D5.4 – Advanced controls in DHC networks

Renewable and Waste Heat Recovery for Competitive District Heating and Cooling Networks

REWARDHeat

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Nomenclature and abbreviations

5GDHC	Fifth-generation district heating and cooling
4GDH	Fourth-generation district heating
AI	Artificial intelligence
ANN	Artificial neural network
CHP	Combined heat and power
COP	Coefficient of performance
DC	District cooling
DH	District heating
DHC	District heating and cooling
DHW	Domestic hot water
DP	Dynamic programming
DR	Demand response
DSM	Demand-side management
DT	Decision trees
ERT	Extremely randomized trees
ETS	Energy transfer station
FDD	Fault detection and diagnosis
GA	Genetic algorithm
HP	Heat pump
HVAC	Heating ventilation and air conditioning
LP	Linear programming
LR	Linear regression
LTDH	Low-temperature district heating
MAPE	Mean absolute percentage error
MAS	Multi-agent system
MILP	Mixed integer linear programming
ML	Machine learning
MLR	Multiple linear regression
MPC	Model predictive control
NTDH	Neutral temperature district heating
PLS	Partial least square
PSO	Particle swarm optimization

PV	Photovoltaic
RBC	Rule-based controller
RF	Random forest
RNN	recurrent neural network
SARIMA	Seasonal autoregressive integrated moving average
SCADA	Supervisory control and data acquisition
SH	Space heating
SVM	Support vector machine
TES	Thermal energy storage
ULTDH	Ultra-low temperature district heating

1 Summary

In advanced district heating and cooling (DHC) systems, peak shaving, demand response, fault identification, pollution and cost containment are some of the key priorities to be reached. Challenges such as supply temperature reduction and load volatility can be overcome with the adoption of advanced algorithms and innovative tools that are entering the market to improve the operation of such infrastructures. Conventional methods of DH control and fault detection and diagnosis could be not able to meet these aims. Therefore, researchers have built dozens of ground-breaking approaches to overcome these shortcomings. This report contains a state-of-the-art review of both advanced control strategies as well as innovative fault detection and diagnosis encountered in the literature or developed in some of the recent European research projects like STORM, OPTi, FLEXYNETS, TEMPO and RELaTED.

DHC is a fundamental technology to decarbonise the heat sector in urban areas. Moreover, it allows bringing renewable heat in the built environment or recovering excess heat from industrial processes, data centres and supermarkets that otherwise will be wasted. In some countries, like Denmark, DHC permits the utilization of excess renewable electricity available avoiding the curtailment of wind farms. The advancement of DHC technology is evolving in the direction of reducing the operating temperature of the network towards low-temperature DH and neutral temperature DHC systems. The latter are operated at a temperature close to the ground, include decentralised heat pumps at the building level and can cover simultaneously heating and cooling loads. From the literature emerges that these innovative layouts are growing and that some new technology like shunt systems for supply temperature reduction have appeared in the market recently.

DHC systems are demand-driven, thus load forecasting or the implementation of demand-side management strategies are needed to improve the operation of the system. This can be done by exploiting thermal energy storage (TES) systems for peak shaving or introducing some mechanisms to shift the demand from peak to off-peak hours. Demand response, widely applied in power grids, is appearing in DHC research. However, this is not so easy to apply since it requires controlling directly the user substation or the introduction of dynamic tariffs. On the supply side, advanced control technologies can be implemented for the operation of complex production plants or for the introduction of renewable sources. Model predictive control in the form of mixed-integer linear programming is one of the most encountered cutting-edge solutions for this. Nevertheless, some innovative approaches based on meta-heuristic optimization algorithms are also growing in interest. Moreover, coordinating mechanisms based on game theory and agent-based control have found applications in decentralized systems like neutral temperature DHC.

As far as fault detection and diagnosis (FDD) is concerned, both hardware and software solutions have been encountered for leakage detection, diagnostic of malfunctioning in substations due to fouling or actuators instability. Among the software solutions, the application of machine learning models is growing in contraposition to physical model-based solutions. The same applies in load forecasting where different data-driven models are emerging and, in some cases, outperform common statistic models. One of the main outcomes of this work is the review of the digital platforms and tools that are available in the market. The capabilities analysed show that some companies provide very complete solutions covering all the aspects for advanced control and fault detection whereas others offer very powerful tools for single features like unit commitment, network planning and what-if scenarios analysis. However, from companies acquisition and new startups born, it is evident that the digitalization of DHC is a growing market.

2 Introduction

The goal of this report is to review recent publications and material from different research projects that provide implementations of both hard and soft computing of advanced control or fault detection for district heating and cooling (DHC) with some applications related to low and neutral temperature networks. The idea is to create common knowledge by comparing approaches and results and assessing their pros and cons. The main content is derived from an earlier version published as [1].

The world's rate of urbanization is anticipated to grow from around 55% in 2018 to 68% in 2050 [2]. In Europe, 74% of the population now lives in urban areas, and this figure is expected to grow by up to 84% by 2050 [2]. In comparison, a colossal amount of low-grade excess heat is lost in urban areas where the heating and cooling demand shows the maximum density and simultaneity. Moreover, cities and towns have been born around rivers, lakes and seasides for historical reasons. These are reservoirs of ambient heat of which usage is highly replicable since it is accessible right where it is required. In some cases, as in London [3], the total heat lost from secondary sources has been calculated to be greater than the total demand for heat in the region.

Several public authorities have recognised the climate crisis in recent years and will take serious steps to mitigate the impact of global warming. As a consequence, 2019 has been described as the year of the "climate emergency" declaration. In this context, the European Union, which has already shown between 1990 and 2018 that gross domestic product (GDP) growth can be decoupled from greenhouse gas emissions [4], has set a very ambitious target for achieving carbon neutrality by 2050. Moreover, the European Commission acknowledged that the existing obligations under the Paris Agreement, which envisaged a complete reduction in greenhouse gas emissions by just 40 percent in 2030 relative to 1990 levels, might not allow achieving this objective. In order to accelerate the global warming battle mechanism, the latest European Green Deal [5] plans to set a more ambitious goal to achieve a 50-55% cut in greenhouse gas emissions by 2030 by dedicated policies for various industries. In particular, the European Green Deal Investment Plan will help the introduction of district heating and cooling (DHC) networks [6] to decarbonize the heating and cooling market and to boost air quality in urban areas. This technology is the most promising way to apply the concepts of circular economy in the heat sector by capturing and sharing local surplus heat that would otherwise be wasted. In addition, it makes it easier to expand the proportion of current renewables to meet the heat demand of homes, which in 2017 was just around 13.6% worldwide [7].

As part of the H2020 project STORM [8], the Digital Roadmap for District Heating and Cooling (2019) [9] carefully presents how digitalization and the principle of Industry4.0 will move the performance and service of DHC networks forward, enabling their role in an interconnected smart energy system. The challenges found that could obstruct the introduction of digital technology in DHC are not technological but are primarily related to restrictions on the operation of the building substation, the absence of business models or dynamic tariffs to stimulate the flexibility of the demand and private data protection regulations.

Advanced control strategies and solutions for fault detection and diagnosis that are relevant to achieve smart and robust DHC systems in the near future are discussed in sections 4 and 0, respectively, with an emphasis on novel applications in low and neutral temperature DHC systems. At the end of both sections, the positive and negative aspects of the various methods found are discussed.

3 DHC as an enabler for greater renewable sources penetration

Heat/cold generation units, pipelines, and consumer substations are all subsystems of a DHC network. Although renewable energy sources for electricity generation, such as solar and wind, have made tremendous strides in recent decades, this is not true for the generation of renewable thermal energy. Despite the technology is advanced, only a few nations, such as Denmark, Sweden and Lithuania [10], have now achieved a substantial share of the production of renewable thermal energy in DHC systems thanks to their ambitious decarbonisation policies.

DHC is the key solution for the scale-up of renewable thermal energy supply in urban areas. On the one hand, due to economies of scale and, on the other hand, by addressing challenges such as the lack of space in urban areas or the protection of architectural heritage. Moreover, it introduces the possibilities of using a multitude of fuels that may change in the years for several reasons like new environmental policies, taxation and technological improvement. DH occupies nearly 12% of the heating market share in Europe [11], and DC covers just 2% of the cooling market share [12]. Worldwide, about 6% of the thermal energy supplied is provided by district energy systems and is heavily dependent on fossil fuels. In fact, only 8% of the energy sources used in DHC were reliant on renewables in 2018, with 95% of this consisting of biomass [10]. This high share confirms that biomass is the most competitive source in many countries for the supply of sustainable heat via DHC systems. Moreover, since the management of the heat generation plant is very close to a standard dispatchable fossil-based one, it is simple to introduce. Biomass plants may be derived from the upgrade of existing coal-fired boilers or with the integration of a gasification process and, in some situations, are paired with combined heat and power (CHP) systems such as organic Rankine cycles (ORC) or internal combustion engine (ICE) plants.

The years between 2020 and 2030 have been described as the 'Geothermal Decade'[13], as geothermal energy extraction in Europe for both electricity production and direct/indirect usage is projected to rise significantly. Even if the location of high enthalpy geothermal reservoirs is geographically limited, there is a greater diffusion of medium enthalpy energy. According to the findings of the GeoDH research project [14], deep geothermal energy for direct use of DH could satisfy the heating demand of around 25 percent of the European population. In this respect, Iceland is the leading country in geothermal DH installed power. Significant market growth for geothermal DH is expected for the coming years, especially in France, Germany, Denmark, the Netherlands and Hungary [13]. Dispatchable baseload power is provided by deep geothermal for direct use in DH, achieving significant equivalent full-load hours. Shallow geothermal can be used almost everywhere, however, to increase the supply temperature requires centralized or localized heat pumps.

Solar thermal has tremendous potential for DH use, but differently from geothermal and biomass, may need more effort on control, which can be helped with forecasting tools for both heat demand and non-programmable solar heat generation. Denmark is the pioneering country in solar district heating (SDH) and the global leader in large-scale solar thermal fields, reaching 1.1 GWth of installed capacity (almost equal to the country's installed PV capacity) in the first half of 2019 [15]. This was possible thanks to the competitive price of solar thermal heat with regard to gas (affected by strong taxes), high penetration and sound experience of DH networks, low land prices and the possibility of the DH community-owned firms to operate as non-profit organizations. According to Danish experience [16], the average solar collector field efficiency is approximately 40% and the cost of heat generation varies from EUR 20 to 40 per MWh. In DH systems, 20 percent of solar fraction over the total thermal energy supplied can be accomplished without thermal energy storage (TES) installation, whereas a greater solar fraction can be achieved with seasonal TES.

Water pit and borehole seasonal TES systems, among the various technologies, result in the most used in combination with SDH. In addition, the installation of the seasonal TES system paves the way for greater stability in heat generation and the introduction of large-scale heat pumps to increase the efficiency of the overall SDH system [17].

Thanks to DHC systems, further penetration of non-programmable renewable power generation can also be accomplished as excess electricity produced can be used directly or stored in the form of heat or cold in TES systems, preventing PV and wind output from being curtailed. In addition, sector coupling, by means of power-to-heat technologies such as electric boilers and heat pumps, enables remunerative power grid balancing services such as frequency control. Finally, an important aspect is that traditional high-temperature DH systems and neutral temperature systems are conceived differently, opposing centralised with decentralised energy conversion systems [18]. Thus, in several cases, they exploit different control strategies that are presented in the next sections.

4 State-of-the-art control strategies for district heating (DH) and district cooling (DC) systems

4.1 Control strategies in traditional DH/DC systems

In a conventional DH network, as seen in Figure 1 and described below, six separate simple control strategies operate simultaneously. These are typically applied in the form of rule-based or PID control. According to [19], at the output and pumping station level, those techniques listed below from A to E are applied, whereas at the consumer substation level only the control technique F is implemented:

A. Supply temperature regulation: the purpose of this control is to modulate the thermal production plant to achieve a specified supply temperature at the supply pipeline. The setpoint is usually calculated by means of a heating curve as a function of the external ambient temperature and is high enough to achieve the minimum temperature needed for all the customers;

B. Minimum supply temperature control: this control is important, particularly in summer, when the DH system operates such that only the DHW load is supplied. For example, a by-pass between the supply and return pipelines at the end of the network during the night enables a slight recirculation to be retained such that the supply temperature still satisfies the level of comfort for the users;

C. Regulation of the minimum differential pressure: the minimum differential pressure between the supply and return pipes must be established at the farthest substation from the pumping station in the network. In this way, it is ensured that the pressure head is adequate to supply all the intermediate substations;

D. Maximum pressure control: the pumps are controlled to prevent the supply pipelines from over-pressuring, which could disrupt the network;

E. Minimum pressure control: the minimum network pressure that occurs at the suction of the pumps is managed to prevent component cavitation and damage;

F. Heat demand and flow management: at the consumer substation level, these control techniques are applied. A climatic regulation, for example, may be applied to set the supply temperature on the secondary side of the substation. Then a modulating valve is used to achieve this set-point by adjusting the flow rate on the primary side of the substation.

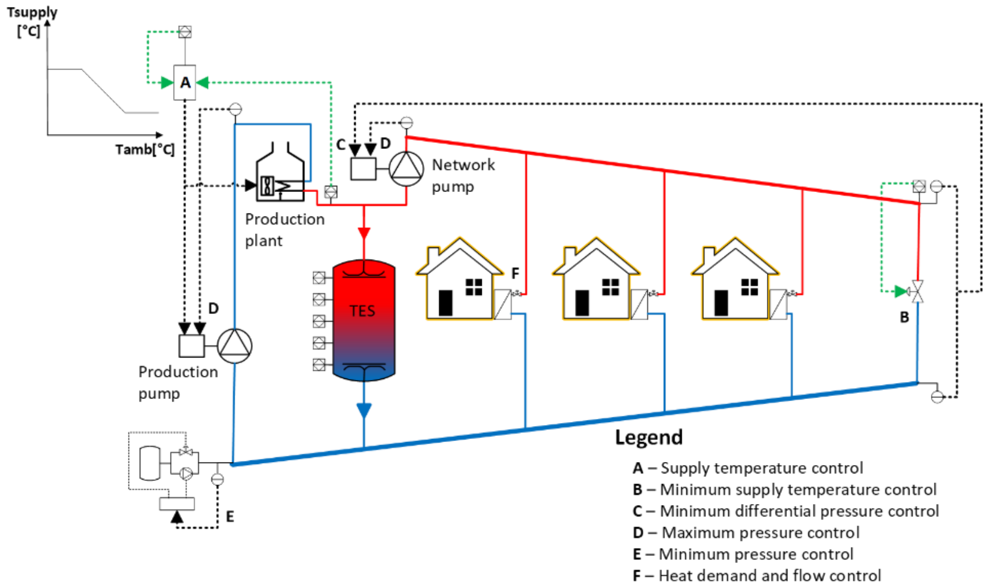


Figure 1 - Layout and basic control strategies applied in traditional DH systems.

Thermal energy storage (TES) systems based on short-term tanks in conventional DH/DC networks have many advantages. They make it possible to equalize the load of the heat production plants even if the heat demand fluctuates and to cover peak demand avoiding switching on peak generation units at high running costs. In addition, TES systems make it possible to run the system when the heat demand is below the technological minimum of the heat-generating plants and to improve the versatility of the combined heat and power (CHP) systems by allowing the production of electricity during off-peak heat load hours without wasting the heat generated. To measure temperature stratification and state of charge, multiple temperature meters are usually mounted along with the height of a TES tank. In order to take advantage of the TES capacity directly connected to the DH network, as seen in Figure 1, there is a need for a few additional control measures: the charging and discharge phases are triggered automatically by producing the necessary amount of positive/negative differential pressure at the TES connections at the supply and return DH pipelines by properly regulating the network and production pumps. In addition, a regulation to restrict the minimum temperature at the top during discharge and the maximum temperature at the bottom during charge will typically be useful to prevent the destruction of the thermocline. Also true for DC systems are the same control methods seen in this section for conventional DH applications. DC systems usually work with a lower temperature difference concerning DH between delivery and return, resulting in higher flow rates and pumping energy usage to supply the same thermal capacity. However, to take advantage of the versatility offered by the TES system and to improve the operational management of the production units in both DH/DC systems, heat/cold load forecasting strategies, presented in section 4.2, are required.

4.1.1 Control strategies in low temperature and neutral temperature district heating systems

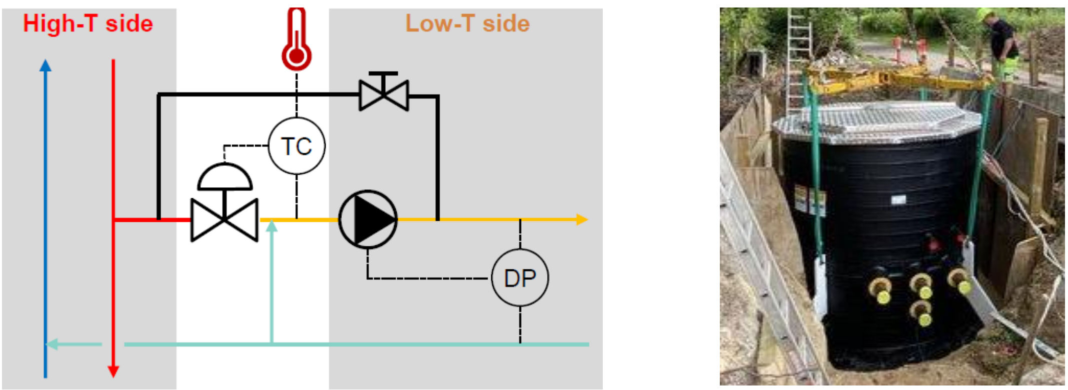
In low-temperature district heating (LTDH) systems, the simple control techniques seen in the previous section are typically implemented as well. LTDH usually have a supply temperature of 50-

60 °C, while if it is lower (like 30–40 °C) as in ultra-low temperature district heating (ULTDH), small booster heat pumps (HPs) are required at the customer-sited substation to meet minimum DHW comfort temperature and restrict legionella proliferation.

The problem facing the existing high-temperature district heating (HTDH) systems in the transition to LTDH is to reduce the temperature of the supply. This is done largely by zoning the DH network, establishing a high-temperature backbone, and low-temperature sub-networks in certain districts with new or refurbished houses. In this respect, in the H2020 TEMPO project [20], a prototype of a mixing shunt device was built in the DH network of Brescia (Italy). Similarly, in the scope of the REWARDHeat, an innovative solution that entered the market has recently been installed in the DH network of Albertslund (Denmark), as seen in Figure 2. The minimum supply temperature and minimum differential pressure controls are normally used in these shunt systems and may unlock the ability of the subnetwork to absorb local peak loads according to a dynamic heat storage strategy. Some advantages of lowering the temperature of the network supply are:

- reducing transmission heat losses as the return temperature decreases;
- growing of the power transmission capacity of the DH network due to the greater temperature difference between the backbone supply and return. The current grid would allow the connection to more customers and a lower flow rate would be required to provide the same thermal capacity;
- a longer life-time of some DH components due to the lower operating temperature;
- increased performance due to the lower return temperature in condensing boilers, CHP plants, HPs and solar thermal systems.

Nevertheless, it is necessary to reduce the return temperature of the subnetwork by intervening on the substation and heating system of the consumer to optimize these advantages. In addition to replacing such critical radiators with high panels or expanding the heat emission surface, it may be beneficial to mitigate the impact of high flow speeds, such as due to night set back control, with regulation using thermostatic radiator valves (TRV) and temperature return sensor [21].



(a) (b)

Figure 2 - (a) P&I diagram of the mixing station installed at the DH system of Brescia [20]; (b) Shunt system installed in the DHC system of Albertslund.

Basic control strategies may vary in neutral-temperature (NTDHC) systems from conventional HTDH and LTDH, since they are conceived according to a decentralised approach. NTDHC networks, which normally run at a network temperature of 0-30 °C, require always heat pumps (HPs) at the customer-located energy transfer station that are responsible for meeting the appropriate supply temperature for heating/cooling. For this purpose, supply temperature control is not typically carried out at a centralized level and most networks work at free-floating temperatures as a result of the year-round equilibrium of heating and cooling loads and the heat source/sink [18]. In certain situations, minimum supply temperature protection is applied to minimize the possibility of extremely low temperatures and the subsequent freezing of the pipes by means of back-up systems. Differential pressure management is typically only present where centralised pumping stations are used and, in some situations when the HPs are isolated from the thermal grid by redundant heat exchangers. Differential pressure control is absent in other situations, as in small loops where localized hydraulic pumps are mounted at the level of the substation.

Remote smart metering is a mature technology and is an important element in improving the operation of both LTDH and NTDHC systems, such as implementing peak shaving demand response (DR) strategies as described in section 4.4 and faults detection in substations as described in section 5.3. Nevertheless, some obstacles to this are still to be overcome, such as the lack of trust between DHC operators and users, as well as additional services like substation maintenance to be provided by DHC companies [22].

4.2 Heat load forecasting

The DH load must be supplied quite fast to meet the comfort of the consumers, with the result that DHC systems are typically demand-driven. Because the heat load of the whole network is the aggregation of the heat demand of every single building plus the thermal losses of the network, it is affected by less variability with respect to the heating/cooling demand of a single building. It is, however, marked by a seasonal variation, a weekly variation and a daily variation between workdays and weekends. For example, the regular and weekly variations of the heat load of a DH system located in Northern Italy during the winter season over two consecutive weeks are shown in Figure 3. Both patterns are a product of collective social behaviour, such as harmonized working hours, resulting in a lower heat load than one of the weekend days over the weekdays. Two peaks describe the daily load variation: one in the morning and one in the afternoon. The night setback control used to cover the need for space heating (SH) may be the cause of the fact that the morning peak is higher than the afternoon one. This might occur since the heating system is turned on almost simultaneously in many buildings or with a time-clock operation a lower room temperature setpoint is set during the night.

Recent advances in the DH load forecast have been investigated and tested in two recent closed EU H2020 projects: STORM [23] and OPTi [24]. Different techniques from simple linear regression to machine learning (ML) algorithms have been investigated and applied to the demo case of Rottne (peak capacity of about 2.5 MW) in the framework of the STORM project. The results show that monitored historical data is not always the best option to develop such models. For instance, the weather forecast could tend in overestimating the outdoor temperature with respect to the measured one in a location [25], therefore since the weather forecast is then used as input for making predictions, it is important to use historical weather forecast data to build data-driven models to forecast the DH/DC loads. A feed-forward neural network with a single hidden layer slightly outperforms an extremely randomized trees model in Johansson et al. (2017) [25] with online periodic training and day ahead forecast once per day achieving the lowest mean absolute percentage error (MAPE) equal to 6.84% over one month. In [26], the same authors presented a different strategy by assessing on the same training and testing dataset of 27 months the performance of different eight data-driven models, based on linear regression (LR), extremely randomized trees (ERT) regression, feed-forward deep ANN (with two hidden layers, each with 12 neurons and the ReLu activation function) and support vector machine (SVM), and developing an expert advice prediction tool that can track the best of these different data-driven models. The results showed that ANNs and ETRs are slightly better than the SVMs achieving a MAPE of about 11.6%, 12.4%, and 14.7%, respectively, whereas the one based on LR is the worst model with a MAPE of 17.3% over a test period of seven months. The expert prediction system tracks very closely the ANN model, but it results to be more robust and accurate in the load prediction during the mid-season period. To set the best hyper-parameter of these models in this work, the authors used an exhaustive search over specified values, whereas in the following paper [27] they used the Tree-Structured Parzen Estimator that is a Bayesian optimization algorithm. Assessing almost the same models on the same dataset, it results that all the models improved a lot their performance, but the best one is still the deep ANN that achieved a MAPE of 8.08%. Considering the assessment of the same models on the DH network in Karlshamn (peak capacity of about 50-60 MW) that is much larger than the one in Rottne, the performance of all the models improves, and the MAPE is more or less reduced by half.

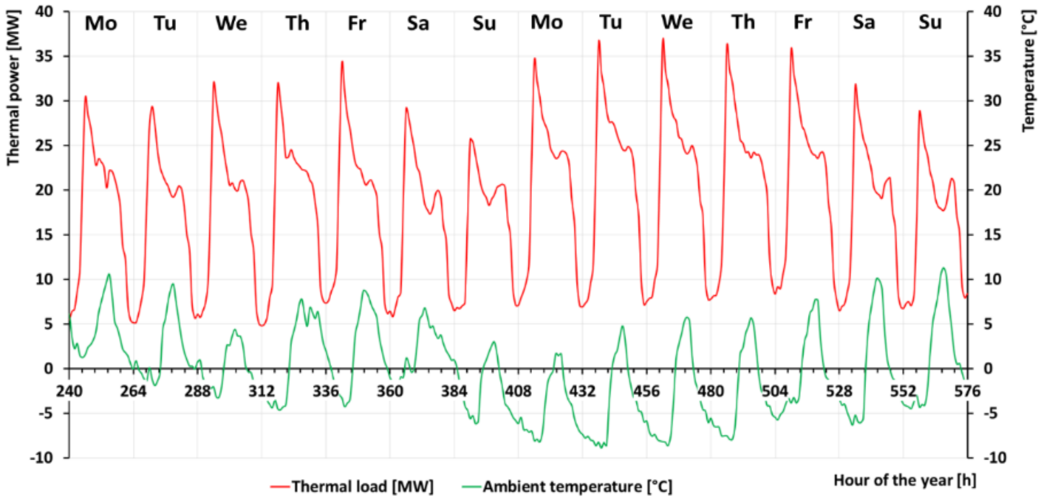


Figure 3 - Heat load of a DH system located in Northern Italy for two consecutive weeks from 10th to 24th January 2016.

In the framework of the OPTi project [24], ML-based black-box models (random forest) to forecast the load of buildings connected to the DH system of Luleå (Sweden) have been studied in [28] whereas grey-box models have been developed in [29]. SVM, Multiple linear regression (MLR), and feed-forward ANN performed similarly and better than regression trees in Idowu et al. (2016) [30] where on average worse results have been obtained in forecasting loads of commercial buildings with respect to residential ones using these black-box ML models. Dalipi et al. (2016) [31] achieved better results using SVM for hourly load forecasting concerning Partial Least Square (PLS) and random forest (RF). The mean absolute percentage error (MAPE) over the testing dataset of one week achieved with SVM was 3.43%. In [32] an adaptive neuro-fuzzy inferences system (ANFIS) has been developed using only previous values of thermal load, whereas a different approach has been adopted in [33] where it has been demonstrated that a feature fusion long short-term memory (FFLSTM) deep neural network model outperforms seven different ML state-of-art models. Regarding the load forecast in district cooling (DC) systems, Kato et al. (2008) [34] demonstrated the improvement achieved using a recurrent neural network (RNN) with respect to a three-layered neural network (TLNN) at the expenses of a slightly higher processing time. The RNN architecture employs the sigmoid activation function in both inner and output layers and the 33 inputs consist of the previous 24h values of the cooling load, day of the week, and daily minimum and maximum forecasted ambient temperature.

In the past, statistical time series forecasting methods have been also successfully applied to DHC systems. For instance, statistical and physical models have been combined in Nielsen and Madsen (2006) [35] according to a grey-box approach. Auto-regressive models with exogenous inputs (ARX) has been used by Saarinen (2008) [36], whereas a seasonal autoregressive integrated moving average (SARIMA) model have been developed in Grosswindhager et al. (2011) [37], and incorporated into a state space framework where on-line load forecasting is obtained exploiting a Kalman filter. Another solution has been adopted by Chramcov (2010) [38], which applied the Box-Jenkins method to model the stochastic behaviour of the social component of a DH load and a cubic function for the outdoor temperature-dependent component.

At the substation level, a linear regression algorithm is proposed in [39], to disaggregate the SH and DHW parts from the total load to be used for forecasting purposes in the framework of the H2020 RELaTED project [40]. However, this model performed worse than an ensemble of decision trees (DT) model. Similarly, a compact black-box model of the building based on a linear system has been developed in Guelpa et al. (2019) [41]. The latter uses as inputs the predicted average temperature of the day, the average, the minimum and maximum temperature of the previous day and it is able to provide as outputs the peak and steady-state load and the peak duration. The building model has been integrated with the physical models of the distribution and transmission DH networks in a multi-level approach to assessing the effect of demand response application on the aggregated load with a high time resolution. For an exhaustive review of models and approaches for district load forecasting, the reader is referred to [42].

4.3 Advanced control strategies in DHC application

Since smart DHC grids are getting more complex than ever due to the utilization of non-programmable renewable thermal energy sources and sector-coupling with the electrical grid, conventional solutions are not adequate to overcome these problems, even though they are robust. Smart control strategies are of paramount significance at centralized and decentralized levels and need to be implemented on top of the simple control strategies outlined in sections 4.1 and 4.1.1. These solutions allow overcoming challenges such as weather variability, user actions, substations operation and attempt to achieve good system performance meeting the system's constraints. According to the literature review performed, two main advanced control approaches are emerging. The first refers to the application of direct centralised control, whereas the second can be identified as indirect decentralised control. The difference between them is that in the first case a high-level entity like the DH operator, has the capacity to control all the production units and when possible to manipulate also the user substations, implementing very complex control algorithms at centralized level with a large number of signals. The indirect decentralized approach instead is based on the possibility of the high-level entity to influence the operation of the decentralised units indirectly, e.g. by manipulating the energy prices. The main implementation of direct centralised control is the application of Model predictive control (MPC) to solve a unit commitment (UC) problem, whereas the application of indirect decentralised control, which is quite rare, is based on multi-agent based modelling. The different solutions for these two approaches encountered in recent publications are reviewed in the following section.

4.3.1 Model predictive control (MPC)

Model predictive control (MPC) has been a high-tech approach to many dynamic control problems in recent years. It has attracted the attention of research communities in various fields, particularly in the DHC market. MPC is based on a predictive mechanism that takes advantage of a dynamic model of the system (surrogate model shown in Figure 4) and allows finding the vector of the manipulate inputs **u**(t) over a time horizon by solving an on-line constrained optimization problem.

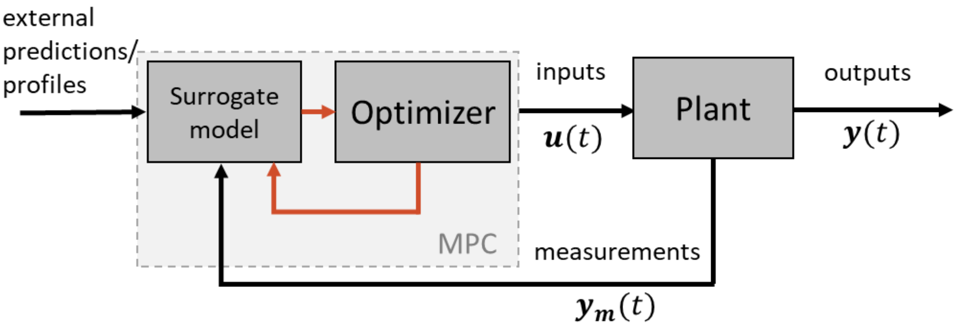


Figure 4 – Block diagram for the model predictive control (MPC) implementation.

The on-line constrained optimization problem is implemented to minimise a cost function in a receding horizon fashion. This methodology consists of a time window that moves forward by one time-step at each control timestep t according to the schematic shown in Figure 5. The length N of this time window is constant and called prediction horizon. It represents the future time interval in which the outputs of the model (**y**(t)) are forecasted according to the trajectory of inputs received (**u**(t)). Only the first element (u_0*) of the optimal input trajectory provided by the optimization algorithm is sent to the plant whereas the rest of the input trajectory is discarded. The optimization process restarts again at the next control timestep after updating the state of the surrogate model with monitored data.

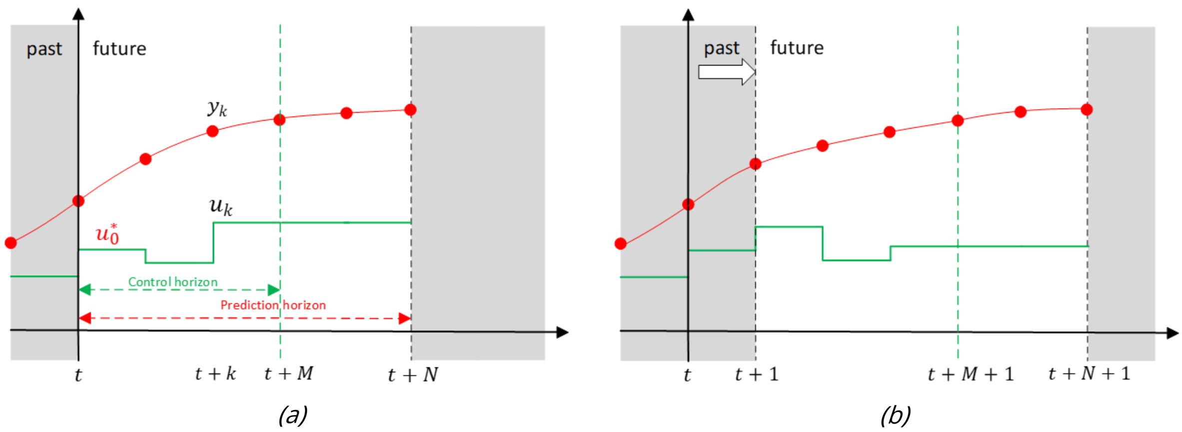


*Figure 5 - Receding horizon principle: inputs (**u**) and outputs (**y**) trajectories over the prediction horizon at the current control timestep t (a) and at the next control timestep t+1 (b).*

An MPC controller based on dynamic programming (DP) optimization algorithm has been presented in Saletti et al. (2020) [43] to supply thermal energy to a school complex located in Northern Italy. Results show a decrease in natural gas consumption of the boiler up to more than 7% in comparison with a standard PID controller. In De Lorenzi et al. (2020) [44], the same tool and approach are applied in different case studies. The comprehensive smart control strategy consists of pledges efficient energy distribution, flexibility, and low-carbon energy integration.

Achievements are a 6% reduction in operating cost and up to 34% in energy consumption, whereas meeting consumers' needs. Moreover, MPC has been applied in Verrilli et al. (2017) [45] by scheduling boilers, TES units, and flexible loads. Results show that the MPC succeeded in reducing operating and maintenance costs in a DH power plant. This methodology integrated projection on fluctuating demand within the optimization problem and answered it in a receding horizon fashion. Labid et al. (2014) [46] developed an MPC to improve the thermal storage tank management in a multi-energy district boiler. The results revealed that the controller reduced fossil energy consumption and CO2 emissions while the economic profit increased. A model predictive control (MPC) introduced in Lennermo et al. (2019) [47] has been applied to decentralised solar thermal collectors (STC) fields connected to a DH network in the return-supply configuration. The authors showed that the MPC implementation in the real SDH system in Lerum (Sweden) operated in a robust way solving the problems of the previous PID controller that was not capable of limiting severe supply temperature and flow rate cycling variations that can be a cause of fatigue problems in buried steel pipes.

Sometimes for covering the disadvantages of MPC and obtaining the best performance and result, MPC has been merged with other methods. For example, to control the supply temperature in the DH network, authors in Grosswindhager et al. (2013) [48] used the combination of the MPC and fuzzy direct matrix control (FDMC). Findings confirm that FDMC can command the inherent nonlinearity in the acknowledgment characteristics of DH systems by considering the volume flow rate at the plant as a fuzzy variable. Also, the trade-off between pumping and heat loss costs can significantly impact minimizing operational costs. A tool named XEMS13 using MPC strategy has been introduced in Lazzeroni et al. (2019) [49] in order to optimise operational costs by considering technical and operational constraints. This tool is developed by the Energy Department of the Politecnico di Torino and LINKS. Different configurations with increasing cost-saving, installation costs, renewable energy source generation, and primary energy saving are presented, and results demonstrated the success of the method.

Linear Programming (LP) and Mixed Integer Linear Programming (MILP) are commonly used to individuate complex energy systems' best size or scheduling. A recent application of LP related to this scope for a 5GDHC system supplying several buildings of a university campus can be found in Wirtz et al (2020) [50] where the problem has been set up in Python and solved by means of the solver Gurobi. A MILP model for the design and operation of an urban energy system in the centre of England has been presented by Samsatli & Samsatli (2018) [51]. This model is based on a flexible value web framework for representing integrated networks of resources and technologies. It can be used for different temporal and spatial scales. Researchers in [52] have applied MILP to minimise the total annual cost for an industrial area located in the northeast of Italy with the integration of solar thermal production. Their results showed that the yearly total cost and primary energy consumption reduce 5% and 15%, respectively. In the framework of the H2020 FLEXYNETS project [53], to reduce the overall heat generation cost of a DH supplied by a large share of low-grade excess heat, Vivian et al. (2017) [54] indicates that the suggested MILP-based controller managed to reduce the system operational costs by 11% with respect to a standard rule-based control. Similarly, in Schütz et al. (2015) [55], the authors applied a MILP method to minimise the total costs. To this end, four different strategies for calculating temperature stratification inside thermal storage is performed. Procedures are tested with an operation scheduling use case that aims at minimizing operational costs by achieving a reduction of 6-7%. MILP has been applied in the work of Giraud et al (2017) [56] using the commercial solver CPLEX in a receding horizon fashion with a timestep of 15 minutes and a prediction horizon of 24 hours. Differently from other works here the optimal scheduling of the generation units assessed takes into consideration the effects on the DH network with the integration of a dynamic model in Modelica. The simultaneous optimization of DH production and distribution resulted in the use of the DH network as storage by increasing the supply temperature prior to a peak of the demand, reducing the differential pressure and avoiding the start-up of expensive peak units. In [57] a more complete overview of the results is provided by the authors showing that with respect to an empirical piling method, the production optimization only was capable to achieve 6.4% of savings on the production costs and no energy savings, whereas with both production and distribution optimization it was possible to obtain 8.3% of savings in production costs and 1.7% reduction in the energy consumption.

An adequate optimization algorithm depends on the problem formulation; likewise, how to formulate the problem depends on the optimization algorithm to use. In some cases, the execution time increases exponentially according to the problem dimensions and deterministic optimization algorithms cannot solve challenging and complicated issues. Meta-heuristic algorithms are a kind of random algorithm that are used to find an optimal response to this problem. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ants Colony Optimization (ACO) are some of the most used population-based meta-heuristic algorithms. Although these methods' performance and ability have been proved in many references, they have rarely been used directly in DH applications. For instance, a two-level optimization algorithm is proposed in Urbanucci et al. (2019) [58]. MILP formulation has plenty of pros for optimal operation problems while overcoming its disadvantages, GA is applied. In the case study, the cogeneration unit directly reaches 70% of both the thermal and electric yearly demand, whereas 16% of the subsequent is met by storage. Likewise, a hierarchical optimization strategy is used in Casisi et al. (2018) [59]. The higher layer for binary decision is dedicated to the genetic algorithm (GA), while the MILP algorithm is used in the lower to choose the system's optimal operation. Results show a remarkable reduction in computing time.

4.3.2 Agent-based control

The multi-agent system (MAS) approach benefits several critical computer applications such as communication network configuration, process control, planning or concurrent systems. MASs are formed by several agents that have a considerable number of communications with each other. In general, agents act to support the users and have different goals and motivations. An agent is defined as an autonomous entity that can be viewed as perceiving and acting upon its environment. An agent must be able to communicate with other agents. To interact successfully, agents must have the ability to cooperate, coordinate, and negotiate with each other, almost as people do. To improve the monitoring and control of a DH system using agent technology, Wernstedt & Davidsson (2002) [62] developed a MAS approach. In order to shave the peaks and prevent entering the boilers in the circuit, the authors of [63] have applied the MAS approach. Yielded results show that MAS was capable of decreasing the peak loads by up to 20%. In the same way, Lacroix et al. (2012) [64] used the MAS approach to control a compressed unit providing heating, ventilation, and domestic hot water production in a low-energy building. However, findings show that the suggested methodology managed to increase costs by only 2.5%, but they improve thermal comfort by 35%. MAS and PSO's combination is the main idea in Wang et al. (2012) [65]. The aim is to maximize the comfort index using minimum power consumption and the findings indicate the effectiveness of the proposed method.

The MAS approach has been recently applied to 5GDHC systems that enable the concept of decentralised prosumers for all the connected substations. In particular, in Bünning et al. (2018) [66] the performance of two 5GDHC systems located in San Francisco and Cologne exploiting an agent-based control have been assessed in comparison with a traditional gas-fired DH and individual chillers solution for space cooling. By exploiting the coordinated balancing effects of several decentralised prosumers with heat pumps and chillers, this control strategy was able to maintain the average temperature of the system within 2 K around the setpoint all year round showing that this approach is beneficial with respect to free-floating temperature control. Future technology could match blockchain with the MAS approach. Blockchain application in 5GDHC have been investigated in the framework of the D2Grid project [67] and is going to be demonstrated at the demo case of Paris-Saclay (France) [68]. The goal is to apply a new business model where smart contracts can be signed automatically and with the exploitation of dynamic energy tariffs to flatten the peaks in the heating and cooling demands by promoting flexibility and demand response (DR) strategies at the customer level. In this regard, an overview of DR applications in the DHC sector is presented in the next section.

4.4 Demand-side management (DSM) in DHC systems

Electrical/ thermal demand is mainly uncontrollable, and its quantity varies during the day and along the season. Accordingly, to flatten the load curve, system operators usually implement demand-side management (DSM) strategies that consist of a portfolio of practices aiming at modifying the demand side of an energy system by promoting information programs, energy efficiency, energy saving but also with the implementation of demand response (DR) programs. Peak-shaving and load management are two main applications of DR that add flexibility to an energy system by making the demand more elastic. In general, DR strategies are classified into price-based and incentive-based programs [69]. To the first group belong all the solutions that aim at influencing end-user choices with time-dependent tariffs like real-time pricing (RTP) or common time-of-use (TOU) tariffs. Differently, incentive-based programs are based on contractual agreements with grid operators or utility companies and foresee a reward to the customer for the reduction of their load upon request or with the direct remote control of some equipment. So far, DR has widely studied to shave the peaks in power grids and on pooling of individual air-source heat pumps-based heating ventilation and air conditioning (HVAC) systems. Recently, aggregation of the HP-based substations in the 5GDHC network of Wüstenrot has been analysed for the implementation of power-to-heat strategies in the context of the Sim4Blocks H2020 project [70]. In particular, heuristic optimization of HP operation for the maximization of PV electricity self-consumption and exploitation of flexible electricity tariffs have been mainly investigated in Brennenstuhl et al. (2019) [71], whereas cluster aggregation for power market participation like frequency restoration reserve (FRR) has been analysed in Romero Rodríguez et al. (2019) [72]. The latter showed how the requirement of a short activation period in the FRR market can be in contradiction with the minimum running time of the HPs for both technical and economic aspects.

As explained in section 2.3, the critical issue in DHC networks is the presence of peak requests, particularly in the morning. Here DR can play a vital role on the demand side to shave these peaks and avoid large investments in centralised TES systems. Thermal peak shaving using DR in a real test case of a distribution network of the Turin DH system is investigated in Guelpa et al. (2019) [73]. A genetic optimization algorithm has been adopted to select the binary values of on/off switching every 10 minutes with strong restrictions like maximum anticipation of 20 minutes and acting only on 32 out of the 104 buildings connected to the distribution network. The field results revealed a reduction of 5% of the global load. However, the authors demonstrated with a simulation activity that if the controller acts on all connected buildings and with maximum anticipation of 90 min, a peak reduction of up to 37% can be obtained. In a previous work [74], the same authors assessed the fact that modelling both supply and return pipelines provide a more precise assessment taking into consideration how the on/off switching of some substations could affect the delay in the temperature distribution to the farthest consumers. Moreover, Guelpa & Marincioni (2019) [75] proposed a simplified approach of DSM to shave the peak of DH substations by means of a modification in the proportional-integral control logic that regulate the flow rate on the primary side. A differential of return temperatures (DRT) control strategy is introduced and it aims at maintaining the temperature difference between the inlet of the secondary side and the outlet of the primary side below a threshold so that during the start-up the valve opens slower, the flow rate on the primary side is reduced and the efficiency of the heat exchanger is increased. Findings indicate that the achieved decline in the peak load of a distribution network supplying 62 buildings is equal to about 24% during a typical winter day.

An integrated demand-supply co-optimization methodology is presented in Romanchenko et al. (2019) [76] and applied to the DH system of Gothenburg (Sweden). The space heating demand in buildings is modelled with one thermal zone and the dispatch of heat production units and internal temperature set point variation in the buildings (only upwards) is obtained by mixed-integer linear programming in GAMS with hourly time resolution. The aim is to investigate the flexibility potential of DR exploiting the thermal mass of buildings for a DH network which characteristics and limitations have been here neglected. All suggested scenarios manage to shave the peaks achieving a reduction in on-off switching of the peak units up to 80%.

In the context of the H2020 project OPTi [77] some specifications for the implementation of automated DR in DHC system are provided in [78], whereas in the H2020 project E2District [79], the authors in Beder et al. (2019) [80], applied behaviour DR to the demo case of the CIT Bishopstown campus (Ireland). A couple of behavioural parameters such as action-regulation-theory, high-performance cycle, and planned behaviour theory have been embedded in their methodology and yielded results show that the proposed model can increase the energy-saving up to 4.5%. Cost-saving and emission reduction considering thermal comfort during DR programs have been investigated in Wu et al. (2020) [81] where also dedicated experimental tests using a thermal manikin to assess the effect of draught from cold windows have been performed. The MPC algorithm exploits the dynamic DH price model and included constraints to restrict the temperature of cold windows.

Sector-coupling between electrical and thermal grids is also possible by exploiting the presence of HPs and TES systems at the customer sited-station level and allowing their participation in more common electrical DR programs. In Knudsen & Petersen (2017) [82] a 4GDH application with ULTDH and a booster HP for DHW production is analysed. Peak shaving and energy-cost saving are the main goals of the suggested MPC strategy that has been implemented in the form of non-convex quadratic programming (QP) and solved with the optimization engine CPLEX. Similarly, in a 5GDHC application, an ANN-MPC algorithm has been developed in [83]. The binary version of PSO has been applied to minimise the user energy bill and the state change with different time-of-use (TOU) DR scenarios exploiting a composite ANN model of the integrated HP and TES systems. The results show that up to 14.2% of electricity consumption has been shifted from peak to off-peak hours.

4.5 Discussion

The implementation of advanced control strategies in DHC systems is challenging since they are affected by time-varying nonlinear dynamics, time-varying set-points and disturbances. Likewise, the implementation in HVAC systems, advanced control strategies applied in DHC can be classified as hard, soft, and hybrid control. In the following, some more details are provided about the hard and soft implementation of model predictive and agent-based control strategies highlighting their strengths and weaknesses. The focus by the authors on these two main approaches is motivated by a bibliographic study that shows the growing number of publications related to the application of these control approaches in DHC systems between 2010 and 2020. The bibliographic analysis, whose results are plotted in Figure 6, has been performed through the database Scopus considering both peer-reviewed and conference papers. It is also evident the growing number of works related to applications of neural networks whereas in very few cases robust control and reinforcement learning have been studied.

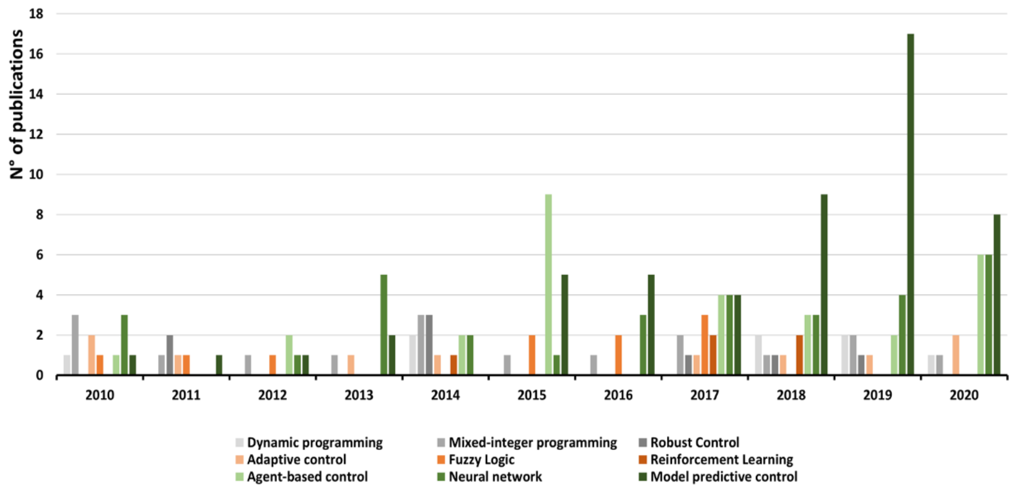


Figure 6 - Number of publications related to different advanced control methodologies for DHC systems between 2010-2020.

MPC can be considered a cutting-edge technology for improving the operation of DHC systems and its implementation has been presented in section 4.3.1. According to the scientific literature reviewed, in several cases the control problem is implemented in the form of economic MPC with the objective of minimization an operating cost function that can be formulated according to the following general expression for a generation system that supplies a DH network with CHP and boiler units:

$$\min \left\{ \begin{array}{c} \text{cost of heat production by fossil fired CHPs} \\ -\text{revenues from electricity production by CHPs} \\ +\text{cost of heat production by fossil fired boiler units} \\ +\text{cost for buying excess heat} \\ +\text{cost for electricity consumtion by auxiliaries} \end{array} \right\} \quad (1)$$

where constraints are foreseen for the minimum and maximum capacity of the units as well as their ramp-up rates. Auxiliaries can be for instance hydraulic pumps and the revenues from the electricity production by CHPs can include subsidies like in [55]. However, some variants of the above general formulation are possible according to the problem and the system analysed. For example, when low-temperature networks with decentralised heat pumps are present at the user substations like in [54], in the problem formulation there is also included the electricity costs for their consumption. In [45] since controllable loads are present, an additional cost is considered in the optimization problem for the curtailment of the flexible loads together with start-up and shut down costs of the boilers and TES charging. In a few cases, the effect of the DH supply temperature on the thermal energy loss through the pipes is taken into account like in [45] and [83]. In some cases, energy consumption minimization is the goal of the problem formulation like in [43] and [83] whereas application of minimization of CO_2 emission or non-renewable primary energy consumption has not been encountered. Moreover, formulations that may be relevant in real applications to take into account also the constraints on the electricity production allocated in the day-ahead electricity market the day before for the following one have not been encountered.

As a synthesis of the material examined in this study, the following strengths (+) and weaknesses (–) have been identified for the application of MPC:

(+) instead of corrective operations, it employs a proactive approach with anticipatory control actions;

(+) load forecast and stochastic disturbances can be handled;

(+) systems with delays and operational constraints are taken into account;

(+) multiple objectives can be formulated in a cost function and achieved by exploiting advanced optimization algorithms;

(+) it can be formulated in both centralised and distributed fashion but also at the master or slave level.

(–) time-consuming for the implementation and model identification phase;

(–) non-technical users require specific background knowledge of the method;

(–) require significant higher expenditures that may not be repaid by additional savings in a short period.

Among the different MPC formulation in DHC application, mixed-integer linear programming (MILP) resulted in one of the most used since it is able to handle both continuous and binary variables that are needed for set-points definition and on-off planning [50]-[52]. This hard-implementation sometimes called also hybrid MPC, which is characterised by [84]-[86]:

(+) good and exact optimal solution;

(+) rigorousness, flexibility and extensive modelling capability;

(–) time-consuming particularly for large problems;

(–) it is known to often have weak linear programming relaxations;

(–) loss of original discrete structure;

(–) introduction of auxiliary binary variables.

With the growth of artificial intelligence (AI) research field, the development of MPC with soft and hybrid control techniques are also appearing in DHC applications. In particular, black-box machine learning (ML) models are mainly used to cope with system non-linearities and meta-heuristic optimization algorithms are used to solve the constrained optimization problem. The latter are usually population-based biological-inspired algorithms and can be mainly distinguished by:

(+) straightforward in coding in any programming languages;

(+) very quick convergence;

(+) no need to do complicated mathematical operations since they are gradient-free;

(–) easy to drop into local optimum;

(–) possible stagnation after some initial stages;

(–) efficiency reduction with an increase in problem dimension.

Adaptive control is a technique that is also applied in some cases in DH. In particular, it emerges their application in controlling the supply [87] or the return [88] temperature from substation heat exchangers. It is a methodology that tries to overcome the problem of low performance of conventional feedback controllers during changes in the process dynamic. In fact, they foresee the self-adaptation of the control law to the changing conditions by means of the correction in the time-variant parameters. In [89], in the framework of the project OPTi, it has been demonstrated for the Luleå district heating system how the multi-input multioutput (MIMO) adaptive controller outperforms a standard multi-loop PID implementation, reducing the oscillations in the controlled variables that is a consequence of the different interaction of components like generation units, pumps, valves in substations that are present in DH systems.

Finally, conversely from traditional MPC, multi-agent systems (MAS) control can be considered a hierarchy-free solution where different entities interact e.g. as in a peer-to-peer market and operate without mandatory signals from a centralised higher-level controller. Even if they are not so widely applied in the DHC sector, some interest is appearing for the operation of decentralised active substations in 5GDHC with good results [65]. Nevertheless, for the MAS control approach, the following positive (+) and negative (–) aspects can be derived [90]-[91]:

(+) based on the goals, agents can act autonomously in their environment, which could be cooperative or competitive;

(+) decreased need for massive data manipulation;

(+) the other agents modify and continue the system functions if one of any controller loses;

(+) according to some rules, allow the manufacturers or loads to embed programmable agents in the equipment controllers;

(+) agents are able to learn from their behaviours and past activities;

(–) communication languages, protocols, and the design of agents' ontologies should be based on common standards;

(–) since plenty of multi-agent platforms have been developed, selecting the most appropriate is a tricky task;

(–) the design of an intelligent agent is challenging.

This section provided an overview of different approaches of advanced control encountered in the literature. The same has been done on fault detection and diagnosis algorithms in the next section.

5 Diagnostic and fault detection in district heating and cooling systems

It is evident that the exploitation of innovative district heating and cooling solutions, with substations that may be more complex including valves, pumps, heat exchangers and even heat pumps (HP) in neutral temperature district heating and cooling (NTDHC) systems, requires the whole system to operate as efficiently as possible [92]. However, [93]-[95] proved that those faults which take place during the energy systems' operation can be responsible for up to 40% of their total energy use. Several factors such as compensations actions triggered by the control algorithms, lack of correct maintenance, improper timing of the flow of energy to/from the buildings and production plants, etc, can make these faults remain unseen for long periods. Indeed, the manual identification of these faults gets very complicated even if the suboptimal operation of the system is known. This makes the tasks of human maintenance operators really costly since they only take actions on the system when indoor environmental thresholds are not met. In this context, automated fault detection and diagnosis (FDD) methods and tools play a key role to assist building and DHC system operators [96].

One typical operating problem in district heating systems indicated in [19] is the heat carrier loss through water leakage. Water losses are benchmarked by the number of water volume replacements that occur for one year, something that is defined as the annual volume of all make-up water added to the network divided by the network water volume at the end of the year. Water losses occur for several reasons and the corresponding magnitudes of losses also vary. A review of FDD methods to address this problem is presented in section 5.2. Other operating problems are higher temperature levels due to high return temperatures caused by typical malfunctions such as set-point errors in substations and customer heating systems, short-circuit flows in the heat grids and lower supply temperatures at high heat losses [19]. Since the reduction of the supply temperature is the main objective of LTDH and NTDHC in order to take advantage of renewable and low-grade excess heat, assuring a low return temperature is a key aspect in these systems [18].

In order to avoid malfunctions and faults, maintenance planning becomes crucial to achieve a good service for customers and maintain an economical retrofit for owners. The concept of maintenance includes the administration, control, implementation and quality of those activities which will ensure that design availability levels and asset performance are achieved in a reasonable way to meet economical and functional objectives. Some definitions of classic maintenance strategies that can be implanted in a building or individual equipment can be summarized as a brief reminder:

- corrective maintenance is performed to determine, separate, and fix a fault so that the failed equipment or facility can be brought back to an operational condition that lies within in-service operations tolerances;
- preventive maintenance is performed on a regular basis on a piece of equipment in order to reduce the probability of failure, and it involves a systematic check-up of equipment, thus enabling to detect and correct potential problems. The preventive maintenance can be scheduled on a time or usage basis;
- condition-based maintenance consists of a strategy that monitors the actual condition of an asset to deciding what maintenance needs to be done. It imposes that maintenance should only be performed when some indicators show marks of decreasing performance or imminent failure. Checking a machine for these indicators may include non-invasive measurements, visual inspection, performance data and scheduled tests. It differs from

preventive maintenance because the maintenance action relies on the actual condition of equipment, rather than average or expected life statistics;

- predictive maintenance is an extension of condition-based maintenance where precise techniques and formulas are used to detect incipient faults and predict their evolution, so the maintenance action can be scheduled before the critical failure in the equipment occurs. Predictive maintenance generally applies non-destructive testing technologies such as infrared, acoustic (partial discharge and airborne ultrasonic), corona detection, vibration analysis, current analysis, sound level measurements, oil analysis, and other specific online tests depending on the type of equipment or process being monitored;
- proactive maintenance sets corrective actions focused on failure root causes, not on failure symptoms, unlike predictive or preventive maintenance.

The following sections present a review of the state-of-the-art fault detection approaches and algorithms that are mainly applied in DHC systems. This overview is useful for the development of a complete automatic fault detection system in REWARDHeat which could be implemented in a predictive or proactive maintenance plan. Since most of the DHC networks include automatic meter reading for monthly billing of actual heat use, the tool can be based on those algorithms which use the most easily accessible variables such as those recorded by smart meters (temperatures and mass flow rates measured at the substations).

5.1 General approaches

Currently, there is a huge range of different fault detection technics. In [97], it is presented a diagram of the classification of the algorithms, reported in Figure 7.

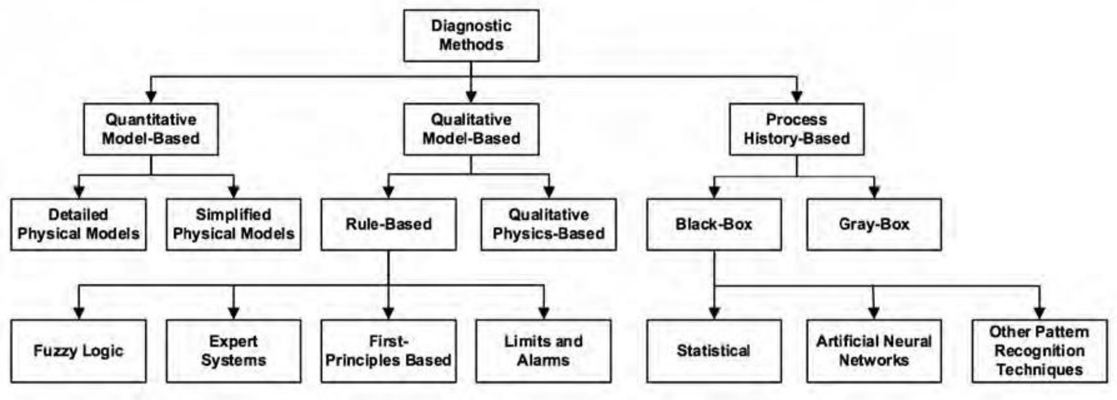


Figure 7 - Depiction of algorithm types [97].

Fault detection methods are divided into *model-based* or based purely on *process history data*, both of them are also called “internally based” methods. The *model-based* methods depend on knowledge of the basic physical processes and principles governing those system(s) being the target of the analysis. *Quantitative model-based* approaches are, currently, not frequently used in commercial tool offerings, however *qualitative model-based* approaches including rule-based fault detection have been largely applied to industrial environments and provide intuitive representations of engineering principles. The *process history-based* also referred as “data-driven FD” approaches do not rely upon knowledge of first principles but they rely upon data from the system in operation from which they may leverage some degree of engineering knowledge. These include statistical regression models, artificial neural networks (ANN), and other methods. Process history-based algorithms are increasingly being explored for use in commercial tool offerings.

Although the distinctions between these method types may become blurry (even to developers), automatic fault detection and diagnosis users may have interest in understanding whether a technology uses rules-based techniques versus newer data-driven approaches, or less commonly employed first principles – or a combination of several approaches. There also exist "externally based" or hardware methods used for fault detection [98], such as visual inspection, infrared image processing or cable methods. However, direct methods are not suitable to include in an automatic fault detection system.

In the following sections, a review of the state-of-art fault detection approaches and algorithms mainly applied in DHC systems is presented with a focus on leakage detection, fault detection in substations and diagnostics of sensors and actuators.

5.2 Leakage detection in DHC networks

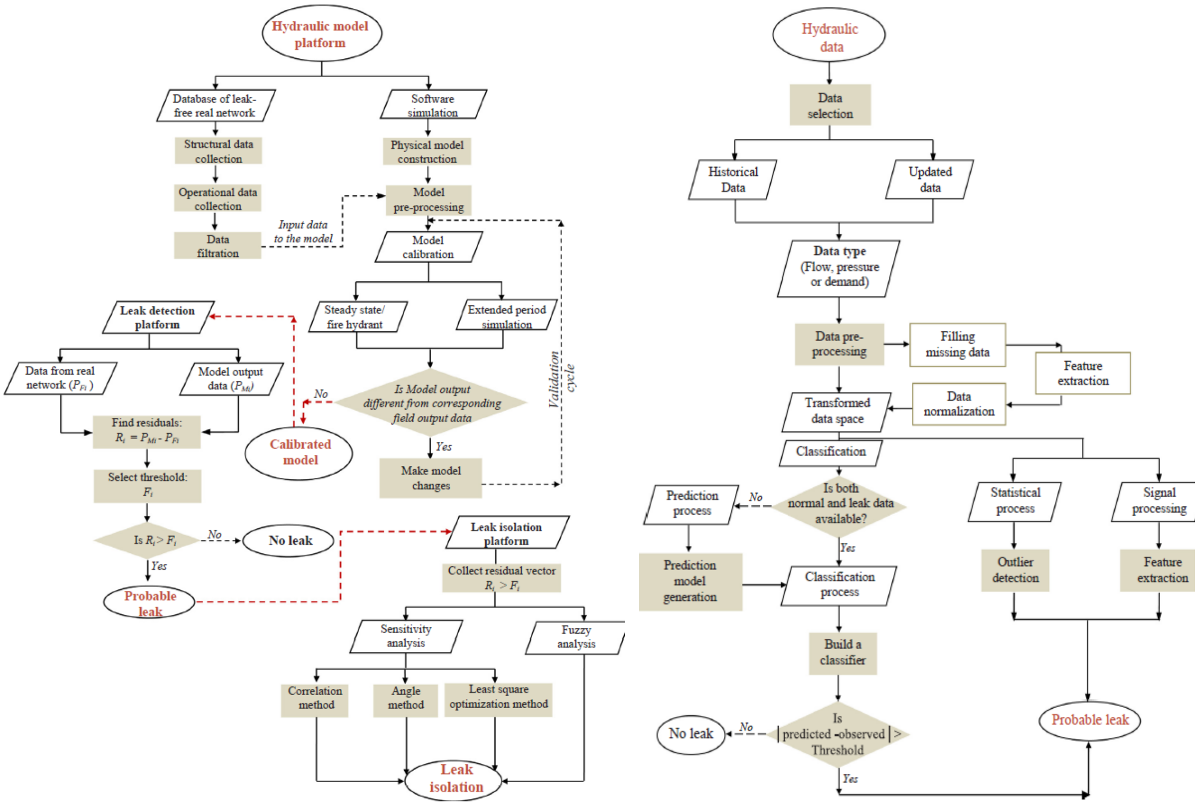
Failures on district heating pipes are often caused by water leaks due to corrosion, mechanical impacts and insufficient or deteriorated performance of the thermal insulation solutions, as indicated by [99]. However, some degree of leakages is impossible to avoid during extended operation since pipeline performance degrades over time. Therefore, an anticipated diagnosis of leakage occurrence is highly necessary in order to improve operational efficiency, reduce operating costs and protect the environment. In comparison with DHC networks, both oil/gas networks and water distribution networks have a longer industrial history. Thus, many established leak detection research results and applications were first applied to these systems. As mentioned above, those methods found in the literature are divided as "internally based" (or "software-based") and "externally based" (or "hardware-based"), as presented in the review of [100] for leakage detection in DHC networks. Some representative techniques developed for specific fluids (oil, gas or water), for different layout patterns, for several lengths of the pipeline as well as for a certain range of different operating conditions can be found in [101].

Zaman et al. [98] developed and compared "software based" solutions, both model-based and data-driven applied through a leakage detection algorithm. In Figure 8, a possible methodology to develop a leakage detection algorithm is shown by means of two flow charts, one for the physical model-based approach and the other for the data-driven approach.

A good example of a physical model-based algorithm is the work made by [102]. This model includes a dynamic monitoring module (DMM) and a static testing module (STM): the DMM can detect larger leakages of background ones analysing waves through amplitude propagation and attenuation models; the STM, based on the pressure loss model, can detect micro-leakages, thus being able to act as an effective compensation for the DMM.

As far as data-driven methods are concerned, an interesting application can be found in [103]. It consists of training a decision-tree-based ensemble machine learning (ML) algorithm called XGBoost using data generated by a simplified physical model and uses it to detect leakage in pipes through the collected data from pressure and flow sensors present in DHC network and substations. A potential obstacle to replicate this approach is the fact that pressure sensors are not always available in the facility.

Two interesting proprietary "hardware-based" solutions deserve mentioning. One of them has been developed by the smart meter brand Kamstrup and consists of a leakage detection system based on the analysis of the signal coming from ultrasonic flowmeter installed in substations [104]. The other one is based on the well-known impedance method using sensing cables located along distribution pipes. When a leak takes place, the cable gets saturated with fluid, thus altering its impedance [105]. The advantages include high accuracy in determining leak location and easy configuration and maintenance. In contrast, the installation has very high costs and wiring requirements.



(a) *(b)*

Figure 8 - Algorithm development methodologies: (a) physical model-based, (b) data-driven [98].

In the field of image processing, infrared (IR) sensors are able to capture variations in the heat flow caused by underground fluid leaks and show them as hot spots in the DHC system route. This process can be accomplished on the ground, but thanks to the availability of high thermal sensitivity and spatial resolution thermal imaging systems mounted on an aerial platform it has become more effective. For instance, data collection can be conducted by an aircraft or drone, which flies over the target area with a camera mounted to the airframe and oriented looking straight down to the ground. This way, thermography reveals sources of heat and the relative differences in heat from one object to another (Figure 9 and Figure 10).

In contrast, postprocessing IR images may be computationally expensive and their analysis could lead to false negatives because some colour differences caused by a leakage could be almost inappreciable. Some authors like [107] and [108] have developed ML algorithms to improve postprocessing and satisfactorily make the difference between true leakages and other potential causes.

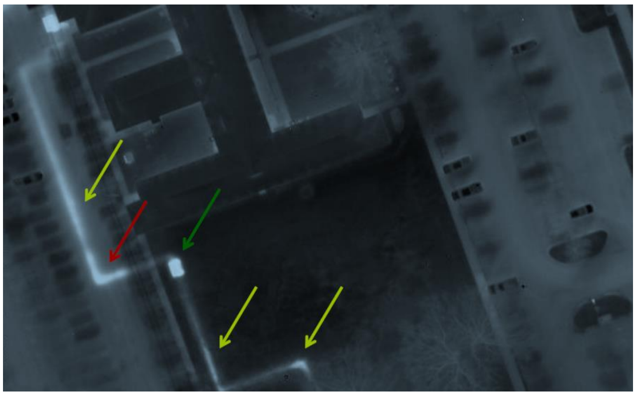


Figure 9 - Typical steam system heat losses [106].

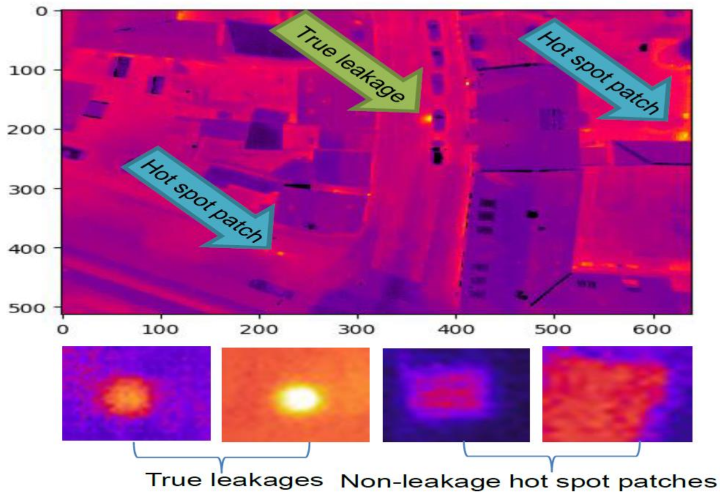


Figure 10 - 8-bit images from unmmaned aerial vehicle [107].

5.3 Fault detection in substations and customer facilities

Nowadays, a current preconceived idea considers that most of the end-use substations in district heating systems work well. This means that it is taken for granted that the facilities deliver or use exactly the right amount of energy to cover the customers' needs. [109] showed that this is not the case and almost three-quarters of the substations analysed presented faults or symptoms of faults which could lead to a higher return temperature. This fact is unacceptable especially in LTDH and NTDHC, where the key factor is the overall temperature reduction within the network.

In an analysis of the most common faults in DHC substations performed as part of the H2020 project TEMPO [20], a survey-based study by [110] found that the largest fault category was leakages (33%), closely followed by faults in the customers' internal heating systems (31%). This fact reveals that it might be difficult for the energy utilities to get access to faults present in the customers' facilities because the DHC operators are usually only allowed to access the substations and not the internal heating systems. Therefore, utilities must make important efforts to establish a good relationship with customers. Common ways to achieve that is to have maintenance contracts with the customers or to include free of charge inspections in the DHC agreement. In addition, a proper fault detection system must include customer-sited substations as the main element to analyse. This can be done by analysing the components of the substation individually, or/and looking at the customer heat load patterns. In the following sections, a literature review of FDD methods for different parts of customer-sited DHC stations is presented.

5.3.1 Heat Load patterns-based methods

The heat load in a DHC system is the sum of individual heat loads from all customer-sited substations connected to the network and the distribution heat losses. DHC heat generation plants might be affected by malfunctions in customer substations and buildings' HVAC systems which are propagated through the network. The operation of the HVAC systems varies depending on the buildings' end-use, so the resulting profile of the heating/cooling load will vary among the different types of buildings. [111] made a study of 141 different buildings and an example of the kind of data found is shown in Figure 11. First, they defined two indicators (annual relative daily variation and annual relative seasonal variation) and then used them to detect failures in the DHC substations based on high or low variation depending on the kind of building. Irregularities of the heat load pattern or no correlation between outdoor temperature and heat demand can also be used to detect that some part of the substation is not working properly.

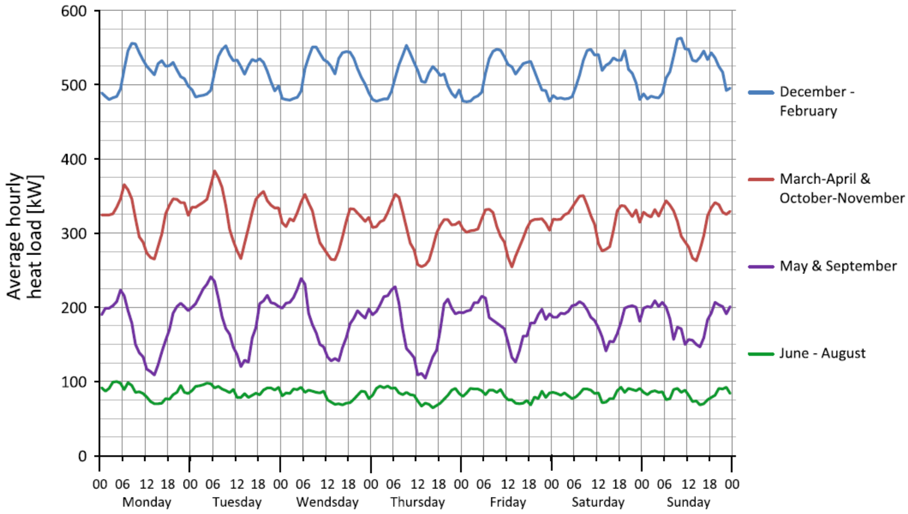


Figure 11 - Average weekly heat load patterns for continuous operation control during four season periods for multi-dwelling buildings [111].

The main challenge related to heat load patterns-based methods is how to deal with so different profiles for various types of customers or how to create reliable predictions of them. Concerning the first point, a data-driven approach enabling large-scale automatic analysis of DHC load patterns was developed by [112] using an initial dataset of 19,6 million hourly measurements. The algorithm applies clustering techniques to aggregate profiles of customers into different groups and extracts their representative behavioural patterns in terms of heat load. This allows owners to assign different control strategies to each cluster. But another advantage of this method is the fact that it detects unusual customers whose profiles deviate significantly from the rest of their group. These outliers can be analysed in depth in order to find problems in the corresponding substations or customer facilities. Figure 12 shows four examples of abnormal heat load profiles. The first building shows an increasing demand from Monday to Saturday and inconsistent daily variations where the reason was a mismatch between the real and design use for the building. The second chart shows an atypical behaviour with increased weekend loads in colder seasons. A possible reason is that the building is partially heated by excess heat from machines during the daytime on weekdays.

The third building exhibits sharp and irregular afternoon peaks which is difficult to interpret and may suppose a problem in the facility. Finally, the fourth chart is an example of seasonal abnormality where the summer load is higher than autumn or even some periods of Winter ones, which was caused by a fault in the substation of the customer.

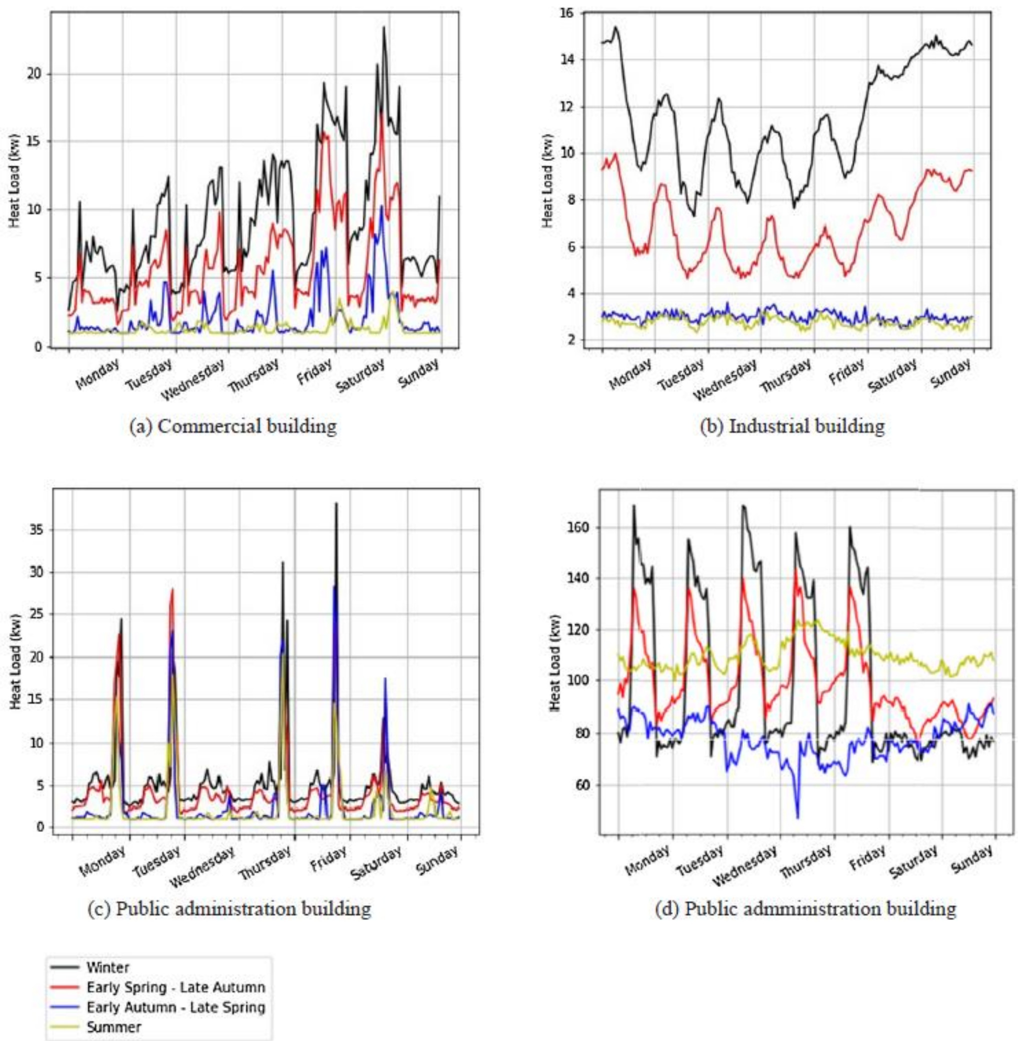


Figure 12 - Example of abnormal heat load profiles found by [112].

In the framework of the H2020 project RELaTED, two tools have been developed for automatic fault detection in DHC substations based on ML algorithms: DH doctor and DH Autotune [113]. The first one exploits clustering and it is based on daily averaged readings. Anomalies can be detected by measuring the distance among the clusters and following the evolution of the centroids related to a particular variable over time. Moreover, it exploits an ensemble of decision trees (DT) algorithm to make predictions that allow assessing deviations of a monitored variable. The second tool is based on hourly averaged readings and allows the prediction of the load, but also a fast reaction is triggered if abnormal behaviour occurs. Alarms are activated if some KPIs, like MAPE, exceeds a threshold. Further applications concerning the prediction of substation heat demand patterns through ML algorithms using the usual metering variables like flows and temperatures can be found in [114] - [116].

5.3.2 Fouling detection in heat exchangers

When focusing on operational faults specifically related to heat exchangers, literature shows that most of them commonly involve fouling formation [110]. This can be described as the accumulation of deposits on heat transferring surfaces which cause a higher thermal and hydraulic resistance in the heat exchanger. An automatic method using the usual metering variables like volumetric flow and temperatures in the substation primary and secondary circuits has been developed by [117]. It consists of the indirect calculation of the global heat transfer coefficient and monitoring its change during the fouling process. This method is easy to implement but involves important calibration challenges when it comes to different kinds of heat exchangers. Figure 13 shows for two cases compares the linear dependency between the transmittance coefficient (UA) and the exchanged power (Φ) before and after a cleaning process of the heat exchangers.

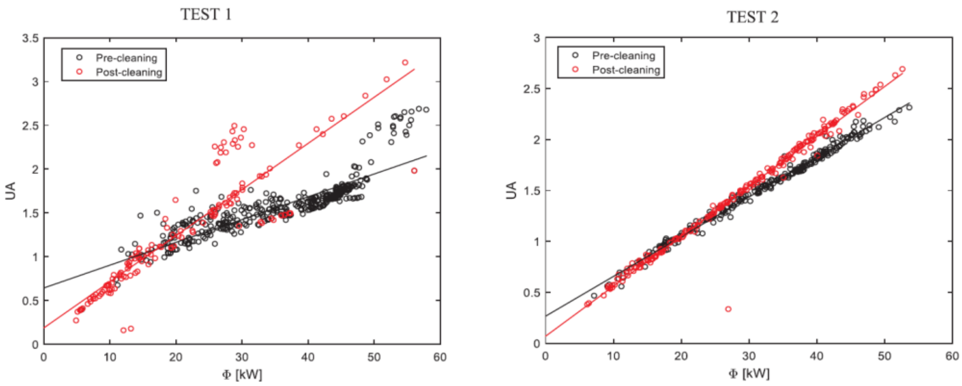


Figure 13 - Experimental data comparison between pre-cleaning and post-cleaning conditions [117].

5.3.3 Detection of regulation valves malfunctioning

The actuators of control valves or the valves themselves may wear and tear during operation or after large periods without use (like control valves of space heating during warm months). This causes uncontrolled flows in the installation, and instabilities of the flow rate (Figure 14). An analysis of frequency variation and stability of the flow in the primary circuit of the substation was performed by [118] leading to a simple and easy method to detect faults in this part.

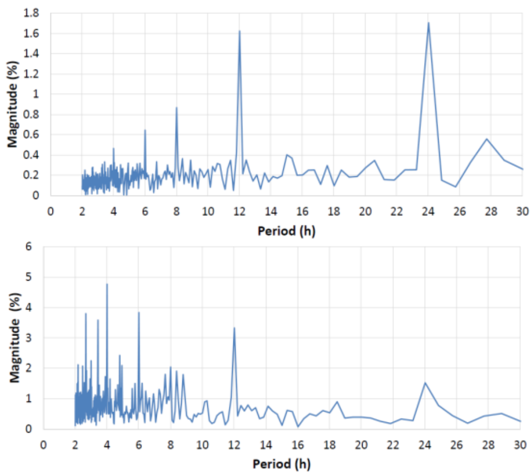


Figure 14 - Frequency signal analysis of flow rate through control valves. Non-blocked valve (above); blocked valve (below) [118].

5.3.4 Malfunction in heat pump components

Heat pumps (HPs) at the customer-sited substations are used in LTDH systems as boosters stations for DHW production whereas in NTDHC systems they are needed to supply both space heating and cooling and DHW loads at the right temperature for the distribution and emission system. Due to that, it is really important to assure an efficient operation detecting possible faults and to prevent them. A comprehensive study that analyses the most important faults which were reported by both original equipment manufacturers (OEMs) and insurance companies in Sweden is presented in [119]. The results state that the issues in control and electronics are one of the most common and costliest faults in all types of HPs. According to OEMs, the shuttle and shunt valves are the second most common faults that occurred in ground source and exhaust air HPs, respectively. Unfortunately, there are not any investigations in the current literature about fault detection applied to these specific parts. Moreover, an additional impediment for the development and implementation of HPs fault detection algorithms is the fact that the equipped software is often a closed system that can only be accessed by the manufacturer. However, there exist some studies leading to detect leaky check and reversing valves using their own test benches or modified commercial heating pumps to be able to measure internal temperatures and mass flow of the refrigerant [120].

Other authors [121] investigated 215 rooftop units of small commercial heating, ventilation, and air conditioning systems and found that 46% of units did not have optimal refrigerant charge amount. Furthermore, it is proven that there is a maximum coefficient of performance (COP) at the optimal charge amount and refrigerant leakages cause performance degradation and a decrease of thermal comfort [122], so it is important to detect these leakages in an early phase to be able to fix them without energy losses.

Several studies have been developed in this direction. Eom et al. (2019) [123] proposed a novel refrigerant charge fault detection strategy for HPs using convolutional ANN trained using a real commercial HP system and the variables used for internal control provided by the manufacturer. Sun et al (2020) [124] defined the sub-health operation concept of HP systems, which is used to define the intermediate state between normal and fault. Moreover, an online undercharge sub-health diagnosis method was proposed. It analyses the theoretical behaviour of the system facing a refrigerant leakage.

5.4 Diagnostics of sensors and actuators

The digitalization of DHC systems is becoming crucial. Moreover, in order to control efficiently the systems and to be able to detect malfunctions, the introduction of more and new sensors and actuators is necessary. However, these components may also fail and it is important to be able to detect them. There are several simple complementary methods that should be implemented in all sensors and actuators of the whole facility:

- monitoring of raw voltage/current sensor signals to detect short circuits to detect out-of-range values;
- monitoring of incoherent values of the measures such as instabilities or impossible values to reach (e.g. ambient temperature above 70°C);
- considering the size of deviation, duration of the fault and average frequency of appearance;
- creation of strategies identifying when the actuators and sensor will be tested, taking advantage of specific operation points such as stationary behaviour, opening/closing of valves,

etc. The continuous diagnosis of some variables may lead to false fault detection which may suppose an extra cost for maintenance companies.

In the literature, there exist some specific methods applied to sensors of HP. Zhang et *al* (2019) [125] propose a data-driven statistical model optimized and applied for sensor fault detection and diagnosis (FDD) using subtraction clustering and k-means clustering combined to identify and classify modelling measurements of unsteady operating conditions. Moreover, in order to calibrate the HP sensors, a method called virtual in-situ calibration (VIC), based on the Bayesian inference and Markov Chain Monte Carlo, resulted very effective to detect and correct the systematic and random errors of various sensors installed in a PVT-HP system [126]. As the VIC method can effectively improve the measurement certainty, the sensors with relatively low accuracy can be used to achieve a higher precision, which is able to significantly reduce the cost of equipment. VIC uses a certain grade of modelling and it seems not so hard to implement.

5.5 Discussion

In general terms, the algorithms used in FDD are divided into physical model-based and data-driven methods. Both can be used to compare the real and the predicted value of one or several variables and deploy an action when this difference reaches a threshold that has to be calibrated for each application. The action to perform can vary from a simple alarm to a complex control action to minimize safety and performance problems and it can be applied at the component level but also at the facility level. To summarise the main findings from the works reviewed, in the following, the main pros (+) and cons (–) of the two approaches are presented.

As far as physical model-based approaches are conceived:

(+) they are made up of simple and usually well-known algorithms based on physical laws and equations;

(+) once the models are calibrated, online data can be used directly to predict some indicators and compare them with the real situation without the need for training the model periodically;

(–) the integration of physical models from different components to create a complete facility model may suppose an important effort to be assumed by developers and testers.

On the subject of the use of data-driven methods the approach is slightly different:

(+) can be useful to represent complex real phenomena that are not easy to explain with equations based on physics;

(+) can be very accurate in the prediction of the behaviour of a system;

(–) the models have to be trained using usually different datasets for the different states of the system, one for a regular state and one for each possible failure state or even a combination of several failures at the same time;

(–) it is necessary to have a huge amount of experimental data that in most of the cases are not available, with the consequence to resort to using small not representative experimental datasets or data coming from simulations or physical models;

(–) the development of ML or ANN algorithms is more complex than physical models and it requires very specialized engineers and development time

By way of conclusion, even though it seems that every time more algorithms used for fault detection are based on ML techniques like ANN, a recent study [92] concludes that some of these approaches are not useful since models trained with laboratory data or data coming from simulations do not achieve a good enough performance when working with online data. On the other hand, these kinds of FDD applications shows a very promising growth and may be a good option to solve complex FDD problems in the near future.

Considering all the information gathered in this review and the specific constraint of this project, it is foreseen to focus the scope of the development of FDD tool in REWARDHeat for its application in a new concept of LTDH substations developed within this project, where it will include an HP to boost low temperature coming from DHC network to use it for SH or DHW. In this way, the variables to monitor and analyse in the FDD tool are:

- heat load patterns: either problems related to inadequate control strategies or faults in substations might be found analysing heat load patterns, as shown in Section 5.3.1. In order to be able to do that, the data of heat delivered by the substation should be recorded and monitored (i.e. *mass flow rates, flow temperature and return temperature used for SH and DHW);*
- heat exchangers fouling: as described in [117], the data needed for an automatic evaluation of fouling are mass flow rate on the primary side of the heat exchanger (HX) and temperatures at the inlet and outlet sections of both sides of the HX. This data will be used to calculate the heat exchange coefficient (UAF), whose trend is to grow when the heat flux exchanged increases as shown in Figure 13. The method is based on monitoring the time evolution of UAF of a clean HX, when the online calculation overcomes a certain threshold, an alarm will be sent to the maintenance operator;
- valves blockage: To analyse malfunctions of valves due to blockage, the *control signal of some valves* should be monitored. Depending on the particular layout of the substation, other approaches may be implemented (e.g. monitoring *temperatures of fluid downstream the valve* during a certain valve opening or closing sequence);
- COP of the HP: it is defined as the ratio between the heating capacity and the electric consumption. The COP of a certain machine depends on the operating point in terms of mass flow and inlet and outlet temperatures at condenser and evaporator. COP is usually specified by manufactures, thus it can be calculated online in order to decide whether the HP is working in a usual operating point or it presents some failure. Then, the data needed to evaluate COP are *condenser mass flow, inlet temperature and outlet temperature at condenser side of HP and electricity consumed by its compressor*.

6 Overview of commercial platforms available in the market

Conversely from HVAC systems in buildings, in DHC applications, there are more chances to find a high-level supervisory control and data acquisition (SCADA) infrastructure in place that allows taking advantage of innovative platforms available in the market for load forecasting, operational planning and anomalies detection. Even if it is out of the scope of this work to perform a detailed technical review of the platforms available in the market, the authors performed a high-level analysis based on a few publicly available information gathered and without pretending to be exhaustive. The capabilities analysed and the commercial platforms surveyed have been listed in Table 1. It has been considered the possibility for the exploitation of a physical thermal-hydraulic model of the DH network for design purposes, the possibility to run an advanced optimization algorithm for optimal production scheduling, supply temperature optimization, local weather forecast, DH load forecast, demand response operation and fault detection capabilities. Only for few platforms, some detailed information has been found. Termis Engineering by Schneider Electric [127] seems one of the most complete and can be applied to both DH and DC systems. It has also dedicated modules for supply temperature, pressures, pumping and TES optimization. The physical model of the DH network in Termis is based on the quasi-dynamic assumption with a static model for the evaluation of pressures and flows, and a fully dynamic temperature assessment [128]. It can be used offline for scenario analysis, but it can also run online predicting the impact of some control inputs in the DH system in real-time applications.

Danfoss after the acquisition of the companies OE3i [129] and Leanheat [130] is capable to provide an advanced modular-based software solution covering almost all the capabilities investigated.

Overall, from the analysis performed on main European players, it emerges that:

- several platforms are conceived in hybrid solution by implementing a digital twin of the network based on physical models but also exploiting artificial intelligence algorithms (Danfoss, DCbrain, Gradyent);
- more and more platforms are using data-driven machine learning models for load forecasting and in some cases also at the building level (NODA, Danfoss);
- Termis, Danfoss and Gradyent have the capability to use the thermo-hydraulic model of the network (in some cases simplified) on-line as an operational support tool calculating optimal hydraulic parameters of the DH network (temperatures, flows and pressures) according to the forecasted boundary conditions;
- some companies even if they have developed thermo-hydraulic models for DH design and planning, they do not integrate them with their optimal dispatching tools;
- stochastic optimization is handled by the dispatch optimization engines provided by Artelys and ENFOR;
- in [131] the developers of OptiEPM™ highlighted their choice in implementing Matheuristics algorithms to achieve a better performance than a direct MILP approach from the computational time point of view that can be relevant in complex problems with a large number of control variables;
- almost all DH production optimization tools surveyed are used to solve the unit commitment problem considering both long-term and short-term planning of the generation plants and considering the participation to the electricity markets (e.g. with CHP units);

- few companies like NODA and Danfoss focus on the demand side of the DH system for the implementation of demand-side management solutions for peak shaving;
- some companies like DCbrain, NODA, Danfoss and Gradyent apply artificial intelligence algorithms to provide predictive or condition-based maintenance and fault detection services;
- Termis Temperature Optimization is capable to transform the non-linear dynamic optimization problem into a linear programming one and solving it [132]. Among the case studies reported about its application in Hjørring [133] and Hørning [134] DH systems heat losses reduction of about 10% (from 23% to 20.7%) have been achieved;
- only ENFOR [135] provides an additional tool called MetFor™ based on machine learning that is able to optimise the local weather forecast up to 10 days ahead from historical weather data and meteorological models, but also capable to detect short-term deviations (12 hours ahead) using real-time weather data.

Another tool that is emerging also in the academic literature is energyPRO [136] that can be used for technical and economic analysis of complex generation systems as well as for short-term operation scheduling. Energy Advice [137] developed a platform that allows creating a thermo-hydraulic model of the network and use it to improve the control of the DH system. Finally, it is worth to mentioning that some companies developed advanced data analytics and visualization tool like Tango [138] with the aim of getting more insight information and future trends, but also integrating applications available by third parties. A new start-up called Arteria [139] was born recently and intends to differentiate itself from the other companies by developing an innovative platform based on a physical model of the DHC network, thermoeconomics optimization and the assessment of the exergy flows in the DHC system.

7 Conclusions

District heating and cooling (DHC) has been identified as a promising technology to meet the thermal energy demands in urban areas mitigating problems related to the growth of urbanization. Nonetheless, from the literature emerges that district heating and cooling is moving towards lower distribution temperatures, the exploitation of decentralized and non-programmable renewable sources and the application of sector coupling with other energy grids. The lack of optimal control strategies and methods for detecting faults, however, causes district heating and cooling systems to waste energy and money. In addition, new challenges have emerged, such as demand-side management, weather uncertainty and environmental efficiency. Those have attracted more and more attention to the design of intelligent, robust control platforms as well as diagnostic methods. In order to propel the district heating and cooling sector ahead in the digital revolution, these innovative technologies, examined in this paper with an emphasis on low-temperature district heating studies and European research projects, must be able to forecast incidents, make real-time choices and be combined with SCADA systems.

As far as advanced district heating and cooling control is conceived, most applications are developed to minimize fossil fuel consumption, increase energy savings, reduce emissions and running costs. Model predictive control (MPC) and multi-agent systems (MAS) (called also agent-based) control have been identified as two key approaches. The multi-agent systems approach has been implemented in a few instances but has the potential to eliminate the need for comprehensive data exploitation, expand the system's access to third parties and implement peer-to-peer markets, but there is still a shortage in the implementation of coordination and standardization. In order to optimize DHC service, model predictive control has a broader scope than multi-agent systems and can be considered a cutting-edge technology. On one hand, it has the primary capacity to take into account weather predictions, occupancy profiles, and stochastic disturbances in real-time optimization, satisfying the system constraints. On the other hand, it can be time-consuming for the identification of the system model and require high-skilled personnel for development and use.

Mixed Integer Linear Programming (MILP) is one of the most used among the hard control implementation of MPC, thanks to certain features such as rigorousness, consistency, finding the exact optimal solution, and comprehensive modelling capabilities. In DHC implementations, several soft and hybrid models of MPC have also emerged with the advancement of swarm intelligence and machine learning. In particular, approaches based on gradient-free meta-heuristic optimization, such as genetic algorithms (GA) and particle swarm optimization (PSO), are becoming increasingly common because they can converge easily, have versatile control parameters and do not require complicated mathematical operations.

Likewise, as in predictive control techniques, two major methods have appeared in fault identification and diagnosis (FDD): physical-based versus data-driven simulation. In software-based solutions, models here are helpful for identifying malfunctions from the deviation of the unit from normal operation. If any calibrated thresholds are surpassed, alarms will be triggered. In district heating and cooling, the usage of machine learning-based fault detection and diagnosis techniques are increasing as they can manage complicated systems with a wide number of variables and provide outstanding performance in non-linear system performance prediction and pattern recognition. These solutions, however, have some drawbacks because large datasets are required for training over different operating conditions in order to avoid poor extrapolation performance in real-time operation. Among the hardware-based fault detection and diagnosis approaches, infrared thermography finds applications for leak detection in district heating pipelines and can be further boosted by means of automated image recognition algorithms. Finally, it emerged that advanced control and fault detection sometimes share common methods and it appears from the market survey that several firms have developed innovative platforms for these applications based on artificial intelligence.

Table 1 - *Overview of the capabilities of the commercial platforms for planning, advanced control and fault detection in DHC systems.*

Proprietary platforms/ capabilities	**TERMIS by Schneider Electric** [127]	**DANFOSS** [140]-[143]	**OPTIT** [144]	**Artelys** [145]-[146]	**NODA** [147]	**ENFOR** [135]	**INeS by DCbrain** [148]	**Gradyent** [149]	**EA-PSM by Energy Advice** [137]
1- DH network planning and design	✓	✓ Energis Designer	✓ OptiTLR	✓			✓	✓	✓
2- DH production optimization	✓ Production Scheduler	✓ Mentor planner	✓ OptiEPM™	✓ Crystal Energy Planner		✓ HeatPO	✓	✓	
3- Supply temperature optimization	✓ Temperature Optimization	✓ Energis Operator, Mentor planner			✓	✓ HeatTO		✓	✓
4- DH load forecast	✓ Load Forecaster	✓ LeanheatA Mentor Forecast™	✓	✓ Crystal Forecast	✓	✓ HeatFor	✓	✓	✓
5- Local optimized weather forecast						✓ MetFor			
6- Demand side management		✓ LeanheatAI			✓				
7- Fault detection and diagnosis		✓ LeanheatAI			✓		✓	✓	

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