



D4.1 - Low- and high-level controls for low temperature DHC networks



Fifth generation, low temperature, high exergy district heating and cooling networks

FLEXYNETS





Project Title: Fifth generation, low temperature, high exergy district heating and cooling networks

Project Acronym: FLEXYNETS

Deliverable Title: D4.1 Low- and high-level controls for low temperature DHC networks

Dissemination Level: PU

Lead beneficiary: EURAC

Marco Cozzini, EURAC

Simone Buffa, EURAC

Ilyes Ben Hassine, ZAFH

Jacopo Vivian, ZAFH (External)

Date: 30 June 2018

This document has been produced in the context of the FLEXYNETS Project.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 649820. The European Commission has no liability for any use that may be made of the information it contains.





Table of Contents

1	Summary	1
2	Control in traditional DHC networks	2
2.1	Main control systems	2
2.2	Grid control: safety controls and operation strategies	5
2.3	Centralized storage control	7
3	General control aspects.....	11
3.1	Advanced control systems	11
3.2	Control levels and hierarchy.....	12
4	FLEXYNETS control.....	14
4.1	Grid control	17
4.2	Energy flow control	20
4.3	User control and network interaction control	33
4.4	FLEXYNETS specific aspects	40
4.5	The extended control problem	41
4.6	Conclusions on complexity levels of control	42
5	References.....	44





1 Summary

This report analyses controls suitable in low-temperature district heating and cooling (DHC) networks.

The general approach adopted distinguishes between two separated control modules, developed in different subtasks:

- Local-level control, related to single substations.
- Central-level control, related to the entire network (including balancing from load plants).

This report starts with presenting an overview of the control systems and strategies typically used in traditional district heating and cooling networks. Many of the issues found in these systems are indeed shared by low-temperature networks (e.g., flow rate related control). Afterwards, a description of the specific aspects related to the FLEXYNETS networks management is provided.

Different levels of complexity are addressed, starting from traditional controls based on deterministic rules and subsequently including more advanced solutions. The latter are based on predictive algorithms (e.g., considering weather forecasts). The proposed solutions were implemented and tested in simulation models. Currently, they are being tested at a small scale in the experiments carried out at EURAC's laboratory.



2 Control in traditional DHC networks

The priority in district heating and cooling is to satisfy the heating demand. The typical situation in traditional networks is that single customers vary their heat load, e.g., depending on environmental conditions, and that the network manager adjusts the heat provided by load plants in order to follow this demand. The control systems operating in a DHC system can then be split into two main categories: centralized control systems managed by the heat provider and local control systems managed by customer substations (and space conditioning plants). This distinction will be kept within the FLEXYNETS project.

Here, most of the discussion will be restricted to district heating networks. The general presented control concepts, however, apply to district cooling networks as well. Differences in certain details will be pointed out when appropriate.

2.1 Main control systems

According to Frederiksen and Werner (2013), the following main control systems are present in a district heating network:

- Local control systems (customer side):
 - Heat demand control, managed by the heating system (e.g., thermostatic valves in radiators) or directly by the user (hot water).
 - Flow control, managed by substations.
- Centralized control systems (heat provider side):
 - Differential pressure control, managed by the circulating pumps.
 - Supply temperature control, managed by load plants.

It is important to emphasize that, at least in the simplest configuration of traditional systems, these four control systems are *independent*. In particular, there are clear boundaries between the roles/responsibilities of the network manager and those of the substation control. Moreover, within the centralized control system, there is a full separation between pressure and temperature control (though different operation modes are typically used to implement different combinations of control strategies for each system). This is made possible by the fact that fluid dynamics is not significantly affected by thermal aspects (water properties do not change much with temperature within the operational range of traditional networks), so that the two phenomena can be treated separately (or at least in sequence).

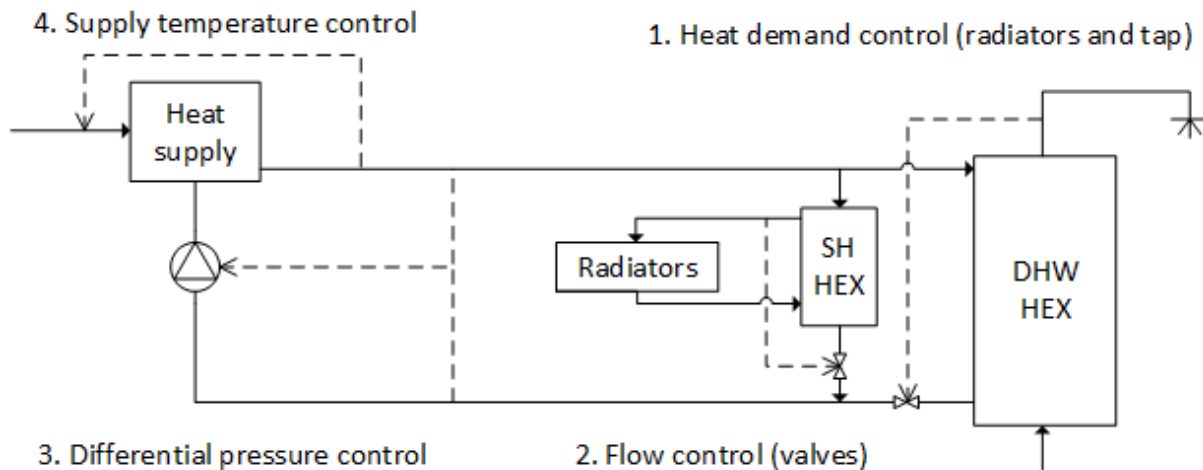


Figure 1. The four typical independent control loops used in traditional district heating (drawn according to Frederiksen and Werner, 2013). Dashed lines correspond to control signals, based on temperature or pressure sensors. Two separate heat exchangers for space heating (SH HEX) and domestic hot water generation (DHW HEX) are included.

- Local control systems (substation level).
- Heat demand control.
- Heat demand in buildings is given by space heating and hot water.

For space heating, this control is typically given by thermostatic valves, regulating the flow within the heat distribution plant (e.g., within radiators), which represents the secondary side of the substation heat exchanger. The increased flow in the building distribution system enhances the heat transfer to indoor spaces. Such flow is usually varied with a feedback from the indoor temperature, through a thermostat (some older systems are based on open loop solutions based on outdoor temperature).

- For hot water, heat demand control is nothing but the manual tap openings.
- Flow control.
- Flow control is located on the primary side of substations (see Figure 1). It is activated by feedback loops driven by the supply temperature for the secondary circuits (space heating and hot water).

The actual layout of a residential substation can actually come in a variety of forms. An example, where indirect connection to district heating for both space heating and hot water is used, is shown in Figure 2. Here, one can see that flow rate control can be slightly different and more complicated than assumed in Figure 1 (regulation valves are located upstream instead of downstream of the heat exchangers and an additional regulation valve is controlled by a flow meter, to avoid exceeding a limit flow and improving balancing between different substations), though the general concept is the same.

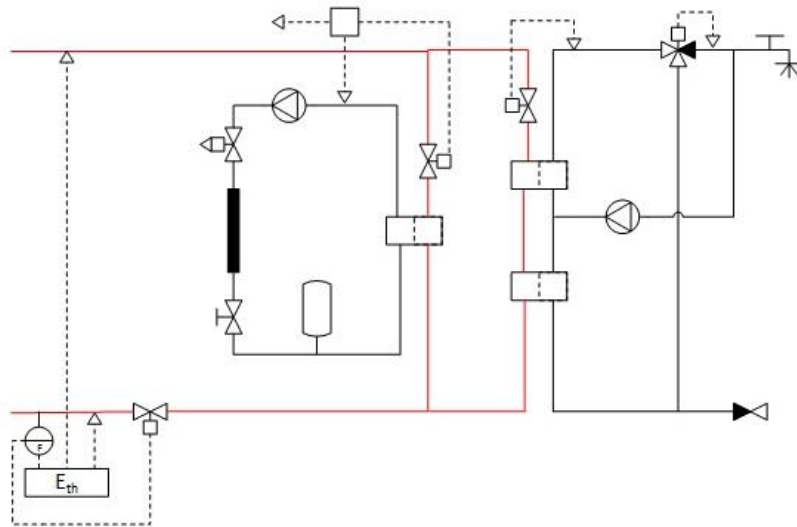


Figure 2. Example of a traditional DH substation (indirect connection for both space heating and hot water). A detailed description of this example can be found in Frederiksen and Werner, 2013. Probes denoted by a triangle are temperature sensors, while the probe denoted with an F is a flow meter.

- Centralized control systems (load plant level).
- Differential pressure control.

This control is managed by the circulating pumps of the network. In the case of multiple load plants, there is typically one base load plant working at a constant power and hence flow rate, supported by one or more peak load plants which adjust their heat supply to the demand. The circulating pump actually implementing differential pressure control is hence that of the marginal heat supply unit (the unit with the highest operation costs and hence the lower priority). This control has the role of guaranteeing the minimum required pressure difference to all substations. In the case of a single heat supply station, the monitoring point is hence the substation with the largest distance from the load plant, where head losses give rise to the minimum supply pressure. A typical minimum pressure difference for substations is 1 bar. In the case of multiple load plants or in the case of a meshed grid, it is less straightforward to identify the point of minimum pressure (its position can even vary depending on the operating conditions). In this case, multiple pressure monitoring can be needed.

- Supply temperature control.

The role of this control is to ensure that the supply temperature corresponds to the desired set point. The latter value is not necessarily constant throughout the year. Note that only the supply temperature is directly controlled by the network manager, not the return temperature, which is instead fixed by the substations. The supply temperature is typically increased for lower external temperatures, thereby loading the network with more energy in conditions of high demand. It can be seen that the heat demand depends approximately *linearly* on the external temperature. The linearity is especially evident when taking daily averages, while on the hourly scale significant



variations can occur (Frederiksen and Werner, 2013). This correlation allows to set up a *deterministic* control for the supply temperature with reasonably satisfactory operation results.

2.2 Grid control: safety controls and operation strategies

The above control systems are the main components of the network control. However, the overall grid operation is typically based on a certain number of operation modes, where these controls are combined in slightly different ways. This holds for the centralized controls, which are under the responsibility of the network manager, while substation controls are typically left unchanged in the different operation modes. Before discussing typical operation modes, it is useful to point out one drawback of the simple supply temperature control described above, along with some possible countermeasures to be taken.

As mentioned above, supply temperature control is typically deterministically controlled by linearly raising the supply temperature when the external temperature decreases. This has the drawback that “the network is loaded at higher heat loads and unloaded at lower heat loads” (Frederiksen and Werner, 2013). In order to get a peak shaving effect, thereby reducing the needed plant capacity and keeping a more constant operation, it would be useful to load the network in advance. This is of course only possible if proper *forecasting* strategies are available (at least at the level of feedforward control). This is a first example of a more advanced control (though still deterministic) with respect to the simplest case mentioned above. Demand forecasting (clearly supported by weather forecasts) is already applied in several traditional networks.

Even without including forecasting strategies, different operation modes are typically used in the network operation, depending on the outdoor temperature (and hence on the demand level with respect to the design conditions). Moreover, the overall grid control requires to include some limiting control systems, which ensure that maximum and minimum temperature and pressure levels are not exceeded. These are (see also Figure 3):

- Central maximum supply temperature control. This avoids that the supply temperature exceeds the design limit. It acts on the heat production at the load plant (e.g., stopping the burner in a boiler).
- Local minimum supply temperature control at the grid periphery. Similarly to the aforementioned case of differential pressure control, it is important to guarantee a minimum temperature level for all substations. This is particularly relevant for substations far from the load plant. Indeed, due to thermal losses, the supply temperature typically decreases along the distribution system. This temperature reduction depends on flow rate: it is typically more pronounced at low flow rates, when a fluid element has more time to lose heat before being exploited at a substation. This can be a strong effect during the night, where little or zero demand occurs on certain branches. The solution is to install bypass valves in critical locations at the grid periphery, so that the obtained circulation preserves a minimum temperature level.
- Central and local maximum pressure control. The purpose of this control is to avoid exceeding the design pressure of the network equipment (including pipes). This of course takes precedence over the differential pressure control (possibly causing flow rate shortages). For simple centralized networks with a single load plant, the maximum pressure can be easily controlled immediately downstream of the circulating pump, but for more complicated networks (possibly including height variations due to specific landscape features) other local controls must be added (e.g., reducing the main pumping power and using booster pumps at intermediate points in the network).



- Central and local minimum pressure control. This control aims to avoid boiling effects in pipes. A pressurization system (with an independent pump with respect to the circulating pump) is used to overcome this problem. Similarly to the previous case, the set point of this control must be carefully chosen in the case of variable heights along the network.

Legend

- A – Supply and maximum supply temperature control
- B – Minimum supply temperature control
- C – Minimum differential pressure control
- D – Maximum pressure control
- E – Minimum pressure control
- F – Heat demand control

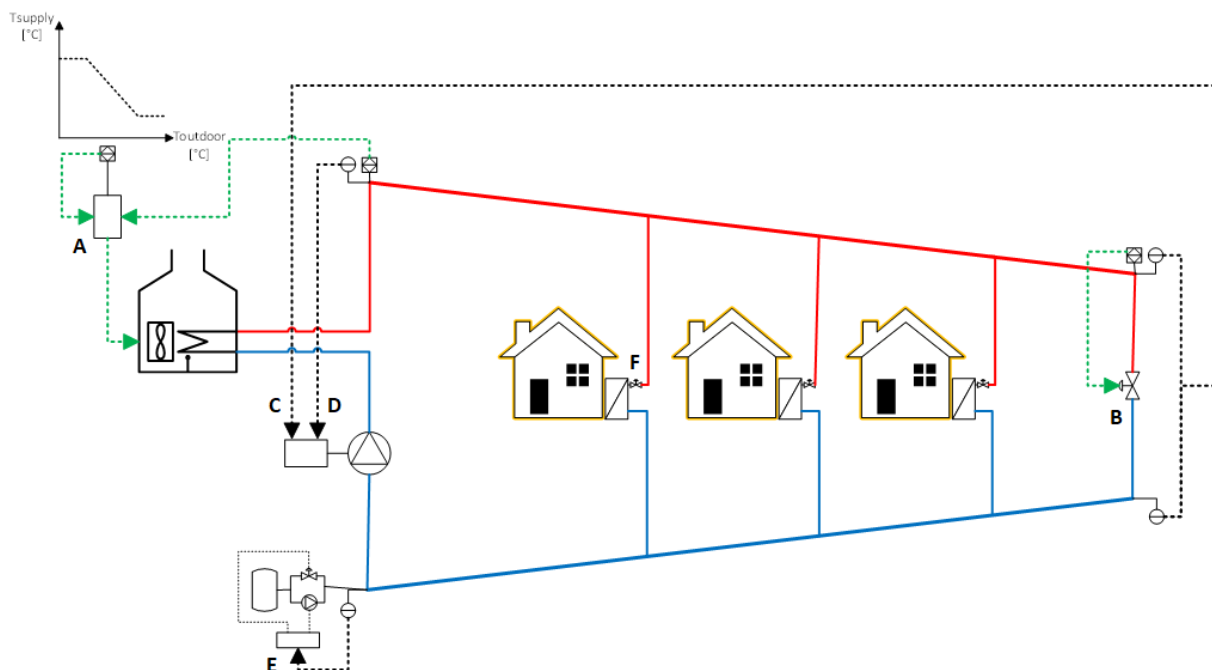


Figure 3. Grid controls (maximum and minimum supply temperature and pressure).

Below, four typical operation modes are described, according to Frederiksen and Werner, 2013. Apart from the fundamental objective of satisfying the demand within the operational limits, the next objective of control strategies is that of minimizing operational costs. While the presented modes do not descend from a mathematical optimization procedure, they have proven to provide cost effective performances and are used in several district heating networks (Frederiksen and Werner, 2013). The modes, here labelled with letters for clarity, are the following.

- A) Mode A is used at the lowest outdoor temperature. In these conditions, it is assumed that the flow rate is set to its maximum level, i.e., the circulating pump works at maximum speed. Only the supply temperature is then varied by the network manager, following linearly the outdoor temperature variations up to the design outdoor temperature.
- B) Mode B is used at higher outdoor temperatures (and hence lower heat demands) than mode A and, besides applying supply temperature variations, also includes flow rate variation.



- C) Mode C is used at even higher outdoor temperatures (lower heat demands) and it only includes flow variations. The supply temperature is kept fixed, at the minimum acceptable value.
- D) Mode D corresponds to the highest outdoor temperature (lowest heat demand) and does not include any variation of supply temperature and flow. This is typically used in summer, when the minimum demand is present. In these conditions, the linear relation between heat load and outdoor temperature is typically broken, as the demand is mainly (or even only) determined by hot water preparation.

While these operation modes are quite used, also different solutions are used in real networks. In particular, to further optimize the system behaviour, one has to take into account the (possibly conflicting) objectives of:

- Maximizing gains from reduced supply temperature (i.e., reduced heat losses and possibly improved performance of CHP plants).
- Minimizing pumping power.

A strict mathematical optimization can be obtained, but its actual form depends on the specific considered network. It is also worth pointing out that, for networks supplying heat to absorption chillers for an indirect district cooling service, the supply temperature cannot be reduced too much because of the operational requirements of these machines.

The previous discussion was focused on district heating. As far as district cooling is concerned, at least two points should be mentioned:

- The fact that lower supply-return temperature differences are used than in traditional district heating. Apart from the consequences on the required flow rate to deliver a certain power, this reduces the margin for operational fluctuations.
- The fact that pumping power, which in the case of district heating contributes with a useful effect to the heat supply, has to be considered a negative effect only. This can affect the choice of operation modes or at least the thresholds between them.

Finally, it is useful to recall that specific components can require dedicated control systems and strategies. This is for example the case for combined heat and power (CHP), thermal storages, and waste heat recovery. Moreover, for these components it is highly beneficial the use of advanced control solutions including demand forecasting for the preparation of the network conditions. For example, one could fix the CHP operation level during the night on the basis of weather forecasts for the next day, properly charging available thermal storages. Similar dynamics can take place with waste heat recovery, if a surplus is available.

2.3 Centralized storage control

In this section, a simple case related to centralized storage is discussed.

We consider the case of a traditional DH network, where heat is produced in a centralised manner and then distributed via primary and secondary pipelines. We assume to have main production units and a Waste to Energy (WTE) power plant located close to each other. The system is completed with



a pumping station and a short-term (daily) thermal energy storage (heat accumulator), able to cover the network load for a few hours. Several networks of this type exist, the present description being largely adapted to the characteristics of the DH network of Bolzano, Italy.

The heat production system uses the incinerator (WTE) plant as main heat source for the DH network. The production system shown in Figure 4 includes:

- The WTE combined heat and power (CHP) plant.
- A certain number of gas boilers as back-up units (shown as an aggregated system).
- A heat accumulator that works also as expansion vessel for the DH network. This accumulator can be classified as pressure-less tank and it is directly connected to the network. Despite this, a minor overpressure is typically maintained in the top of the tank with a steam blanket to prevent oxygen penetration and corrosion.

The pipelines that supply these units are connected to hot and cold manifolds located in the pumping station. From these manifolds, heat is supplied to the DH network via the main pipelines.

In general, the availability and quality of the waste heat from the incinerator depend on different factors, which are usually defined in an agreement between the WTE company and the DH network manager.

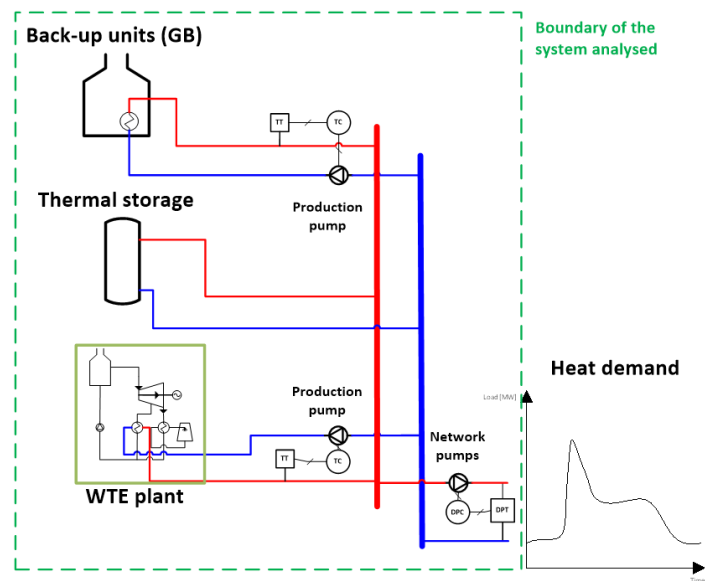


Figure 4. Scheme of the heat production stations of the example described in the text.

The goal of the heat accumulator in the DH network is, on the one hand, to cover the peak load with the heat stored, on the other hand, to absorb the volumetric variation of the water inside the system. This latter is achieved in a simple and cost-effective way through the direct hydraulic connection with the network. The tank accomplishes this function automatically without any control mechanism.

The main functions of the heat accumulator are to avoid fluctuating operation of the WTE plant and to limit the operation of the back-up units characterised by a high operational cost. WTE plants use a



fuel classified as “difficult” (Thomsen and Overbye, 2016). This means that plant capacity is regulated more slowly than for gas or liquid fuel-fired plants. Thus, in this case the storage capacity is useful to balance the rapid fluctuations of the demand.

The control of the heat production and distribution systems consists of:

- *Differential pressure control*: the network pumps are regulated so that adequate differential pressure (e.g. 1 bar) is maintained at the critical node(s) of the network: generally this node is located at the farthest customer from the pumping station. See the discussion of previous sections.
- *Supply temperature control*: water is pumped by the production pumps from the return line through the production plants to the supply line. Supply temperature can be regulated by varying the pump speed or, at least for backup units, the burner level. This matches the heat production maintaining a constant supply temperature to the network.

For the centralized heat accumulator, which is directly connected to the network, no any further control is needed. The charging and discharging phases are controlled automatically by means of the differential pressure between the supply and return manifolds. This differential pressure is generated by the balance between the network pumps and the production pumps. The charging and discharging phases can be managed in the following way:

- **Charging** of the storage (see Figure 5) occurs when the WTE plant runs at a power higher than current demand. This creates a **positive** differential pressure between the hot and the cold manifolds, which allows part of the hot water to be diverted into the heat accumulator (at the top), while, at the same time, the same amount of cold water is displaced (from the bottom) to the cold manifold.
- **Discharging** of the storage (see Figure 6) occurs when the heat demand exceeds the available production capacity. Then, a **negative** differential pressure takes place between the hot and the cold manifold. This is because the minimum pressure point of the system is at the suction point of the network pumps, thus, at the hot manifold. This creates a flow circulation within the heat accumulator where the cold water enters into the bottom of the storage and in the meantime hot water is drawn from the top of the tank to the hot manifold.

Hot water is supplied/drawn from the top of the storage while cold water is supplied/drawn from the bottom to preserve the thermal stratification inside the heat accumulator. Moreover, two diffusers are typically located in the inlet/outlet points in order to limit the inlet/outlet fluid velocity for minimising inflow turbulence and mixing effects.

We do not enter here in the details of the backup control, i.e., when it is activated or not. Anyway, once the control of the WTE pump and of the backup pump is defined, the storage follows automatically. Indeed, the storage is charged or discharged depending on the balance between the circulation pumps.

As mentioned above, this works well for the specific case of a *single* storage located close to the heat sources. It is important to specify that this configuration needs to be modified in the case where *multiple* storages are present. In this case, dedicated circulation pumps are needed and more complex control solutions need to be implemented.

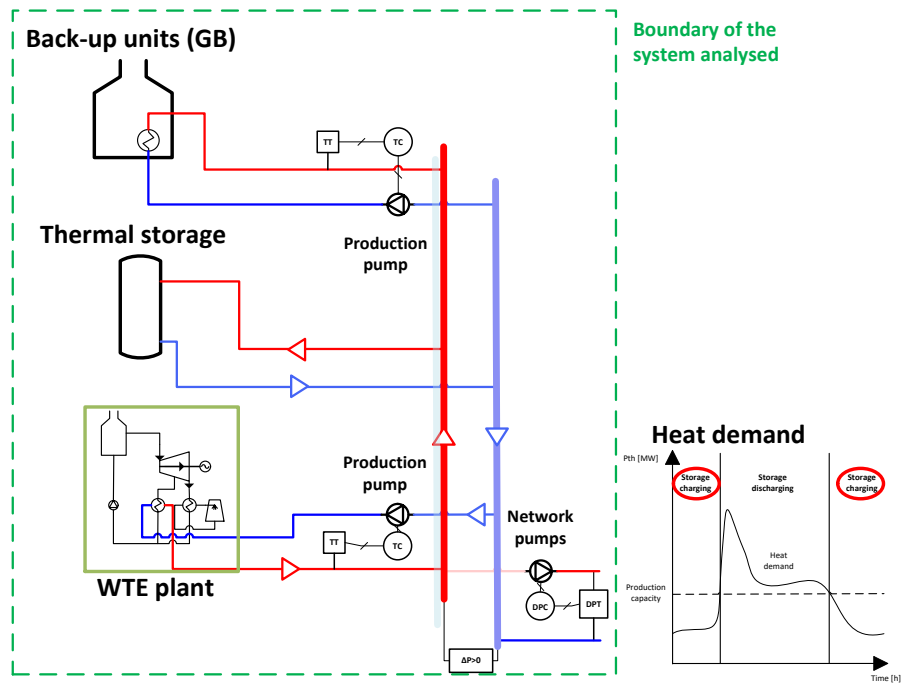


Figure 5. Thermal energy flows during the charging phase of the heat accumulator ($\Delta p_{\text{manifolds}} > 0$). Pipes with light colours refer to low pressure conduits (see light blue used here for the cold manifold).

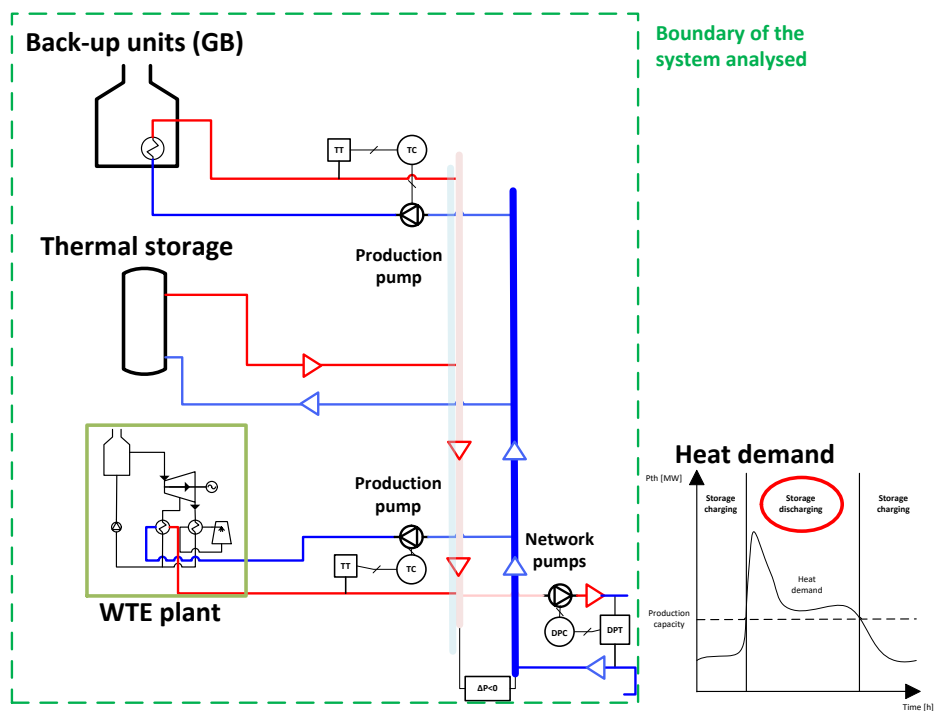


Figure 6. Thermal energy flows during the discharging phase of the heat accumulator ($\Delta p_{\text{manifolds}} < 0$). Pipes with light colours refer to low pressure conduits (see light red used here for the hot manifold).



3 General control aspects

Before entering in the details of local-level and central-level controls for FLEXYNETS, some general comments are in order. This section will describe a few cases of general interest.

3.1 Advanced control systems

As seen before, the basic control of typical district heating and cooling networks, despite involving multiple control systems, is rather simple in nature. However, more refined solutions can be used in order to perform an operational optimization. It is important to consider these solutions in view of the flexibility which a FLEXYNETS network might require.

To provide a short overview, a first important distinction regards the difference between *classical* control methods and *intelligent* control methods. A typical example of classical control methods is represented by ordinary feedback loops regulating manipulated variables. In this case, all the control algorithm parameters are deterministically fixed from the beginning, being implemented by the designer. In some cases, it is useful to go beyond this paradigm, introducing the possibility to change the control strategy during operation. In its simplest form, this is done through *adaptive* control, where control parameters are adjusted with changing operating conditions.

Moving a step further, intelligent control techniques can be used, where, for example, *self-learning* algorithms can be implemented to optimize the control strategy during operation. This is especially useful for stochastic systems, subject to non-deterministic disturbances (as it can be the case for weather fluctuations affecting heating and cooling demand). *Model predictive control* (MPC) is another form of advanced control, which tries to identify the best control actions by analysing the future behaviour of the system (based on a given model and within a certain time horizon). In this way, the system can be manipulated before a given disturbance takes place, based on a certain forecast (e.g., about weather, Papakonstantinou et al., 2016). This allows to reduce the response times, significantly improving control in cases where the system actuators are relatively “slow” compared to certain relevant disturbances. For example, in a thermal network the propagation of temperature occurs on rather long times, so that a variation in the heat demand cannot immediately be compensated by a variation in the supply temperature at the load plant. To provide an order of magnitude, since temperature propagates with the average flow velocity, which is typically no more than 2 m/s, a wave front would take at least 1.5 h to reach the grid periphery in a network of 10 km. While quick adjustments can be obtained concerning flow rate regulation, with the integration of proper prediction capabilities one could better exploit thermal regulation, adding flexibility to the control system and optimising its operation.

Two other cases are worth to be mentioned in this context, namely artificial neural networks (with related self-learning techniques) and multi-agent control systems.

Artificial neural networks (ANN). Artificial neural networks are inspired to the human brain, where “nodes” representing neurons are used to propagate and manipulate information through properly connected links. In practice, the network processes multiple inputs and provides multiple outputs, according to its internal structure. The key-feature of ANNs is that they can be trained, tuning their parameters (e.g., link weights) with a set of “known” cases. The larger the training set, the more reliable the operation. It was proven that networks with certain minimum requisites can approximate any process function arbitrarily well, provided the parameters are properly tuned. This allows to build models of unknown and complicated processes, just “training” an ANN on a set of data. This is also related to the idea of self-learning algorithms, where the system operation can be improved adapting the initial rules according to the ongoing results, measured with a proper cost function. The



internal structure of the resulting ANN does not need to be understood; for this reason, ANNs can be classified as a type of black box models, as opposed to physical models based on an explicit understanding of the system by the model developer.

Moreover, ANNs can be used in cooperation with MPC to implement sophisticated control system (Vasičkaninová et al., 2011). Given the complexity of a large district network, having an adaptive system which autonomously seeks the optimum operation can significantly ease the control design.

Multi-agent control systems (Dounis and Caraiscos, 2008). An Intelligent Agent consists of a virtual entity (software) that mainly has the following features:

- It is able to communicate and interact with its environment.
- It has the capability to perceive the local environment (via sensors).
- It is guided by basic “goals”.
- It has feedback behaviours.

A multi-agent control system (MACS) consists of a series of cooperative agents which operate to fulfil common and individual goals. The architecture of a MACS can be distinguished into (Wernstedt, 2004):

- Hierarchical architecture. Some agents can have authority power over other agents and coordinate them to achieve a global goal.
- Decentralised architecture. Agents are autonomous and could interact in a cooperative way or in a conflicting way.

In a district heating network, substations can be represented as agents, acting independently of a centralised control. Considering the particular dynamics possible in a prosumer system, these systems are expected to be a useful tool for its control.

Apart from the specific case of MACS, it is worth emphasizing that for the case of FLEXYNETS a fully centralised approach presents some drawbacks. Indeed the FLEXYNETS approach typically gives rise to an increase of the fluctuating sources in the energy system (renewables, waste heat). In order to use a centralised system, one should then cope with a possibly large computational effort, due to the high number of control loops related to producers and prosumers. According to Bøhm et al., when the complexity of the DHC system reaches approximately 100 components, the present computer and software technology would already be insufficient to find a global optimum operational strategy.

3.2 Control levels and hierarchy

In several contexts, arranging a system with a hierarchy of levels helps in organizing producers and operational flow. A similar approach can be used for control (in software control it is sometimes defined a hierarchical control system). From the operational point of view, a similarity can be found with the functional hierarchy model often used in manufacturing, as reported in Figure 7. Here different levels are described, starting from the lowest level 0 (related to production processes) to the highest level 4 (related to business planning and logistics).

A similar hierarchy can be found in control and acquisition architectures, where the lowest level is related to operating hardware (sensor and actuators), the next level often consists of distributed PLCs (Programmable Logic Controllers) managing the corresponding signals at a local level, and the upper level is given by the software of a SCADA (Supervisory Control And Data Acquisition) system running on a server (from the software perspective, correspondences with the higher levels of the



factory functional model of Figure 7 can be found considering Manufacturing Execution System (MES) software for Level 3 and Enterprise Resource Planning (ERP) software for level 4).

A preliminary classification of hierarchical control levels for district heating will be shown in the next chapter.

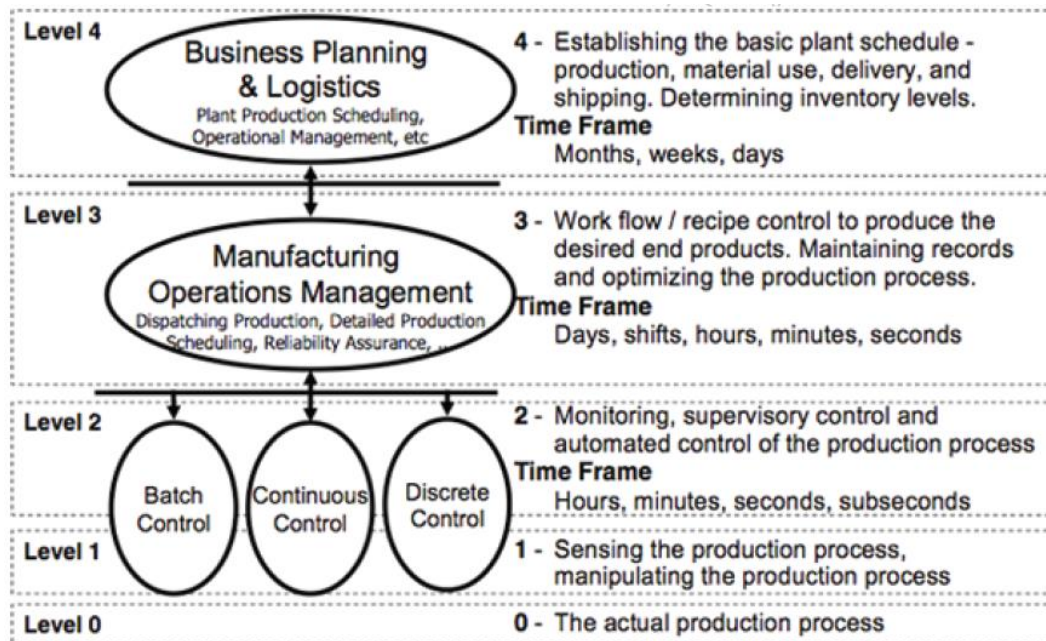


Figure 7. Factory functional hierarchy model according to IEC 62264-1.



4 FLEXYNETS control

Within FLEXYNETS, with respect to the control description presented in the chapter about the control of traditional networks, it is suggested to adopt a hierarchical approach, distinguishing between different levels of control.

System control. The highest level is related to the overall system operation. With reference to the traditional case, the definition and choice of the various operation modes, where independent controls of Section 2.1 are combined in different ways, can be considered part of this control level. This clearly belongs to the central-level control described in the initial summary.

Substation control. In traditional district heating networks, the term substation is only used for energy delivery points, where energy is transformed in a lower quality form (supply temperature is changed). This is similar to the case of the traditional electric grid. Substations are then related to heat demand, as opposed to heat generation points, typically referred to as load plants or (thermal) power stations (exploiting different types of equipment: boilers, CHP, storage, waste heat recovery exchangers). Clearly, in the case of district cooling the energy flow direction is reversed and the “quality” transformation at substations refers to the useful effect, i.e., cold distribution.

When the prosumer concept is introduced, the energy transformation direction can be reversed at residential substations at different times. In the FLEXYNETS proposal, therefore, the terminological distinction between generation and delivery points was relaxed and the term “substation” was used to refer to any major component connected to the network. This terminology was kept in Deliverable D2.1, FLEXYNETS substations. While the term substation is hence used for any thermal energy source or sink, it is useful to introduce some further classification, as done in D2.1.

Substations proposed in deliverable D2.1.

- Substation nº 1 – Residential Building (Block of Flats)
- Substation nº 2 – Residential Building (Semidetached House)
- Substation nº 3 – Special Building (Hospital)
- Substation nº 4 – Special Building (Hotel)
- Substation nº 5 – Tertiary Building (Shopping mall)
- Substation nº 6 – Tertiary Building (Office)
- Substation nº 7 – Industrial Application (Agro-alimentary)
- Substation nº 8 – Industrial Application (Ceramics)
- Substation nº 9 – Power Station (Solar Thermal)
- Substation nº 10 – Power Station (PV)

Here, we point out some further categories which can be used to regroup substations.

- *Unidirectional/bidirectional.* For the case of residential buildings (as well as for many special/commercial buildings), the prosumer concept is expected to apply, therefore introducing a bidirectional (reversible) energy flow. However, for some substations (e.g., some power stations or industrial waste heat recovery substations) only unidirectional energy flow will take place. One can then consider separate cases for this.



- *Reschedulable/non-reschedulable* (or balancing/non-balancing). This is a distinction of interest for power stations. It makes indeed a significant difference from the point of view of control whether a power station has to be run to balance the network (following the demand and properly compensating operational changes due to user behaviour, as it is expected for load plants owned by the network manager), or it can be run independently, according to an internal logic (as it is expected for industrial waste heat or for applications based on solar energy). Note that also the case of a “pool” of balancing substations can be considered, possibly located in different points of the network, but all with similar flexibility features.
- *Owned/non-owned* by the network manager. This distinction is similar to the previous one (as owned plants are expected to be balancing and non-owned plants are expected to be non-balancing), but it emphasizes decisional boundaries and market aspects rather than the control objective. In principle, there could be balancing plants not owned by the network manager, as in the case of the electric grid. In this case, special contracts can be made in order to guarantee that these plants are activated according to certain rules. Still, the practical implementation of control can be different, as feedback signals can be substituted by high-level communication, with consequences on the hardware choice and on safety requirements.
- *Small/large*. For certain details, the size of the substation can give rise to some differences in equipment and hence in control.

For example, one can imagine that residential substations as Substation 1 of D2.1 will be bidirectional, non-balancing, owned by the network manager (though this is not the only possibility) and relatively small. The solar thermal power station given by Substation 9 of D2.1 could instead be unidirectional (unless a chiller is present), non-balancing (to maximize solar exploitation and hence economic feasibility), non-owned (an independent company could offer solar heat to the network) and relatively large. A balancing station could be a subcase of Substation 9 where only a modulating boiler is present. Different combinations are clearly possible in practice.

From the control point of view, these main cases were investigated:

- Supply stations.
 - Reschedulable. This will include for example modulating boilers and storage.
 - Non-reschedulable. This will include for example industrial waste heat and solar power stations.
- Residential substations for prosumers (i.e., bidirectional).

Moreover, it is planned to keep clear decisional boundaries between the network manager and the non-owned substations. Hence, while demand side management policies could be considered (from the point of view of price strategies), it is assumed that it will not be possible for the network manager to directly operate customer substations (as with dispatching rules). Still, a bidirectional exchange of information will be allowed, therefore making possible to adapt the substation operation to the network conditions (heat temperature and price).

As far as the distinction between local-level and central-level control is concerned, while most of substation cases belong to the local-level control, it is clear that balancing substations (including all related components, e.g., large storages) share central-level control aspects.



Distribution and grid control. The grid control includes aspects similar to those described in Section 2.2 for traditional networks. Distribution control is partly overlapping with substation control for balancing supply stations. In small networks, indeed, the circulation pumps for the network are located at the (balancing) load plant. For a large and complicated network with distributed generation, however, it can make sense to separate this control from that of single supply stations. In very large networks, one can even distinguish between heat transmission in main pipes and heat distribution in local subnetworks (with independent companies taking care of the two tasks), introducing a distinction as in the electric grid, where one has the Transmission System Operator (TSO) and Distribution System Operators (DSO).

This control also belongs to the central-level control described in the initial summary.

Some analysis and hierarchical classification of control elements relevant for FLEXYNETS is reported in Table 1. The level-3 control concerns the overall management of the system and is generally implemented on a standing machine owned by the operator. Level 2 distinguishes between four fields of control: 1) the grid control of the physical measurable variables head and temperature, 2) the energy flow control to solve the unit commitment problem and to manage the storage capacity in the system, 3) the user control (a list of detailed user controls was developed in deliverable D2.1), 4) the network interaction control (discussed in deliverable D4.2).

Table 1. Hierarchical classification of control levels.

Level-3 control	Level-2 control	Level-1 control	Level-0 control
System control Highest level. It can be compared with the definition and choice of operation modes in classical district heating networks.	Grid control Ensures energy transfer within the network (distribution control)	Head/pressure control	Critical pressure driven, main pressure driven, outdoor T driven
		Temperature control	Outdoor T driven, set point tracking
		Distribution optimization	-
	Energy flow control Ensures optimized generation and transmission to the network	Utility operation (including unit commitment)	On/off, continuous
		Storage	Charging/ discharging
	User control Ensures energy transfer to/from customer and optimizes generation by directly manipulating consumption	Flow/temperature control substation	-
		Sensor manipulation	Shift measured value
		Set-point manipulation	Shift T set point
		Local storage (fast = tanks, slow = buildings)	Charging/ discharging
		Response to tariff variation	-
		Consumer cooperation	Shift supply set point
	Network interaction control Takes other networks (electric, gas) into account	Gas network	-
		Electricity network	-

The rest of the chapter is organized as follows. The first two sections deal with the first two level-2 controls (grid and energy flow) reported in Table 1. A clear focus is given to the unit commitment



problem and how to solve it. The third and fourth level-2 controls in Table 1, namely user control and network interaction control, are addressed in the third section of this chapter. Discussion focuses only on the demand side management perspective, since other aspects related to these controls were already discussed in deliverables D2.1 and D4.2. The remaining sections of the chapter deal with some FLEXYNETS specific aspects, decision making aspects, a short summary of encountered complexity, and some more material on distributed storages.

4.1 Grid control

This section deals with the level-1 controls related to the level-2 “Grid control” of Table 1. The differential pressure control builds the basis for homogeneous flow within the whole network structure. The temperature control can be seen as part of the energy flow regulation, but it is considered here separately. The third level-1 control of Table 1, distribution optimization, is not discussed in a separate section: some aspects of pumping optimization are directly discussed in the section on differential pressure control.

4.1.1 Differential pressure control

As discussed in Subsection 2.1, in DH networks hot water is pumped by variable speed pumps to the different substations. Open loop control of the head elevation in the supply plant is still applied in many installations, leading to pressure differentials which are unnecessarily high during the low demand season. However, closed loop algorithms use the measured pressure differential at a critical consumer (generally the most distant) to adapt the head elevation of plant pumps (see again Subsection 2.1). This control is currently implemented for the two-pipe system model in FLEXYNETS. The flexibility in the simulation environment allows to locate the substation with the lowest pressure differential around it and to regulate the pump speed accordingly.

Another – more advanced – closed loop algorithm uses the central plant’s pressure differential as control variable. In this case, the total volume flow \dot{V} is feed-forwarded to the pump drive. The required head elevation is calculated in a way to approximate the supply characteristic curve of the pump (see Kunst and Geck, 2005)

$$\Delta p = f(\dot{V}),$$

that is the curve which theoretically guarantees a minimum Δp at the critical consumer. This curve is generally network specific and should be calculated during a measurement campaign, within which several distributed pressure transmitters are installed and monitored for different operation scenarios. The transmitters are then taken out and costs for sensor maintenance and signal transmission can be avoided. In Ben Hassine and Eicker (2013) an adapted second order polynomial approximation of this curve was used to determine the necessary head elevation:

$$\Delta p = a \cdot \dot{V}^2 + b.$$

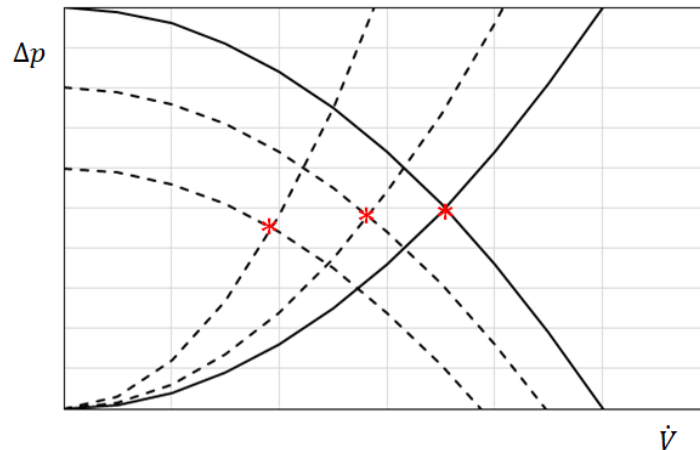


Figure 8. Schematic representation of the relation between differential pressure and flow rate. Upward curves correspond to network pressure drop functions for different numbers of active users. Downward curves correspond to pumping pressure drop functions at different pump speeds. Operation points are represented by red crosses. When the number of active substations increases, the flow rate increases while the network hydraulic resistance decreases (more open circuits), and the operation point moves from the left to the right.

4.1.2 Temperature control

In general, supply temperature control for FLEXYNETS networks can be very similar to that of high temperature networks. A heat exchanger transfers heat from the source to the network, exploiting standard control solutions for regulation.

A particular case, however, deserves some separate comments. Indeed, an interesting possibility for supplying heat to low temperature networks consists in using the return line of high-temperature networks. This offers a low-cost possibility for the extension of existing networks which are already at their limiting capacity in terms of flow rate: instead of substituting all pipes in order to carry larger flow rates, a higher supply-return temperature difference is exploited to increase the thermal power. In this way, investment costs for the network extension only include the new pipes and not a substitution of the old pipes.

Two typical connection possibilities can be considered: direct connection with mixing or indirect connection through a heat exchanger. Below, each of these examples is discussed in some detail.

If the temperature difference between the FLEXYNETS network and the source (the higher temperature network) is small (< 15 K), the return line of the FLEXYNETS grid can be used to lower the temperature of the supply. One example in the context of 4th generation district heating is reported in (Dalla Rosa et al., 2014), where a low temperature network is connected to an existing DH grid which has a temperature of 65°C. The figure below shows simplified pressure and hydraulic diagrams of the system. The temperature of the new district heating grid is controlled via a 2-way valve, which forces the return flow through the hydraulic shunt and lowers the supply temperature from 65°C to 55°C.

When the temperature difference is higher than 15 K, the use of a heat exchanger is instead advised. One example was reported by (Ilanakiev et al. 2017), where a low temperature DH grid was connected to the existing DH of Nottingham, which has supply temperatures ranging from 85°C to 120°C and return temperatures of 70°C. The figure below represents the installed connection to the existing DH. The connection is realized with a return-return configuration with the possibility, in case the temperature of the return is not sufficient, to mix water from the supply line. The supply



temperature of the low temperature district heating network is controlled via the 3-way valve on the primary side of the heat exchanger, which lowers more or less the inlet temperature to the heat exchanger and thus the outlet temperature on its secondary side, which is the supply temperature of the low temperature DH.

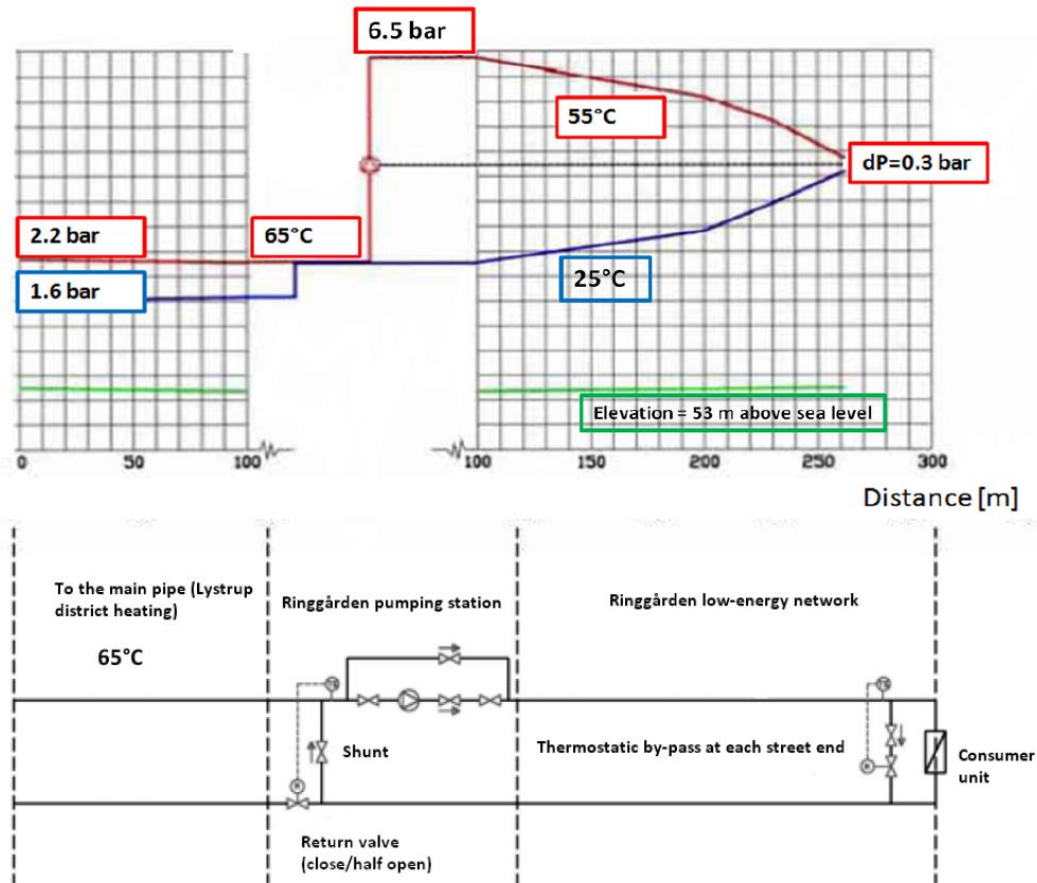


Figure 9 : Simplified pressure/temperature diagram of the mixing shunt of the Ringgården (Dalla Rosa et al., 2014).

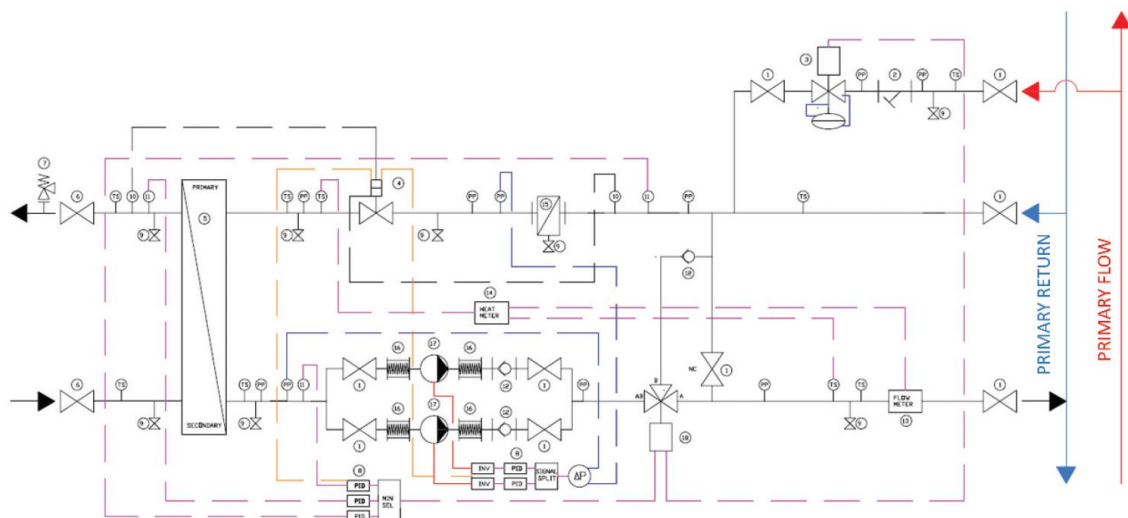


Figure 10. Schematic layout of LTDH connection to existing district heating system (Ianikiev et al., 2017).



4.2 Energy flow control

This section deals with the level-1 controls related to the level-2 “Energy flow control” of Table 1. Three consecutive subsections are devoted to utility operation in a unit commitment perspective. While this also includes storage related aspects, a fourth subsection is added to specifically focus on this point.

Energy flow control mainly refers to the control of generation substations. For example, in the case of multiple generation units, one has to deal with the problem of which units should be run at a given instant and to what extent. In other words: one has to solve the unit commitment and the load dispatch problem. To this purpose, one can either use simple (deterministic) priority rules (e.g., always use renewable – and hence typically non-reschedulable – units first, then compensate the rest with backup boilers, etc.), or more advanced optimization algorithms (e.g., based on the minimization of operational costs, thereby identifying at any instant – or on a given time horizon – the generation units with the least marginal operation cost and giving priority to them). A second pillar of the energy flow control is the storage management which is generally carried out to e.g. shift peak loads or to save capacities. The storage management is seen as part of the unit commitment problem. As it can be seen in chapter 4.2.3, the operator can follow economic or ecologic targets.

The general structure of the energy flow control designed within FLEXYNETS is shown in Figure 11. The controller has three layers (high, supervisory and low level). It is provided with input data based on forecasts and related to the technical parameters of the system. The controller generates operation profiles (schedules) for the different schedulable units based on an optimization algorithm and trying to minimize a target function. The operation of the units themselves is presented on the physical level along with the network and the other non-schedulable substations. Depending on the weighting/cost factors within the target function, the optimization tries to e.g. minimize the operational costs, reduce CO₂ emissions or maximize operator revenues.

As indicated in the introduction, reschedulable or controllable units are mainly supply stations with e.g. boilers or energy buffers. Bidirectional prosumers with certain storage flexibility are also considered as schedulable. Further distinction in curtailable and sheddable units is here not considered. Non-reschedulable units are all other network participants. These substations have their own low-level controllers.

The input data provided to the high-level optimizer are of two types: forecast and system parameters. The heat load data of residential buildings (based on e.g. weather forecast) or the waste heat availability of industrial sites are calculated and provided for the coming time horizon (see below for more details). Fuel and electricity prices can also be provided. There are many load forecast models available in literature. They can be classified into black box and physical models. Black box models are generally built out of empiric data sets where an output model of the load is fitted by use of measurements of a so-called training phase. Neural networks are an advanced representative of this model family. The physical models range from simple RC- to detailed building models considering all heat sources and sinks (walls, glass facades, windows, internal lighting, internal loads etc.). The physical parameters in the input section are the supply stations’ characteristics like capacities, efficiencies, minimum load and ramp times. Storage capacities, heat losses and discharge rates are also specified in this level.

The high-level control uses a look-ahead planning structure. It consists of an optimization that uses the mentioned input data to schedule the operation of the (reschedulable) generation units for a time horizon of several hours, currently set to 10-12 hours in the models used for FLEXYNETS. From this schedule, the values of the first hour are used as targets within the two levels below. One hour later, the optimization restarts following a rolling horizon scheme. The supervisory-level control



translates the scheduled energy flows into physical quantities (e.g. flow) whereas actuators (like pumps and valves) are regulated one level below. The supervisory-level controller checks whether the heat amounts of one hour are transferred as planned or not. The most intuitive implementation of this structure is presented in Figure 12 as a cascade control for storage charging. This SL controller is meant to react to deviations from the situation assumed in the planning phase, which typically arise in the real system due to the simplifications done in the optimization and, in the real world, due to the uncertainty of predictions as well as physical disturbances.

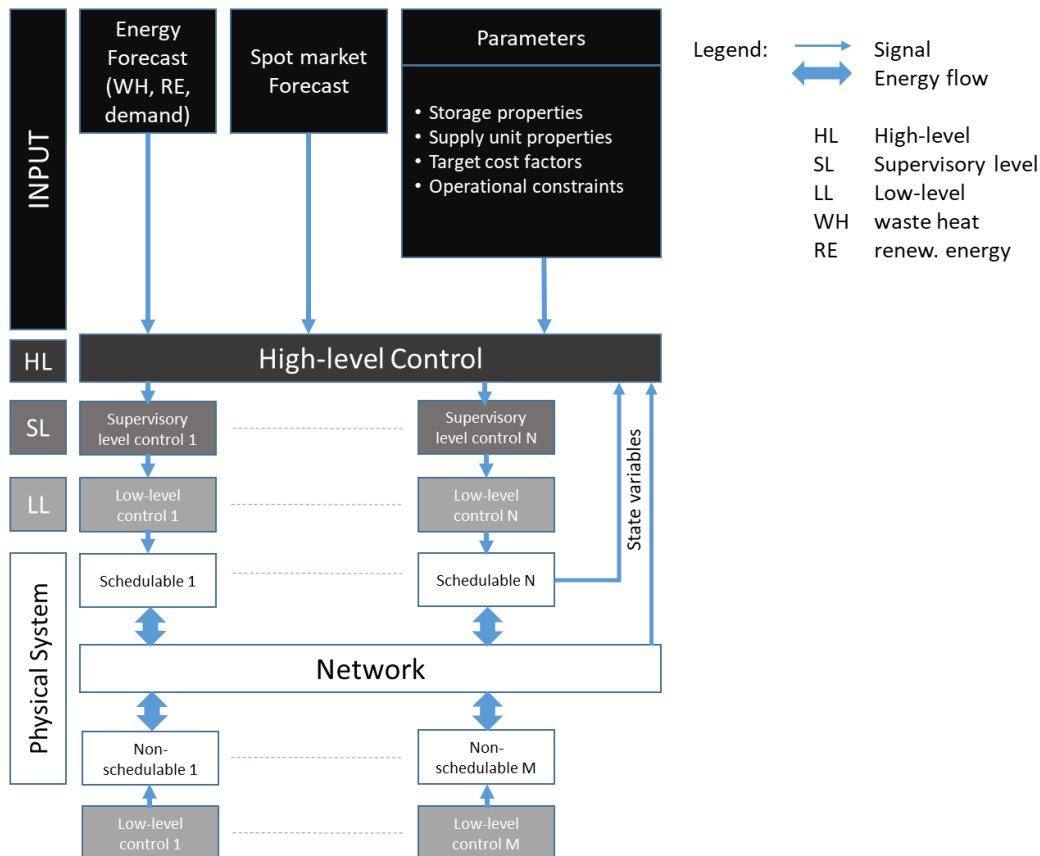


Figure 11. The general control structure for the generation system.

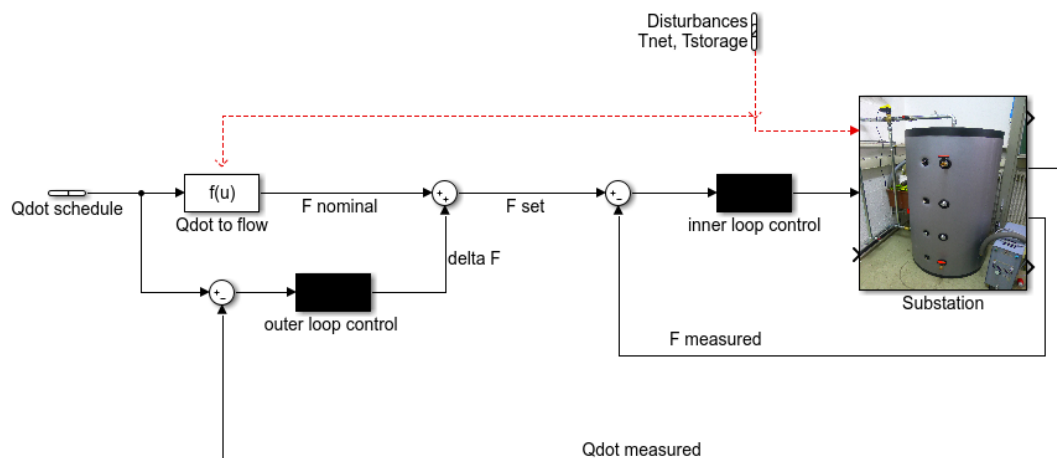


Figure 12. Cascade control for storage discharging. The variable $Qdot$ represents the heat flow, while F is the flow rate.



The ideal open loop control computed with the help of the high-level optimizer is expected not to be robust enough in real installations because of the mentioned model simplifications and load prediction errors. To circumvent this problem, a closed loop control is defined by feeding the so-called state variables back to the top level. For each hour, the resulting network temperature as well as the storages' state of charge are provided. The optimization model is then 'updated' and relaunched for the next time interval of 12 hours.

Summarizing, one can hence recognize that here a hybrid combination of classical and intelligent controls (as described in section 3.1) is used. In particular, the intelligent control is a model predictive control, based on the forecast of the system on a certain time horizon. The MPC algorithm is here based on a detailed system model and on an optimizer. As it will be described below, two different implementations were realized, one based on a linearized objective function and on a Mixed Integer Linear Programming (MILP) optimization and the other based on a non-linear approach solving the unit commitment and load dispatch problem.

The presented structure is implemented in the software Matlab and applied to a numerical model emulating the network and the different substations. A TRNSYS 17 simulation is used to reproduce the behaviour of the system with a higher level of detail and to provide the state updates (time-step of 5 minutes within the real-time control) to the optimization. By simulating the system with a 5-minute time-step, it is possible to reproduce the behaviour of the system with an acceptable approximation. The control algorithm itself was coded into a new TRNSYS Matlab type and was connected to the network model and to the control macro in the TRNSYS deck.

There are – at least – four points where the detailed simulation brings an actual improvement over linear models:

- (a) The model spHeat (see deliverable D3.3) is used to reproduce the hydraulic and thermal behaviour of the District Heating system (Ben Hassine, 2013)
- (b) Stratification in the central thermal storage system is considered by using TRNSYS Type 4 (Klein 1976).
- (c) The behaviour of the heat pumps is calculated using a TRNSYS Type developed ad-hoc, that calculates the COP based on the performance maps of the selected compressors.
- (d) The heat output and the electrical power output of the CHP are calculated with non-linear performance curves based on data provided with the TRNSYS TESS libraries.

4.2.1 High-level optimizer: description

Two different approaches have been adopted to solve the optimization problem in the high-level control layer. In the first approach, scheduling is formulated as a MILP problem, meaning that all the relations between physical variables (e.g. energy balances) are expressed as linear equality and inequality constraints. A linear model related to a case study in the city of Aarhus is provided in (Vivian, 2017). For a system containing a gas-fired combined heat and power (CHP) plant, two waste heat sources (wh), and distributed heat pumps with coefficient of performance COP , the objective function of the optimizer is formulated as

$$f = c_{gas}Q_{chp,in} - p_{el,sell}(W_{chp} - W_{chp,self}) + x_{su}SUC_{chp} + c_{gas}Q_{gb} + c_{wh}(Q_{rec,1} + Q_{rec,2}) + p_{el,buy}(COP^{-1} \sum_{c=1}^{NC} D_c - W_{chp,self}), \quad (1)$$

with c for cost and p for revenue. Q designates the heat flow rate and W the electric power. The start-up costs of the CHP unit are considered using SUC and x_{su} indicates if the unit is committed.



Equation 1 refers to an economic target function where the running cost of the system are needed to be minimized. As indicated later in chapter 4.2.3, one can add further cost factors c_{CO_2} to account for the environmental impact of the operation strategy and to e.g. minimize the CO2 equivalent emissions.

In the second approach, scheduling is divided into two separate tasks which are carried out in parallel: the unit commitment problem and the load dispatch. The unit commitment problem is the first step in order to set the variables describing when each supply unit is to be turned on or off. The load dispatch problem then sets the share of the produced energy among the running units. For each hour, the algorithm first solves the unit commitment problem by finding all possible combinations of committed units. Second, the share of heat supply between these units is calculated before switching to the next hour. The supply units are committed in order to cover the energy demand within a defined time horizon. Like in the first approach, the demand of the whole analysis period is considered to be known at the optimization starting time.

In the classic unit commitment problem formulation, the state vector is defined as a unique combination of committed and non-committed supply stations. In FLEXYNETS, the state vector is extended by the decision taken for each storage (either charge, discharge or keep). For each hour, the algorithm finds the potentially feasible states, takes all feasible states from the previous hour and checks if the transition to the current state (in the current hour) is possible. If the transition is possible, then the transition costs are calculated.

Production costs c_{prod} for the current hour are calculated based on demand taking into account production at previous hour (ramp-up and down constraints) as well as the level of charge in the connected storages. The share of the current production is calculated as part of the load dispatch problem. Actually a quick linear dispatch prioritizing units with the lowest specific fuel costs is applied. Finally, the total costs are the sum of the transition cost, production cost, and the total cost at the state in previous hour. The production costs consist of the fuel (generation) and auxiliary energy costs for e.g. pumping. This procedure is repeated until the time horizon of e.g. 10 hours is reached. Dynamic programming (Nielsen 2005) is used to solve the unit commitment problem. It minimizes the accumulated state transition cost f at each time step

$$f(s_n) = f(s_{n-1}) + c_{trans}(s_n, s_{n-1}) + c_{prod}(s_n), \quad (2)$$

taking the state transition cost $c_{trans}(s_n, s_{n-1})$ into account. The state transition cost is related to the start-up and eventually shut-down of supply units. The state path with the lowest cumulative costs is chosen at the end of the time horizon.

The level of charge is limited by a min and a max value, which is checked at every state transition (storage constraint). Two parameters were found to have significant impact on the convergence, accuracy and calculation time of the optimization algorithm. These are a) the number n_{enum} of state vectors to be evaluated at current hour and b) the number n_{pred} of strategies saved at each hour (e.g. number of predecessor state vectors to be considered from previous hour). At each time step the algorithm takes the best n_{pred} paths from the last hour, adds n_{enum} state vectors for current hour and calculates the accumulated state transition cost f for all transition combinations.

Lowering the first number n_{enum} will decrease the optimization time but can lead to convergence problems if the demand cannot be fully covered under the few combinations evaluated. Following a deterministic approach by considering all possible states at each hour is recommended for small systems (less than four units). Lowering the number n_{pred} of strategies to be followed can eliminate good state paths, especially if the optimization is run over more than six hours.



A simple storage model with ten levels of charge is considered in the optimization algorithm. The problem size significantly increases by adding storages to the system. Figure 13 shows the number of theoretically possible state vectors depending on the number of storages for a 6-hours time horizon.

The state of charge at the end of the analysing period is also an important factor, since the optimizer tends to empty the available storages as 'cheap' source of energy. Nielsen, 2005 suggests to extend the evaluation horizon to avoid ending up with empty storages as shown in the following figure.

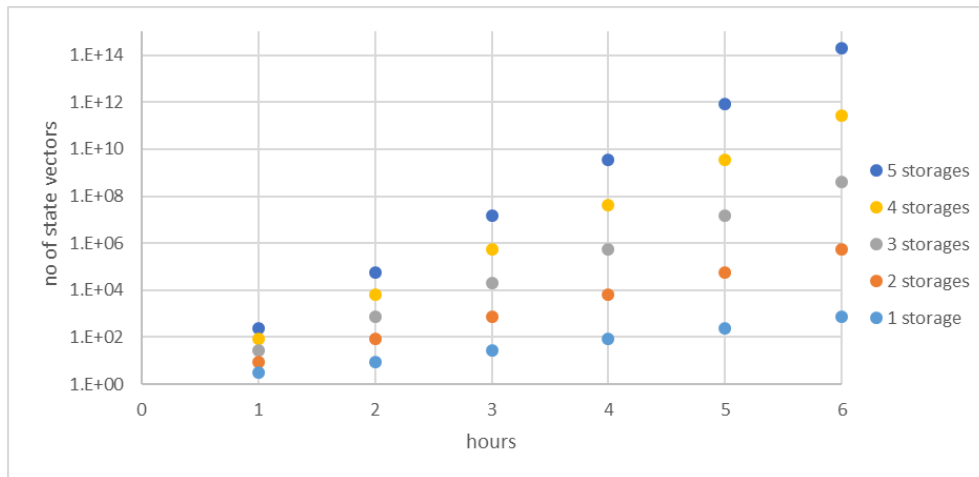


Figure 13. Evolution of possible state vectors depending on the number of storages considered.

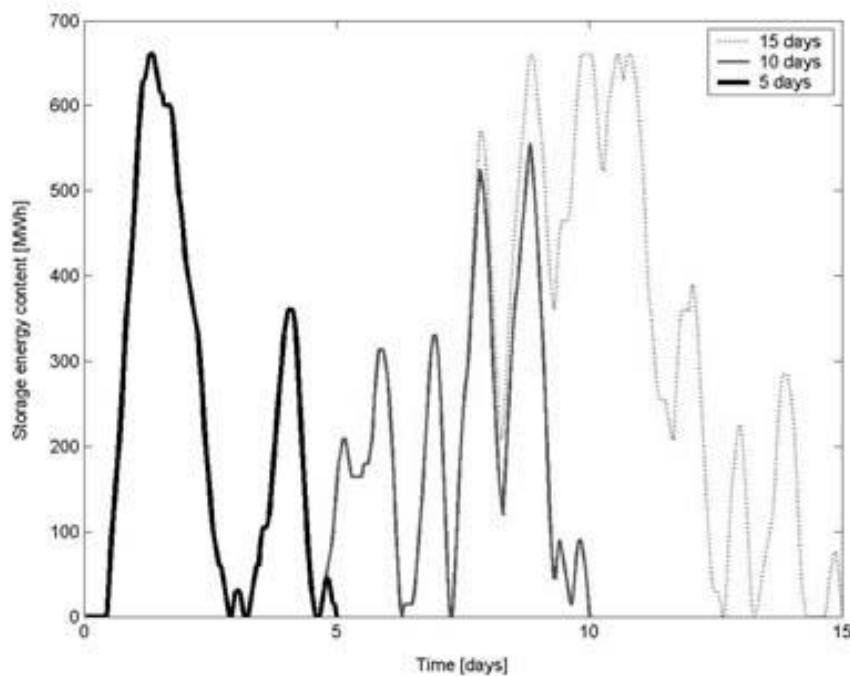


Figure 14. Horizon extension in Nielsen, 2005. Three different optimization horizons are chosen: 5, 15, and 15 days. Far from the horizon border, all the optimization procedures yield the same result (curves overlap). However, at the end of the horizon, the corresponding optimizer yields an empty storage (while optimizers with longer horizon times not necessarily do). This shows that, in order to obtain reliable results up to a certain time, the horizon limit has to be set a bit further (up to 3 days according to Nielsen).



The conclusion from Nielsen's investigations is that the evaluation horizon has to be extended at least three days in order to eliminate the influence from the final state. For large systems, Nielsen's recommendation would lead to long optimization times. Therefore, we applied mathematical restrictions on final state by adding a cost penalty for those paths ending up with low states of charge.

Dynamic programming has been intensively applied to solve the unit commitment problem in the power sector. It has also been applied for district heating systems (Ranzer, 2015). The more advanced MILP formulation promises shorter optimization times and the ability to cope with extended systems (more than 100 prosumers). However, a linear formulation of the system dynamics is always needed.

4.2.2 High-level optimizer: results

Figure 15 shows the input profiles and the results obtained with the MILP algorithm for a small network containing the following entities:

- 22 heat consumers
- one CHP unit
- one gas boiler GB
- one sensible heat storage CS
- two waste heat sources WH

The forecasts (heat demand, electricity price and waste heat availability) and the schedules calculated for a typical winter day are presented. The first graph of Figure 15(b) shows that the CHP produces around 1100 kW electricity, i.e. it runs at its minimum capacity of 50% in order to supply heat to the network and at the same time cover the power demand of the heat pumps. Due to the low thermal output of the CHP, the CS is discharged during the first 3 hours (see reduced temperature) to allow a higher production during off-peak hours (between hour 6 and 7), when the electricity price is highest and the CHP is running at full capacity. During the first 3 hours there is a significant amount of heat available. Thus, the gas boiler stays off. Then, it is switched on (hour 4) as the waste heat sources are forecasted to inject less heat. From hour 8 to hour 11, the GB lowers its production and now the CS that was charged during off-peak hours by the CHP, delivers thermal energy to the network. Most of the remaining part is covered by the WH sources. The network temperature stays stable at 20°C in order to maximize the share of electricity self-consumption. This allows to maximize the heat recovered by the low temperature waste heat and to minimize the heat demand of the network.

During summer, the policy adopted by the smart controller is completely different as it can be seen in Figure 16. Due to the low heat demand, the share of electricity self-consumption is not sufficiently high to justify switching on the CHP. If this had done, a great part of the generated electricity would have been sold to the market (with low revenues, in this case). Thus, the strategy is to reduce the electric power demand further by increasing the network temperature, consequently increasing the COP of the heat pumps. This policy is driven by the high electricity purchase price. As a drawback, a higher heat demand occurs at the network side and the waste heat recovery share slightly decreases. Thanks to the high amount of waste heat available from hour 3, this strategy allows to minimize the



costs and at the same time to cover all the heat demand forecasted for the next 12 hours by only relying on the low grade heat sources. The thermal inertia of the water in the pipelines is used to match the profiles of supply and demand between hour 1 and hour 5. Other simulations – not shown here – showed that when the waste heat available is not enough to cover the heat demand, also the gas boiler is switched on.

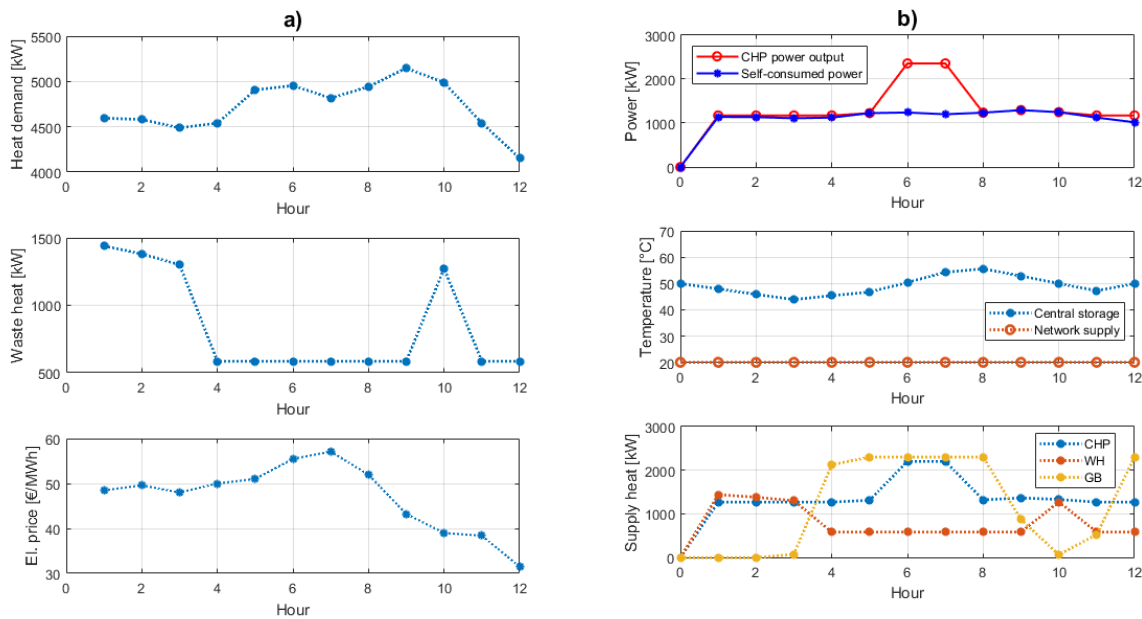


Figure 15. Synthetic forecast data (a) and MILP optimization output (b) for a typical winter day. (Vivian, 2017)

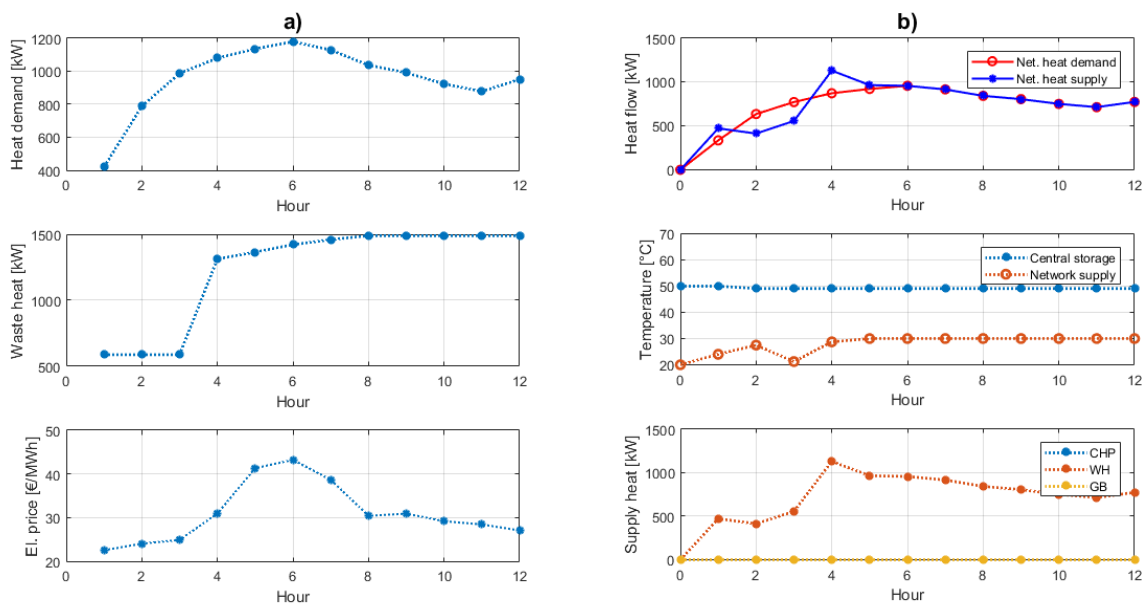


Figure 16. Forecast (a) and MILP optimization output (b) in a typical summer day.



During the middle seasons, the supply temperature is kept most of the time at 30°C to decrease the power consumption of the heat pumps. The waste heat using the network as a buffer covers the heat demand. If the waste heat is not enough and the electricity price is high enough to justify its operational costs, the CHP is turned on at minimum load. Otherwise, the missing heat is provided by the gas boiler as in summer. When the CHP is turned on at minimum load, the supply temperature decreases again to 20°C to increase the power consumption, with the aim of maximizing the share of self-consumed electrical energy.

The dynamic programming algorithm (second approach) was first implemented for a small system comprising three boilers and two heat storages. The gas boilers have ascending running costs, so that boiler 1 was the most efficient and cheapest unit.

Table 2 Units considered in the commitment problem

Boiler/Stroage no	min capacity, MW	max capacity, MW
B1	5	45
B2	5	30
B3	1	80
Sto 1	-15 (charge)	15 (discharge)
Sto 2	-5 (charge)	5 (discharge)

The evaluation horizon was set to six hours with a total heat demand of 214MWh. The end state of charge was restricted/wished to be equal to the starting one. The number of n_{pred} was set to 200 and the system is able to end up with the desired level of charge (5) as it can be seen in Figure 17. The optimization takes around 7 sec using an i5-4690 CPU @ 3.5 GHz under the OS Win10 Pro.

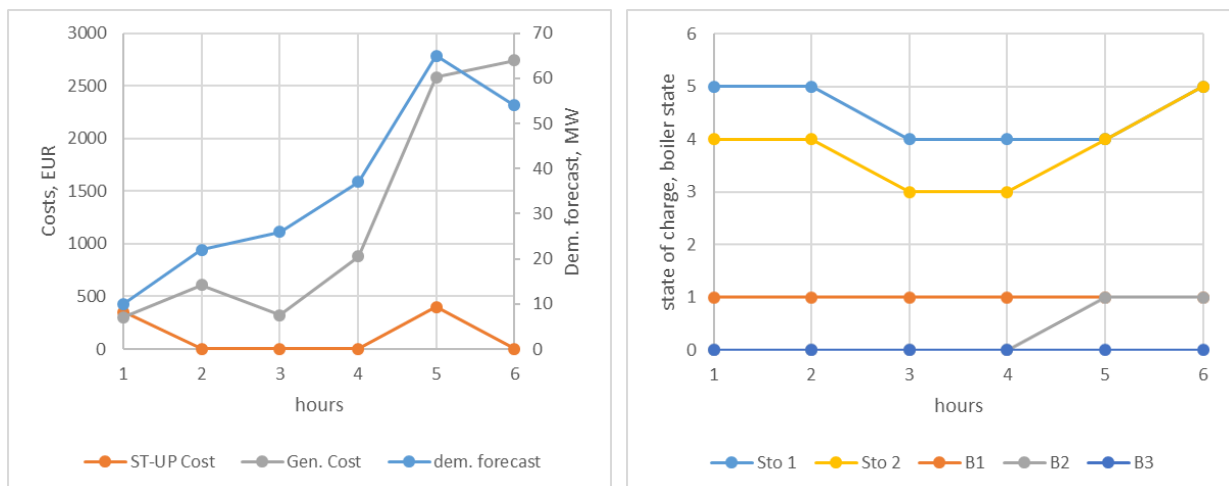


Figure 17. Results for a 6h evaluation horizon (unit commitment).

If the evaluation horizon is extended to 10 hours, the optimization will take approximately double the time needed in the example of Figure 17. Figure 18 shows the CPU time proportionally increasing with the number of strategies taken into account at each step (n_{pred}). However, there is no



enhancement of the cumulative cost beyond $n_pred=1000$. The algorithm is unable to find a better pathway for the generation and storage combination.

Independent of n_pred , the algorithm was unable to end up with the desired level of charge due to the very high number of feasible states as indicated in Figure 13. The intuitive measure to cope with this problem is to increase n_pred , which again implies higher calculation times.

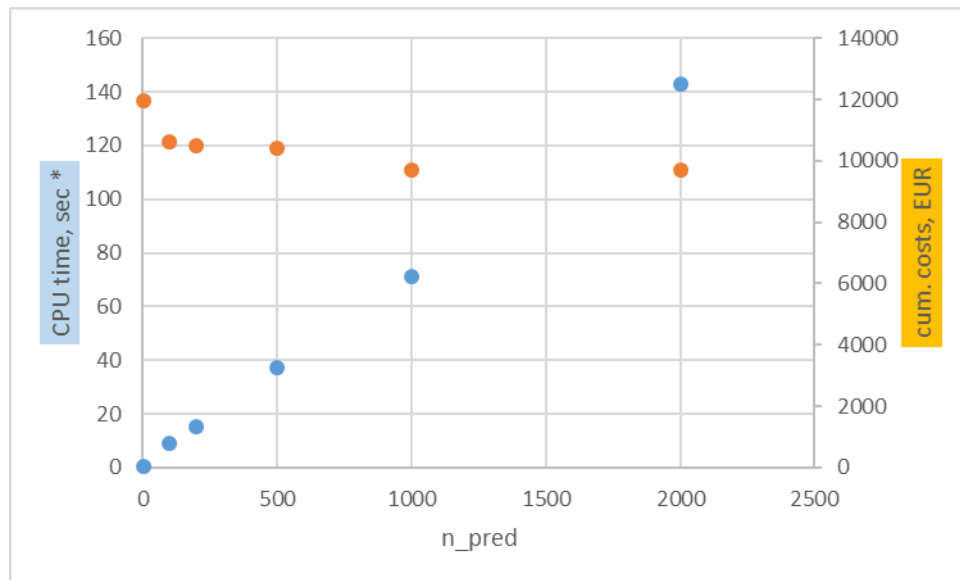


Figure 18. Optimization time and final costs for a 10h horizon with regard to n_pred (unit commitment).

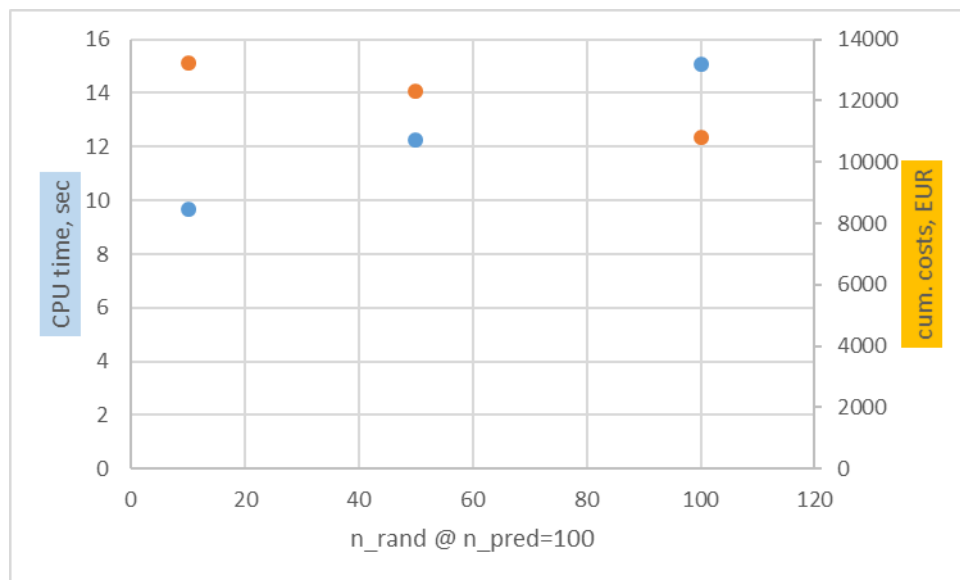


Figure 19. Optimization time and final costs for a 10h horizon with regard to n_rand (unit commitment).

The algorithm was additionally extended by a random function to not only consider the best n_pred strategies but also randomly choose n_rand paths with higher accumulated state transition cost before the end of the evaluation horizon. In other words, the algorithm randomly takes 'less



attractive' paths into account, moves to later hours in the analysis horizon and sees if these paths lead to good results at the end. The third parameter n_{rand} was varied to assess its impact on the solution. The algorithm was already able to much faster converge with $n_{enum} = 100$ and $n_{rand} = 10$ without ending up with empty storages. The evolution of the CPU time and cumulative final costs are presented in Figure 19.

4.2.3 High-level optimizer: impact of optimization objective and dependence on demand forecast

The cost function in both approaches can be adjusted to follow either economic or ecologic targets. For example by increasing c_{gas} in equation 1, the gas boiler will be less attractive, the CHP unit will be operated longer/independent of the electricity price and the CO₂ emissions will be less. Rising c_{trans} for the gas boiler in equation 2 will also lead to the same result. It is also possible to add penalty costs for the CO₂ emissions to equation 1 or to the production costs within equation 2 in order to schedule the system more environmentally friendly.

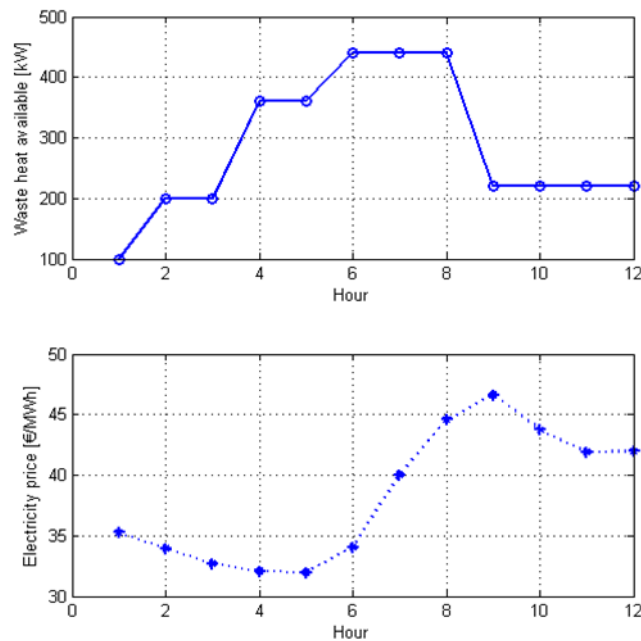


Figure 20. Waste heat and electricity price forecast.

The system of Figure 15 was scheduled with the MILP algorithm for the waste heat and electricity price shown in Figure 20. Depending on the optimization target, the obtained schedule varies. To run the system more environmentally friendly (ecologic target), the gas boiler is shut down all the time as presented in the right side of Figure 21. This allows the system to gain more waste heat and to keep the CHP unit running at full load.

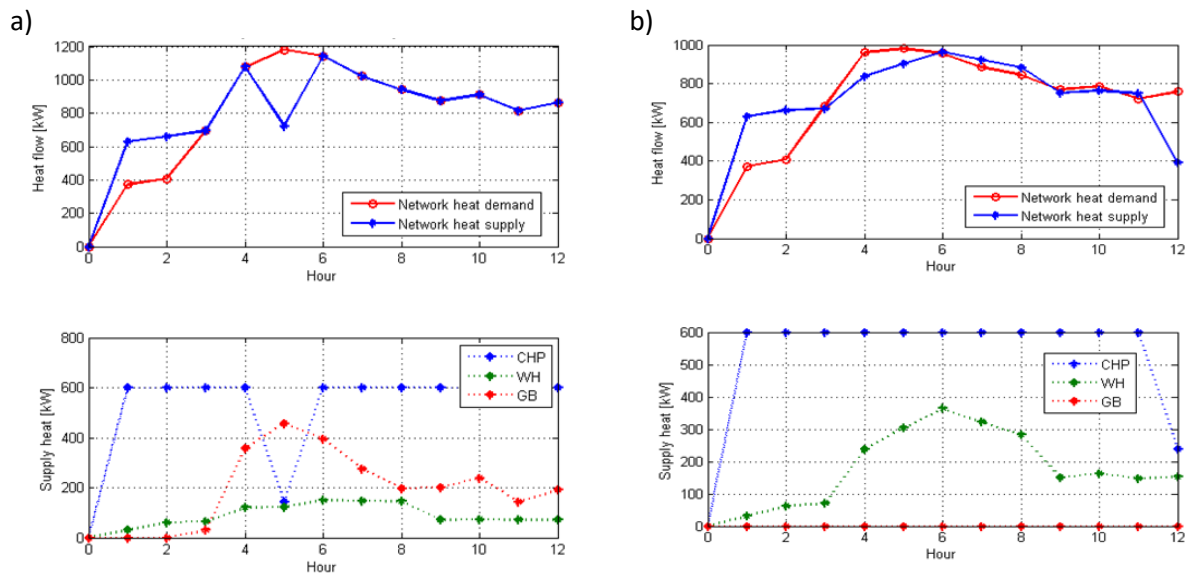


Figure 21. Schedule (MILP) for a) economic and b) ecologic target.

An illustrative example of the system dependency on the demand forecast is shown in Figure 22 and Figure 23. Here we consider two generic profiles (see figures) representing opposite trends of the demand. The total energy demand over 10 hours remains the same. The demand of the first profile increases gradually whereas the second one drops significantly at hour 7.

Load shedding is achieved with the dynamic programming approach for both ascending and descending demand characteristic. For an increasing demand, the storages are first charged and then discharged to the desired end level of 5.

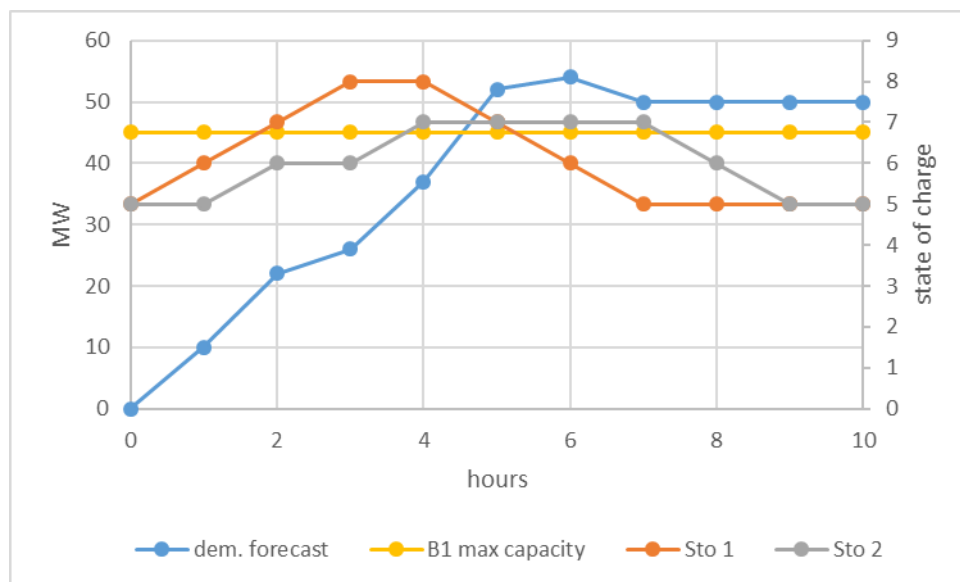


Figure 22. Storages' state of charge for the first demand profile.

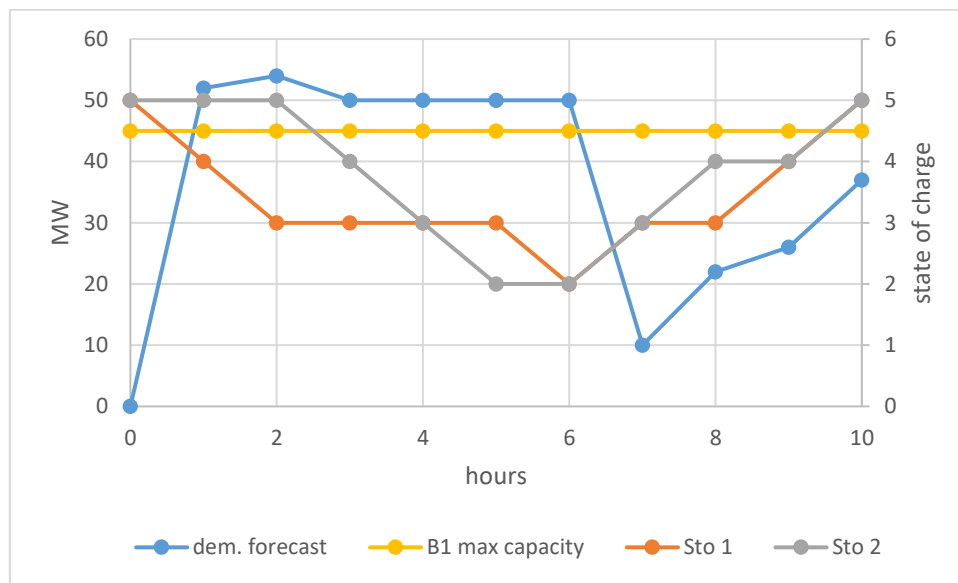


Figure 23. Storages' state of charge for the second demand profile.

4.2.4 Control of distributed thermal energy storages

In Section 2.3 a discussion about centralized storages was presented. In the case of FLEXYNETS, the specific issue of distributed storages arises, either using local storages at substations (e.g., DHW tanks) or the network pipes themselves. This allows to store energy just at the needed location, thereby significantly reducing flow rate peaks.

The main operational tasks of thermal energy storage (TES) systems are (Petersen and Aagaard, 2004, Holler, 2013, Wiltshire, 2016):

- Equalizing the heat load of the heat source plants while heat demand by consumers is fluctuating.
- Increasing of operational efficiencies of generation units by more stable operation;
- Covering of heat peak demand avoiding temporary switching on of peak generation units with high operational costs.
- Yielding the possibility to operate when the heat demand is below the technical minimum of heat generation.
- Decreasing of water losses in the network, exploiting the storage as an expansion vessel.
- Increasing the flexibility of CHP systems by allowing electricity generation in time of off-peak heat load without wasting the by-product heat.
- Balancing the excess electricity production from non-programmable renewables through the Power-to-Heat concept via heat pumps or electrical boilers.

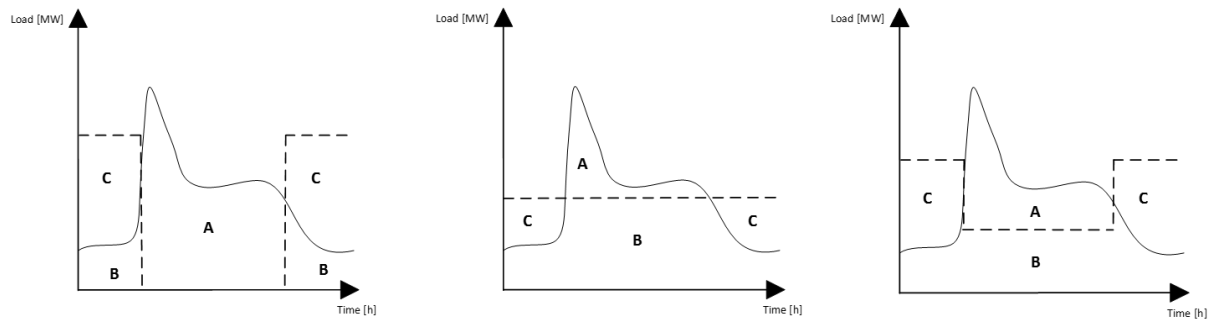


Figure 24. Operational strategies for thermal storage considering the load profile of a traditional DH network: A – The storage meets (part of) the load, B – The generation unit meets (part of) the load, C – The storage is being charged. Left: full storage. Centre: partial storage for load levelling. Right: partial storage with demand limiting.

Some typical operational strategies (Dinçer and Rosen, 2014) for thermal storage are the following (see Figure 24).

- Full-storage. This strategy shifts the entire peak load to off-peak hours. Hence, it fully decouples the operation of the generation system from the peak load. It is applied when the availability or the economic convenience of the source is higher during off-peak hours and when peak duration is short. This option more often used for cooling than for heating.
- Partial-storage for load levelling. The generation unit operates to meet only part of the peak load. The generation system can then be designed at a smaller capacity than the design load and runs at constant (full) capacity for 24 h.
- Partial-storage with demand limiting. The generation system runs at reduced capacity during peak hours. This can be applied when there are different prices of the energy tariff during the day and is more frequent for cooling. The opposite option (not shown in the figure) can be found for heating (the generation unit is run at a higher level during peak periods than during off-peak periods, but it is never shut down completely).

The second operation strategy listed above (partial storage for load levelling) is that described in section 2.3.

FLEXYNETS specific issues which can be highlighted concerning distributed storages are reported below:

- The above presented strategies can be applied at an aggregated level, but a distributed system needs to integrate considerations about local operation. For example, a local DHW tank must always satisfy the user demand and is hence operated also independently of the network needs.
- Local storages at substations allow to reduce flow rate peaks on the network. Indeed, storing locally during off-peak periods part of the needed energy would reduce the “energy traffic” on the network during peak hours. This is especially important in FLEXYNETS, as the small temperature differences involved in the network need higher flow rates to deliver the same thermal power. Hence, the possibility to reliably level out the demand would be highly beneficial for the network sizing (and hence for investment costs).
- Local storages can have different states of charge even when close to each other in terms of network path. This has to be properly taken into account when implementing the charging/discharging control. Moreover, the fact that the storages are at the *same* place of the



user substations, prevents the use of the automatic charging logics described in Subsection 2.3 for a single centralized storage.

- Local storages need distributed sensors to keep track of the “load state” of the storage. This is however not to be considered an additional cost: temperature sensors for set point reading are anyway needed in conventional DHW tanks. Similarly, the usage of the network pipes as distributed storage would need distributed sensors (especially for the 1-pipe option). Substations based on heat pumps are expected anyway to integrate these sensors for the HP operation.
- The control design needs a clear definition of the decisional boundaries, in order to understand who orders storage charging/discharging. At the moment, it is planned that the network manager acts on local substations through price incentives or similar policies, rather than with direct control.

The identification of the optimal operation of such a dynamic system can largely benefit of the advanced control techniques mentioned in Subsection 3.1.

The use of local storages in the context of demand side management will be discussed in the next section.

4.3 User control and network interaction control

The third and fourth section in the level-2 control of table 1 are dedicated to the user and network interaction control. Most aspects of these two controls were already discussed in D2.1 and D4.2 and are not repeated here. Here, instead, we focus on a possible demand side management strategy to be applied at the level of user control, combining together user control, electric-thermal network interaction, and local storages.

Demand side management (DSM) includes a series of strategies aiming at modifying the electricity demand, with benefit for electricity generation and distribution. More specifically, demand response (DR) introduces incentive-based or price-based programs to push customers to adapt their consumption patterns to the grid convenience.

Major examples are peak shaving and load shifting, where the objective is to reduce the load peaks in order to decrease the required installed power and to move consumptions to periods more convenient for energy production. This is especially relevant for non-programmable RES, which, in the case of excess production with respect to demand (or with respect to the grid transmission capacity) could be subject to curtailment, with environmental and economic disadvantages (Lund, 2015).

Here we focus on the case of price-based DR, assuming time-of-use (TOU) pricing (i.e., pricing based on a limited number of tariffs applied during different periods of the day, as opposed to real-time pricing where the electricity price can continuously change as in a stock exchange context). It is assumed that the DHC network operator sends this price signal to each user substation and that the user control reacts on the basis of this signal. This is simpler than some of the network interactions considered in D4.2, where participation to electricity markets was considered. However, when considering all user HPs as a pool, the same strategies mentioned here could be applied even in the context of the electricity market. Moreover, the aggregated operation of the different heat pumps can be seen as an example of a multi-agent system (Section 3.1). The network manager is the agent with authority power, coordinating the substation agents which obey simple operation rules.



The concept considered here is as follows. The operation of heat pumps is shifted (anticipated or delayed in time) in order to exploit the most convenient electricity prices. In order to perform this operation shift, the domestic hot water (DHW) tank connected to the HP is exploited. It is worth noticing that, in principle, the residential environment could offer other thermal storage possibilities (space heating or space cooling buffers or even the building thermal capacity itself). This analysis was however limited to the DHW tank due to its simplicity and its constant availability/use throughout the year, without significant seasonality effects.

4.3.1 Simple estimates for intervention thresholds

Before presenting the investigation carried out with detailed simulations, it is useful to briefly discuss some simple relations which highlight the different effects at play.

Operating the heat pump during off-peak hours, gives the obvious advantage of exploiting lower electricity prices. On the other hand, anticipating DHW production typically requires increasing the tank temperature, during the storage charge. One then has the drawback of operating the HP at higher temperatures at the condenser, reducing its coefficient of performance (COP). These two competing effects must both be taken into account when evaluating the overall balance: the final cost is indeed the electricity price times the amount of used electricity, and if the electricity amount increases more than the price decreases, then the convenience is lost.

Neglecting additional thermal losses and effects on the network side, the consumed electricity is $E_{el} = E_{th}/COP$, where E_{th} is the thermal energy needed for DHW. One can then write the following simple inequality

$$\frac{c_{el,off-peak}}{COP} < \frac{c_{el,peak}}{COP_{max}},$$

where c_{el} is the unit electricity price, the subscripts “peak” and “off-peak” have obvious meaning, and COP_{max} is the maximum COP (obtained when the storage temperature is lowest). The above inequality must be satisfied in order to make the system economically convenient.

Exploiting typical formulas for the COP dependence on temperatures, one can use this relationship to estimate how big could be the temperature increase in the tank set point before worsening the COP too much. Typical values for HPs and typical variations of electricity prices suggest a limited range of about 5 K. In the more detailed calculations presented below, a larger range was however used, as this simple estimate neglects effects related to network heat (both in terms of amount and prices) and it was considered interesting to extend this variation.

4.3.2 Simulation model

In order to test this type of control, detailed TRNSYS simulations based on the models developed in deliverable D2.1 were carried out. This work is also reported in the paper “Potential study on demand side management in district heating and cooling networks with decentralized heat pumps”, by Buffa, 2018. For completeness, we report below the details of the building associated to the user control.



A multi-family house consisting of 10 apartments subdivided into 5 floors was considered. The single apartments have a floor area of 50 m². From the point of view of energy efficiency, performances typical of a recent or refurbished building were assumed, corresponding to consumptions of about 45 kWh/(m² y) for space heating (SH). The climate conditions of Rome (Italy) were applied, in view of a setup also interesting for cooling. For the domestic hot water (DHW) profiles, the DHWcalc software was used, with a time resolution of 1 min. The applied occupancy level is 2 people/apartment with a DHW demand of 40 l/(person day), finally yielding a specific DHW load of about 24 kWh/(m² y). The SH and space cooling (SC) demands of the building have been assessed by means of dynamic simulations using TRNSYS Type 56. The peak thermal power for SH results in 22.7 kW. Some space cooling (SC) was also considered, though its description is not relevant for this work. The thermal energy storage (TES) for DHW consists of a stratified water tank and it has been sized according to the Italian standard UNI 9182 (2010) resulting in a volume of 450 litres (centralized storage for the entire building). The water source heat pump used for the plant was slightly oversized, with a peak power of 25 kWt. Since DHW must be readily supplied to the single apartments, a continuous recirculation within the distribution plant is assumed. This gives rise to non-negligible losses. However, to decouple these losses from the DHW TES temperature (which can be set higher within DSM-related control strategies), a 3-way mixing valve was assumed at the TES outlet. In this way, the DHW circulation temperature can be assumed equal to the minimum set point of 50 °C even for higher TES temperature. The plant scheme is reported in the figure below.

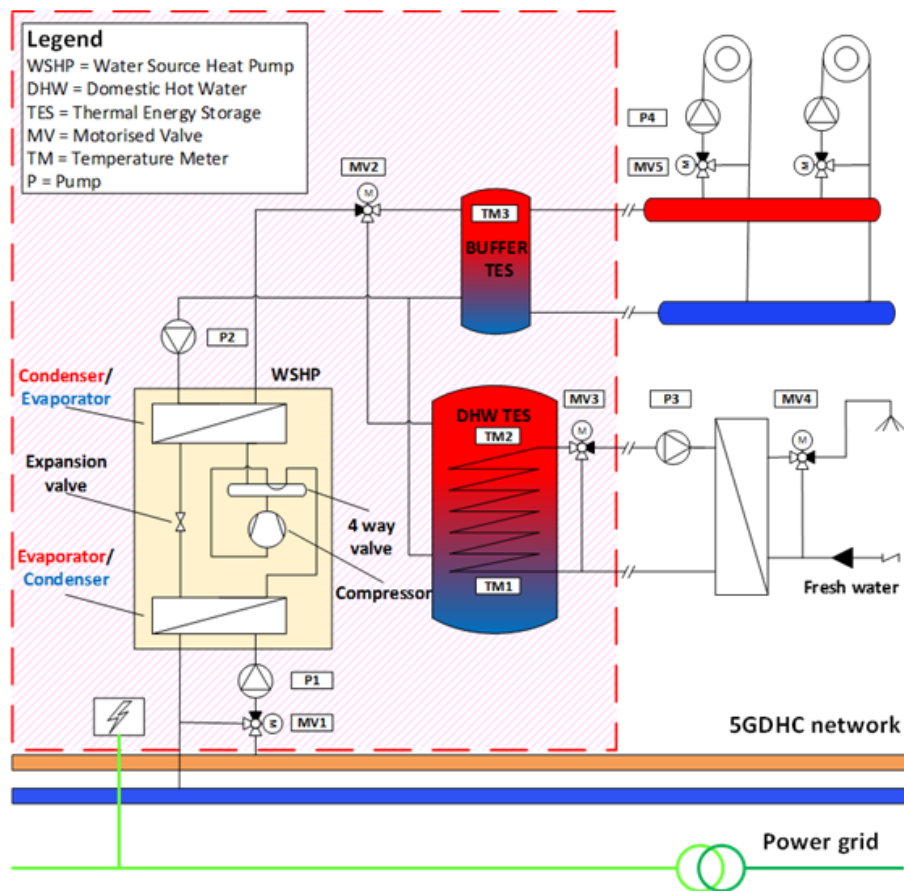


Figure 25. Plant scheme of the residential substation based on a reversible heat pump.



4.3.3 Control logic and simulation results

As mentioned above, a time-of-use pricing is considered. The Italian tariff D1 is used, distinguishing peak hours (08:00-19:00, working days) from off-peak hours (remaining hours and weekends). The DR signal is hence activated during off-peak hours, in particular during the two hours preceding the starting of off-peak hours, to pre-charge the DHW tank.

- Tank set points without DR. The maximum tank temperature is set to 50 °C, with a bandwidth of 5 K for the tank hysteresis cycle.
- Tank set points with DR. The maximum tank temperature is set to 60 °C, with a bandwidth of 15 K for the tank hysteresis cycle.

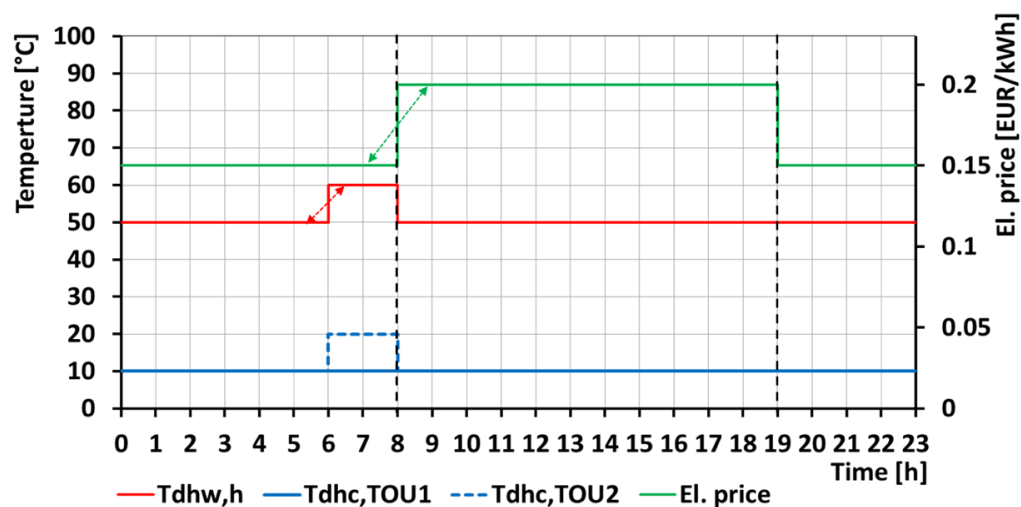


Figure 26. Temperature and price signal along a typical day.

For electricity prices, an off-peak electricity price of 0.15 EUR/kWh was assumed, while two cases were considered for the peak electricity price, namely 0.17 EUR/kWh and 0.20 EUR/kWh (exploited in different simulations). In this way, a minimal sensitivity analysis could be performed. Similarly, to cases for the network heat price were analysed: 0.05 EUR/kWh and 0.10 EUR/kWh.

In addition, two cases for the network temperature were considered. In the first case the network is operated at a constant temperature of 10 °C. In the second case, an increase of the network temperature in correspondence with the DSM operation was allowed. This approach clearly assumes an involvement of the network manager in the entire control. Without entering here in the details of how this temperature increase could be applied (one could for example imagine higher temperature sources available only during part of the day, e.g., due to its low size with respect to the overall heat demand), this second case is relevant to understand the interplay between the network management and the substation operation. Synchronizing the network temperature increase with the tank temperature increase, the decay in the HP performance (i.e., the COP reduction) can be possibly avoided.

The quantitative results obtained in simulations are summarized in the tables reported below, one for the energetic performances and the other for the economic performances. In general, it can be seen that the observed effects are small and that in some case the results are not favourable from the economic point of view. Moreover, the additional flexibility comes at a cost of a slight energy



consumption increase. On the other hand, the energy shift from peak hours to off-peak hours can be of the order of 20 % (with respect to the reference peak hour consumption for DHW), already a sizable effect.

It is worth mentioning some possible extensions of this work. First of all, the application of similar control strategies to the real-time pricing case could be considered. Additional points could involve parametric analyses of the tank temperature variation and of the tank size, possibly including space heating and space cooling buffers. Moreover, a more detailed investigation of the coupling with the thermal network (both in terms of network temperature variations and in terms of combined effect of multiple substations) would be important. Application of advanced control solutions is instead discussed in the next section.

Table 3. Energetic performances of the considered DSM strategies. The reference scenario refers to the case without DSM. The 2 TOU scenarios refer instead to the same DSM strategy, but applied with the two different network temperatures mentioned in the text.

		Unit	Ref. scenario	Scenario TOU1 Tdhc const. (10°C)	Scenario TOU2 Tdhc var. (10±20°C)
DHW use	SCOP _{DHW}	-	2.36	2.32	2.42
	Q _{dhw,load}	MWh	11.96	11.96	11.96
	Q _{dhw,in}	MWh	16.20	16.21	16.21
	$\Delta Q_{dhw,in}$	MWh		0.01	0.01
	Q _{loss}	MWh	4.24	4.25	4.25
	ΔQ_{loss}	MWh		0.01 (+0.24%)	0.01 (+0.24%)
	Q _{stored,DR}	MWh	0.38	1.36	1.27
	$\Delta Q_{stored,DR}$	MWh		0.98 (+258%)	0.89 (+234%)
Electricity use	Eel,dhw peak hours	MWh	1.64	1.30	1.36
	$\Delta E_{el,dhw}$ peak hours	MWh		-0.33 (-20%)	-0.28 (-17%)
	Eel,dhw off-peak hours	MWh	5.25	5.72	5.36
	$\Delta E_{el,dhw}$ off-peak hours	MWh		0.46 (+8.7%)	0.11 (+2.1%)
	Tot Eel,dhw	MWh	6.89	7.02	6.72
	$\Delta E_{el,dhw}$	MWh		0.13 (+1.8%)	-0.17 (-3.2%)
DHC use	Q _{dhc} TOU	MWh	9.53	9.41	9.70
	ΔQ_{dhc}	MWh		-0.12 (-1.3%)	0.17 (+1.8%)



Table 4. Economic performances of the considered DSM strategies. The reference scenario refers to the case without DSM. The 2 TOU scenarios refer instead to the same DSM strategy, but applied with the two different network temperatures mentioned in the text.

		Unit	Scenario TOU1A Tdhc const. (10°C)	Scenario TOU1B Tdhc const. (10°C)	Scenario TOU2A Tdhc var. (10÷20°C)	Scenario TOU2B Tdhc var. (10÷20°C)
	Peak hour Eel Price incr.	%	15%	30%	15%	30%
	Cel off-peak /Cel peak	-	0.87	0.77	0.87	0.77
	Eel prices off-peak hours	€/kWh	0.15	0.15	0.15	0.15
	Eel prices peak hours	€/kWh	0.17	0.20	0.17	0.20
	Tot Eel costs ref.	€	1070.5	1107.3	1070.5	1107.3
	Tot Eel costs TOU	€	1082.2	1111.5	1038.7	1069.3
	ΔTot Eel costs	€	11.7(+1.1%)	4.2(+0.4%)	-31.8(-3%)	-38.0(-3.4%)
C _{qdhc} =0.05 €/kWh	Total costs Qdhc ref.	€	476.6	476.6	476.6	476.6
	Total costs Qdhc TOU	€	470.5	470.5	485.2	485.2
	ΔTot Qdhc costs	€	-6.1(-1.3%)	-6.1(-1.3%)	8.6(+1.8%)	8.6(+1.8%)
	Total costs ref.	€	1547.0	1583.9	1547.0	1583.9
	Total costs TOU	€	1552.7	1582.0	1523.8	1554.5
	ΔTot costs	€	5.7(+0.4%)	-1.9(-0.1%)	-23.2(-1.5%)	-29.4(-1.9%)
C _{qdhc} =0.10 €/kWh	Total costs Qdhc	€	953.1	953.1	953.1	953.1
	Total costs Qdhc TOU	€	941.0	941.0	970.4	970.4
	ΔTot Qdhc costs	€	-12.1(-1.3%)	-12.1(-1.3%)	17.2(+1.8%)	17.2(+1.8%)
	Total costs ref.	€	2023.6	2060.4	2023.6	2060.4
	Total costs TOU	€	2023.2	2052.5	2009.0	2039.6
	ΔTot costs	€	-0.4(-0.02%)	-7.9(-0.4%)	-14.6(-0.7%)	-20.8(-1%)

4.3.4 Implementation of advanced control

Advanced controls were also considered for user control in the case of DSM strategies, though results are reported in deliverables kept confidential by the project consortium. In the previous section, the implementation of a deterministic control was discussed. In order to optimize this control, an MPC approach coupled with ANNs was used (see section 3.1). The general structure of the control is as follows:



- First, the predictive part was developed. As mentioned above, a detailed TRNSYS model of the substation was available. Coupling it with the DHW profiles predicted by the DHWcalc software tool, a full model of the system can be obtained. This is however rather computationally intensive and not much convenient to be used on-line with a control software, especially taking into account the optimization task (see below). Therefore, an ANN model was trained with the detailed model, yielding a fast-running black-box model accurately reproducing the starting physical model. This provides the behaviour of the system on the requested horizon.
- Second, an optimizer was chosen. Having an underlying black-box model, both non-analytic and non-linear, classical optimization methods are not recommendable. It was hence chosen to adopt a heuristic algorithm, namely a Particle Swarm Optimization (PSO) algorithm. The optimizer performs multiple iterations varying the control parameters and testing their performance (on the basis of a suitable objective function) with the forecast obtained from the ANN model, until suitable parameters are found (convergence can be fixed in terms of number of iterations and/or in terms of residual variation of the objective function). The objective function was chosen as the overall operation cost function of the system (including electric and thermal energy prices). Since the optimizer typically performs many iterations, the underlying ANN model is called a large number of times. This makes evident how the computational performance of the prediction model is crucial.
- The overall MPC scheme consists in repeating the optimization procedure at proper intervals and on a certain horizon. An horizon of a few hours can be chosen for DHW applications, though this choice depends also on the expected electricity price schedule.

One can see some differences with respect to the MPC implementation done for the energy flow control of the network. Here, the underlying model is not a physical model but a black box model – namely a neural network with little computational burden. The ANN coefficients were calibrated in advance – off-line with respect to the control execution – with a training process which is an example of machine learning methods. Once this is done, the execution of the ANN can be very fast, thanks to its relatively simple internal structure. On the other hand, a more elaborated optimizer – typically requiring many iterations – is used with respect to, e.g., the MILP optimizer usable with a linearized cost function. This shows how under the concept of MPC several possible arrangements are feasible, possibly with quite different algorithms.

Due the possibly strongly fluctuating nature of DHW load profiles, the effectiveness of this optimization procedure is expected to be typically lower than in the unit commitment problem described for the energy flow control. This however depends on the size of the substation. For example, for a substation serving a large building, with many individual apartments, the overall profile can result much smoother and more predictable than for small buildings.



4.4 FLEXYNETS specific aspects

4.4.1 The sensible heat storage

Due to the low temperature difference between supply and return line in FLEXYNETS, distributed sensible heat storages that are connected to the network have less capacity than those in e.g. 4th generation DH systems (e.g. a 20K system will theoretically offer 50% less capacity than one with 40K temperature drop). Increasing the number of ‘reschedulable’ storages would enlarge the margin for heat management but also increase the dimension of the online optimization problem.

The storage state of charge is calculated using the temperatures in its different levels (nodes from 1 to nS) and the two reference temperatures T_{min} and T_{max} :

$$E_{storage} = 1 + \frac{\sum_1^{nS} (T_i - T_{min}) \cdot dV_i}{(T_{max} - T_{min}) \cdot V_{total}} \quad (3)$$

dV_i and V_{total} are the volumes associated to each node and to the whole storage respectively. The relative error in state estimation is proportional to the relative errors of all temperature sensors. Due to the narrow range between the reference temperatures T_{min} and T_{max} in network side buffers, the sensors need to be accurate.

The charging/discharging capacity of the storage depends on the temperature difference between its inlet and outlet temperature. To account for this, Verrilli et al. (2015) introduced the so-called storage charging and discharging efficiencies. In FLEXYNETS we take both top and bottom temperature of the storage and feed them back to the high level controller. By doing this, realistic heat transfer capacities are considered in scheduling.

4.4.2 Control robustification

Control algorithms for unit scheduling generally need to be ‘robustified’ in order to cope with model inaccuracies, prediction errors or general operational disturbances (temperature drops, leakages). The loss of robustness leads to a mismatch between expected and achieved state variables and could result in too low supply or return temperatures. In FLEXYNETS, fluid temperatures down to 5°C are considered. While the first countermeasure against freezing can be to use water-glycol mixtures instead of pure water, in the presence of proper robustification strategies the use of such additives could be avoided.

A possibility is to increase the robustness of the system by using the thermal storage property of the distribution network: the energy supplied can be always set slightly higher than needed to cope with those situations. As the heat losses are expected to increase, a trade-off between running costs and robustness should be found. Another ‘mathematical’ way to minimize the subcooling/frost risk consists of replacing the deterministic optimization problem with a stochastic one, considering the uncertainty in the forecasts (Rantzer 2015). Stochastic methods were however not pursued within FLEXYNETS.

4.4.3 Control of substations in 1-pipe networks

In 1-pipe systems, the same temperature control logic is adopted, though with a different flow control. The figure below illustrates that the main and the prosumer’s pumps are regulated to



maintain a minimum pressure drop and therefore avoid recirculation in the substation circuit. Although recirculation could also be avoided by controlling a valve in the main line between both prosumer's junctions, it is more convenient to avoid such components due to the large pipe size in the main loop. In large systems, the main pump should be preferably operated in open loop mode to avoid interferences between both pumps.

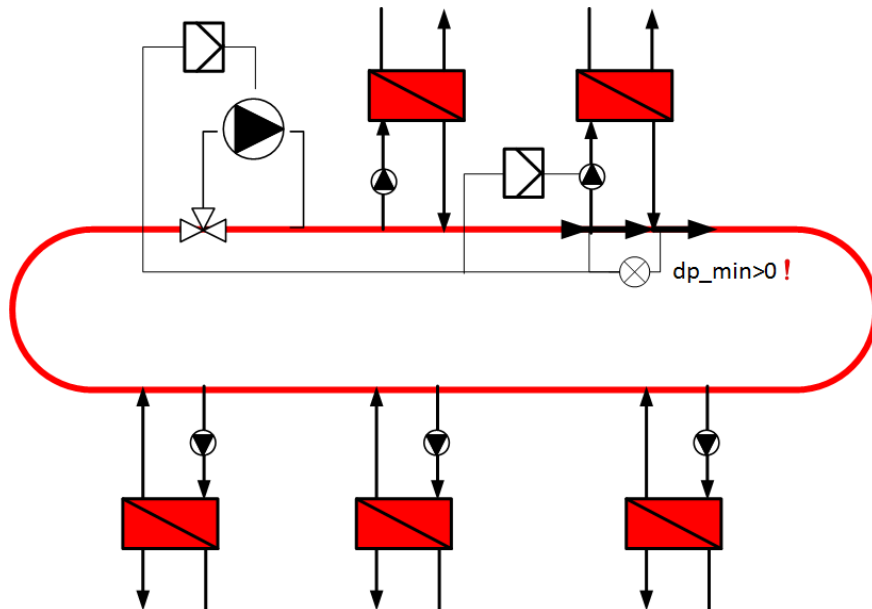


Figure 27. Connection scheme for the 1-pipe network case. Pressure control to avoid undesired recirculation at substations is shown.

4.4.4 Control of non-balancing substations

As far as non-balancing substations (e.g. waste heat) are concerned, the following approach is being adopted in simulations. When in operation, these units take cold water at the return line temperature T_r and feed-in hot water into the supply pipe. While these non-balancing units provide part of the power needed by the network, the manager continues supplying the system with hot water through balancing plants, but at reduced flow rates.

If the overall power supplied to the network exceeds the demand, the return temperature starts increasing. Once T_r exceeds a given threshold, the network manager starts cooling down the system by feeding colder water (in practice, this could correspond to charging a centralized storage). This logic implements the higher priority given to non-balancing (and typically cheaper) plants, with respect to balancing (and hence more expensive) plants. From a point of view of control details and based on the network simulations, the return line in the waste heat node offers a good placement for temperature measurement. Its signal incorporates a wide hysteresis allowing for control stability and less control signal fluctuations.

4.5 The extended control problem

One can follow different operation strategies by adapting the input files in Figure 11. For example applying time variable fuel costs for a generation unit will automatically let it run at reduced capacity during high tariff periods which means partial storage charging for demand limiting. Load levelling



can be achieved if e.g. the maximum heating capacity of the unit in the input file is reduced. The high-level control problem can be extended to an offline optimization in order to compare different storage management strategies (see Figure 28). Provided an input forecast for one year, one could calculate optimum operation versus the operational constraints and cost parameters as indicated in Figure 28. At the end of the offline optimization, the operator is able to e.g. find out which strategy will yield lowest annual costs.

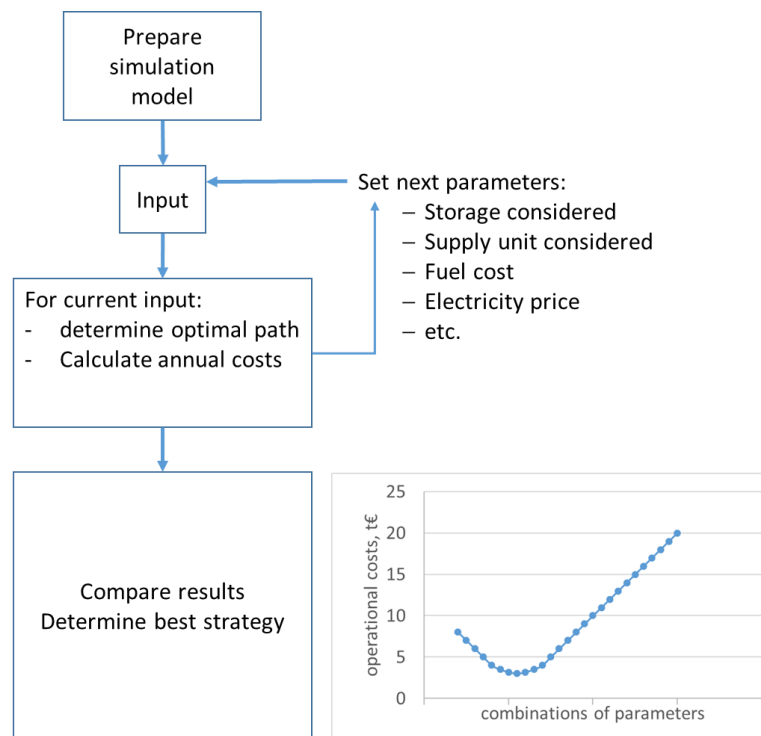


Figure 28. The extended optimization problem.

4.6 Conclusions on complexity levels of control

In the previous sections, basic and advanced controls were discussed, showing how one can improve simple deterministic solutions (e.g., unit commitment based on fixed priority rules) with, e.g., predictive techniques.

Advanced controls can be installed either at substation level or at network level. The table below summarizes the complexity levels analysed in FLEXYNETS. Other input/output combinations could be devised, but reported elements were considered of primary importance within FLEXYNETS.

An example of the benefits provided by the application of advanced control in FLEXYNETS is provided in Vivian, 2017. Here, a reduction in operational costs of about 11 % was observed in simulations when applying the MILP optimization to energy flow control (with respect to basic control based on simple priority rules). While it is difficult to extrapolate general rules about the expected level of improvement obtainable with advanced control, this order of magnitude (10 %) is in line with the results obtained by project partners in other heating and cooling applications.



Table 5. Table representing the different levels of control complexity analysed in the FLEXYNETS project, distinguishing between centralized and local/diffused controls.

	Centralised	Local/diffused
Basic control (minimum control for the operation of the system)	Inputs / controlled variables: <ul style="list-style-type: none"> - State of charge of the central storages - Network temperature - Network pressure difference Acts on: <ul style="list-style-type: none"> - Energy sources (ON/OFF) - Network pumps Objective: <ul style="list-style-type: none"> - Reliable and economically efficient operation (no real optimum) 	Inputs / controlled variables: <ul style="list-style-type: none"> - DHW tank set point temperature - Building set point temperature - Hysteresis parameters Acts on: <ul style="list-style-type: none"> - Heat pumps - Substation hydraulic pumps Objective: <ul style="list-style-type: none"> - Reliable and economically efficient operation (no real optimum)
Advanced/adaptive controls (optimized)	Inputs / controlled variables: <ul style="list-style-type: none"> - Weather/demand forecasts - Electricity/gas price Acts on: <ul style="list-style-type: none"> - Energy sources (ON/OFF) - Set point of the basic controls Optimization with a cost function depending on: <ul style="list-style-type: none"> - Primary energy - Operation cost 	Inputs / controlled variables: <ul style="list-style-type: none"> - Weather/demand forecasts - Electricity price - COP Acts on (e.g.): <ul style="list-style-type: none"> - Set point of the basic controls Optimization with a cost function depending on: <ul style="list-style-type: none"> - Primary energy - Operation cost



5 References

- Ben Hassine, I., Eicker, U. Impact of load structure variation and solar thermal energy integration on an existing district heating network. *Applied Thermal Engineering* Vol 50, Issue 2, pp. 1437–1446, 2013.
- Ben Hassine, I., Ursula Eicker, Control aspects of decentralized solar thermal integration into district heating networks. SHC 2013, International Conference on Solar Heating and Cooling for Buildings and Industry September 23-25, 2013, Freiburg, Germany.
- Bøhm B., Ha S., Kim W., Kim B., Koljonen T., Larsen V., Lucht M., Park Y., Sipilä k., Wigbels M., Wistbacka M., Simple Models for Operational Optimization, IEA District Heating and Cooling, ANNEX VI, Technical University of Denmark, Kongens Lyngby, Denmark, 2002.
- S. Buffa, M. Cozzini, G. P. Henze, C. Dipasquale, M. Baratieri, and R. Fedrizzi. Potential study on demand side management in district heating and cooling networks with decentralized heat pumps. ISEC 2018, Graz.
- Dalla Rosa, A., Li, H., Svendsen, S., Werner, S., Persson, U., Ruehling, K., ... Bevilacqua, C. (2014). IEA DHC Annex X report: Toward 4th Generation District Heating: Experience and Potential of Low-Temperature District Heating.
- Dinger I. and Rosen M.A., Thermal energy storage systems and applications, Wiley, Lund, 2014.
- Dounis A. I. and Caraiscos C., Advanced control systems engineering for energy and comfort management in a building environment—A review, *Renew. Sustain. Energy Rev.*, vol. 13, no. 6–7, pp. 1246–1261, Aug. 2009.
- Frederiksen S., S. Werner, District Heating and Cooling, Studentlitteratur AB, Lund, 2013.
- Holler S., Prospects and Challenges of Thermal Energy Storage in Future Energy Systems, in Proceedings of the conference “Environmental and Climate Technologies 2013”, Riga, Latvia, pp. 27 - 30, 2013.
- Ianakiev, A. I., Cui, J. M., Garbett, S., & Filer, A. (2017). Innovative system for delivery of low temperature district heating.
- Kunst B., Geck C, (2005), Optimierter Netzbetrieb mit drehzahl-veränderlichen Pumpen, *EuroHeat&Power* 34. Jg Heft 6
- Lund, P.D., Lindgren, J., Mikkola, J., and Salpakari, J. (2015), Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renew. Sustain. Energy Rev.* 45, 785–807
- Papakonstantinou N., J. Savolainen, J. Koistinen, A. Aikala, V. Vyatkin, District heating temperature control algorithm based on short term weather forecast and consumption predictions. IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA), Berlin, 2016.
- Petersen M.K., Aagaard J., Heat accumulators, News from DBDH, Danish Board of District Heating, Frederiksberg, Denmark, 2004.
- Thomsen P.D., Overbye P.M., "Energy storage for district energy systems," in Advanced District Heating and Cooling (DHC) Systems, R. Wiltshire, Ed., Cambridge, Elsevier, Woodhead Publishing, 2016, pp. 146-166.
- Vasičkaninová A., Bakošová M., Mészáros A., and Klemeš J. J., Neural network predictive control of a heat exchanger, *Appl. Therm. Eng.*, vol. 31, no. 13, pp. 2094–2100, Sep. 2011.





Wernstedt F. and Davidsson P., Software Agents for Distributed Load Balancing, in Proceedings of the 9th International Symposium on District Heating and Cooling, Espoo, Finland, 2004.

Wiltshire R., Advanced District Heating and Cooling (DHC) Systems. Elsevier, WoodHead Publishing, Saint Louis, 2016.

Klein, S.A., A Design Procedure for Solar Heating Systems, Ph.D. Thesis, Dept of Chemical Engineering, University of Wisconsin-Madison, 1976.

Vivian J., Jobard X., Ben Hassine I., Pietrsuchka D., L. Hurink J.: Smart Control of a District Heating Network with High Share of Low Temperature Waste Heat. Proceedings of the 10th Conference on Sustainable Development of Energy, Water and Environment Systems. September 27 - October 2, 2017, Dubrovnik, Croatia

RANTZER J. ROBUST PRODUCTION PLANNING FOR DISTRICT HEATING NETWORKS. Master's thesis 2015:E43 Lund University

Francesca Verrilli, Seshadhri Srinivasan, Giovanni Gambino, Michele Canelli, Mikko Himanka, Carmen Del Vecchio, Maurizio Sasso, and Luigi Glielmo. Model Predictive Control-Based Optimal Operations of District Heating System With Thermal Energy Storage and Flexible Loads. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING 2015

John Rune Nielsen: *Two-step decision and optimisation model for centralised or decentralised thermal storage* in. DH&C. SP Swedish National Testing and Research Institute. Report 8DHC-05.02.

