the present time interval. It is demontrated in [18] and [21] that methods which include predictions lead to more optimal solutions. But as mentioned in the previous, MPC methods have the drawback of complexity and limited scalability. Is it possible to combine both methods?

Arguments for combining multi-agent modelling, auction based strategy and predictions are formulated as future work in [11]. In Section 6 we discuss that multi-agent modelling is a suitable method to model decentral or distributed systems. Agents can also include predictive models, for instance of household space heating demand and the buffering capacity of a floor heating system. Although it may be difficult, it does not seem to be impossible to include such model predictions within an auction based strategy.
At this stage only a few comparisons are found in literature which provide evidence that a DHS control system that uses model predictions leads to better results than a controller which uses e.g. an auction based strategy without predictions. As an example, in [18] the Triana (MPC) concept is compared with ILP and auction based control (both originally used for real time control in the paper). The auction based control method used here is based on Powermatcher as described in [21]. In Figure 16, results from [18] are shown. The ILP+ and Auction+ results include a planning step which is based on model predictions with known prediction errors. From the results, the authors conclude that the auction strategy is able to cope better with prediction errors than the ILP strategy which was given a similar planning.

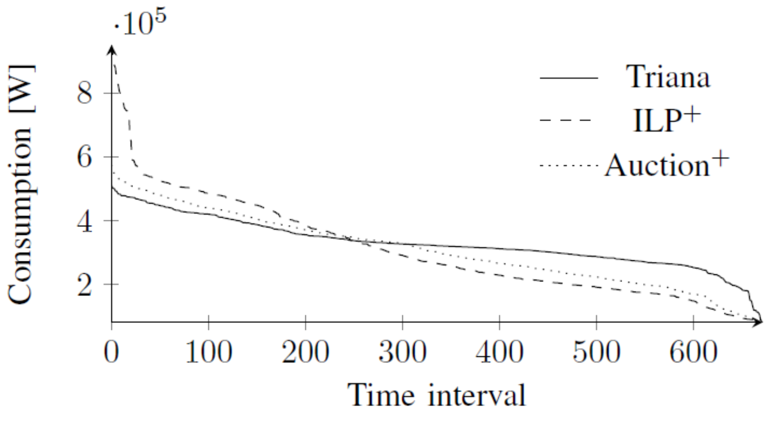

Figure 16: resulting load duration curves for 3 control strategies [18] including planning

Based on these results, it is important that besides a planning step (based on model predictions), the results also depend on the ability of the controller to cope with prediction errors. If warming up proceeds to develop an MPC controller for DH networks, this ability should be taken into account.

Based on Figure 16, the Triana method seems to follow an effective strategy to cope with prediction errors. Therefore we explain more about this control method. The strategy used is based on efficient algorithms which are capable to perform fast replanning during the real time control phase [27]. More recently, Triana is applied to different domains than smart grids, i.e. district heating or multi-energy systems. Also, the methodology is recentely updated with the name Profile Steering [22] and a simulation and control tool is developed under the name Demkit [23] which has also been demonstrated in practice in a number of cases and implemented into real control systems using low cost computers. Profile Steering and the Demkit tool apply some form of multi-agent system modelling, although Demkit is developed in the Python programming language and uses object oriented programming using object classes. A typical Demkit control system hierarchy is shown in Figure 17, which shows the use of agents on different levels of hierarchy.

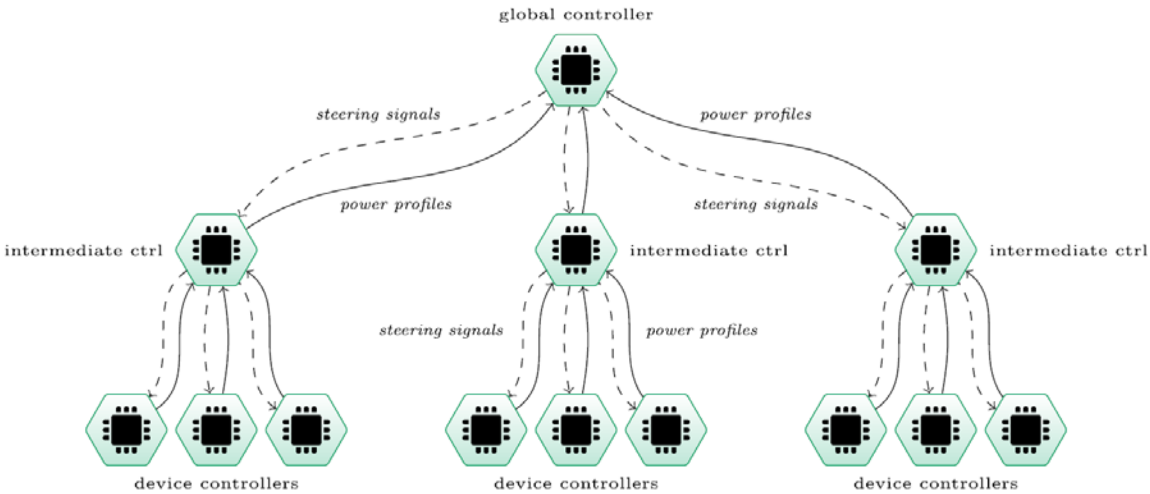

Figure 17: structure of controllers for profile steering methodology [25]

Power production and consumption profiles are steered as a result of three steps:

(step 1) each agent makes a prediction of energy consumption to determine priorities,

(step 2) an optimization which leads to a planning of devices, and

(step 3) real time control which reacts on disturbances which involves a short term correction on the planning. For the third step, an auction based strategy may also be used as explained in [18] and as demonstrated in Figure 16.

Profile steering has been implemented for optimal control of a small scale DHS involving 16 houses [25]. The modelling scheme is shown in Figure 18 and includes a multi-energy system consisting of a CHP, heat buffer and decentral solar PV, batteries, flexible and fixed demand and these are modelled using agent based system modelling. The home agents include predictive models for space heating and hot water demand. Like in [24] the heat network (temperatures, flows, heat loss) is not modelled while this adds considerable complexity and the purpose of [25] is to find optimal control for the CHP, flexible electric demand and batteries.

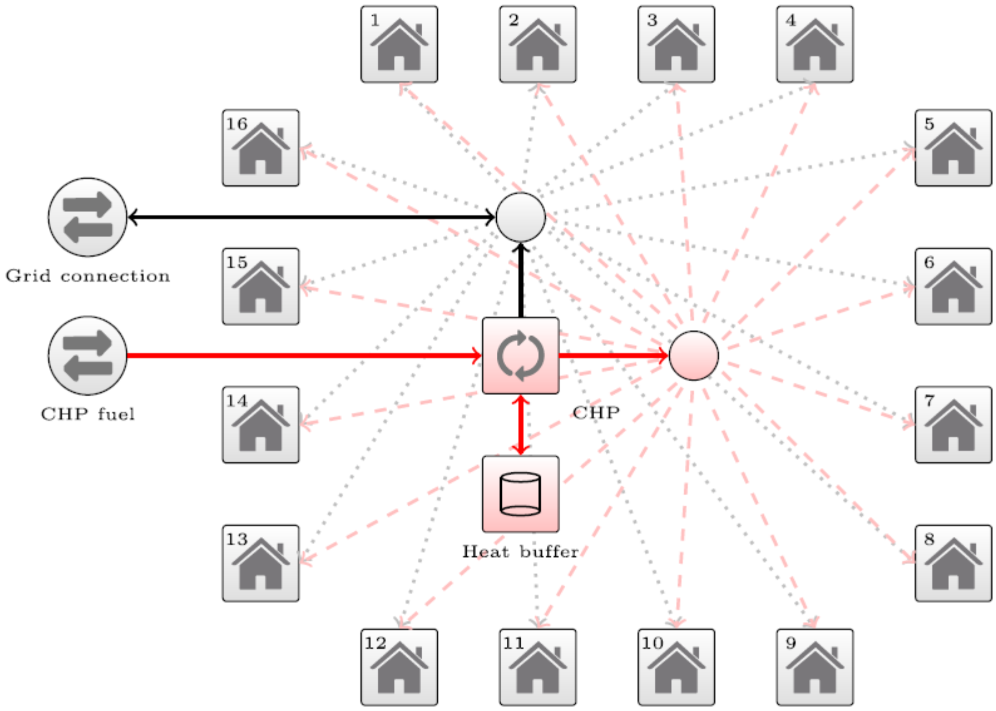

Figure 18: Multi-agent system modelling schematic for the 16 house case DHS

Hence, there is sufficient evidence (auction+ and profile steering, Figure 16) that a control strategy which contains a planning step based on model predictions (or other forecasting method) and a real time control step based on fast replanning, e.g. by using an auction based method and cost functions, leads to robust and optimal control results. Although applicability of such a control strategy is not investigated thoroughly for district heating networks, we assume that the results may even be better than for electricity grids. The argument for this is that both production and consumption of heat within such district heating networks varies less dynamic in time than electric energy within electricity grids and thus, it is easier to forecast production and consumption of heat, probably also with better accuracy and there is more time for a more optimal replanning during the real time control phase.
Besides the challenge to develop and implement such a control strategy for district heating networks, another challenge is to develop an approximation method for the model of the district heating network itself which is used for forecasting during the planning phase. Because of the non-linear nature of flow, pressure and temperature within the pipes and the possible complex structure of the network (nodes and branches), an optimal controller should use a simplified model of the network.

7. Conclusions and future work

Conventional district heating systems are operated with relatively high supply temperatures from a central heat source which may contain a heat buffer for peak heat supply. The control system aims at keeping pressure and temperature between minimum and maximum bounds and in relation to this, the pumps and heat source are controlled. The control system is based on feedback control principles in which setpoints are used and control actions are triggered by deviations from setpoints.

Due to the requirement of lower supply temperatures and the integration of multiple, renewable sources and decentral buffers, finding optimal control schemes to achieve the lowest possible operational costs becomes difficult if not impossible with conventional control methods. Setpoints have to be defined in time by using the "smartness" of operators who oversee the operation. However, there are optimization methods available which can support or overtake this complex task from humans. For the development of an optimal control system, the highest priority should be given to operational cost minimization which can be achieved by aiming for lowest possible supply temperatures, preventing peak heat demands and optimal production scheduling of central or decentral heat sources and buffers. For the design of a district heating network, priority should be given to topology optimization considering minimal investment costs and grid losses (heat and pumping losses).

A suitable optimal control framework for existing and new district heating networks contains a forecasting method to generate inputs for a mathematical optimization problem which can be solved within a given period of time repeatedly and which generates outputs in the form of set points in time for the conventional control system layer. We identified four different classes of optimization problems in relation to district heating systems:

First class – energy balance of tree structured networks:

- Design phase: capacities of heat sources and energy storages (static, dynamic)
- Operational phase: scheduling in time of heat sources, i.e. centralized heat sources or distributed heat sources (dynamic)
- Operational phase: scheduling of charging and discharging in central or distributed energy storages (dynamic)
- Operational phase: scheduling of primary and secondary mass flows, supply and return temperatures (dynamic)

Second class – optimal network layout:

- Design phase: network pipe diameters and section lengths (static)
- Design phase: optimal network layout (static)

Third class – operational control and demandside management of tree structured networks:

- Operational phase: scheduling of flexible loads at customer level (dynamic)
- Operational phase: peak or load shifting flexibility options along the network or at customer level (dynamic)

Fourth class – operational control of flow and distributed prosumers in complex networks:

- Design phase: capacities of heat sources and energy storages (static, dynamic)
- Operational phase: scheduling in time of distributed heat sources and energy storages (dynamic)
- Operational phase: scheduling of pipe section flow directions in time (dynamic)
- Operational phase: scheduling of primary and secondary mass flows, supply and return temperatures (dynamic)

Solving district heating optimization problems can be difficult due to the non-linear nature of the system model and the large amount of variables involved, depending on the complexity of the network. By simplification and approximation, the problem can be linear and reduced in complexity.

Mixed Integer Linear Programming (MILP) is used by most references in literature and problems are solved by common open source or commercial solvers.

For operational control of heat sources, buffers and demandside management, model predictive control is often used. The model that is used to generate forecasts may be a system dynamics model when only heat sources, buffers and some network valves and pumps are to be controlled. The network model should then be approximated to avoid non-linearity. However, when demandside management is part of the control problem, or a larger number of distributed heat sources and buffers, a distributed modelling method like multi-agent systems model is much easier to use than a system dynamics model.

A MILP solver is often used to generate a planning of set points as output. However, especially in case of a lot of variables, it is often difficult to solve the system of equations within the available timeframes of an online control system. Price based control based on an auction between heat sources and consumers or the use of other heuristics may greatly reduce computational time, but there may be drawbacks in terms of finding a general, and uniform method for different cases, and the result may be less optimal than results obtained from MILP.

Recently, some of these methods have been combined and applied within the smart grid area and results are compared with MILP solutions and results of a controller based on an auction method such as Powermatcher. An example is the profile steering method of the University of Twente which combines forecasting methods and MILP to generate solutions for the planning phase and fast replanning heuristics for the real time control phase. Replanning is often required due to inaccurate forecasts. Replanning during the real time control phase may also be done by an auction method.

Future work may consist of the following challenges identified in this report:

- Developing a universal approximation method for complex district heating networks in order to generate a linear network representation (from an original, more elaborate, non-linear model) with a limited number of nodes and branches.
- Automating the process of defining the model which will be used to generate forecasts from a more elaborate design topology model which defines the network layout, pipe lengths and diameters, loads, heat sources, heat buffers, etc.
- For the planning phase, integrating a forecast model of the system (preferably based on multi-agent system modelling) and suitable solving method (MILP as likely candidate).
- For the real time control phase, developing a suitable method for replanning due to inaccurate predictions. A price based method based on an auction seems to be a suitable candidate for this. Otherwise algorithms developed as part of the profile steering method may be evaluated as an alternative. The challenge is to develop a methodology which can easily be used in practice by different stakeholders to define cost functions for the heat suppliers and heat consumers within the network.
- Integrating the planning phase and real time control phase into a powerful model predictive control framework which generates robust control set points for any type of district heating network.
- Developing the backend (all of the above) and the frontend of the controller such that it can communicate with conventional control systems for district heating networks (Scada, Bacnet, etc.).

References

[1] Wang, Y. et al, “Operation stability analysis of district heating substation from the control perspective”, Energy and Buildings 154 (2017) 373–390.
[2] Frederiksen, S. ‘District heating and cooling’, student literatuur, 2013
[3] Cogas presentation of case study Vriezenveen, 2018.
[4] Wang, Y, et al, Hydraulic performance optimization of meshed district heating network with multiple heat sources, Energy 126 (2017) 603-621
[5] District energy in cities, UN, 2015.
[6] Leeuwen, R.P. van, Towards 100% renewable energy supply for urban areas and the role of smart control, PhD thesis, University of Twente, 2017.
[7] Lund, H. et al, 4th generation district heating integrating smart thermal grids into future sustainable energy systems, Energy 68 (2014) 1-11.
[8] Mazhar, A.R. et al, A state of art review on the district heating systems, Renewable and sustainable energy reviews 96 (2018) 420-439.
[9] Sameti, M., Haghighat, F., Optimization approaches in district heating and cooling thermal network, Energy and Buildings 140 (2017) 121–130.
[10] Fink, J., Leeuwen, R.P. van, Earliest Deadline Control of a Group of Heat Pumps with a Single Energy Source, Energies 2016, 9, 552; doi:10.3390/en9070552.
[11] Wernstedt, F., Multi-Agent Systems for Distributed Control of District Heating Systems, Blekinge Institute of Technology, Doctoral Dissertation Series No 2005:10, ISBN 91-7295-078-1.
[12] Haltas, I., Anaerobic Digestion: A prime solution for water, energy, and food nexus challenges, 1st Int. Conf. on Sustainable Energy and Resource Use in Food Chains, ICSEF 2017, 19-20 April 2017, Berkshire, UK.
[13] Jie, P. et al, Operation optimization of existing district heating systems, Applied Thermal Engineering 78 (2015), 278-288.
[14] Cai, H., You, S., Wu, J., Agent-based distributed demand response in district heating systems, Applied Energy 262 (2020).
[15] Brand, L. et al, Smart district heating networks – A simulation study of prosumers’ impact on technical parameters in distribution networks, Applied Energy 129 (2014) 39–48.
[16] Vandermeulen, A., Heijde, B. van der, Helsen, L., Controlling district heating and cooling networks to unlock flexibility: A review, Energy 151 (2018) 103-115.
[17] Borshchev, A., Grigoryev, I., The Big Book of Simulation Modeling, ISBN 9780989573177, Anylogic, 2013.
[18] Molderink, A. et al, Comparing Demand Side Management approaches, 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Berlin, 2012.
[19] Kok, K., The PowerMatcher: Smart Coordination for the Smart Electricity Grid, Thesis, Vrije Universiteit, 2013.
[20] TNO, https://www.tno.nl/en/focus-areas/energy-transition/roadmaps/sustainable-energy/smart-energy-system-solutions/heatmatcher-innovation-in-control-for-heating-and-cooling-systems-and-networks/, retrieved 17-5-2020.
[21] Claessen, F.N., et al, Comparative analysis of tertiary control systems for smart grids using the Flex Street model, Renewable Energy 69, 2014.
[22] Klauw, T. van der, Decentralized energy management with Profile Steering, thesis, University of Twente, 2017.

[23] Hoogsteen, G., et al, DEMKit: a Decentralized Energy Management Simulation and Demonstration Toolkit, IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), 2019.
[24] Putter, Y.C.C., Distributed Control Design for District Heating Networks, master thesis, Delft University of Technology, 2018.
[25] Homan, B., et al, Maximizing the degree of autarky of a 16 house neighbourhood by locally produced energy and smart control, Sustainable Energy, Grids and Networks 20, 2019.
[26] https://www.energyville.be/en/storm-controller, retrieved 15-7-2020.
[27] Bakker, V., Triana: a control strategy for smart grids, PhD Thesis, University of Twente, 2011.