Renovation and optimization of existing district heating networks: towards smart low carbon thermal grids

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DECLARIATION

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Summary

District heating and cooling (DHC) systems are attracting increased interest for their low carbon potential. However, most DHC systems are not operating at the expected performance level. Optimization and Enhancement of DHC networks to reduce (a) fossil fuel consumption, CO_2 emission, and heat losses across the network, while (b) increasing return on investment, form key challenges faced by decision makers in the fast developing energy landscape. This thesis hypothesises that optimization of existing district heating networks can contribute to the development of smart thermal grids by integrating sustainable energy and intelligent management technology. This requires an accurate simulation capability at the district level factoring in building fabric and optimization of the system through energy generation, energy distribution, heat substation and terminal users.

First, the thesis presents a novel concept to determine building envelope thermal transmittance (known as U-values) and air infiltration rate by a combination of energy modelling (DesignBuilder and EnergyPlus), regression models and genetic algorithm at quasi-steady state conditions. The calibrated U-values and air infiltration rate are employed as inputs in EnergyPlus to model one workday heat consumption. When compared with thermal demand from measured data, the accuracy of the calibrated model has improved significantly.

Next, dynamic simulation of distribution network is demonstrated. A numerical simulation model is developed in Simulink to analyse dynamic heat losses in the pipe network at different periods of the week. Results show that heat losses vary between 1-2% during the weekday daytime, while the heat losses increase to 8-12% at other time periods. Supply and return temperatures of each building are presented and simulation results are in line with measured data. Meanwhile, Heat losses of the next generation DH are investigated based on the constructed model. Results show that lower distribution temperature and advanced insulation

technology greatly reduce network heat losses. Also, the network heat loss can be further minimized by a reduction of heat demand in buildings.

Finally, a holistic district heating simulation capability is proposed. The simulation capability is carried out under the BCVTB (Building Controls Virtual Test Bed) environment. And the results display the operational schedule under the current operation scheme. Economic and environmental evaluation of the current operation scheme shows that biomass boiler is the cheapest option for heat generation due to renewable heat incentive. This district simulation capability is used to perform day-ahead optimization to determine the optimal schedules, targeting operation cost minimization. MILP is employed for optimization as it can be used to represent non-linear boiler efficiency without sacrificing the advantages brought by linear programming. Efficiency with respect to heat output level is introduced. The results indicate that smart control can be used for peak shaving, installation capacity reduction and operation cost saving. Future work involves investigating the optimization in a broader perspective sense toward smart thermal grid realization.

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Nomenclature

List of Abbreviations

ACH	Air changes per hour
AHP	Absorption heat pump
ANN	Artificial neural network
BEMS	Building Energy Management system
BCVTB	Building Controls Virtual Test Bed
CCHP	Combined cooling heating and power
CHP	Combined heat and power
COP	Coefficient of performance
CUSP	Computation urban sustainability platform
CV-RMSE	Coefficient of Variation of Root Mean Square Error
DC	District cooling
DH	District heating
DHC	District heating and cooling
DHW	Domestic hot water
EMS	Energy management System
GA	Genetic Algorithm
GHG	Greenhouse gas
GUI	Graphical User Interface
HP	Heat pump
HVAC	Heating, Ventilation and Air Conditioning
IEA	International Energy Agency
KPI	Key Performance Indicators
LP	Linear programming

MILP	Mixed-Integer linear programming
NMBE	Normalized Mean Bias Error
PCM	Phase change materials
RES	Renewable energy source
STG	Smart thermal grid
TES	Thermal energy storage

1 Introduction

1.1 Research background

Energy consumption has increased progressively in the past decades as a consequence of industrialization and intensive urbanisation, leading to negative environmental impacts [1]. Under the present framework, fossil fuel is still the dominant energy source, which impedes future sustainable development. Countries worldwide have realized the importance of altering current energy supply patterns, steering towards affordable and environmental-friendly approaches.

Globally, buildings account for 40% of the annual energy used and contribute towards 30% of the total CO_2 emissions [2] and [3]. Buildings are the largest consumer of energy in the European Union, accounting for up to 40% of the total energy consumption and approximately 36% of the greenhouse gas emissions [4]. Buildings' share of CO_2 emissions is much higher in some countries. In the UK specifically, this sector represented 50% of the total of 570Mt CO_2 emissions in 2013 [5]. Energy used in buildings is mainly for heating and cooling, hot water, lighting and appliances, and the majority of this energy comes from the burning of fossil fuel, which amounted to 80.8% of global energy consumption in 2014 [6]. Associated GHG emissions from the burning of fossil fuels have been attributed as the likely cause of anthropogenic climate change [7]. According to the International Energy Agency (IEA) [8], global greenhouse gas (GHG) emissions are rapidly increasing and the pressing challenge is to hold the increase in the global average temperature to well below 2°C above pre-industrial levels and pursue efforts to limit the temperature increase to 1.5°C.

Addressing the issue of global climate change and reversing the trend of rising energy consumption are essential to reduce the impact of climate change to a 2 °C rise in global average temperature [7]. The building sector, therefore, plays a significant role in mitigating the impacts of climate change – first, through reducing the demand; i.e. energy conservation, and second, by maximizing the use of renewable energy – both aimed at reducing GHG emissions [9]. This has increased the need for new energy substitutes and conversion methods to meet an increasing energy demand and pave the way to cost-effective heating and cooling solutions.

In particular, carbon legislations and various incentive policies for exploitation of local available resources have raised great interest in sustainable energy. In addition, the emergence of small- to medium-scale generation units together with storage technologies are enabling an increasing utilization of distributed generation [10]. District Heating and Cooling (DHC), with its potential to integrate local renewable energy generation and industry or municipal surplus energy, is attracting increased interest from local authorities and developers. It has been considered as the most promising solution for future energy and environmental issues [1]. Meanwhile, it brings about a series of benefits. Evidence suggests that investment in local district heating (DH) solutions can enhance energy security and efficiency, create economic impacts through job creation, while contributing to CO_2 reduction [11]. From a health and safety perspective, adoption of DH systems will contribute to eliminate the need for individual gas boilers and thus reducing drastically the potential risk with respect to carbon monoxide poisoning and gas explosion. Moreover, DH facilitates the continuous introduction and increase in the share of renewable energy in the overall energy mix. In fact, countries in the EU with high level DH generally exhibited higher renewable energy penetration [12].

1.2 Definition and evolution of district heating and cooling

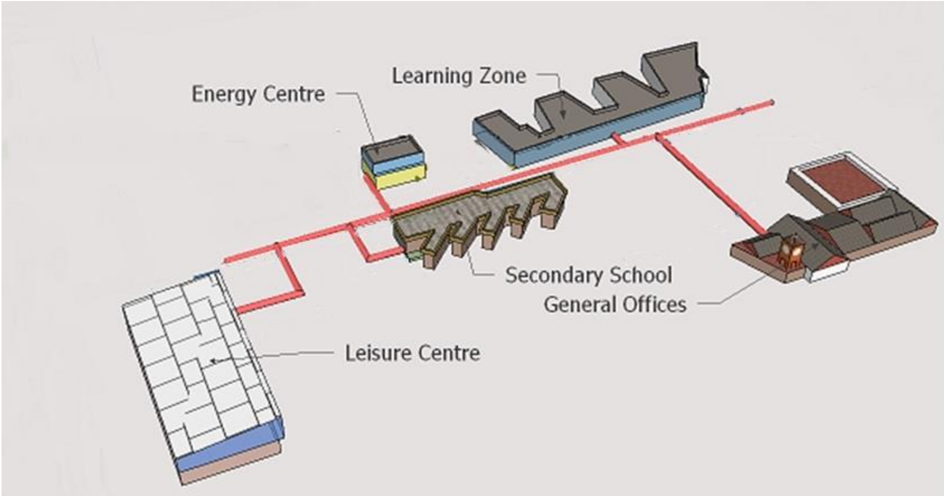

Fig. 1-1 District heating system of Ebbw Vale [13]

District Heating is a system that delivers hot water or steam derived from a central plant to buildings via extensive underground pipe network. Fig. 1-1 is a district heating network in Ebbw Vale, south Wales, which is the experiment site of this thesis. The energy centre provides heat to four public buildings, including general office, learning zone, secondary school and leisure centre. DH has gone through three generations [14] and [15]. The first commercial DH network emerged in the 1880s and dominated the market until the 1930s: High temperature steam was applied as the heat carrier causing serious heat loss and steam explosions, thus leading to pressing demands for network improvements. Pressurized hot water with a temperature over 100°C was used to phase out steam in the second generation (until the 1970s). A scarcity of heat control and poor overall quality of DH led to the third and present generation. The biggest evolution of the third generation is reflected in lower supply temperatures, less than 100°C, with improved energy-efficiency and cost saving. While deployment policies tend to be country specific, the driving incentives are motivated by performance and economic considerations [14]. DH enjoys high popularity in northern European countries. For instance, Sweden has installed a length of 30,000 km DH system, which supplied over 61% heating capacity of the country by 2011, as illustrated in Fig. 1-2. Fossil fuels are the primary energy source for DH. The successful implementation of Combined Heat and Power (CHP) is the main driving force for extensive use of DH in the Danish energy network, with 52% of electricity met by CHP [16] and [17]. This situation is similar to the United States, which had experienced a growing interest across cities in the deployment of DHC as a result of advances in CHP technology [18]. Nevertheless, the development of DH is disparate. In Iceland the share of DH was as high as 92% given its abundance in geothermal energy, while Norway and UK lagged far behind with a share of 1%. Although the current share of DH in UK is low, it is projected that 15% of the UK heat demand will be met by DH by 2030 and around 43% by 2050 [22]. Cheap fossil fuel and electricity prices and the focus on short term investments are the major barriers for DH deployment in Europe [19]. Research indicates that increasing the adoption of DH will remarkably contribute to the European Energy Roadmap 2050 of 80% CO_2 emission reduction [20].

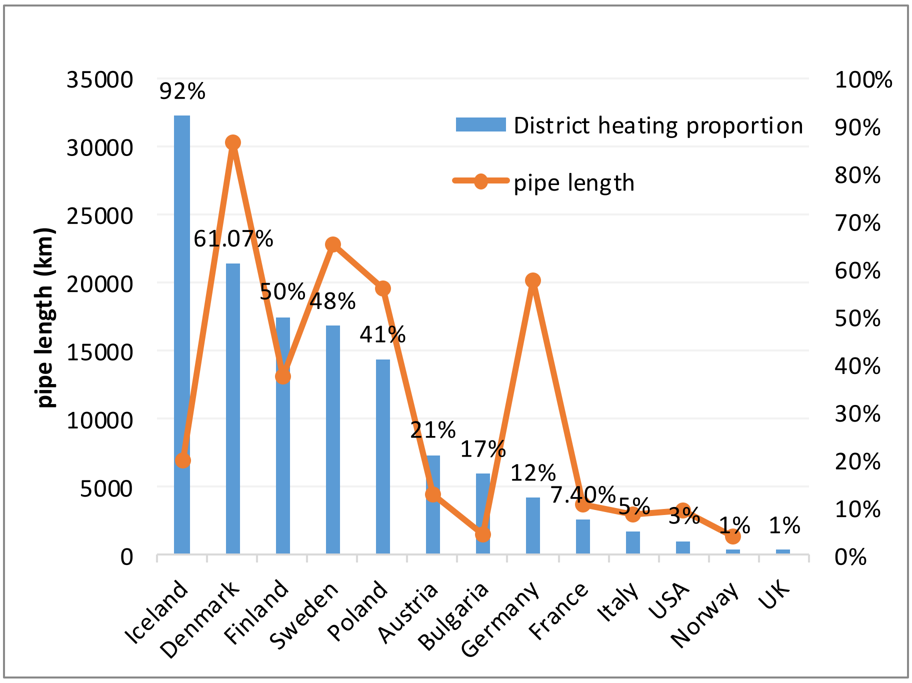

Fig. 1-2 District heating proportion and pipe length in 2011 [21]

Conversely, District Cooling (DC) delivers chilled water from a central plant to buildings via pipe network. The essential difference between DC and DH is the temperature of the distribution medium. Fluid temperature for DC is normally under 10 °C. The development of DC can also be characterized into three generations [14]. The first DC system originated from the 19th century and was used at Denver's Colorado Automatic Refrigerator Company in 1889. Refrigerant was used as the distribution medium at that time. Large DC systems were in operation in New York in the 1930s [23]. It firstly spread to Europe in the 1960s in countries such as Germany, Italy, Sweden and Finland [23], where the second generation DC developed. Cold water was then applied as the delivery medium. The third generation was based on various cold supply technologies, including absorption chillers, mechanical chillers, natural cooling from lakes, excess cold waste and cold storage, which became popular in the 1990s [14]. However, the development of DC is much slower than that of DH and much less DC systems have been installed to date. The main reason is that temperature differential for supply and return temperatures in DH network is larger than DC network, which means the pipe size for DC is much bigger for the same effect transmission, leading to a more expensive investment in DC network [24]. The major users of DC are densely populated areas such as schools, hospitals, offices and airports. Given the prospect of global warming, it is expected that cooling demand will increase in the future. The efficiency of DC may be 5 to 10 times higher than traditional power driven air-conditioning by making use of resources that otherwise would be wasted or difficult to use [25]. This indicates a necessity for the development of DC in Europe, where almost all individual cooling systems rely on electricity [26].

1.3 Problem statement

Although DHC has attracted increased attention in recent years reflected by higher adoption rates, there are still problems to overcome to trigger large-scale acceptance for consumers and investors. Evidences suggest that some systems are not running as efficiently as advocated. The system can malfunction or be wrongly designed, configured or operated resulting in low performance. Moreover, the share of renewable energy should be further enhanced since fossil fuel still dominates the energy supply in the current networks. In Directive 2012/27/EU, Article 2 (41) [27], an efficient district heating and cooling has been defined as "a district heating or cooling system using at least 50% renewable energy, 50% waste heat, 75% cogenerated heat or 50% of a combination of such energy and heat". Many existing DH systems require modification or modernization to bring them to a more reliable and sustainable standard [28] and [29].

Recent figures suggest an increasing disconnection trend from DH systems with the adoption of personalised heating solutions. A research conducted by Herrero and Ürge-Vorsatz [30] stressed that by the year of 2010, 5% of the DH-served Hungarian households had disconnected from the system and another 9% were planning to disconnect from the system. Meanwhile, Article 24 [31] released by European Commission in 2016 has empowered consumers to stop buying heat from low efficient DH network if there is a better energy performance alternative. Disconnection trends from DH networks can be explained by a wide range of problems and barriers preventing wide adoption, including: (a) huge investment for the deployment or renovation of new or poorly performing DH, (b) inefficient operation of the generation units and lack of smart control system, (c) poor delivery quality of the distribution network, and (d) cheap fuel and electricity prices and the focus on short-term investment [32]. Thus, it is necessary to upgrade current systems towards low cost and high efficiency networks to improve their competitiveness in the future energy market.

Based on the state of current systems, researchers proposed a wealth of approaches to optimize DHC networks with a view of improving their competitiveness in the future heating market. The Scopus scientific search engine is applied here to study recent publications related to DHC optimization. Data obtained are based on the search keywords ‘district heating’ or ‘district cooling’ and ‘optimization’ included in article title, abstract and key words. Fig. 1-3 illustrates the number of publications about DHC optimization from 1991 to 2015. DHC optimization boomed in the past decade as the development of computer science for smart control.

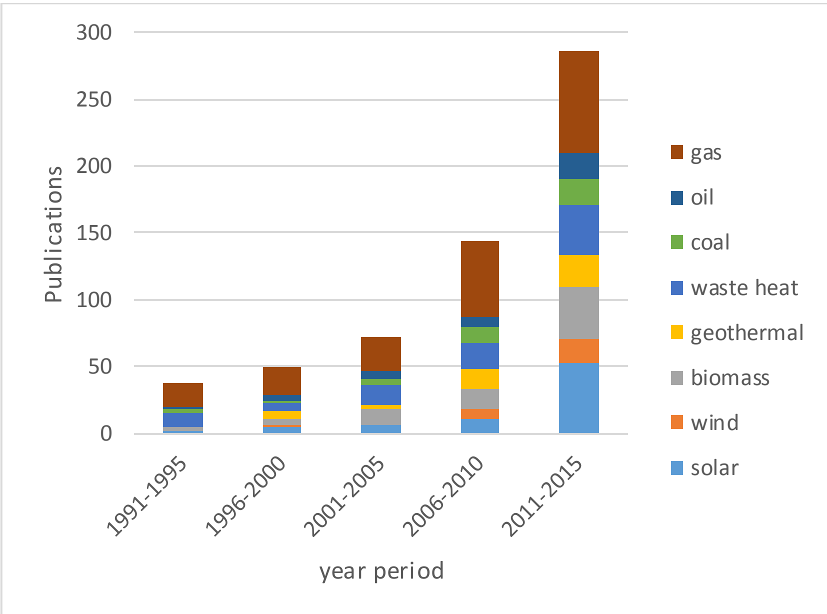

Fig. 1-3 Publication related to district heating optimization from 1991 to 2015

1.4 Research objectives

The overall objective of this thesis is to understand the current DH network and to optimize it towards a smart thermal grid through literature review, simulation and optimization approaches. The research is based on an overarching hypothesis and four specific research questions.

The hypothesis to be tested is:

Smart thermal grids provide a means for enhancing the performance of district heating systems by integrating sustainable energy and intelligent management technology through a holistic simulation and optimization capability.

Based on the research targets and in pursuit of evaluating the hypothesis, the research objectives will endeavour to address the following research questions:

1. What is the current state of district heating systems and how those can be enhanced towards achieving the smart thermal grid vision?
2. How to calibrate envelope thermal transmittance and air infiltration to improve the accuracy of building simulation?
3. How to model district heating networks to deliver a reliable district simulation capability?
4. How to meet heat demand with minimal operation costs when considering the efficiency variation at partial loads of the generation units?

The technique developed in this thesis will pave the way to the vision of smart thermal grids, which requires optimal design and operation and smart control to support future sustainable development.

1.5 Thesis overview

The following chapter presents a critical review of the literature related to district heating simulation and optimization, leveraging on four aspects: energy generation, energy distribution, heat substations and terminal users. The chapter then elaborates on smart management of DH networks for day-ahead demand response.

The 3rd chapter presents the basic methodology applied in carrying out the research work. This begins with building simulation and validation. The chapter then proceeds with a description of the distribution network simulation before presenting a co-simulation platform and its interactions with other simulation tools. This chapter also introduces and justifies the selection of mixed integer linear programming, which is the algorithm used for optimization of the operational schedule of the generation units in the research work.

The 4th chapter demonstrates approaches developed by the author to conduct the research. The formed approaches are based on the methodology discussed in the previous chapter. This starts with building a calibration method for U-values and air infiltration. Afterwards, a co-simulation method for the current operation scheme is presented. This is followed by a demand response optimization of the DH network with operation cost minimization.

The 5th chapter presents the main results and outputs of the research. Firstly, it displays the results for the calibration of building U-values and air infiltration rate. Secondly, the simulation of the distribution network is presented with a discussion on heat losses in the next generation DH network. It then presents the co-simulation results of a DH network under the current operational scheme. Economic and environmental evaluation of the existing scheme is described. Finally, this chapter presents the results of the operation schedule targeting operation cost minimization.

Chapter 6 discusses the research outputs and results. This begins by discussing the contribution of the research to academy. The chapter next outlines the contribution of the research to practise. In the end, a computational urban sustainability platform under development by the author’s research team is presented.

The last chapter concludes the thesis by discussing the posited research questions that underpin the research. Firstly, the main research findings are presented, followed by a discussion of key contributions of the thesis. Finally, the research directions for future work are proposed.

2 Literature review

2.1 Introduction

A wealth of studies have been carried out to investigate DH through multiple approaches, including simulation and optimization methods. This section identifies the literature within research questions proposed previously. The DH simulation reviews the research from building simulation, distribution network simulation to the whole network simulation. The optimization field is explored in depth from four aspects: heat generation, heat distribution, heat transformation and heat utilization. Next, research directions towards smart thermal grids are proposed. The thesis then presents a review of the DH from the perspective of smart management of the generation units, highlighting the reasons for choosing multi-integer linear programming as an optimization algorithm for examining a case study. Finally, the concluding remarks are presented.

2.2 District heating simulation

Many research works have applied simulation models for DH network investigation. However, most of the DH simulation studies separate the buildings from the distribution network, concentrating either on the distribution network or on the building stocks. This section presents a review of the simulation from separate study to whole system simulation.

2.2.1 Building performance simulation

Building energy consumption, which is mainly resulted from space heating/cooling, domestic hot water, lighting and appliances such as refrigerator and washing machine, is a major sector for energy consumption. The amount of energy consumed for a building is highly dependent on the physical characteristics of the building, appliance application, HVAC (Heating, Ventilation and Air Conditioning) system, occupant behaviour and climate condition [33]. Existing publications related to building energy assessment are mostly based on simulations and experiments. Due to the disadvantages such as time consuming and heavy manual work brought by on site experiment, energy simulation is widely used given its practicality in energy profiling of a building. Building simulation seeks to quantify the energy demand as a function of the input parameters. It has been widely used to provide guidance on building design, operation and retrofit. Owning to the complexity of the building physical characteristics and a lack of field-measured data, the simulation results may significantly deviate from reality. Validation of the model is necessary before it is used to represent actual building energy performance.

2.2.1.1 Building simulation

Building simulation not only supports decision making towards cost effectiveness of energy saving design, facilitates the efficient operation of building, but also helps to provide guidance on building optimization and retrofit. Building energy models are approximations for energy usage in physical buildings and are widely used to quantify building energy demand. Data driven models and physical models are two typical approaches to analyse energy use in buildings. Data driven models predict energy demand according to historical energy loads regardless of the building structures. Only a minimal set of parameters that are sensitive to energy demand are required in this approach [34]. Those models are normally based on regression models and do not account for retrofit saving and installation of new equipment. In contrast, physical models are normally over-parameterised, computing operational energy with much more inputs [34]. However, the significant advantage of using physical models is that they can forecast the changes brought by previously unobserved conditions.

Building simulation tools allow detailed calculation of energy demand at discrete time steps based on building physical properties as well as dynamic input variables such as weather condition, occupancy, HVAC system and operating strategies. Those tools fall into the category of physical models and the most popular ones are EnergyPlus [35], Trnsys [36], DOE-2 [37] and ESP-r [38]. Limitations apply to almost all the available simulation tools to date. Crawley et al. [39] presented a comparison of the features and capabilities of 20 simulation programs. EnergyPlus is among the most widely used tools, which is able to represent detailed physical charactestics for building energy performance evaluation and occupants thermal comfort assessment.

The data driven models predict building energy performance based on past performance, thus a large amount of historic data are required to obtain adequate accuracy. Artificial Neural Network (ANN), which is inspired by the biological neural network of human brain, is the dominate method among mathematical models. Historical data are used to train the network to learn the rules that control a specific result, and then the analytic skill is used to identify the consequences for new situations. It has been successfully applied in many research fields including building energy prediction. Magalhães et al. [40] developed an ANN model to characterize the relationship between building heating load and indoor setup temperature at different occupant behaviour. Building simulation tool ESP-r was used to produce a large number of data sets for model construction. They concluded that accurate building performance simulation reduces the gap between predicted and measured building energy demand.

2.2.1.2 Buildings U-values and air infiltration

Due to the complexity of built environment and interacting variables, it is impossible to fully represent the real-world building performance through simulation tool. The discrepancy is mainly caused by uncertainties from four aspects [34]: specification uncertainty from inaccurate or incomplete model parameters such as geometry, material properties, operation schedules and HVAC configurations; modelling uncertainty from simplification of complex physical models; numerical uncertainty from discretisation of the models; and scenario uncertainty from external conditions caused by occupant behaviour and weather information.

Various approaches to model calibration have been proposed to narrow down the disparity. Significant accuracy improvements in simulation results have been achieved after calibration [41] and [42]. There is no consensus on the optimal calibration approach. In general, those methods can be broadly categorized into manual and automatic calibration [34]. Manual calibration relies on expert experience and knowledge to characterise the physical and operational properties [43]. Automatic calibration depends on optimization techniques and alternative modelling techniques such as ANN to assist the process of calibration.

Thermo-physical properties of the building are key factors affecting building energy consumption. The thermal transmittance (U-value) of envelope and the air infiltration rate are the most critical aspects from a thermal performance perspective. As a result, determination of envelope thermal properties and air infiltration are essential for energy modelling. Envelope U-values rely on several factors, such as envelope surface roughness, air flow pattern and wind speed. Thermal losses from building surface account for a large proportion of respective thermal balance [44]. Field U-value measurement is normally fulfilled through heat flux. Temperature sensors and heat flux sensors are attached to both sides of a building element to measure temperature and heat flux respectively at a steady state. In order to obtain an average value of the whole building, this process is replicated in several locations, which is time consuming and involves repetitive tasks with a substantial cost implication. If the wall or roof is not homogeneous, thermal bridges should be considered. The heat losses affected by thermal bridges should be measured separately to obtain validated U-values [45]. Meanwhile, users may easily affect the precision and bias of the results. Even with the same operator and the same equipment, the results still can differ due to measurement uncertainty [46]. Alternatively, U-value not influenced by thermal bridging can be obtained through theoretical calculation using equation (2.1) by knowing the thermal resistance of each layer that constitutes the envelope (R) and its inside (R_i) and outside (R_o) surface thermal resistances.

$$\mathrm{U-value} = \frac{1}{\sum R + R_i + R_o} \tag{2.1}$$

When the influences of building thermal bridge are considered, the calculated U-value should be multiplied by an incidence factor to obtain a validated data [47].

Interest in air permeability in building envelopes has increased, owing to the increasing concern about building energy performance and indoor environmental quality [48] and [49]. Air infiltration is generally defined as the unexpected or accidental introduction of air from outdoor into a building. Building thermal performance requires strict envelope air tightness to reduce energy demand, especially when designing low carbon buildings. However, sufficient air exchange is also recognized as essential to enhance airflow circulation and ensure indoor thermal comfort. Air infiltration is primarily measured by the rate of air change in a building, which is defined as the number of times that the air within a fixed space is replaced by the infiltrated outdoor air. The air infiltration per hour can be expressed by equation 2.2.

$$\mathrm{ACH} = \frac{60V_a}{V} \tag{2.2}$$

where ACH is the number of air changes per hour (h^{-1}). V_a denotes the volume of air flow per minute (m^3/min), and V represents the volume of the fix space (m^3).

Many researches are devoted directly to measuring air infiltration rate on-site, which is usually obtained through two typical methods: (1) tracer gas equipment to trace concentration values of inert gas; or (2) fan pressurization method at a pressure difference of 50 Pa. For the former, given the stratification of tracer gas, it is impossible to obtain a uniform concentration within the building [50]. The later could not be used to evaluate the airflows at natural conditions. Uncertainties caused by the current empirical assessment impact the accuracy of the building performance evaluation [51]. The inaccurate evaluation of the air infiltration may result in oversizing of the ventilation system [52].

2.2.2 Building stock simulation

Extensive research work has been carried out to evaluate thermal performance of buildings from the district level. Those building stock energy models are mainly from the perspective of top-down modelling approach and bottom-up modelling approach [53]. Top-down models deal with the building stock from an aggregated level rather than individual building models and end users [54] and [55]. Bottom-up models estimate energy demand from single or a group of buildings and then aggregate the results to stand for a whole district. Top-down models are in fact data driven models that predict energy demand according to statistical techniques such as regression models [54] and [55]. Historic energy performance information is used to establish the relationship between energy demand and sensitive parameters. These models can be used from community scale to city and national scale. This approach deals with the building stock without investigating individual building structure, appliance, heating and cooling system and operation schemes. The main disadvantages of the data driven models are that they only focus on historical data and do not account for technology evolution and a large amount of historical data is required. Talebi et al. [56] developed a simplified method to predict buildings' thermal energy consumption in a district, accounting for internal heat generation, thermal mass and shading. The results were benchmarked with validated simulation tools and they showed good agreement. The bottom-up approach depends on statistical model and detailed physical building models to obtain single building energy demand, which is then extended to building stock with similar geometry and technical characters [57]. The statistical approach predicts individual building energy consumption using a range of historical data and extrapolating to a district. The later computers individual building energy usage by using simulation tools and the results are scaled to stand for the whole district, city or nation. Shimoda et al. [58] predicted residential energy consumption from city level by summing up simulation results of various household categories. Each category is simulated separately and then multiplied with the number of households. De Carli et al. [59] addressed the energetic and economic performance of a small DHC network. TRNSYS was applied to determine each type of building's dynamic heating and cooling loads. The results were scaled to a whole district.

2.2.3 Distribution network simulation

The main difference between DH and traditional individual heating is the distribution system that delivers heat, mostly hot water, from generation units to heat consumers. The system usually contains a reliable supply and return pipeline with a lifespan of over 30 years. The investment on the distribution network constitutes the major cost for DH deployment.

Distribution system simulation facilitates the understanding of the network dynamic performance. Field measured data or software predicted building energy demand profiles are used for network simulation. Mattias et al. [60] conducted a simulation based on Simulink to study network behaviour of a DH network. The pressure drop and temperature drop at the serving nodes were assessed. Building energy consumption related data were obtained directly from a local company. Vesterlund and Dahl [61] proposed a method to understand the mass and energy flows in a looped distribution network. Simulink was used for physical model construction. The flow distribution and the influence of bottlenecks were presented. Gabrielaitiene et al. [62] using node method combined with software TERMIS studied the temperature dynamics of a DH system. Results showed that a larger gap between simulation and measured data for remote consumers owing to abundant bends and fittings. In another study carried out in Simulink by Lim et al [63]., the building simulation was included into the modelling. However, the buildings were simplified to heat transfer through the building envelopes without considering the human interference.

An important reason for distribution network simulation is to understand the heat loss of the network, which can be sizeable and may reach over 20% of the delivered heat [64]. There have been a number of studies aiming at decreasing heat losses in the DH systems. Lim et al. [63] developed a numerical model in Simulink/Matlab to study heat loss in DH system and pointed out that around 10% of the heat loss came from the pipes. Byun [65] adopted a heat supply control algorithm to minimize heat loss of a DH network while satisfying heat demand of the households. Heat loss of the pipes in the building side was successfully reduced from 24.1% to 13.6% by simultaneously regulating secondary supply water temperature and flow rate according to the ambient temperature. Fang and Lahdelma [66] developed a matrix model to estimate water flow, temperature and heat loss of the pipes in distribution network. The model could be used to identify the state of flow in the pipes and to detect faults in the network. Bram et al. [67] described an analytical model for piping system simulation to understand heat losses at steady-state. The influence of pipe dimensions and mass flow rates were studied. Results indicated that the heat loss depends on pipe diameter and pipe length and the influence of mass flow is minor. Li et al. [68] theoretically simulated a 300MW CHP integrated DH system. They stressed that reducing supply temperature would result in a higher overall efficiency.

Those studies are mainly based on the current generation DH network. As the advancement toward the future smart thermal grid, the heat loss in the next generation should be discussed. Only a few researchers have investigated the next generation DH system. Paiho and Reda [69] discussed the motivations for next generation DH centred around low energy buildings (25 to 50% less), renewable energy adoption and increased efficiency of the heating network resulting from decrease of supply temperature. Lund et al. [14] pointed out that the next generation DH network will have to meet the challenges of delivering low-temperature DH system, low grid losses, integrating sustainable energy sources and integrating with other smart energy grids (electricity, gas, fluid and thermal system). The existing literature reveals a wealth of research in the area of green buildings with a view of improving the performance of the building envelope and reducing energy consumption [70], [71], [72] and [73]. Green buildings have the potential to reduce heat consumption by 80-90% [74] and [75]. Nevertheless, the development of new green buildings will not be able to overcome the disadvantages of existing buildings. Because of buildings' long lifetime, around 70% to 80% of existing poor performance buildings will still be in service by 2050 [76]. Those low performance buildings will have to be retrofitted and refurbished to satisfy future regulations [77]. It is a promising project and has been put into practice in many countries [78]. Research indicated that building renovation has the feasibility of saving up to 68% heating load of the building [77]. Another study by Tommerup [74] even pointed out that heating-related energy for buildings in Denmark has the potential to be reduced by 80% after renovation. The next generation DH system has proposed that supply of 50 °C and return of 20 °C will be sufficient to satisfy the demand for space and water heating [14]. The lower temperature distribution network requires a higher performance heat exchanger which can absorb the same amount of heat from the low distribution medium. Sun et al. [79] and [80] studied a new ejector heat exchanger which could limit the primary heating network return water temperature to 30°C, reduce steam extracted from steam turbine by 41.4% and recover more heat without altering water circulation flow rate. The development of building entrance AHP (absorption heat pump) makes it possible to cool the temperature of the primary side even lower than the secondary side. Heat capacity increases to 1.3 - 1.8 times without extra investment in heat production units and heat delivery network [32]. In order to meet the target of high efficiency distribution network, the performance of the pipeline should be enhanced. Polyurethane foam is the most widely used insulation material with a thermal conductivity ranging from 23 mW/(m·K) to 27 mW/(m·K) for different pipe companies and production technologies [81]. The insulation of the piping network could be improved through using advanced insulation materials, adopting gases with lower conductivity in the insulation pore system and adopting hybrid insulation technology by using material with higher performance closer to the pipe [81] and [82]. Based on those studies, distribution network heat loss of the next generation DH system will be discussed from three aspects: lower building energy demand, decreased distribution temperature and advanced insulation technologies. The results are presented in section 5.2.5.

2.2.4 Whole system simulation

There are some challenges for DH network design and operation. Simulation tools are among one of the essential lacks [56]. As the booming of DH, it is no longer sufficient to address the issue from building stocks assuming isolation from the energy network that they are in, or to model the distribution network regardless of the buildings that it serves [83]. Only limited simulation tools have been developed for simulation from the perspective of district-level and each has its limitation. CitySim was developed for sustainable urban planning by modelling energy flows [84]. Only simple models can be used for building stock energy performance simulation, which is addressed through a resistor-capacitor and temperature nodes linking the corresponding points. The uncertainties caused by occupant behaviour are implemented through a stochastic model. It accounts for radiation exchange between environment and external wall. Some energy models such as heat pumps, boiler and PV systems are also integrated into the tool. It is mainly used for modelling of general energy flow from district or city level. TRNSYS [36] was originally developed for solar heating system simulation. It has currently become an energy system modelling program. It can be used for detailed simulation of thermal plants (solar panels, heat pumps and combustion boilers), storage, building and DH system. The limitation is that the energy loss through the distribution network uses a constant conductance without considering the convective effect. Modelia [85] is an equation based platform that allows various processes to proceed in a single model. Several libraries in Modelica under development are seeking to solve the problem of simulation from district level [86]. 'Districts library' and 'Integrated District Energy Assessment Simulation' models are available for simulation.

Based on the complexity of the DH network, different tools are required to address planning, design and operation issues at different resolution of accuracy and time. There is an increasing trend towards the use of district level simulation tools for design and analysis. The tools attempt to report different aspects of the urban system at one simulation. This allows the buildings to capture the interactions between different buildings. CitySim is a typical tool of this category. Another trend is towards the integration of specific models to address a particular issue in a combined environment, such as Modelica. The models can share inputs and be executed simultaneously to produce outputs.

The investigation will present a co-simulation platform, which is the second trend for DH network simulation, to overcome the limitation of a single DH simulation tool. It takes advantages of validated building simulation tools for building thermal performance modelling and uses broadly adopted Simulink models for distribution network construction. The computation time is less than running the programs separately.

2.3 District heating optimization

By effectively utilizing DHC systems, heating and cooling can be achieved with lower emission and reduced exploitation of fossil fuel resources. Optimization is the most effective way to improve the performance of DHC networks [87]. Before reviewing more details of the DH network optimization, publications related to this topic can be categorized as using optimization algorithms (as shown in Table 2-1) and using simulations, experiments, and other methods (as shown in Table 2-2).

Table 2-1 publications related to DHC optimization and related algorithms

Authors	Network Type	Optimization Method	Optimization targets and scenarios
Söderman 2007 [24]	DC	mixed-integer linear programme modelling	Optimization from cooling plants location and capacity, cold medium storage location and capacity, distribution layout, operation strategy to minimize the overall cost
Burer et al. 2003 [88]	CCHP	multi-objective evolutionary algorithm	Optimizing energy output of multi-generation units to achieve minimal CO_2 emission at a given investment or to achieve minimal cost at a given CO_2 emission
Chow et al. 2004 [89]	DC	genetic algorithm	A proper mix of consumption buildings to achieve a shorter payback period
Sakawa and Matsui 2013[90]	DHC	Interactive fuzzy satisficing method	Optimal control of generation units and thermal storage to minimize running cost and primary energy amount

Feng and Long 2008 [91]	DC	Single parent genetic algorithm	Optimal piping layout to reduce annual equivalent cost of piping network
Keçebaş et al. 2014 [92]	DH	Artificial neural network	Evaluation of energy input, losses, output, efficiency and economic optimization to provide information for the optimal design and operation of the system
Khir and Haouari 2015 [93]	DC	Mixed-integer programming model	Optimal chiller capacity, storage tank capacity, pipe size and layout, quantity of cold water produced and stored to minimize investment and operation costs
Fang and Lahdelma 2015 [94]	DH	genetic algorithm	Optimal power generation from different generation plants to minimize cost in fuels and pumping cost
Haikarainen et al. 2014 [95]	DH	mixed-integer linear programme	Further development of the network at different network distribution and operation scenarios to achieve the lowest annual cost while satisfy heat demand
Omu et al. 2013 [96]	CHP	mixed-integer linear programme	Optimal design of generation unit size and location, distribution network structure to minimize annual cost and CO_2 emission
Byun et al. 2015 [65]	DH	Heat supply control algorithm	Simultaneously regulating the secondary supply water temperature and flow rate to minimize heat loss of a district heating network while satisfying heat demand

Jiang et al. 2014 [97]	DHC	Group search optimizer	Optimal number of generation units and operation strategy to optimize the running cost
Ameri and Besharati 2016 [98]	CCHP	mixed integer linear programming	The optimal size and operation of several different generation units, including gas turbines, boilers, chillers, PV units, to minimize capital and operational costs in DHC networks
Lozano et al. 2010 [99]	CCHP	mixed integer linear programming	An installation of thermal energy storage to reduce annual operation cost

Table 2-2 publications related to DHC optimization based on simulation, experiments and other approaches

Authors	**Network**	**Methods**	**Targets**
Ortiga et al. 2013 [100]	CCHP	Scenario analysis	Maximum utilization of fossil fuel and renewable resources in the energy supply system to reduce energy consumption and CO_2 emission
Kuosa et al. 2013 [15]	DH	Model based on Excel/Visual basic environment	A ring distribution topology to reduce operation cost
Keçebaş et al. 2011 [101]	DH	Life-cycle cost analysis	Different fuel, pipe size and insulation thickness to analyse energy saving and payback period of a district heating system
Kayfeci 2014 [102]	DH	Life-cycle cost analysis	Different insulation materials with variable diameter to investigate energy saving and payback period

Dodoo 2010 [103]	CHP	Software ENSYST	Building renovation to reduce primary energy consumption in DH
Yan et al. 2013 [104]	DH	Hydraulic model	Pump power saved by using a distributed variable speed pump to replace conventional central circulating pump
Calise et al. 2015 [105]	CHP	TRNSYS	Different operation control strategies to analyse fuel consumption of the network
Udomsri 2012 [106]	CCHP	Software TRNSYS	Installation of higher efficiency pumps and reduction of dry cooler's return temperature to increase electrical COP
Li et al. 2015 [68]	CHP	Software Ebsilon	Simultaneously considering heat source, piping system and heat users to optimize heat loss, pressure drop, pump power consumption and supply temperature
Pirouti et al. 2013 [107]	DH	Software PSS SINCAL	Different operation strategy to minimize the annual total energy consumption of the system, including pump electric energy consumption and pipeline energy loss
Sun 2014 [79]	DH	Experiments	A new heat exchanger to improve distribution network and generation unit efficiency

The objectives of the above-mentioned methodologies and algorithms centre on reducing investment costs, operation costs, CO_2 emission and payback periods. The decisive factors for improving of the network performance can be categorized into four interrelated perspectives: (a) energy generation, (b) energy distribution, (c) heat substations, and (d) terminal users. In order to effectively optimize the DHC network, a comprehensive and critical understanding of each sub-process is necessary as elaborated in the following subsections.

2.3.1 Future district heating and cooling system

The definition and evolution of DHC have been discussed in section 1.2. The problems existing in the current system form the research gaps. Beyond this however, it is pertinent to discuss the next generation DH network. Lund et al. [14] have defined future smart thermal grids (STGs) as "a network of pipes connecting the buildings in a neighbourhood, town centre or whole city, so that they can be served from centralised plants as well as from a number of distributed heating and cooling producing units including individual contributions from the connected buildings". Future STGs will be more intelligent, involving automatic metering, control and configurable equipment, integrating with electricity and gas grids [14].

Traditional fossil fuels are the dominant energy source for existing DH systems. However, combustion of fossil fuels has brought about severe issues such as environment pollution, price rise and health problems. Consequently, an enhancement of present systems is a prerequisite for more cost-effective and efficient DH to deliver a clean and sustainable energy system without overexploiting natural resources. DH has been proved to be capable of working together with various sustainable energy sources, including solar, wind, biomass, geothermal and industry waste heat [108], [97], [109], [110], [111], [112] and [113]. A high penetration of renewable and waste energy greatly diminishes the dependence on fossil fuel.

Moreover, heat loss in current DH systems is sizeable, ranging between 7.6% and 27.8% [114] in DH networks. A slight change in the temperature of the distribution medium can effectively enhance the performance of the whole system. Several publications have identified the possibility of low temperature DH [115] and [116] which can (a) improve the efficiency of the generation units by reducing recycling times, and (b) lower heat loss of the distribution system by narrowing down temperature differential. A supply of 50°C and return of 20°C will be sufficient to meet the demand for space and water heating [14]. Furthermore, this would facilitate the utilization of renewable energy such as solar, geothermal, and waste industrial heat as more low-grade energy is used. Intelligent monitoring and management of DH is another interesting trend. This enables energy producers to adjust heat production according to dynamic weather variation and consumers requirements.

In summary, future DHC systems have the potential to deliver sustainable, reliable, affordable and intelligent energy to customers. These smart systems are characterized by the following capabilities:

1) Integration with a variety of renewable energy solutions, industry excess heat or cold and combined cooling heating and power to maximize the utilization of local energy sources for future sustainable energy strategy and GHG mitigation target.
2) Adoption of a lower temperature for heating or a higher temperature for cooling to both improve the efficiency of the generation units and transportation network so as to maximize economic and environmental benefits.
3) Working together with thermal energy storage systems for peak-shaving and addressing effectively the fluctuation of renewable energy to reduce investment cost and to improve network stability.
4) Interacting between customers and energy companies to ensure that allocated energy can satisfy energy demand while not causing waste to further improve the DHC system efficiency.

5) Relying on intelligent energy management technology that allows users to visualize and control energy consumption and indoor thermal comfort from smart interfaces (including smart phones).

2.3.2 Energy generation enhancement potential

In DHC networks, heat and cold are normally produced from central plants using large generation units with higher efficiency and more advanced air pollution control methods. Despite the fact that DHC is able to work together with a variety of energy sources, the efficiency and output of generation units are variable. An over-generation or under-generation may result in energy waste or consumers' complaints, respectively. It is vital to ensure optimal management of the generation units to guarantee that the energy hub provides sufficient energy to terminal users at its optimal efficiency, economy and minimum emission.

2.3.2.1 Integration with sustainable energy

DHC networks are able to use highly flexible energy mix. This facilitates the deployment of energy and carbon reduction plans with a view of gradually decarbonizing heat and cool production. Meanwhile, providing heating and cooling from energy centres is easier and cheaper compared with installing renewable energy conversion facilities in individual buildings [117]. Renewable energy such as biomass, geothermal and solar thermal can generate heat directly and are widely applied for DH. When they are used for cooling, an adsorption or absorption cooling driver - chiller is adopted to convert heat, in the form of steam, hot water or exhaust gas into cooling power. More detailed technologies concerning thermal activated cooling are introduced in reference [118]. This greatly reduces electricity consumption as primary energy is used more efficiently [119]. Renewable electricity such as solar PV, wind power and hydropower can also be used for DHC by equipping electric boilers, heat pumps and compression chillers in generation plants to convert renewable electricity into heat and cold. Natural cooling from deep sea, lakes and rivers is another interesting option for DC given their relatively stable temperature, as evidenced by their successful use in Sweden [120], Canada [121] and China [122]. Most of the DHC networks are established in urban cities with high population densities, making it difficult to rely on renewable energy [119]. Therefore, it is important to make good utilization of local available low grade energy, an additional energy source to ease the pressure on environment and fossil fuels. The principle for using low valued energy such as waste incineration and industry waste heat for heating and cooling is similar to biomass and geothermal. More information about converting waste to energy is found in reference [123] and [124].

Using renewable energy and waste energy for DHC is an effective way to reduce GHG emission as no extra pollutant is generated during the process of operation. In addition to that, it also increases energy security as less primary energy is imported from other countries. However, the technology for the utilization of some renewable sources such as solar and wind is not as mature as fossil fuel and is not yet competitive in the market. The cost for DHC is relatively expensive when compared with fossil fuels because of the high investment in installation and materials procurement, but there is nil or little operational cost for fuels during the running process. As a result, innovative techniques should be developed to reduce the costs for the investment on infrastructure construction and to make the utilization of renewable energy more affordable and competitive in the energy market. It is essential to better balance the infrastructure investments, operation costs and production interest in the life cycle of the holistic DHC network. When payback periods and GHG emissions are taken into consideration as important factors for choosing generation units in a DHC system, an integration of renewable and non-renewable energy generation units is the optimal approach for the production of heat and cold.

2.3.2.2 Combined cooling heating and power

DHC is making substantial progress towards environmental target not only due to the reason that it is an extremely flexible technology which can incorporate with any renewable energy and waste energy, but also because of its capability to work together with CCHP units, which is also known as trigeneration. CCHP is an extension of CHP, which has been proved to be more environmentally friendly and cost effective when compared with conventional power generation process by further utilizing excess heat. The efficiency of a typical thermal power plant ranges from 20% to 38% for power generation, but it exceeds 90% when heat and power are generated simultaneously [125] and [126]. Linking heat and electricity in a district level can eliminate CO_2 emission by 81% - 90%, raise energy efficiency by 53% - 55%, and reduce peak load electricity by 73% - 79% [127]. CCHP is actually a combination of CHP and thermally activated chillers that extract waste heat from CHP for cold generation [118] and [128]. Using waste heat for cooling can both reduce electricity demand and further enhance overall efficiency of a traditional CHP [106].

The schematic diagram of a typical CCHP system is illustrated in Fig. 2-1. It consists of a combustor, turbine, generator, heat exchanger and a chiller. Liquid water absorbs heat derived from fuel combustion in the combustor to produce high temperature steam, which is used to drive the steam turbine and the mechanical work is converted into electricity by the generator. During winter, the heat of exhaust steam from the turbine is transferred to water through the heat exchanger for heating. During summer, the heat is used to drive the chiller to generate cold water for cooling. The exhaust steam is finally converted to liquid water and goes back to the combustor for another cycle. Kong et al. [129] claimed that 33% primary energy could be conserved to generate the same amount of energy flow when compared with traditional independent generation system.

Although the share of renewable energy is growing, fossil fuels are still the dominant energy for technical restrictions [130]. The penetration of CCHP offers an optimal option for exploitation of natural resource, which can even out the disadvantages of uncertainties and intermittences of renewable energy, strengthening system reliability and stability.

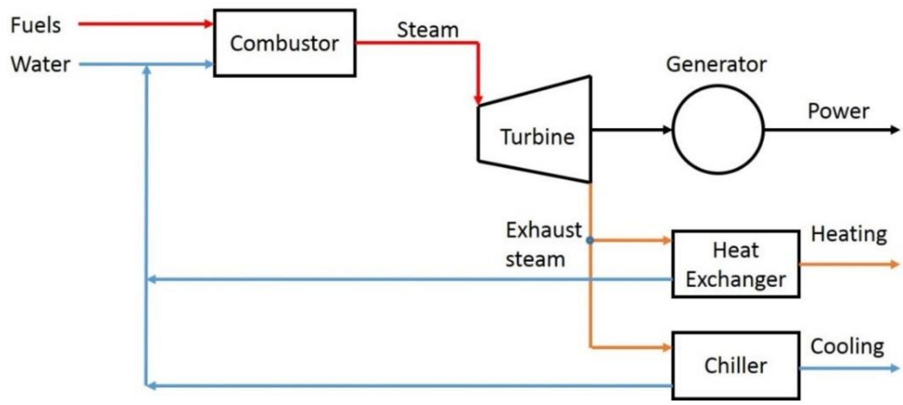

Fig. 2-1 Schematic diagram of a typical CCHP system

2.3.2.3 Intelligent meters for heat demand prediction to control heat generation

It is essential to guarantee that the amount of energy produced is able to satisfy heat demand while not causing waste from over-generation, especially in a complex network where there are multiple heat generation plants. When intelligent meters are not available, energy producers tend to supply more heat or cold than demanded to ensure customers obtaining sufficient energy. Over-generation causes less temperature differentials between supply and return lines, which implies less condensed steam from the boilers, resulting in lower efficiencies of the generation units [131]. The return temperature is higher in an over generation system, which leads to higher distribution losses. Intelligent control of the generation units helps the energy managers to control heat production effectively. Smart meters working together with weather forecasts is a good solution to accurately predict energy demand of the district for the coming day, which can be applied to control heat and cold generation in the energy centre. Such an energy generation system can achieve the target of supplying heat and cold with less fuel, less emission and higher efficiency. This will be further discussed in section 2.3.5.3 from the consumers' perspective.

2.3.2.4 Thermal energy storage

There are two challenges for renewable resources utilization. The first challenge is focused on the intermittent feature of energy generated from solar and wind energy. The second challenge is related to dynamic characteristics. It is impossible for such kind of renewable energy fuels to work individually to meet all the heat or cold load of a community without the help of other technologies. Thermal Energy Storage (TES), which can store heat or cold, has been used to level off the constraint of short-term variation and to provide a continuity of energy supply [132]. The development of TES is a promising technology to aggrandize resources utilization and conservation from a variety of fuel sources. Approximately 1.4 million GWh could be saved and 400 million tonnes of GHG could be reduced annually by the application of TES in Europe [133]. There are three types of TES technology: sensible thermal energy storage, latent thermal energy storage and thermochemical energy storage. Sensible TES and latent TES are more common [134]. Latent thermal energy refers to energy that is released or stored during the process of phase change. Phase change materials (PCMs) are widely used for latent TES. Sensible thermal energy relies on specific heat of storage medium, which is related to the amount of energy variation during the process of temperature alteration. Table 2-3 displays some frequently used materials for sensible TES. The higher specific heat indicates a higher capability for heat storage. Water is the most extensively used TES medium due to its cheap price and favourable thermal properties [135].

Table 2-3 Thermal capacities at 20°C of some frequently used sensible TES materials ([136] and [137])

material	Density (kg/m^3)	Specific heat (J/(kg*K))	Volumetric thermal capacity (MJ/(m^3*K))
Clay	1458	879	1.28
Brick	1800	837	1.51
Sandstone	2200	712	1.57
Concrete	2000	880	1.76
Mineral oil	1700	1300	2.21
Glass	2710	837	2.27
Iron	7900	452	3.57
Steel	7840	465	3.68
Water	988	4182	4.17

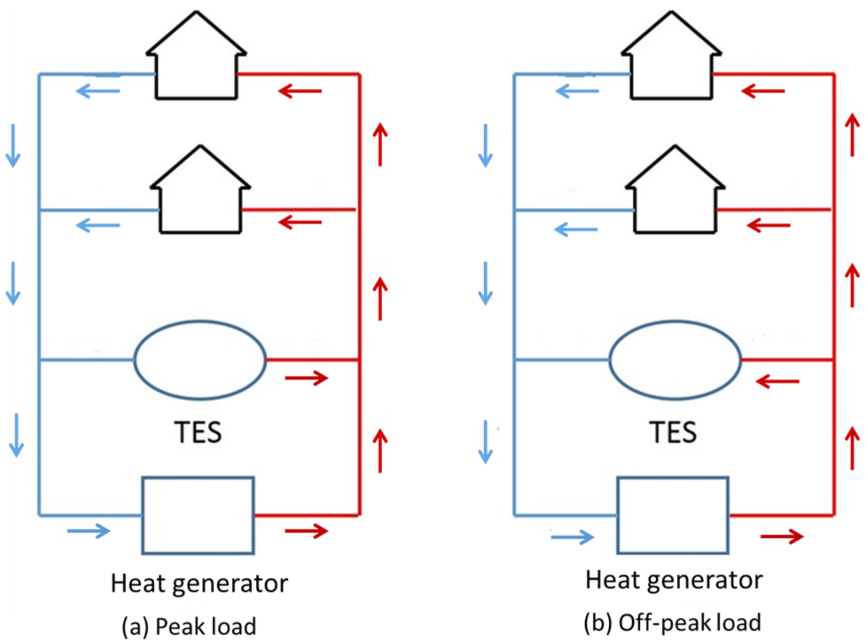

Fig. 2-2 A simplified thermal energy storage for heating

TES not only buffers the fluctuation of renewable energy generation and ensures the security of energy supply, it also significantly levels out peak load in DHC system as energy produced during off-peak hours can be used for peak hours. Fig. 2-2 provides a simplified flow diagram of TES used in DH network at peak hours and off-peak hours. The TES tank is charged at off-peak hours to provide heat at peak hours. Although this peak energy only covers a small amount of the total energy demand, it leads to a large investment in generation units. Meanwhile, It provides an extra advantage of reducing operation cost as all generation units work continuously at or nearby their rated conditions [99]. The advantages of TES in DHC are concluded as:

- Peak-shaving.
- Providing time-varying management.
- Relieving renewable energy intermittence.
- Increasing overall efficiency.
- Reducing initial investment cost.
- Lowering operation cost.
- Realization of smart thermal grids.

Except for the aforementioned advantages, TES has an additional superiority when compared with other storage systems, particularly with batteries. It is more economical because of the cost, lifetime, stable capacity and cycle efficiency [138]. The investment cost for electricity storage electricity is 170 €/kW while the price for thermal energy is 0.5-3 €/kW in the year of 2014 [126].

2.3.3 Optimization from energy distribution perspective

Distribution network optimization is also regarded as a key approach to reduce excessive fuel consumption and to ultimately eliminate CO_2 emission. A distribution network is typically comprised of a buried piping system for water circulation together with one or multiple pumps. Pumps are usually selected to meet the maximum pressure difference for the most remote users to provide sufficient pressure for circulation [107]. The optimal design of the distribution system involves but not limit to network layout, pipe insulation, operation control. Optimization of the distribution system will result in a more sustainable and efficient transmission network.

2.3.3.1 Pipe layout

The expected performance of DHC system cannot be achieved without an efficient pipeline system [98]. Pipe layout is generally arranged in three forms, namely branched, looped, and branched-looped network, as shown in Fig. 2-3. Branched network is simple and unreliable. Heat running into the consumer only comes from one direction. Looped network increases reliability of the system at the expense of a higher investment. The network can still deliver heat to the consumers with pipeline failures. Branched-looped network is a combination of both. The topology directly affects the construction cost, heat loss and pressure differential of the pipeline. The capital cost for the distribution network accounts for 60% of the total cost on infrastructure construction investment [93]. Heat losses in piping networks for DH are 10-30% of the distributed heat while the data for DC surpass 10% during peak cooling season [139] and [140]. Those data may be even higher in sparse districts [64]. Because of the substantial investment cost and distribution loss, a structural optimization on the topology of the distribution network is crucial for successful implementation of DHC system.

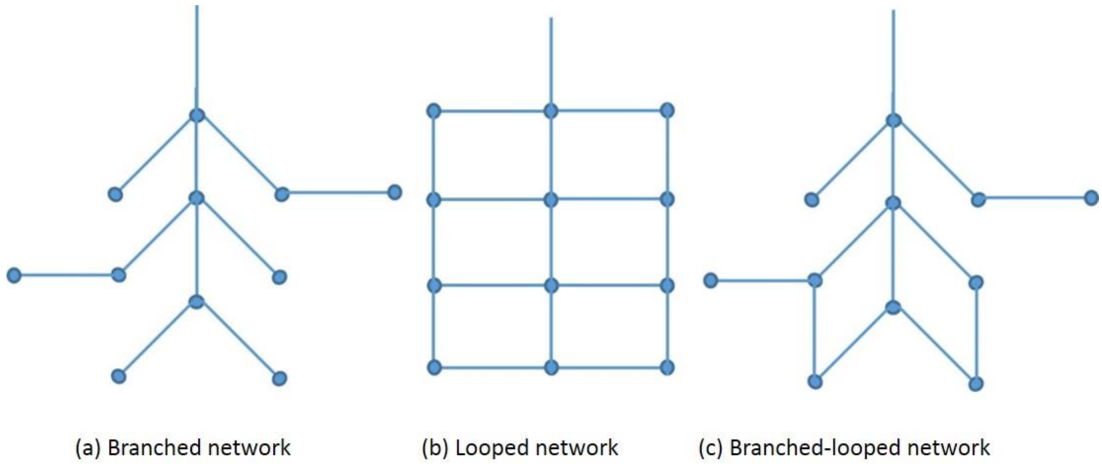

Fig. 2-3 Three types of distribution network

Here reviews typical techniques for handling the optimization of pipe layout. Sustainable development advocates that consumption should be close to the site of generation to minimize the length of the distribution line, which is critical to pressure drop, heat loss and investment cost. In terms of solution approaches, it is feasible to evaluate the optimal configuration of the piping network using mixed-integer programming models, genetic algorithm, and probabilistic search heuristic [91], [93], [141], [142] and [143]. Alternative distribution schemes are assessed thoroughly at the planning stage to understand the distribution system configuration and to further minimize the installation expenditure and operation cost.

2.3.3.2 Underground depth and soil conductivity

Heat loss of the distribution network is attributed to the thermal conductivity of the insulation and thermal conductivity of soil. The influence of soil is not as obvious as the insulation. Thermal conductivity of soil varies between 0.5 W/(m·K) and 2.5 W/(m·K) subjecting to the composition, structure and moisture content [144]. Higher thermal conductivity results in bigger heat loss. Due to the high thermal inertia of soil, underground temperature variations decrease with the increase of depth. The depth of DHC pipe is around 0.6 - 1.2m, where the soil temperature is relatively stable.

2.3.3.3 Pipe insulation and size

Table 2-4 Thermal conductivities and price values of insulation materials (adapted from [102])

Insulation materials	Conductivity (mW/(m·K))	Price ($/m^3)
Foam board	0.027	193
XPS	0.031	224
Rockwool	0.040	95
EPS	0.028	155
Fiberglass	0.033	350

Heat loss of the distribution network plays a significant role in the network cost effectiveness. Pipe size and insulation materials have a remarkable effect on the thermal performance of the piping system. An increased insulation thickness leads to a better thermal performance of the pipe but it also has a cost implication. Table 2-4 describes thermal conductivities and price values of different insulation materials. Polyurethane foam is the most widely used insulation material with a thermal conductivity ranging from 23 mW/(m·K) to 27 mW/(m·K) for different pipe companies and production technologies [81]. Adopting gases such as carbon dioxide or cyclopentane with a lower conductivity in the pore system and smaller pore sizes to reduce molecule collision offers a good solution to improve the thermal performance of the insulation [81]. Hybrid insulation as shown in Fig. 2-4(b), with higher performance material closer to the centre of the cylinder, is a paramount method to both control heat loss and insulation cost. The effect of hybrid insulation using vacuum insulation panel can decrease heat loss by 15-20% when compared with insulated with pure polyurethane [82].

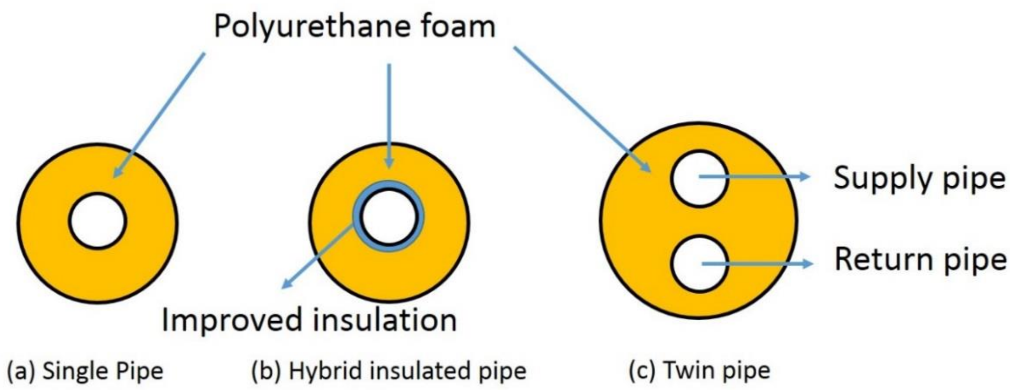

Fig. 2-4 Description of the concept of insulated pipes

The selection of proper pipe size is another crucial task in the design process. Pipe size should be considered together with insulation thickness and pump power consumption to achieve the shortest payback time. Optimal design of pipe cross sectional area in accordance with the maximum flow rate and maximum pressure drop can be obtained through size-searching algorithm and life cycle assessment so as to ensure the minimal cost of piping network for purchase, installation and operation [145].

2.3.3.4 Twin pipe or double pipe

A twin pipe as shown in Fig. 2-4(c), with supply and return pipe under the same carrier has a better thermal insulation than one single pipe with concurrent higher economy for its smaller pipe size [146]. The heat loss from the supply line is partially transmitted to the return line. An asymmetrical insulation of twin pipes can reduce total heat loss by 3.2%, with a reduction of 4% to 8% heat loss in the supply pipe without causing increased investment in the pipes [147].

2.3.3.5 Pump and operation control strategy

Pumps in a DHC system should be able to overcome the flow resistance of the piping network, including pressure losses through heat exchangers, chillers and auxiliary devices. The operation of the pumps directly influences the supply strategies of the distribution network and the pump power consumption. Up to 70% pump power can be saved by using distributed variable speed pumps to replace conventional central circulating pumps [104]. It has been proved that variable flow – variable temperature can achieve the lowest energy consumption when compared with variable flow – constant temperature, constant flow – variable temperature and constant flow – constant temperature [107].

2.3.3.6 Low energy DHC

The potential of recovering abundant surplus heat and waste incineration is far less exploited as would be expected [148]. Such discrepancy, to some extent, can be attributed to the high supply temperature of today's DH network. The supply temperature of current heating system is over 80 °C. Some surplus heat and renewable heat cannot meet the distribution temperature requirement, impeding their exploitation. As the development of low energy building and better performance heat exchanger, less energy will be required in future (These will be discussed later in section 2.3.4 and section 2.3.5). The next generation DH system calls for a supply temperature of 50-55 °C and a return temperature of 20-25 °C [14] and [149], which will reduce the temperature gap. It is also regarded as one of the most important approaches to reduce heat loss of the distribution network [150]. A reduction in supply temperature will also result in a higher efficiency for the boilers [151]. The same is true for DC with higher distribution temperature. Research has already revealed that higher supply temperatures in DC network increase COP (coefficient of performance) of the absorption chillers [152] and [153].

A lower temperature for DH and a higher temperature for DC have several advantages, including 1) lower heat loss in distribution network; 2) easier to meet heat load from geothermal and waste heat; 3) enhancing the efficiency of solar thermal collector and heat pump; 4) promoting the use of waste heat and cold recovery from industrial processes; 5) higher energy output from biomass/ waste incineration plant; 6) increased efficiency of CHP [147]; 7) increased performance of thermal energy storage system [147].

2.3.4 Optimization from heat substation

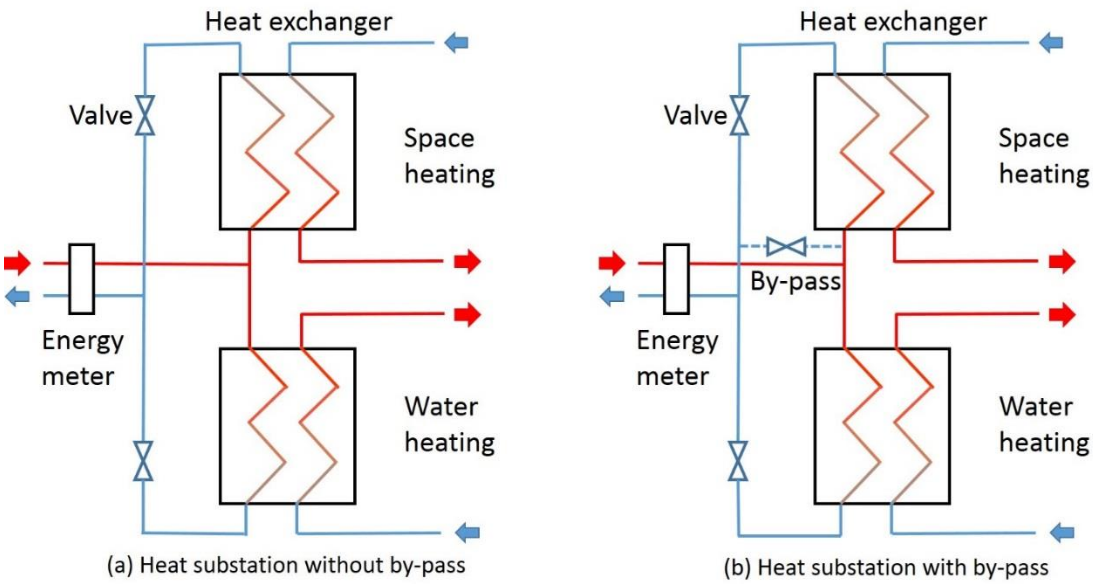

Fig. 2-5 simplified heat substation

Heat substation is a heat transfer interface between the distribution network and the building pipe circuits, usually including the following parts: heat exchanger, energy meter and control valve, as shown in Fig. 2-5(a). The valve is a thermostatic valve, which controls the return temperature by adjusting the flow rate. Energy meter is installed to measure building energy consumption through measuring flow rate and temperature differences of supply and return in the substations. In most European countries, energy consumptions in DHC system are billed according to energy meters. The performances of the heat substations affect not only the energy capacities delivered to buildings, but also the prices that customers pay for heating and cooling. However, some substations are not working in an appropriate way. Gadd and Werner [154] unveiled that around 75% of the analysed substations exhibited certain kind of faults in a case study of 140 substations. It is important to optimize the heat substation to ensure effective heat transfer. This will be reviewed in terms of heat exchanger performance and by-pass system.

2.3.4.1 Increasing the performance of heat exchanger

Yamankaradeniz [155] used advanced exergy analysis to study a geothermal district heating system, and pointed out that heat exchanger has the highest priority when focusing on system components to improve network performance. Heat exchangers in the heat substations lead to substantial heat loss due to the temperature gaps between the primary and secondary networks. Improving the efficiency of the heat exchanger can directly enlarge heat transmission capacity and allow more customers to be connected to the system. It can also affect the temperature of the circulation medium and influence the efficiency of energy generation units. The biggest challenge for future low energy DHC network is how to improve the efficiency of the heat exchanger so as to extract more heat or cold from the primary line with the purpose of generating greater environmental and financial benefits.

A higher performance heat exchanger can absorb more energy from the distribution medium, namely more energy transfer per unit volume, which directly impacts on the effectiveness of the network heat transfer capacity. Sun et al. [79] and [80] studied a new ejector heat exchanger which could limit the primary heating network return water temperature to 30°C, reduce steam extracted from steam turbine by 41.4% and recover more heat without altering water circulation flow rate. Increasing ΔT by 10°C contributed to a reduction of ~55% pump power consumption depending on the heat production method and contributed to a total of 0.1~14% fuel-source saving [131]. The development of building entrance AHP (absorption heat pump) makes it possible to cool the temperature of the primary side even lower than the secondary side. Heat capacity increases to 1.3 ~ 1.8 times without extra investment in heat production units and heat delivery network [32]. The increased investment in application of AHP can be compensated from the heat network as it provides the same amount of heat with reduced pipe diameter, around 20% investment reduction on the distribution network [32]. The advancement of technology results in a compact size for AHP which can be installed in each independent building [124].

Heat exchanger with an insulated water storage tank attached to the primary side allows a smaller pipe size in the distribution network as it reduces heat transportation at peak hours [149]. The small dimensioned pipe leads to lower investment cost in the construction stage. In addition, when the heat load is low, the heat can be met by the storage tank directly, reducing heat loss during operation. Meanwhile, the control of the heat exchanger is another key factor affecting the performance of the heat substation. By adjusting the pump rotation speed to achieve lower flow rate in the heat exchanger can further cool the return temperature by 5°C on yearly average [156]. This will bring about obvious energy and environmental benefits.

2.3.4.2 Installation of by-pass

To ensure the thermal comfort of the consumers and guarantee that heat can be supplied to them promptly, an installation of by-pass between the supply and return pipes is necessary, as shown in Fig. 2-5(b). The valve in the by-pass is a thermostat valve with a temperature control system, which allows a tiny amount of hot water running through under a pre-set temperature. This is to ensure that the pipeline would not be cooled down to a low temperature when there is no heat demand. The temperature is usually set between 35°C and 40°C [157]. The by-pass will inevitable result in a certain amount of heat loss by decreasing the temperature difference, but it is necessary for preventing freezing and reducing waiting time for heating up the heat exchanger [150]. Brand [158] proposed an innovative method of redirecting the by-pass water to bathroom with the purpose of both improving thermal comfort and reducing heat loss.

2.3.5 Enhancements from terminal users perspective

Residential houses, hospitals, schools and commercial buildings are common terminal users of DHC systems. Several issues with regard to building energy conservation, energy price and residents awareness of energy saving directly or indirectly affect energy consumption and thereby the efficiency of the entire DHC system. Optimization from the heat users will result in less energy consumption, which facilitates the advancement of future 100% renewable DHC and low energy DHC network.

2.3.5.1 Future low energy building

Future low energy building should be able to provide thermal comfort to occupants at a lower energy consumption with reduced GHG emission. The less energy demand building also promotes the evolution towards next generation DHC system. This section discusses low energy building from three aspects: envelope thermal insulation, phase change materials and heat recovery.

The most widespread technology to bring down thermal loss is to improve the insulation of envelopes. A better insulation aiming at reducing heat dissipation, which intrinsically features envelope thermal inertial, is an efficient method to minimize energy demand for heating and cooling. Polymeric (plastic) foams and inorganic wools are the most widely used insulation materials in Europe [159]. The share of different insulation materials in European market in 2010 is shown in Fig. 2-6.

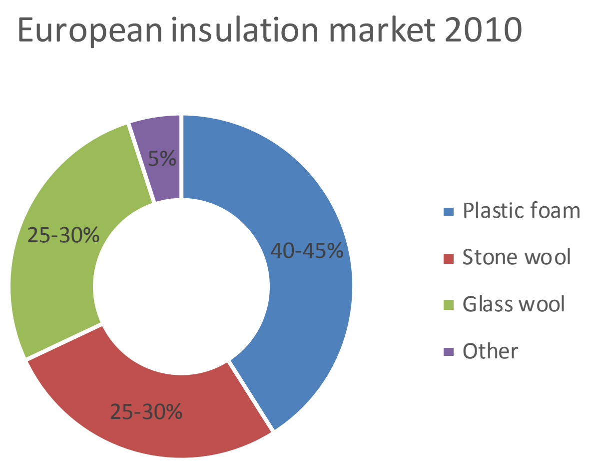

Fig. 2-6 European insulation market in 2010 [160]

Using chemicals embedded into windows, envelopes and floors to store or release heat during the process of solidification/fusion can also improve the thermal inertial of buildings to meet thermal comfort and energy conversion purposes [161]. Those chemicals are Phase Change Materials. Under passive heating and cooling conditions, a melting temperature ranging between 17 °C and 25 °C is able to offer a comfortable living condition in most countries at any climatic condition [162]. Salt hydrates as PCMs are seldom used for passive heating as they are highly corrosive to building construction materials if used without capsules and have high cost with capsules [162]. Organic PCMs which overcome the above disadvantages are deployed for building thermal regulation. Table 2-5 lists some organic PCMs that are suitable for passive heating and cooling in buildings.

Table 2-5 organic PCMs suitable for passive heating and cooling (adapted from [162])

Material	Melting point (°C)	Heat of fusion (J/cm^3)	Freezing point (°C)	Heat of freezing (J/cm^3)
Methyl Stearate-Cetyl stearate eutectic blend (90.6-9.4 mol%)	22.2	180	21.8	175
Thermotop 20 (Butyl stearate blend)	21.5	126	18.5	125
CA-LA eutectic blend (73-27 mol%)	18.2	120	16.6	119
CA-MA eutectic blend	21.7	168	21.4	165
CA-PA eutectic blend	21.8	171	22.1	173
CA-TD (62-38 wt%)	19.1	153	13.3	148
LA-TD (46.4-53.6 wt%)	24.4	163	24.4	146
CA-MA (55 wt%)/ expanded perlite	20.7	85	21.7	88
CA-LA (20 wt%)/ expanded vermiculite	19.1	27	17.1	31
CA-LA (40%)/expanded vermiculite	19.1	61	19.2	58
EPT (57 wt%)/ diatomite	19.6	111	18.8	101

Buildings require adequate fresh air to displace indoor air pollutants in order to provide occupant comfort and to maintain a healthy environment. An increased air infiltration has a negative effect on thermal comfort, but it is not economic to sacrifice thermal comfort for air quality. Heat recovery from buildings is an effective way to alleviate heating and cooling requirements while guaranteeing enough fresh air and thermal comfort. Research showed that 80% to 90% ventilation losses can be recovered through heat recovery system [74]. Using heat exchangers or heat pumps to retain energy in exhaust air as heat source or heat sink is an effective way to pre-heat or pre-cool incoming fresh air, thereby diminishing energy demand for heating and cooling [75]. A typical heat recovery scheme is shown in Fig. 2-7.

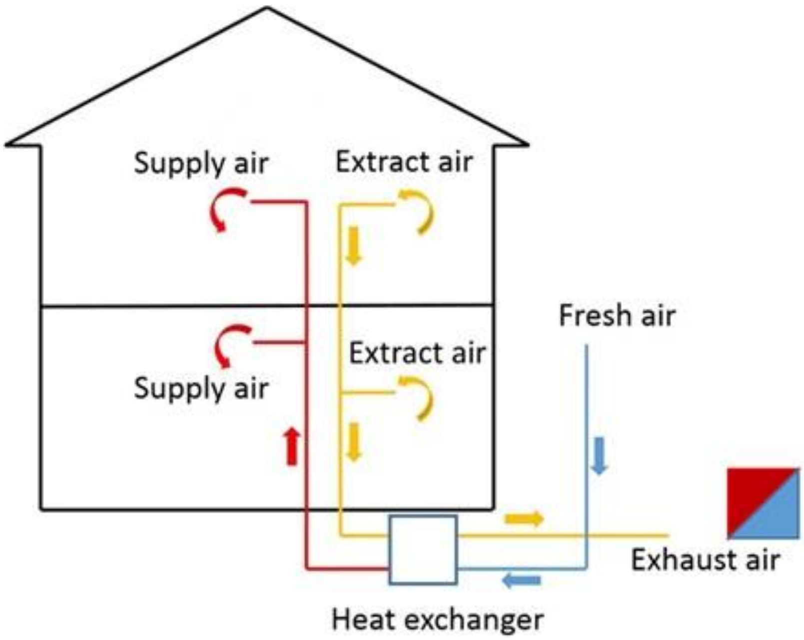

Fig. 2-7 Building heat recovery

2.3.5.2 Energy-efficient renovation of existing buildings

Owning to the long life time of buildings, around 70% to 80% of the existing poor performance building stocks will be still in service by the year of 2050 [76]. The low performance building will not be able to meet future legislation and should be retrofitted to meet the new standard. Building renovation has the potential to save up to 68% building heating load [77]. Another study by Tommerup [74] pointed out that heating-related energy for buildings has the potential to be saved by 80% in Denmark after renovation.

The purpose for renovation of existing buildings is to improve the thermal performance of the buildings, including installation of better insulation for walls and ceilings, energy efficient windows and doors and heat recovery system. Those approaches are vital options for implementing the transition into future low-energy green building. Using heat recovery can reduce heat demand for heating up the fresh air. By increasing wall insulation and replacing energy-cost windows with energy-efficient ones, less heat or cold is transferred through from indoor to outdoor, resulting in less energy consumption of the buildings. Dodoo et al. [103] studied a multi-story building. By retrofitting with energy-saving doors and windows, 39% space heating was saved.

2.3.5.3 Effective building energy management system

Building Energy Management systems (BEMSs) aiming at optimizing energy utilization by simultaneously guaranteeing air quality and thermal comfort are attracting increased attention through the application of smart meters and sensors. Previously, heat meters were read manually which entails a big amount of man-hour and they have been only utilized for billing. Smart meters can read and send data to BEMS through a virtual network for further analysis. The system is linked to a cloud environment where rich data sources are stored for intelligent management and measurement of building performance. Alternatively, they are able to identify whether energy usages are at their anticipated level at an early stage [163].

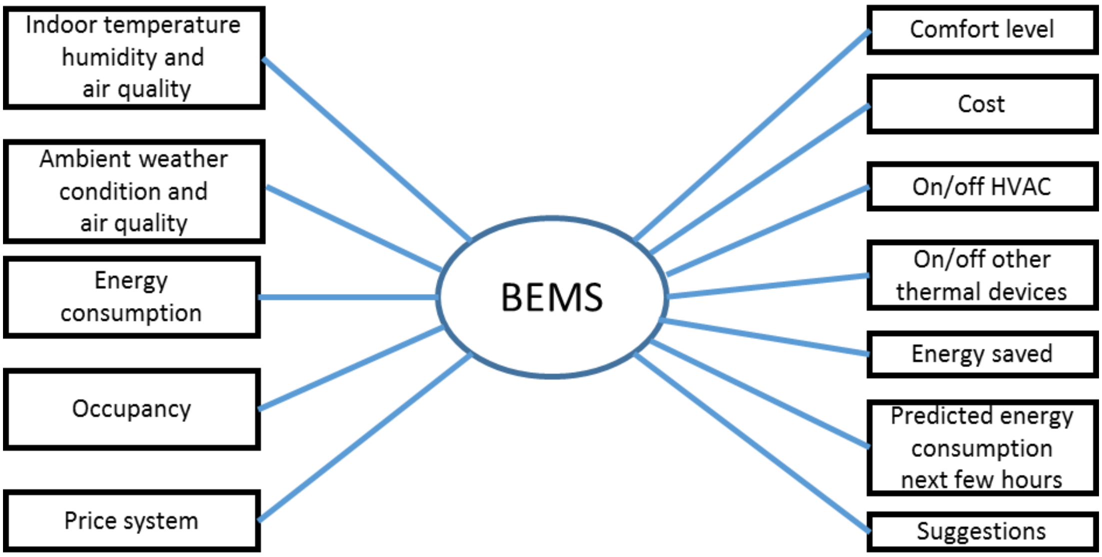

Fig. 2-8 Configuration of BEMS focusing on heating and cooling

Fig. 2-8 shows a BEMS based on heating and cooling. Smart meters and smart appliances are included in the system. Smart meters collect real-time information about room temperature, humidity, air quality, occupancy together with weather conditions. The gathered data are transferred to BEMS for processing and then the system dispatches heat and cold according to predicted heat and cold consumption, which is based on historical data. Meanwhile, it simultaneously sends instructions to energy providers about the amount of energy that should be generated in the next few hours. The application of smart appliances in the network enables the system to automatically adjust individual consumption according to energy demand and energy price. For example, during peak periods it turns off other thermal devices to reduce heat demand, and during off-peak periods it turns on these devices. This will also take advantage of price difference to save money in system where real time price is introduced. The realization of BEMS provides a more efficient, reliable and affordable energy network. The most important factor for BEMS is digital processing and communication compared with traditional control systems, which enable quick response and efficient energy management. In future, these systems will be more intelligent. Users can even monitor and control from smart interfaces such as smart phones by installing a BEMS App. Electricity and gas consumption should also be incorporated into this system for a comprehensive understanding of building energy consumption.

2.3.5.4 A better pricing system

Heating and cooling prices are challenges for the wide adoption of DHC system, which should be transparent, fair and competitive. Traditional DHC price in some countries is billed according to heated areas regardless of the amount of heat or cold consumed, leading to issues: the properties lose interest in improving building insulation and the residents lose interest in using energy effectively. A good pricing system should not only ensure that energy transmitted to households is the amount of energy required, it should also be a financial driver to speed the development pace of future green buildings and an enlarged share of sustainable energy. A real-time pricing mechanisms established on smart metering in electricity systems has been proved to be efficient in demand management, and be able to improve economic benefit and promote transparency [164]. If smart meters are installed in the DHC network, a real-time pricing mechanism should also be a good solution to DHC network [164].

2.3.5.5 Improving public awareness of energy conservation

User awareness of energy conservation directly influence the usage of equipment therein installed. Under the context of future smart thermal grid, human behaviour is still an important factor for the management of the smart network. The role of individuals must not be understated as consumer behaviours such as opening the window and controlling of the thermostat are substantially responsible for building energy consumption. In particular, residents activities result in 50% higher heating demand and 60% higher peak load than the expected values that are computed from the standard energy demand of energy-efficient buildings [149]. Energy saving is the prerequisite for implementing zero carbon emission building. It is important to encourage people to turn off air conditioning when natural ventilation can provide thermal comfort to occupants. Furthermore, for the reason of personal control, occupants in naturally ventilated buildings are able to bear a higher room temperature than those that stay in air-conditioned buildings [75].

Recent years have seen unprecedented growth in network communication and mobile devices. This has led to significant change in the integration of physical and cyber domain. In future smart system, with the popularization of BEMS in smart phones, customers can share their energy saving obtained from BEMS in social networks, which can both make them feel proud and stimulate their social connections to save more energy.

2.4 Research directions towards smart thermal grids

An outlook of the future DH has been presented in the first chapter. Optimization of the current DH network towards smart thermal grids can potentially deliver economic, environmental and social values. The concept of smart thermal grids has never been tested so far but successful examples of low-temperature DH systems have been demonstrated in Lystrup, Denmark [165] and in Slough, UK [166]. It is important to further develop, optimise, design and test the concept of DHC smart grids with a view to transform existing buildings to smart DHC ready buildings, i.e. buildings that can both withdraw and supply heat to the grid, favouring decentralised production. Decentralised production will allow low overall capital cost, a better matching between production and demand, decreased maintenance, reducing impact of system failure, and reducing oversizing. The following challenges form avenues for future research as elaborated in the Table 2-6 - Table 2-10:

- How to convert/extend existing DHC grids to the low energy DHC smart grid concept with typical supply/return temperatures of 50/20°C (Table 2-6)?

- How to supply low energy DHC smart grid for space heating and cooling and domestic hot water (DHW) to existing buildings, energy-renovated existing buildings and new low-energy buildings (Table 2-7)?
- How to recycle heat from low-temperature sources and integrate renewable heat sources such as solar (Table 2-8)?
- How to connect the surplus heat to the STGs in the most efficient way (Table 2-9)?
- How to ensure suitable planning, cost structures in relation to the operation as well as to strategic investments related to the transformation of existing buildings to smart DHC ready buildings (Table 2-10)?

Table 2-6 Migration through Retrofit of existing DHC grids to the low energy DHC smart grid concept

Migration through Retrofit of existing DHC grids to the low energy DHC smart grid concept	
Existing State-of-the-Art	Proposed Progress beyond State-of-the-art
The trend throughout the three generations of DH systems has been towards lower distribution temperatures, material lean components, and prefabrication leading to reduced manpower requirements at construction sites [14]. Various advantages in the use of low-temperature DH have been shown (increased efficiency in heat distribution, and the exploitation of low temperature renewable	STG will promote a migration through retrofitting of present district heating into low-temperature networks interacting with low-energy buildings. STG is based on a future generation of district thermal technology that involves lower distribution temperatures, assembly-oriented components. Lower supply and return temperatures will bring additional benefits, including higher distribution efficiency, higher power-to-heat ratios in CHP plants, higher heat

energy sources such as geothermal sources, and solar energy and waste heat from industry). District heating technologies must be further developed to decrease grid losses, exploit synergies, and thereby increase the efficiencies of low-temperature production units in the system.	recovery from flue gas condensation, higher coefficients of performance in heat pumps, higher utilisation of geothermal and industrial heat sources, higher conversion efficiencies in central solar collector fields, and higher capacities in thermal energy storages if they can be charged to a temperature above the ordinary supply temperature. Also, STG will solve the endemic grid thermal losses problem through optimisation with a focus on: heat generation units, heat distribution, heat substation and heat users.
Existing DHC is a standalone system that does not involve any interaction with other grids. Most of the existing DHC are oversized resulting in a large amount of energy waste.	STG is a new generation of DHC system which involves more interactions with electricity and gas grids within a given community/district, while factoring in existing individual gas boiler heating and power driven air-conditioning systems through the proposed concept of smart DHC. STG will promote heat production based on real-time demand to efficiently match supply, while promoting efficient storage of excess energy and peak shaving strategies.

Table 2-7 Retrofit existing buildings to become DHC smart grids ready

Retrofit existing buildings to become DHC smart grid ready	
Existing State-of-the-Art	Proposed Progress beyond State-of-the-art
Conversion of individual buildings, including natural gas areas, to DHC should be informed by a socio-economic assessment of the retrofitted overall system efficiency and its environmental impact. Hourly balances of heat and power demand and the use of conversion and storage facilities are essential to maximize the efficient use of renewables and end-use efficiency measures.	STG design will first develop a geo-clustered, building typology aware, heating and cooling technology catalogue, publicly available. This catalogue will serve as a base for the design technology packages associated with a design and simulation environment, and a dedicated toolbox. STG technological packages rely on state of the art technologies enabling demonstration of replicability on representative pilots
Most of the existed heating appliances in Europe are gas-fuelled, with a market share over 45%, while the share of heating oil appliances is just under 20% [167]. A wide range of renewable and energy-efficient technologies are already available to replace the two thirds of the heat market which today are covered by fossil fuels.	STG technological packages moves beyond the state of the art in two significant directions. Firstly, the cutting edge and market ready heating technologies such as GAHP (gas absorption heat pump) and microCHP will be utilised to further reduce domestic heating from gas network. Secondly, as the market and legislation moves towards a systemic approach, STG technological packages will deliver the tools necessary to select and size the technologies for the customer needs both within and outside the DHC

	network.
Existing generations of heating and cooling systems do not fully exploit demand management solutions nor try to optimise local generation systems. Peak load for space heating during a day may be reduced by making good use ofbuilding thermal inertia or by using space heating systems with a peak shaving control system. This may be realised in a simple way by use of a maximum flow controller, an intelligent scheduler or control system based on weather forecasts.	STG will rely on state of the art internet enabled heating and cooling appliances to gather additional local and network wide intelligence. Domestic control system will be able to communicate with the DHC control to enable the smart exchange of heat and control of energy use. This will be achieved by inferring at residence level parameters such as available thermal storage, potential building inertia storage, predicted heat (and electricity in the case of microCHP) demand and supply.

Table 2-8 Technologies to recycle heat from low-temperature sources and integrate renewable heat sources

Technologies to recycle heat from low-temperature sources and integrate renewable heat sources	
Existing State-of-the-Art	Proposed Progress beyond State-of-the-art
Geothermal heat exploitation as a renewable energy source implies the use of absorption heat pumps that may be operated in an efficient way together with steam production from e.g. waste CHP	STG will promote the large-scale integration of RES into existing energy systems and will therefore address the challenge of coordinating fluctuating and intermittent renewable energy production with the rest of the DHC

plants. The CHP can increase the geothermal production temperature. Another option is to use compressor heat pumps in which case integration with the electricity supply becomes essential.	system. STG will also fully exploit the integration of RES in CHP stations. The regulation in supply may be facilitated by peak boilers, for example, fossil fuel boilers and electric boilers. Moreover, the integration can be helped by energy storage technologies (water tank & building inertia).
The energy source for DHC systems are fossil fuels or other energy sources, and mixed systems combining two or more energy sources, like natural gas, wood waste, municipal solid waste and industrial waste heat, can be feasible economically. Heat suppliers can also include heat from CHP, waste-to-energy, biomass and geothermal energy plants, as well as industrial excess heat. hybrid systems combining renewable or alternative energy technologies like solar collectors, heat pumps, polygeneration, seasonal heat storage and biomass systems are being used as the energy source [168].	As a minimum baseline, STG will devise appropriate use of DHC energy sources to achieve the Europe carbon emission target. As such, STG will promote the wide use of CHP together with the utilisation of heat from various industrial surplus heat sources and the inclusion of heat from renewables. The proposed DHC retrofitting will be scalable to accommodate various technology evolutions, including processes of converting various forms of biomass into bio(syn)gas and/or different types of liquid biofuels for transportation fuel purposes, among others [169] and [170]

Allowing entities to be connected to a thermal network to generate thermal energy will promote greater use of renewable energy (e.g., solar thermal, geothermal, biomass), by establishing a market for excess thermal energy.	STG will deliver methods and tools to assess the potential advantages of different forms of renewable energy in the context of integrated thermal networks, so that a holistic (socio-economic and environmental) comparison of the different sources of energy can be performed and the most advantageous options determined for thermal networks and applications.

Table 2-9 Surplus heat use in the smart thermal grid

Surplus heat use in the smart thermal grid	
Existing State-of-the-Art	Proposed Progress beyond State-of-the-art
Many domestic heating systems are installed with extra capacity either due to fixed power outputs of available products or mismatches between demand types. This can lead to sub-optimal operation when running in isolation. Decentralised intelligent metering to get a close link between the power and the energy used by the buildings may be used for the continuous commissioning and the payments.	STG will fully exploit the innovation potential of a smart grid in terms of maximising installed asset utilisation in the most cost effective way. STG will exploit metering informed by weather forecast to estimate thermal demand for the next few hours so that DHC companies can rely on those readings to distribute energy effectively, thus helping shift peak load as well. Thermal trading can enable the efficient use of over capacity to serve the district and to provide further incentives to homeowners or asset owners to operate the systems most efficiently. This will lead

	to novel business models on the district level.
Thermal load shifting in thermal networks is rarely implemented, mainly because the absence of suitable smart meters and the lack of motivation [171].	STG will propose a district thermal management approach, aggregating the end-user production/consumption needs. Advanced control techniques for storing heat in the network will be explored and assessed by simultaneously varying supply temperature and pressure in the pilots.
The academic and industrial literature is pointing at the advantages of low supply temperature in DH networks. There is an urgent need to develop technologies to recycle heat from low-temperature sources (extra solar heat from individual solar panel install in buildings).	STG will fully utilise the advantages of lower supply and return temperatures in distribution networks by fully exploiting the potential of decentralised production proposed. The surplus heat from individual buildings will be incorporated into the grid.

Table 2-10 Planning, cost and motivation structures for the transformation of existing buildings to smart DHC ready buildings

Planning, cost and motivation structures for the transformation of existing buildings to smart DHC ready buildings	
Existing State-of-the-Art	Proposed Progress beyond State-of-the-art
The DHC planning process needs to enable a transition into STGs in existing and future supply systems. There is a need to facilitate a planning procedure where the energy supply side is synchronised with the energy conservation side in such a way that the increasing proportion of intermittent renewable energy systems is integrated in an economical way in the total energy system. Coordination between implementing lower temperatures and planning for energy conservation is necessary, which involves planning requirements.	STG will promote the development of a DHC planning framework in which infrastructural planning is used to identify and implement where to have DHC and where not to have DHC as well as cost principles and incentives in operation with the aim of achieving an optimal balance between investments in savings versus production and an optimal integration of fluctuating renewable energy in the overall energy system.
The identification of optimal plans for the levels of heat/cold saving versus heat/cold production and which technologies to apply can only be carried out on the basis of a combination, on the one hand, of detailed data on the location of energy demands and, on the other hand, of knowledge on the future system of which	STG proposes to develop a geo-clustered, building typology aware, heating and cooling technology catalogue, publicly available. This catalogue will serve as a base for the STG planning.

DHC should be a part.	
Tariff policies of the present DHC tariff system are dominately characterised by the short-term marginal costs of the existing supply systems. In a smart district heating and cooling system, a synchronisation of supply system and demand system, and the technological change to renewable energy supply systems, require price signals (via the tariffs) that support this synchronisation. Basically, this means a change to a tariff policy where the long-term costs of future renewable energy systems will be the tariff base.	STG system will lead to measures that incentivise investment in retrofitting or deploying new DHC systems. STG will deliver methods and tools that support the demand side so energy conservation takes place as buildings and districts are being energy retrofitted / renovated.

2.5 Smart control of generation units

Much technology focused research has been labelled as 'smart', where the term 'smart' is mainly about 'digital', 'sustainable', 'green' and 'future'. And mostly this targets at improving the operation of network and emphasising value delivery through intelligence. The purported benefits of smart management are better access to information, better decision making and efficient control. The outcomes of smart control in DH network are to secure robust heat delivery whilst reducing environmental impact and simultaneously bringing economic interest to local residents.

Central to smart thermal grid is the use of data and analytics in intervention across multi-objective. Recent advances in smart meters, along with big data mining, and low cost communication solution have created an approach for smart management of the DH network by using artificial intelligence, optimization algorithms, fuzzy system [172], machine learning [173] and neural network [174]. Identifying all the avenues toward smart thermal grid is out of scope, but smart control of the generation units in Hybrid DH system is pertinent.

Hybrid DH systems with mixed energy sources have gained an increased importance in DH systems for costs and emission reduction. Optimal management of the generation units to make the best use of each unit is vital as their performance depends on heat output. Meanwhile, the problem of mismatch between demand and supply in a DH system is pronounced. In most of the systems, more heat than required is generated to meet the demand which causes increased distribution losses and lower efficiency for the generation units [1]. DH optimization has been considered as one of the best solutions for optimal management of energy generation in DH networks [1]. Demand respond based on smart control of the generation units and thermal storage is an option to reduce peak heat demand without sacrificing the thermal comfort of the users [67]. Short and long term planning of energy generation according to load forecasts is able to maximize the overall efficiency of the generation units and to reduce operation cost.

Extensive optimization models, including linear, non-linear and mixed-integer linear optimization have been applied for DH optimization [175]. Under the linear model, the efficiency is considered constant over the load range. Hawkes and Leach [176] designed a linear programming for choosing the optimal capacities and operation schedule in a decentralized generation system. Constant efficiency is applied for the CHP aiming at meeting the demand at minimum cost. Cho et al. [177] demonstrated the optimal load dispatch from a CCHP with the purpose of reducing primary energy consumption, carbon emission and operation costs. In this study, a linear relationship between the electricity output and fuel consumption is assumed, thus constant efficiency. Within the linear models, the plant operating at a lower load is as efficient as at a higher load, which is not the case in reality. This approximation over-simplifies the problem and produces less accuracy to avoid turning the issue into non-linear problem [178]. Some proposed using MILP (Mixed-integer Linear Programming) to address this issue. A high minimum start load is employed to enforce the units running at a relatively stable efficiency, and the generators have to continuously operate in the same model regardless of the needs [178]. Ameri and Besharati [98] developed a MILP model for a complex district energy system. The model was used to identify the best mix for energy generation units to meet heat and cooling demand with the minimum operation cost. Constant operation efficiencies for boilers, CHP and chillers are used to linearize the constraint equations. Milan et al. [179] put forward a planning methodology to achieve minimum costs in a renewable energy based system, taking into account the supply from different technologies. The results suggested the optimal installation capacities, building load reduction and operational schedules. This problem was formulated as a MILP and constant efficiency was applied to CHP. Liu et al. [180] conducted an environmental performance and energy systems efficiency study in commercial buildings. A multi-objective mix-integer optimization was developed by using constant efficiencies for all technologies. Another optimization was developed based on MILP for long term planning of CHP plants [181]. Constant efficiencies were applied for load dispatch to maximize the profit of the system. Some solved this problem from a different perspective by converting the non-convex problem into a convex problem. Linear programing is used to minimize the operation cost of the CHP in a DH network when considering heat storage [67] [182] [183] [184]. The cost of operating the CHP with respect to the heat and power was evaluated through a convex within the operating region area. Characteristic points were applied to represent the relationship among cost, heat and power. There are some research works, which adopt variable efficiencies at partial load by using nonlinear formulations. Convex quadratic functions were used to compute the output through heuristic methods such as Cuckoo Search algorithm [185], Mesh Adaptive Direct Search [186], Genetic Algorithm [187], Evolutionary Programming [188]. Nevertheless, heuristic does not ensure to find the global optimal solution given the addressed complexity [189]. Furthermore, non-linear models are computationally expensive [178]. As a result, for large-scale optimization issues with a great amount of variables, linear and mix-integer linear programming is preferred. Ommen et al. [178] compared the use of linear, MILP and Non-linear programming for an energy dispatch problem. Results revealed that non-linear and mixed-integer linear programming displayed better results compared with linear programming and the gap between the two was small.

Generation units' performance relies on specific conditions that they operate. The performance drops sharply when running at partial load [178] and small changes may result in significant efficiencies variation. Constant efficiency is not sufficient to evaluate the performance of the generation units. In order to fill the gap, an optimization approach is proposed in this thesis to obtain the optimal selection of energy mix and the operation level of the generation units aiming at minimal operation cost.

2.6 Discussion and summary

Building simulation tools are extensively applied to understand building energy performance. Due to the complexity of built environment and independent interacting variables, it is impossible to fully represent the real-world performance. Accurate building performance simulation reduces the gap between predicted and measured building energy demand. U-vales and air infiltration rate are among the most sensible parameters influencing the accuracy of building heating load simulation, which are normally obtained from design values. Uncertainties are involved at the construction stage, together with weathering and aging, so the real values deviate from the design values. On site measurement requires a large amount of labour force and time, still random error exists.

DH simulation is an approach to understand the thermal dynamic performance of the distribution network and energy performance of the building stocks. It has been widely used to provide guideline for robust design, operation and retrofit of the network. However, work to date is mainly from the perspective of separate simulation either focusing on the building stocks or on the distribution network. Seldom tools have been developed targeting at whole network simulation and each has its limitation.

DH provides an optimal solution to future energy and environmental issues. There are still problems existing preventing its large acceptance. Review of current publications concerning experiments, modelling and algorithms reveals that the aim for improvement is to reduce investment costs, operation costs, CO_2 emission and payback periods. The decisive factors for improvement can be categorized into four main processes: generation, distribution, transformation and consumption. Conclusions are: 1) Integration of sustainable energy, CCHP and TES are the major solutions to alleviate fossil fuel depletion, reduce GHG emission and enhance system stability and efficiency. 2) Optimal design of the heating and cooling networks (piping network), including pipe layout, pipe insulation, underground depth, supply temperature, and an optimal operation of pumps to ensure the efficiency of the distribution network. 3) Improving the performance of the heat exchanger and an installation of by-pass can enhance the effectiveness of the heat substation and reduce response time to guarantee efficiency and comfort. 4) Less energy demanding buildings, BEMS, a stimulating price and strengthening public awareness of energy saving are the key approaches to reduce energy consumption in building and to facilitate the development of future low energy DHC.

The problem of mismatch between demand and supply in a DH system is pronounced. Recent advances in smart meters, along with big data mining, and low cost communication solution have created an approach for smart management of the DH network based on day-ahead demand response. Optimization algorithms such as linear, non-linear and mixed-integer linear optimization have been applied for DH optimization. For linear programming, constant efficiency is adopted which over simplifies the problem. For non-linear programming, it is computationally expensive and does not guarantee an optimal solution. Mixed-integer linear programming displays better results compared with linear programming and the gap between mixed-integer linear programming and non-linear programming is small.

Based on the literature review, the observed gaps are:

1. A requirement for the calibration of building U-values and air infiltration through a simple and rigorous approach to improve the accuracy of building performance simulation.
2. A DH simulation platform with validated and recognized tools to overcome the limitation of existing simulation tools.
3. Day-ahead demand response optimization by considering the efficiency variations at partial loads.

This thesis continues by presenting the methodology with an effort to bridge these identified gaps.

3 Research methodology

3.1 Introduction

This chapter presents the methodology adopted to address the gaps identified in the literature review chapter. Each research question involves methods and/or algorithms further elaborated in the follow on chapter. This chapter, therefore, provides a bridge between the review chapter and the research approaches chapter, on which the outputs and results are based.

The study is based on a district heating system in Ebbw Vale, as shown in Fig. 1-1. At present, the energy centre is used to meet heat demands for four buildings, including two public schools, one office building and one leisure centre. The energy centre was built to integrate more commercial buildings and residential houses, so currently the installed capacity is oversized. Four gas boilers, one CHP boiler and two biomass boilers were installed. During a normal winter day, the CHP, biomass boilers and only one or two gas boilers are in operation.

3.2 Building U-values and air infiltration calibration

This section starts with a theoretic study on building heat consumption at quasi-steady state when human behaviour is not considered. The use of building performance simulation, regression model and genetic algorithm in the field of building energy analysis are put forward. Together, introductions to the three methods are presented, which are the basic means that form the approach to building U-values and air infiltration calibration.

3.2.1 Related work

Valuable works have been published related to building simulation calibration which highly contributed to the fidelity of simulation models [190] [191] [192] [193] and [194]. The purpose of these calibrations is to determine the appropriate parameters that are most sensitive to energy consumption, some focusing on specific variables and some focusing on all the determinants. Human related activities are involved in the calibration process. The credibility of the calibrated variables is questionable since they are easily affected by some difficult to measure variables such as human related behaviours (e.g. door and window openings and human activities) [195]. Research revealed that human behaviour can result in up to 50% higher heating demand and further investigation on this aspect should be carried out in order to precisely predict users heat load profile through simulations [149]. In terms of physical properties that affect building energy consumption, building U-values and air infiltration are among the most sensitive parameters. The influences of U-values and air infiltration on building heating demand are discussed in this section.

Building heat consumption is an important element to evaluate the energy performance effectiveness of an entire building. The main driving forces for heat consumption ($Q_{consumption}$) are building surface heat loss ($Q_{envelope}$), air infiltration ($Q_{infiltration}$), domestic hot water (Q_{DHW}), window and door openings ($Q_{openings}$) and mechanical ventilation ($Q_{mechanic\ ventilation}$), which can be concluded as:

$$Q_{consumption} = Q_{envelope} + Q_{infiltration} + Q_{DHW} + Q_{openings} + Q_{mechanic\ ventilation} \tag{3.1}$$

Energy consumption caused by human behaviours is still underexploited because of its complexity and insufficient approaches to deliver an accurate estimation [196].

When evaluating the thermal performance of a specific building, the influence of human related heat consumption coming from domestic hot water, openings and mechanical ventilation can be excluded from the total heat consumption as they are not caused by the inherent characteristics of the building. Therefore, formula (3.1) can be simplified as:

$$Q_{consumption} = Q_{envelope} + Q_{infiltration} \tag{3.2}$$

Heat loss through building envelope is caused by the temperature deviation between the indoor and outdoor environment. Indoor temperature is relatively stable at a constant set temperature to meet the requirement of occupant thermal comfort. Outdoor temperature varies with local weather conditions. However, as the weather evolution is slow, the whole process can be regarded as a quasi-steady state. A quasi-steady state is similar to a steady state, which is generally applied to reduce system dimensions and to make problems more tractable, especially in reduction of parameters for identifying problems. Building envelope consists of the exterior wall, windows, roof and floor. The heat loss through exterior wall ($Q_{exterior\ wall}$), window (Q_{window}), roof (Q_{roof}) and floor (Q_{floor}) at a quasi-steady state can be described as:

$$Q_{envelope} = Q_{window} + Q_{exterior\ wall} + Q_{roof} + Q_{floor} \tag{3.3}$$

$$Q_{window} = \int_0^t U_{\mathrm{window}} \cdot A_{window} \cdot \Delta T \tag{3.4}$$

$$Q_{exterior\ wall} = \int_0^t U_{\mathrm{exterior\ wall}} \cdot A_{exterior\ wall} \cdot \Delta T \tag{3.5}$$

$$Q_{roof} = \int_0^t U_{\mathrm{roof}} \cdot A_{roof} \cdot \Delta T \tag{3.6}$$

$$Q_{floor} = \int_0^t U_{\text{floor}} \cdot A_{floor} \cdot \Delta T \tag{3.7}$$

Where, t is the time duration. U_{window}, $U_{exterior\ wall}$, U_{roof} and U_{floor} denote U-values of window, exterior wall, roof and floor respectively. As these are average values so the effect of thermal bridges is included. A_{window}, $A_{exterior\ wall}$, A_{roof} and A_{floor} are the areas for windows, exterior wall, roof and floor. ΔT is the temperature difference between indoor and outdoor.

Apart from the thermal loss through building envelope, another implication to heat consumption is the air leakage. Warm indoor air that leaks out of the building carries some heat, resulting in more heat demand. Heat consumption caused by air leakage can be quantified by:

$$Q_{infiltration} = \int_0^t C_{pa} \cdot \rho_a \cdot V_a \cdot \Delta T \tag{3.8}$$

where, C_{pa} is the specific heat of air. ρ_a is the density of air. V_a is the volume of air exchange, which can be obtain by knowing air change per hour from equation 2.2.

From the above equations, it is easy to conclude that for an existing building under certain weather condition operating at quasi-steady state, U-values and air infiltration are the decisive parameters affecting heat demand when human interference is not considered.

3.2.2 Experimental study

This section summarizes the studied building used as a basis to implement the calibration process. The test was performed in a two-story old office building in south Wales, built in 1915. The building was refurbished in 2011 to meet the requirements displayed in Table 3-1. The targets do not always match with the true values as a result of the aging process and installation features. The heat consumption in this building is higher than predicted using the design value. The building is currently occupied by Blaenau Gwent Borough Council Office, the Gwent Archives and Ebbw Vale Works Museum. The office and museum zones open from 9:00 am to 17:00 pm during workdays. The archives open from 9:00am to 17:00pm daily. The heating system in the office zone and museum zone run from 7:00am to 17:00pm workday and the archives run 24 hours. The archives zone is heated based on 24 hours 7 days a week. The exact structure and materials of the building are provided by the company in charge of the refurbishment.

Table 3-1 Targets for post refurbishment in 2011

Air infiltration (ACH)	External Walls U-value (W/m^2K)	Roof U-value (W/m^2K)	Ground Floor U-value (W/m^2K)	Window U-value[1] (W/m^2K)
0.25～0.5	0.35	0.25	0.25	2.2

[1] The exterior door was described as a window; ACH = air change per hour

Smart meters were deployed in different zones after retrofit and are accessible for data collection. As the foresaid description, the interference of human related heat consumption, caused by openings, mechanical ventilation and domestic hot water,should be eliminated. The experiment was performed on Sunday where no human activity was involved. The heating system did not shut down on Friday after work and kept on operating to ensure that the building could achieve a quasi-steady state on Sunday. Heat consumption data for that day were gathered, which will be used for the following study.

3.2.3 Numerical study

Building performance simulation is an established method to understand building energy demand. It has been applied to analyse energy performance at design, retrofit and operation process, which facilitates the reduction of a great deal of capital and labour investment when compared with field experiments. Nowadays, high-performance buildings depend heavily on validated models as simulation tools are available for parametric studies in order to choose the optimal solution from structural, material and operational schemes. A great effort has been devoted to sensitivity analysis of input variables to improve the quality of energy simulation, which provides information about how buildings react to various parameters when a given parameter is altered [197] [198] and [199]. The studies are important steps towards improving the accuracy of simulation by better accounting for various parameters as input variables. The sensitivity study is mostly based on the scenario study to examine the influence of occupancy, orientation, materials and control technology, which is often impractical and not completely reliable if the non-linear interaction among input variables are involved [195]. Evidences suggest that Building occupants highly affect building energy consumption [200] and [201], forming the main cause of discrepancy between simulation and measured data. Despite the advanced abilities of building simulation tools such as EnergyPlus, IES and eQuest, they typically fail to quantify the impact of uncertainty in human activities such as occupancy and interaction with building elements (e.g. openings), resulting in substantial prediction errors [202]. This is also another reason why human related activities should be eliminated from the system. Isolating occupants' activities should greatly improve the simulation accuracy.

The simulation study was carried out in EnergyPlus, which is one of the most reliable tools used for energy analysis in the field of simulation-based optimization. It can be used to simultaneously model building loads, HVAC and other associated components and has been accepted as a powerful tool for building energy simulation [203] and [204]. This calibration simulation is purely based on the easy to find parameters such as geometry, orientation, construction materials, heating set point temperatures and outdoor weather conditions.

Fig. 3-1 structure of the general office

Fig. 3-1 displays the general office in Ebbw vale DH network. This office building is used as an example to demonstrate the calibration of U-values and air infiltration. DesignBuilder was firstly used to develop the physical model of the whole building from plans. This includes geometrical information, building materials details, a detailed description of the HVAC system and HVAC schedules. The building was partitioned into 19 different thermal zones based on the installed heat meters, functional purposes (office, toilet, archives, kitchen etc.) and set point temperatures as shown in Fig. 3-2 and Fig. 3-3. The model was then exported into EnergyPlus for further computational simulation, which was applied to develop a mathematical model to identify thermal performance of the building. Weather data from a nearby weather station was collected and converted to EnergyPlus readable (epw) file. Eventually, EnergyPlus calculated the heating demand at a specified day in line with the focus of the experiment. 47 set of simulations were conducted in EnergyPlus under various design U-values of the wall, roof, floor and window and air infiltration conditions, listed in Appendix 1. Convective heat transfer balance algorithm adopted for inside surface is TRAP model, while DOE-2 model is used for outside surfaces [205].

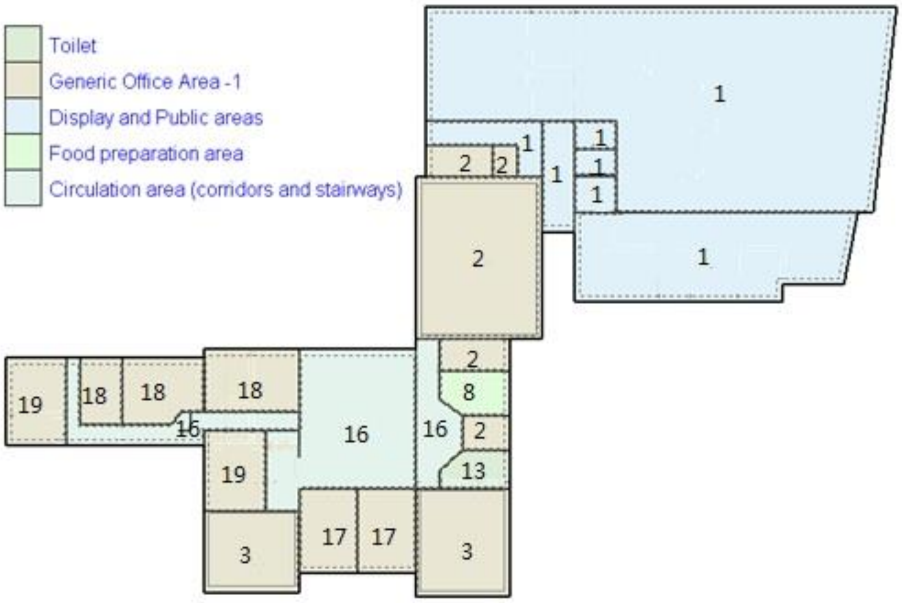

Fig. 3-2 plan view of first floor

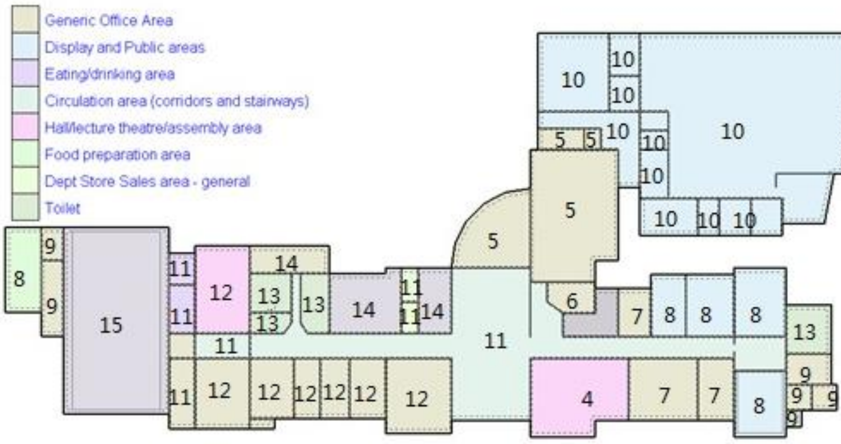

Fig. 3-3 plan view of ground floor

3.2.4 Regression model

Regression modelling is a statistical process to analyse the relationships among variables. It explains the change of one variable that is associated with the other variables and it is primarily used for prediction. Regression models have been widely employed to understand energy usage in buildings, as it is computationally expensive to run all possible simulations in building simulation tools. The major merits of regression methods are that they are comparatively simple and efficient. They allow the establishment of relationships among inputs and outputs for computation within the shortest time. Kavousian et al. [206] examined the impact of climate, building characteristics, appliance stock and occupants' behaviour on residential electricity consumption based on historical data by a weighted regression model. Walter and Sohn [207] developed a multivariate linear regression model to predict energy saving at multiple alternative retrofit options. Yuce [2] adopted linear equation derived from simulation and sensitivity analysis in EnergyPlus to predict energy generation. Yin [208] estimated residential and commercial building demand response by using regression models to fit dataset. Wang et al. [209] explored variables' sensitivity in EnergyPlus by using a stepwise regression method.

Linear regression is the most elementary type of regression model. The independent variable is expressed as X and the dependent variable is expressed as Y. The independent variable is the cause of the changes in the dependent variable. A simple linear regression model can be expressed by the following equation:

$$\mathrm{Y} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{X} \tag{3.9}$$

a_0 and a_1 are coefficients representing the intercept parameter and the slope parameter. The linear regression can be described in Fig. 3-4. a_1 is the slope of the regression model and a_0 is the intercept with y axis.

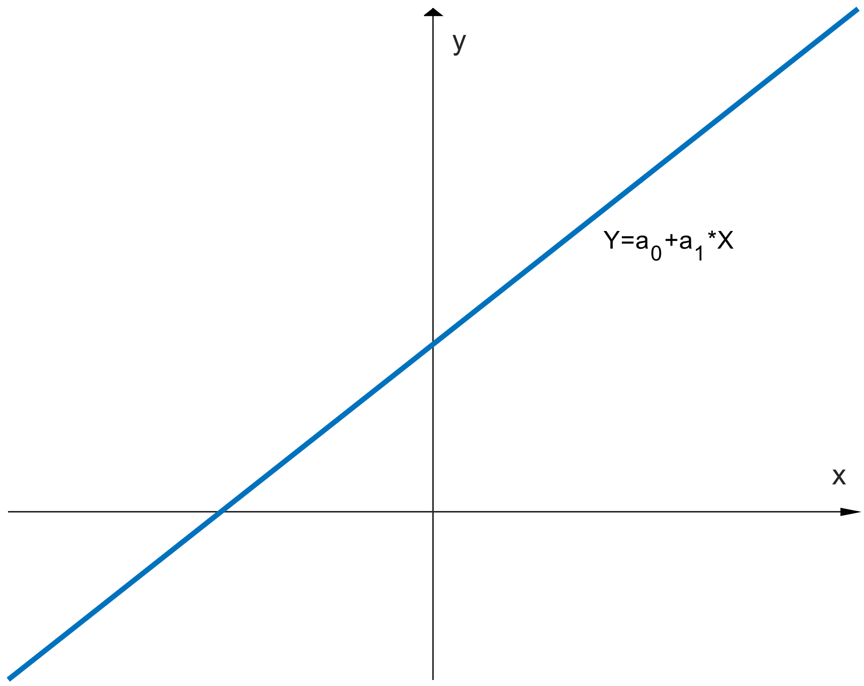

Fig. 3-4 Sample regression function

For a particular sample, it can be written as following:

$$Y_t = a_0 + a_1 X_t + u_t \tag{3.10}$$

The subscript t represents the observation of a particular sample. Each sample comprises an observation of independent variable X_t and an observation of dependent variable Y_t. u_t is the error term for observation t. The variables Y_t, X_t and u_t are specific to observation t. while a_0 and a_1 are variables for all observation.

For most of the problems, more than one independent variable are involved which formulate a multivariable linear regression model. Multiple dependent variables X_1, X_2, , X_n are used to predict the dependent variable Y.

$$Y = a_0 + a_1 X_1 + a_2 X_2 + \dots + a_n X_n \tag{3.11}$$

As it is discussed in section 3.2.1, U-values and air infiltration are key parameters affecting building heat demand at quasi-steady state, so multivariable linear regression model is used to replace EnergyPlus model for establishing the relationship between building heat demand and these parameters.

3.2.5 Genetic algorithm

The optimization tool adopted to calibrate the building U-values and air infiltration is genetic algorithm (GA), which is a popular heuristic search algorithm derived from biological evolution. It has been used in mathematics to mimic natural evolution in the process of optimization. It can be applied for both constrained and unconstrained optimization. The process for optimization can be described as [210]: GA generates an initial population of chromosomes. It then evaluates the fitness of each chromosome and selects the best individuals to produce their offspring in each iteration. The offspring are produced by crossover and mutation of the parent generation. The best ones of each generation have the highest possibility of generating the next generation. Generally speaking, GA cannot ensure the ultimately best solution will be achieved. However, it can produce a near-optimal solution. An example for genetic algorithm is shown in Appendix 2. The process of the GA is summarised in Fig. 3-5.

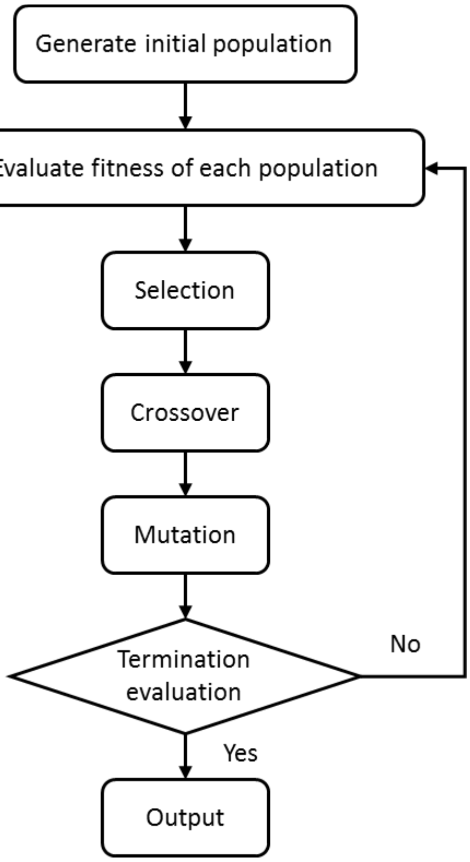

Fig. 3-5 Genetic algorithm flow chart

3.3 Distribution network simulation

Distribution network simulation is to understand the dynamic performance of the system. This study targets thermal performance, which mainly refers to distribution heat loss. Heat loss of the buried pipes depends on the thermal physical properties of the pipes, insulation, soil and the surrounding environment. The geometry of the buried pipe is shown in Fig. 3-6.

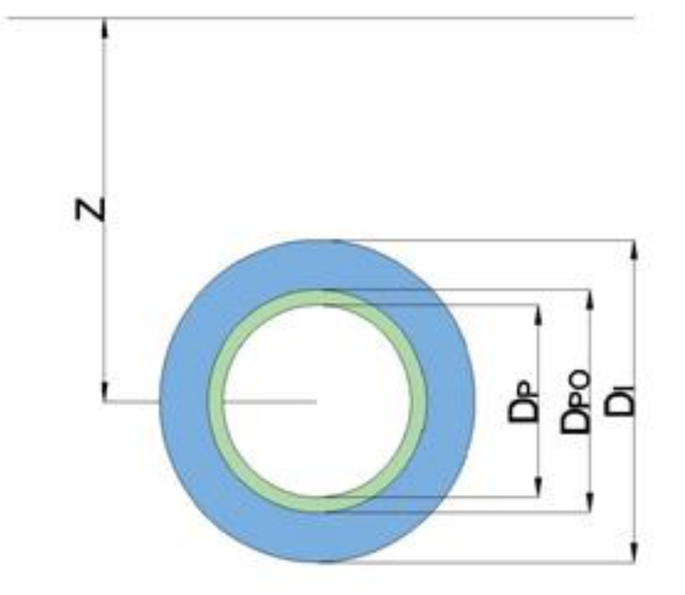

Fig. 3-6 Geometry of the buried pipe.

Heat transfer between the water-pipe interface is through convection, which can be expressed by the following equation:

$$Q_h = hA_p\left(T_w - T_{pw}\right) \tag{3.12}$$

Where, h is the convective heat transfer coefficient. T_w denotes the water temperature in the pipe. T_{pw} represents pipe inner surface wall temperature. A_p is the internal surface area of the water-pipe interface, which is given by:

$$A_p = \pi D_{Pi} l \tag{3.13}$$

D_{Pi} denotes pipe inner diameter. l is the length of the pipe. Heat transfer coefficient h is given by:

$$h = Nu\frac{k_w}{l} \tag{3.14}$$

k_w is the thermal conductivity of water. Nu is the Nusselt number, which depends on the flow regime at a boundary within a fluid. Whether the flow is a laminar or turbulent flow is based on the Reynolds number Re, which is defined by:

$$Re = \frac{D_{Pi} v_w}{\gamma} \tag{3.15}$$

γ and v_w denote kinematic viscosity and velocity of water. In the laminar regime (Re < 2000), the coefficient value Nu_l follows from Sieder and Tate correlation:

$$Nu_l = 1.86 \left(Re\mathrm{Pr}\frac{D_P}{L} \right)^{\frac{1}{3}} (\frac{\mu_w}{\mu_{pw}})^{0.14} \tag{3.16}$$

μ_w and μ_{pw} are water viscosity at water temperature and pipe inner surface wall temperature. Pr is the Prandtl number, given by:

$$\mathrm{Pr} = \frac{c_w \mu_w}{k_w} \tag{3.17}$$

Where c_w refers to specific heat of water.

In the turbulent flow regime (Re > 4000), the coefficient value Nu_t follows from the Colburn correlation:

$$Nu_t = 0.023\ Re^{0.8} Pr^{0.33} \tag{3.18}$$

For $2000 < Re < 4000$

$$Nu\ =\ Nu_l + (Nu_t - \ Nu_l)\frac{Re\ -\ Re_l}{Re_t\ -\ Re_l} \tag{3.19}$$

Heat transfer through pipe and insulant is through conduction, which can be expressed as:

$$C_p M_p \frac{dT_p}{dt}\ = Q_h -\ 2\pi k_p l \frac{T_{PO} -\ T_{PW}}{ln\,\frac{D_{PO}}{D_{PW}}} \tag{3.20}$$

$$C_{ins} M_{ins} \frac{dT_{ins}}{dt} =\ 2\pi k_p l \frac{T_{PO} -\ T_{PW}}{ln\,\frac{D_{PO}}{D_{PW}}} -\ 2\pi k_{ins} l \frac{T_{ins} -\ T_{PO}}{ln\,\frac{D_I}{D_{PO}}} \tag{3.21}$$

C_p, M_p, k_p, C_{ins}, M_{ins}, k_{ins} are specific heat, mass and conductivity of pipe and insulation. T_{PO} and T_{ins} represent pipe and insulation outer surface temperature. D_{PO} and D_I are pipe and insulation outer surface diameter.

The heat transferred through the insulation goes to the soil, and finally released to the environment.

$$2\pi k_{ins} l \frac{T_{ins} - T_{PO}}{ln \frac{D_I}{D_{PO}}} = q \tag{3.22}$$

Soil heat loss q is expressed as:

$$q = S\, k_{soil}(T_{ins} - T_{soil}) \tag{3.23}$$

T_{soil} is the soil surface temperature, which is assumed to be air temperature in this investigation. K_{soil} is soil thermal conductivity. S denotes the shape factor, which is given by:

$$S = \frac{2\pi l}{\ln\left(\frac{4z}{D_I}\right)} \tag{3.24}$$

z represents the distance between the ground surface and the centre of the buried pipe.

When analysing heat loss from the distribution network, the flow rates are obtained directly from the site. The results are displayed in section 5.3. When the model is used for DH network co-simulation in section 4.3, the mass flow rate is controlled through thermostatic by controlling the return temperature from the heat exchanger.

The heat from the energy centre flows to the buildings as a result of the temperature differential. Heat exchanger is the heat transfer medium between the distribution network and the buildings. The model for the heat exchanger is built in Simulink based on energy balance, as shown in Eq. (3.25). It is used to obtain the mass flow rate of the distribution network in order to meet the heat demand, so the equation can bere-arranged to Eq. (3.26).

$$Q_b = \left(C_w m_w (T_s - T_r)\right)\eta_{ex} \tag{3.25}$$

$$m_w = \frac{Q_b}{C_w (T_s - T_r)\eta_{ex}} \tag{3.26}$$

The building heating load Q_b is obtained from the building simulation models, which is equal to the distributed energy multiplied by the heat exchanger efficiency η_{ex}. T_s and T_r is the supply and return temperature before and after the heat exchanger. The heat exchanger is controlled through a thermostatic valve to maintain a constant return temperature. C_w and m_w are the specific heat and mass flow rate of water.

3.4 BCVTB

BCVTB (Building Controls Virtual Test Bed), developed by Lawrence Berkeley National Laboratory, is a modular and freely available open-source software platform that allows researchers to couple different simulation programs for data exchange at each time step. The BCVTB is based on Ptolemy II environment. It overcomes the limitation of a specific tool and gives users the option to employ the best applicable tools with significant expertise for co-simulation. Currently, it can be used to link EnergyPlus, Matlab, Simulink, Modelica etc. The purpose of developing BCVTB is to offer users an option for building energy system simulation and control. The computation time is less than computing from individual programs. It has been successfully used for the control of HVAC [211] and [212]. EnergpyPlus performs the building energy simulation; Modelica or Matlab are applied for HVAC system control; and the final results are outputted as the simulation purposes. In this study, the co-simulation environmental combines EnergyPlus, Simulink and Matlab for DH network modelling. This section describes the configuration for coupling Energyplus, Simulink and Matlab with BCVTB. The data exchange configuration between the simulation tools is shown in Appendix 3.

3.5 Mixed integer linear programming

As has been discussed in the literature review, mixed integer linear programming is selected for optimization. It is basically a linear programming (LP) with some variables required to be integer values. In order to understand MILP, a simple LP example is given. The target of the LP is to minimize the objective function in Eq. 3.27. Variables x and y are subject to the following constraints in Eq. (3.28-3.30).

Minimize:
$$z = 5x + y \tag{3.27}$$

Subject to:
$$3x - y + 10 \geq 0 \tag{3.28}$$

$$0.5x - y + 2 \leq 0 \tag{3.29}$$

$$2x + y - 12 \leq 0 \tag{3.30}$$

The feasible area can be easily found by graphing the constraint equations, shown in Fig. 3-7. The minimal value of the optimization equation will be obtained by moving the objective function within the feasible area. The optimal value locals at the intersection of Eq. 3.28 and Eq. 3.29.

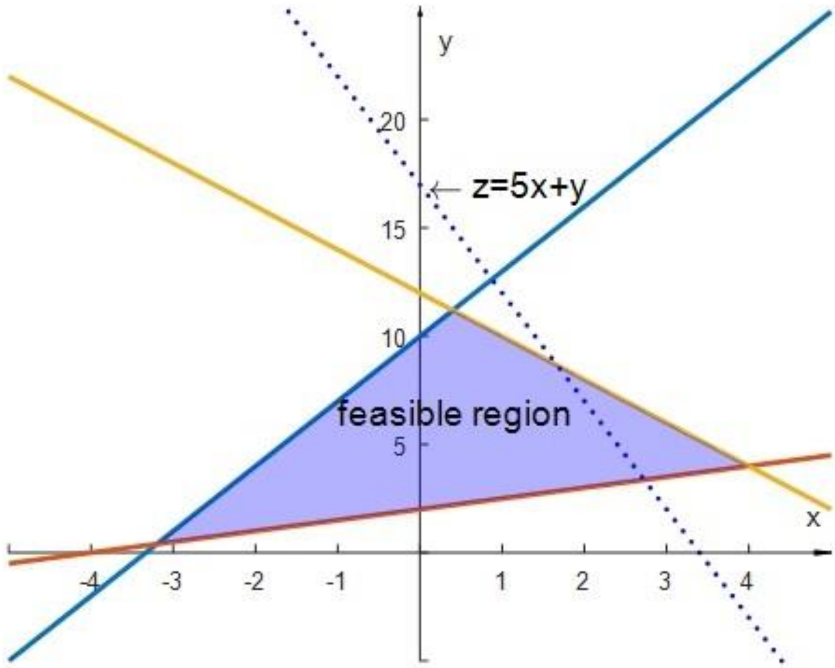

Fig. 3-7 linear programming model

However, in real life, many variables are not continuous but are integers. For a mixed integer linear problem, both integer and continuous variables are involved. When x is restricted to be an integer, the results can only be located along the vertical blue lines vertical within the feasible area, shown in Fig. 3-8.

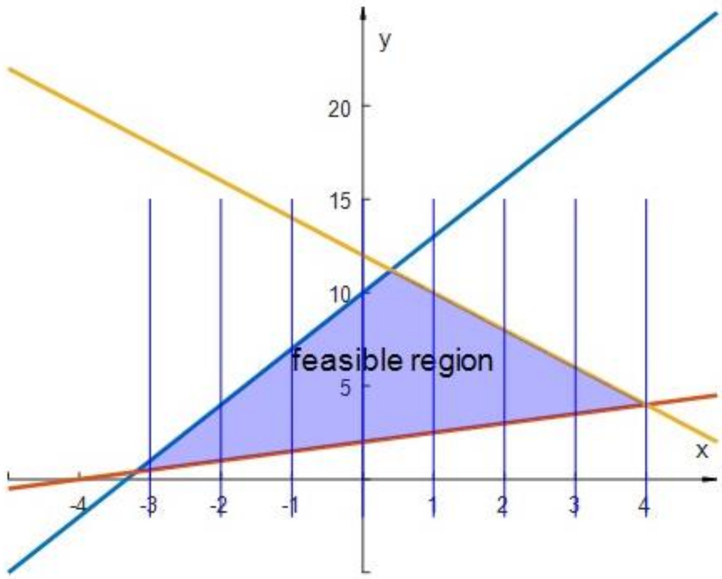

Fig. 3-8 Mixed integer linear programming model

A typical MILP usually has the following characteristics:

Minimize $$Z = f(x,y) \tag{3.31}$$

Subject to:

Equality $$A_{eq}(x,y) = B_{eq} \tag{3.32}$$

Inequality $$A(x,y) \le B \tag{3.33}$$

$x \in \{0, 1\}$ $or\ integer, lb \le x \le ub$

where Z is the target function to be optimized. A and B are inequality constraints for the system. A_{eq} and B_{eq} are equality constraints in the system. x denotes any binary or integer variable and y represents any continuous variable. lb and ub are lower bound and upper bound for the variables.

3.6 Summary

This chapter has presented the basic methodologies adopted for carrying out the research. The first stage begins by stating heat consumption of the building at quasi steady state, excluding the interference of human activity. It concludes that building U-values and air infiltration are the decisive parameters affecting heat demand under such circumstance. Next, the simulation of an office building is introduced by using DesignBuilder and EnergyPlus. The simulation is carried out under different U-values and air infiltration rates. Finally, an introduction to regression model and genetic algorithm is presented.

In the second stage, the thermal dynamic performance of the piping system is displayed in the first place. The heat from the distribution water transfers to pipe through heat convection from water-pipe interface. The heat then goes through pipe, insulation materials, soil and finally goes to the ambient environment by heat conduction. The control of the heat exchanger is given in the end.

In the next stage, a short description to BCVTB is presented. Then it describes the usage of BCVTB in this thesis.

In the last stage, a simple example for linear programming is illustrated to facilitate the understanding of mixed integer linear programming. Finally, the typical features of the MILP are presented.

4 Holistic district heating optimisation

4.1 Introduction

This chapter elaborates on the methodology developed to deliver holistic district heating optimisation, leveraging on the research methods described in chapter 3. The proposed methodology aligns with the overarching research questions posited in Chapter 1. The mapping between the holistic district heating optimisation approach proposed in this chapter and the posited research questions is as follows:

1. The second research question is answered by Section 4.2 “calibration approach”
2. The third research question is answered by Section 4.3 “DH co-simulation” .
3. The fourth question is answered by Section 4.4 “cost optimization”.

4.2 U-values and air infiltration calibration approach

Evidence suggests that existing approaches for determining U-values and air infiltration rate are time consuming and not fully reliable. In situ measurement of U-values and air infiltration rate as discussed involves big uncertainty resulting from devices accuracy issues and user intervention. To address this gap, this section introduces a novel method to calibrate U-values and air infiltration rate through simulation and experimental measurements.

After the numerical study in section 3.2.3, the computed heat consumption of the 19 thermal zones can be obtained at different inputs. For a quasi-steady state without the involvement of human activities, the most influential parameters for heat loss are the aggregated envelope U-values and air infiltration rate. The SPSS software is used for linear regression analysis to establish the relationship between different inputs and heat consumption. The generalized formula of the multivariate linear regression model with 5 indicator variables is as follows:

$$\mathrm{Q} = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \tag{3.34}$$

Where, Q denotes simulated heat consumption. X_1, X_2, X_3, X_4 and X_5 represent the input variables such as air infiltration and U-values for wall, roof, floor and window. a_0, a_1, a_2, a_3, a_4 and a_5 denote the regression coefficients. The regression model is used in the following study to replace EnergyPlus for heat consumption prediction.

The process of calibration is the procedure for searching the optimal variables to verify the elaborated models. The decision parameters requiring calibration are U-values and air infiltration rate. Fig. 4-1 depicts the process of optimization and regression analysis used for implicit calibration. The possible parameters are fed into the regression model to predict thermal demand. The optimization tool then adopts an evaluation function to limit the discrepancy between heat consumption data collected from the test period and predicted value. The ability of a mathematical model to precisely predict thermal conditions relies on the validity of the associated model parameters.

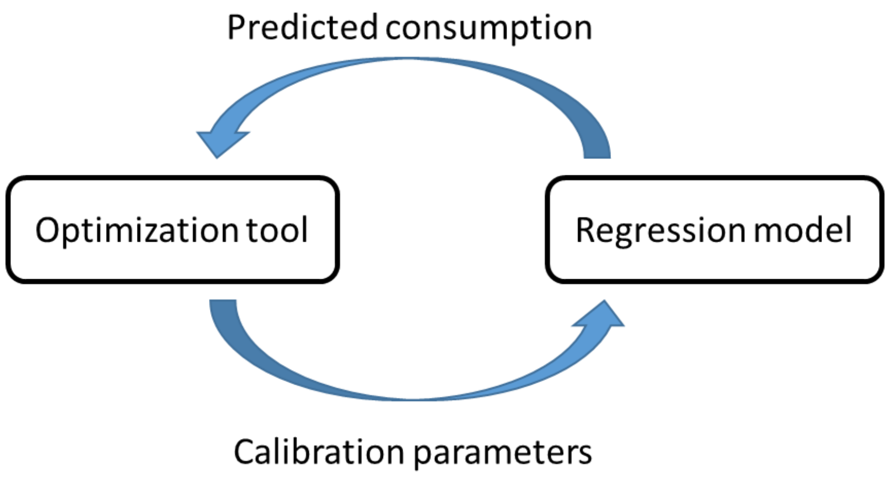

Fig. 4-1 Implicit Calibration

GA is the optimization tool used to figure out the real values for X_1, X_2, X_3, X_4, X_5. These values represent the minimum heat consumption difference between measured data from the site and predicted value from the regression models. The constraints of the decisive variables, air infiltration and U-values, are set according to the design values shown in Table 3-1. The true values can either be better or worse than the design values. It should be noted that the U-values of the building vary with temperature and moisture content. In reality, the values of the parameters might be in a great range due to the aging and corrosion processes. For the purpose of covering a wide range of potential values in real operation and also taking into account the design values, the true values for air infiltration and U-values should satisfy the requirements displayed in Table 4-1, where the lower bound and upper bound are the possible minimum and maximum values for the variables.

Table 4-1 variation range of the variables

	Lower bound	Upper bound
X_1	0.05	2
X_2	0.025	2.5
X_3	0.025	2.5
X_4	0.025	2.5
X_5	0.2	10

The most important part of the GA is to define the fitness function. Research has revealed that the discrepancies between model prediction and real performance mainly result from the differences between initial design and actual operation [191], [214] and [215]. The objective function here is to minimize the difference between predicted and measured heat consumption in order to find the real U-values and air filtration rate. The fitness function is addressed as:

$$\text{Min f(x)} = \sum_{i=1}^{19} (\frac{Q_{ns} - Q_{nm}}{Q_{nm}})^2 + (\frac{Q_s - Q_m}{Q_m})^2 \tag{3.35}$$

Q_{is}, Q_{im}, Q_s, Q_m are predicted and measured heat consumption of individual zone and whole building.

The overall process of the methodology for the calibration of the U-values and air infiltration is depicted in Fig. 4-2.

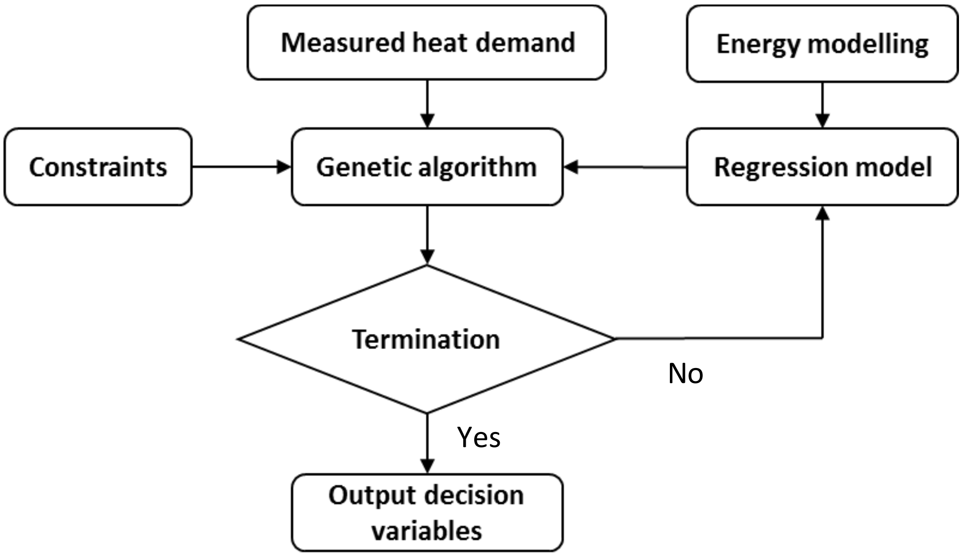

Fig. 4-2 Flow chart for the calibration of U-values and air infiltration rate

4.3 DH co-simulation

The co-simulation is based on a DH system in Ebbw Vale, Wales. According to the energy operators from the energy centre, the current operation scheme of the network is simple, implementing the standard operation scheme. The operation follows a load track scheme, which means the heat production is used to meet the heat demand in the DH network. As CHP can generate both heat and electricity in a single process, and the electricity can be sold to the national grid, interesting savings are achieved with the CHP having a higher priority than the other boilers. When CHP cannot meet the demand, the two biomass boilers are put into production as renewable heat incentive (RHI) tariff makes operating biomass more economical. The last choice goes to one or several of the four existing gas boilers.

This section presents the approach proposed for DH network simulation in the BCVTB environment. Detailed energy models related to the control of the gas boiler, biomass boiler and CHP are not constructed in this study as the current control scheme is quite simple. If those models are required, they can be built from TRNSYS or Modelica and can be linked with BCVTB. In this investigation, Matlab programming is used to explain the standard operation and is coupled with BCVTB to compute heat output from each generator. Under the current operation scheme, the efficiencies of the generators are constant and are obtained from the site, which represents the average efficiency of the generator over a whole year. The methodology flow chart under the standard operation is displayed in Fig. 4-3. For each time step, the exchange of data information goes through six steps. Each step is explained as:

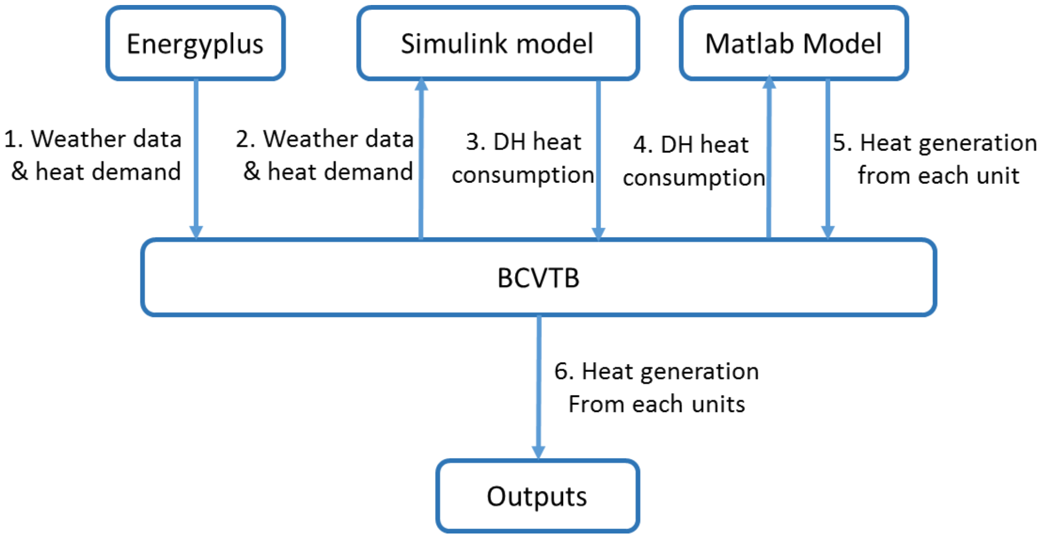

Fig. 4-3 Flow chart for co-simulation under standard operation

Step 1. Energyplus computes the heat demand of each building in the district according to inputs such as weather file, configured schedule, and HVAC system. Four Energyplus models are incorporated representing the existing four buildings. The outdoor temperature from the weather file and heat load of each building are exported from EnergyPlus and then transferred to BCVTB.

Step 2. BCVTB sends the load demands and temperature received from step 1 to the Simulink model.

Step 3. The Simulink model dynamically calculates the heat losses from the network based on the heat demands and the outdoor temperature sent from the BCVTB. After that, it outputs the heat consumption of the distribution network and the information is transmitted to BCVTB.

Step 4. When BCVTB receives the data forwarded by Simulink, it sends the message of heat consumption from the system to Matlab for further computation.

Step 5. The Matlab programming computes the amount of heat that should be produced from each generator based on the standard operation scheme, unit capacity and average efficiency of each generator. The heat generated from each generator is sent back to the BCVTB.

Step 6. BCVTB plots the heat generation of each generator.

After the 6 steps have been implemented, the process proceeds with the next time step until the end of the simulation.

4.4 Cost Optimization

Under the standard operation, the average efficiency simplifies the control of the units. It assumes that the generators at lower output are as efficient as at higher output. The generators start operating when there is a heat demand. In order to maximize the economic benefit of the system, an optimization control method is proposed to improve the performance of the network. Nonlinear efficiency is integrated into the optimization problem. MILP is selected for programming in the case study by using both binary and continuous variables, which makes it It is possible to approximate non-linearity by applying discrete linear relationships and constraints [61] and it also exploits the advantages brought by linear programing. The optimization delivers day-ahead control of the generators according to the predicted heat consumption exported from the BCVTB. As long as the weather condition for the next day is provided, the co-simulation can be used to compute the heat consumption from the DH network. The optimization will take the advantage of higher efficiency at larger output and reliance on the storage tank for operation cost minimization.

4.4.1 Constraints:

It should be noted that the efficiency of the generator varies with the output load. It is important to consider the varying efficiencies under different output regimes when considering the control of the generation units. The efficiencies of the biomass boiler, gas boiler and CHP at different output loads are displayed in Fig. 4-4. The generation units exhibit apparent efficiency variation at part load and demonstrate significantly worse performance at lower operation load levels. A non-linear relationship between the load and efficiency can be observed.

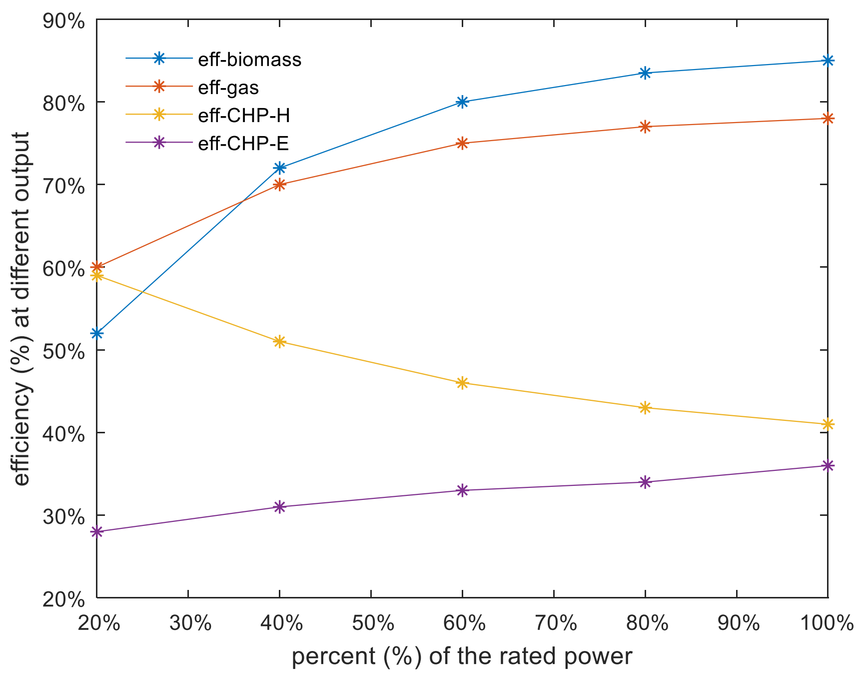

Fig. 4-4 Boiler efficiency at different output level

In order to keep computational efforts within acceptable range, 5 levels ($nlevel$) are assumed at the operation condition: 20%, 40%, 60%, 80%, 100% of rated power respectively. At each time period the generators can only operate at one output level. A minimum output of 20% is selected to ensure the performance of the boilers.

Although the efficiency varies over the operation profile, depending on the energy output level, the efficiency at a fix level is constant. The fuel consumption at each level is linear to the output. Thus, it allows linearizing the non-linear efficiency problem into MILP.

$x(i, j, k)$ is a binary variable representing the on and off condition of each operation level corresponding to generator j at time period i. When $x(i, j, k) = 1$ means at time period i, the generator j is working at k level. In order to ensure that the generator can only operate at one output level or the generator is off, for each generator, it should meet the constraint in Eq. (6) – (7). Since the operation decision is time-independent, these equations should be applied for the entire optimization period.

$$\sum_{k=1}^{k=nlevel} x(i, j, k) \leq 1 \tag{3.36}$$

$$x(i, j, k) = 0, 1 \tag{3.37}$$

Time step used in this study is 15 mins, so one day is divided into 96 periods. In order to represent the startup of the generator, indicator z(i, j) is introduced, which is also a binary variable. z(i, j)=1 means at time period i the generator j starts working. More specifically, generator j is off at time period i ($\sum_{k=1}^{nlevel} x(i, j, k) = 0$) and it is on at time period i+1 ($\sum_{k=1}^{nlevel} x(i + 1, j, k) = 1$). The startup indicator is turned on (z(i, j)=1). Therefore, the linear inequality constraints can be determined by:

$$-\sum_{k=1}^{nlevel} x(i,j,k) + \sum_{k=1}^{nlevel} x(i+1,j,k) - z(i,j) \leq 0 \tag{3.38}$$

$$\mathrm{z(i,j)} = 0, 1 \tag{3.39}$$

As z(i, j) is included in the objective function cost, the solver will ensure that z(i, j)=1 only when it meets the requirements.

When it is required to startup the biomass boiler, the priority is given to biomass boiler 1 and then biomass boiler 2. The same principle is applied to the gas boilers as well. Then they should satisfy Eq. (10).

$$\sum_{k=1}^{nlevel} x(i,j,k) - \sum_{k=1}^{nlevel} x(i,j+1,k) \geq 0 \tag{3.40}$$

The energy storage ($Storage_i$) in the storage tank at time period i should be equal to the difference between the sum of energy generation at period i and the energy stored until time period i-1 ($Storage_{i-1}$) multiplied by the storage tank efficiency ($eff_{storage}$), and the energy demand at time period i ($Demand_i$). The storage loss per hour is assumed to be a constant of the stored energy [216]. $P_H(j,k)$ denotes the heat production of generator j working at output level k. The heat stored should be less than the size of the storage tank, as expressed in Eq. (12).

$$Storage_i = (\sum_{j=1}^{nGens} \sum_{k=1}^{nlevel} P_H(j,k)x(i,j,k) + Storage_{i-1}eff_{storage} - Demand_i) \quad (3.41)$$

$$\mathrm{Storage_i} \leq Size_{tank} \quad (3.42)$$

When i=1, i-1 equals nPeriod.

4.4.2 Objective function

The objective is to minimize the daily operation cost (C_{total}) of the network, which includes the fuel cost (C_{fuel}) for heat and electricity generation, the startup cost ($C_{startup}$) of the boilers and revenue ($C_{electricity}$) for selling electricity to the grid. Eq. (13-16) are used to describe the operation cost.

$$C_{total} = C_{fuel} + C_{startup} - C_{electricity} - C_{RHI} \quad (3.43)$$

$$C_{fuel} = \sum_{i=1}^{nPeriod} (\sum_{k=1}^{nlevel} \frac{P_H(1,k)x(i,1,k)}{\eta_{CHP}(1,k)} price_{gas} + \sum_{j=2}^{3} \sum_{k=1}^{nlevel} \frac{P_H(j,k)x(i,j,k)}{\eta_{gas}(j,k)} price_{gas} + \sum_{j=4}^{5} \sum_{k=1}^{nlevel} \frac{P_H(j,k)x(i,j,k)}{\eta_{biomass}(j,k)} price_{biomass}) \quad (3.44)$$

$$C_{startup} = \sum_{i=1}^{nPeriod} \sum_{j=1}^{nGens} (z(i,j)price_{start}(j)) \quad (3.45)$$

$$C_{electricity} = \sum_{i=1}^{nPeriod} \sum_{k=1}^{nlevel} P_{chp_e}(1,k)x(i,1,k)\ Price \tag{3.46}$$

$$\mathrm{C}_{RHI} = \sum_{i=1}^{nPeriod} \sum_{j=4}^{5} \sum_{k=1}^{nlevel} P_H(j,k)x(i,j,k) \cdot RHI \tag{3.47}$$

The fuel cost in Eq. (14) is expressed as the fuel cost from each generator. $\eta_{CHP}(j,k)$, $\eta_{gas}(j,k)$ and $\eta_{biomass}(j,k)$ represent heat generation efficiencies for CHP, gas boiler and biomass boiler operating at k level respectively. $price_{gas}$, $price_{biomass}$, $price_{start}(j)$ and $Price_e$ are gas price, biomass price, startup cost for generator j and electricity price sold to the grid. $P_{chp_e}(1,k)$ is the electricity production from CHP working at level k. RHI is the renewable heat incentive price.

The flow chart for optimization is shown in Fig. 4-5.

As BCVTB is used for time step data information exchange and the optimization is for day-ahead prediction of the control schedule, the optimization should run independently and cannot be coupled into the BCVTB. Under the optimization condition, the first three steps are the same as the standard operation. In step 4, one day heat consumption is outputted for the optimization. In the end, the optimal schedule for control of the generators is displayed.

Several assumptions and simplifications are made in the co-simulation and optimization process:

1) The supply temperature from the energy centre is constant at 90°C and the return temperature after the heat exchanger is constant at 60°C.

2) The heat exchanger efficiency between the distribution network and the building is 95%.

3) The current operation is carried out strictly according to the standard operation scheme and the measured average efficiencies from the site are used to represent the efficiency at current scheme.

4) The heat loss from the storage tank is 1% per hour.

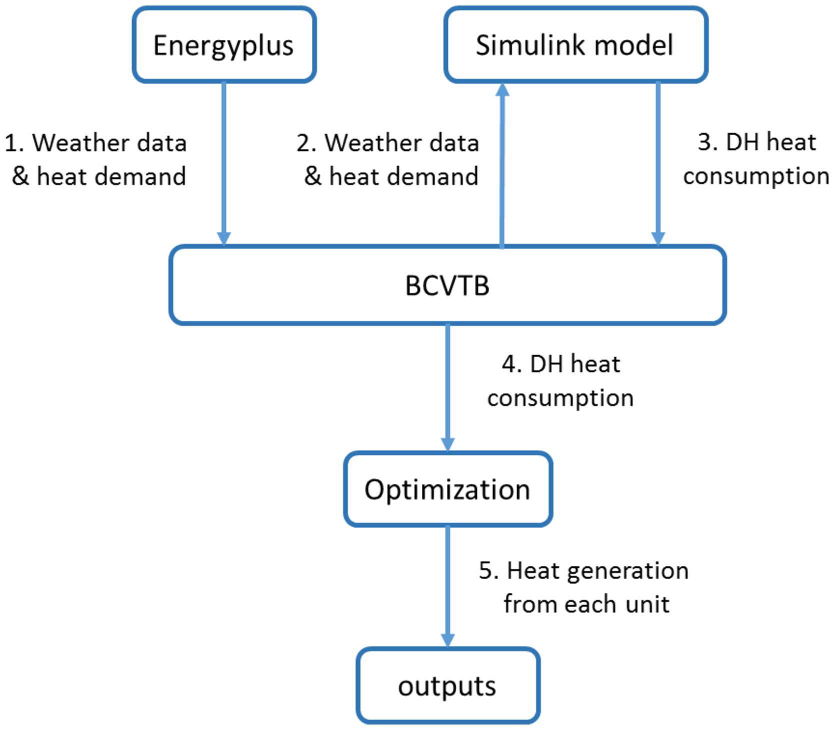

Fig. 4-5 flow chart under optimization scheme

4.5 Conclusions

This chapter presents the research approaches developed based on the methodologies introduced in the last chapter. The proposed approaches address research question 2, 3, and 4 posited earlier in this thesis. Key insights from the implementation of the proposed approach are summarised below.

A novel concept to determine building envelope U-values and air infiltration rate by a combination of Energy modelling (DesignBuilder and EnergyPlus), regression models and genetic algorithm at quasi-steady state conditions is proposed. DesignBuilder and EnergyPlus are used to construct the simulation model for the building, set up the input variables, schedules, detail the HVAC system and run the simulation. A number of datasets with respect to U-values and air infiltration rates are used to investigate energy consumption of different zones for a single day under different circumstances. Regression models are established, based on the datasets and corresponding energy consumption, to replace the EnergyPlus models for simulation purposes. Subsequently, GA is introduced for optimization. A fitness function to evaluate the gap between the measured and predicted heat consumption is presented to search for the most appropriate U-values and air infiltration rate.

The next approach proposed is to provide a co-simulation method for DH network. The simulation is carried out under the current operation scheme. EnergyPlus is used for building level performance simulation. The distribution network simulation is implemented through Simulink and the energy hub is simulated in Matlab based on the current operation scheme. BCVTB is then applied to couple the different clients for time step performance simulation.

This chapter also explores the approach for day-ahead optimization to determine the optimal operational schedule of the generation units, targeting operation cost minimization. MILP (Mixed integer linear programming) is employed for optimization as it can be used to represent non-linear boiler efficiency without sacrificing the advantages brought by linear programming. Efficiency with respect to heat output level is introduced. A number of binary variables representing the operation levels of the units and their on/off status are adopted in the optimization model. The optimization aims at operation cost minimization.

5 Outputs and Results

5.1 Introduction

To evaluate the developed solutions, the proposed holistic district heating optimization approach is applied to study a district heating network, starting with the calibration of building U-values and air infiltration rate. This is followed by the results of distribution network simulation together with a discussion on heat losses for the next generation DH network. A co-simulation implemented in BCVTB platform is demonstrated in the next stage. Finally, the results for day-ahead optimization are presented.

5.2 Building simulation and validation

The first stage of the case study is to obtain validated models for building energy simulation. This section summarizes the outputs of this process by presenting the results for the calibration of envelop U-values and air infiltration rates.

5.2.1 Regression validation results

EnergyPlus model and the weather data are used to carry out the building energy performance simulation at quasi-steady state. 47 sets of different inputs (shown in Appendix 1) with respect to different U-values and air infiltrations were tested under the same model to obtain 47 sets of simulation results. Heat consumption of each zone and the whole building were exported from the simulation results. The 47 simulation instances were applied to train the regression model and to establish the relationship between the energy demand and u-values and air infiltration rate. Six zones and the whole building were selected to demonstrate the regression models. The fitted regression models for each zone and the whole building are listed as follows:

$$Q_1 = -3.751 + 239.108 \cdot X_1 + 111.77 \cdot X_2 + 127.311 \cdot X_3 + 43.75 \cdot X_4 + 4.899 \cdot X_5 \tag{4.1}$$

$$Q_2 = 3.041 + 137.868 \cdot X_1 + 83.337 \cdot X_2 + 52.666 \cdot X_3 + 28.611 \cdot X_4 + 13.867 \cdot X_5 \tag{4.2}$$

$$Q_3 = -18.112 + 90.449 \cdot X_1 + 47.95 \cdot X_2 + 34.695 \cdot X_3 + 18.084 \cdot X_4 + 11.368 \cdot X_5 \tag{4.3}$$

$$Q_4 = -0.849 + 53.405 \cdot X_1 + 77.821 \cdot X_2 + 7.189 \cdot X_3 + 159.323 \cdot X_4 + 3.327 \cdot X_5 \tag{4.4}$$

$$Q_5 = -15.046 + 101.484 \cdot X_1 + 55.591 \cdot X_2 + 49.179 \cdot X_3 + 124.894 \cdot X_4 + 12.639 \cdot X_5 \tag{4.5}$$

$$Q_6 = -1.039 + 3.253 \cdot X_1 + 2.762 \cdot X_2 + 3.5 \cdot X_3 + 8.971 \cdot X_4 + 0.767 \cdot X_5 \tag{4.6}$$

……

$$Q = -195.447 + 1239.142 \cdot X_1 + 742.934 \cdot X_2 + 579.198 \cdot X_3 + 998.006 \cdot X_4 + 121.642 \cdot X_5 \tag{4.7}$$

Where Q_1, Q_2, Q_3, Q_4, Q_5, Q_6, Q denote heat demand for zone 1, zone 2, zone 3, zone4, zone 5, zone 6 and the whole building, respectively.

The objective of the linear regression model is to set up an efficient and accurate model to predict steady state heat demand for each zone at different inputs. The regression model is then used to take the place of EnergyPlus for building energy performance simulation as it is more efficient for computation. The predicted values for thermal consumption derived from the fitted regression models are compared with the simulated data from EnergyPlus. More specifically, the predicted heat consumptions are calculated from the linear regression model by taking inputs corresponding to the independent variables (e.g. U-values and air infiltration rate) into the above regression equations. The simulated values from EnergyPlus and computed data from regression model are compared as shown from Fig. 5-1 to Fig. 5-7.

Following the development of regression models, the regression models' fitting and predicting ability is evaluated. The goodness of the regression model is verified by two metrics: Normalized Mean Bias Error (NMBE) and Coefficient of Variation of Root Mean Square Error CV-RMSE [217]. NMBE gives the difference between predicted and simulated energy demand. CV-RMSE reflects the accumulated magnitude of error, providing an indication of the regression model's ability to replace the simulation tool. The NMBE and CV-RMSE are displayed corresponding figures.

NBME and CV-RMSE are defined in Eq. (4.8) and Eq. (4.9). Where y_i is the simulated value and $\hat{y}_i$ is the predicted value. $\bar{y}$ is the average value of y_i. N denotes the total number of data set. p is the degree of freedom.

$$\mathrm{NMBE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{(N-p)\,\bar{y}} \times 100 \tag{4.8}$$

$$\mathrm{CV-RMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(N-p)}}}{\bar{y}} \times 100 \tag{4.9}$$

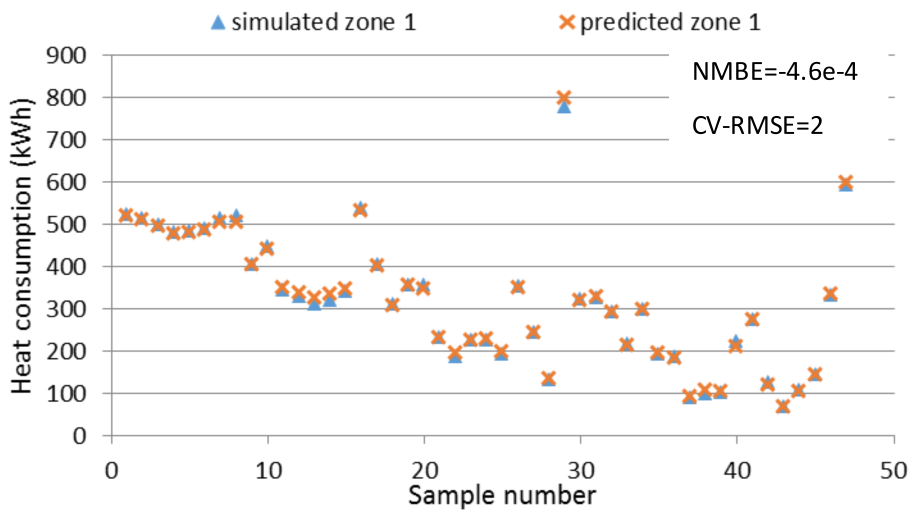

Fig. 5-1 simulated and predicted heat consumption of zone 1

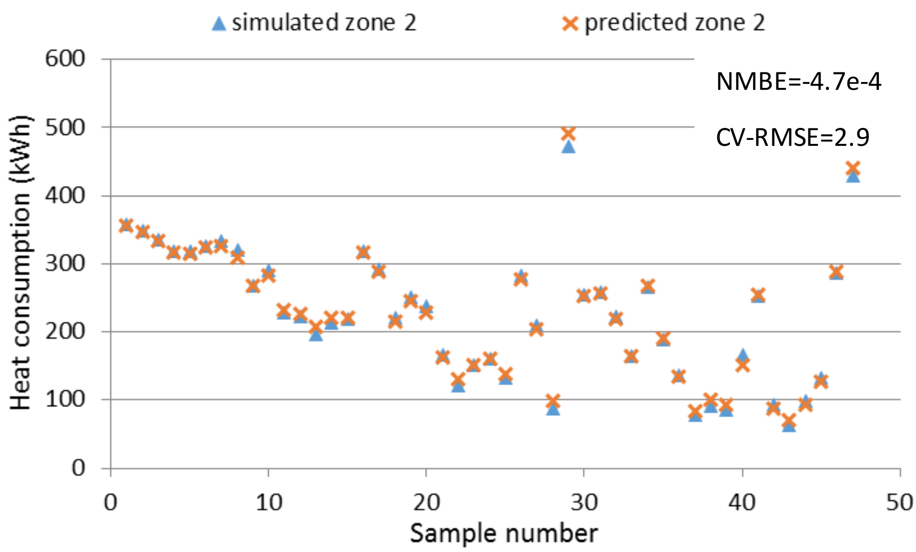

Fig. 5-2 simulated and predicted heat consumption of zone 2

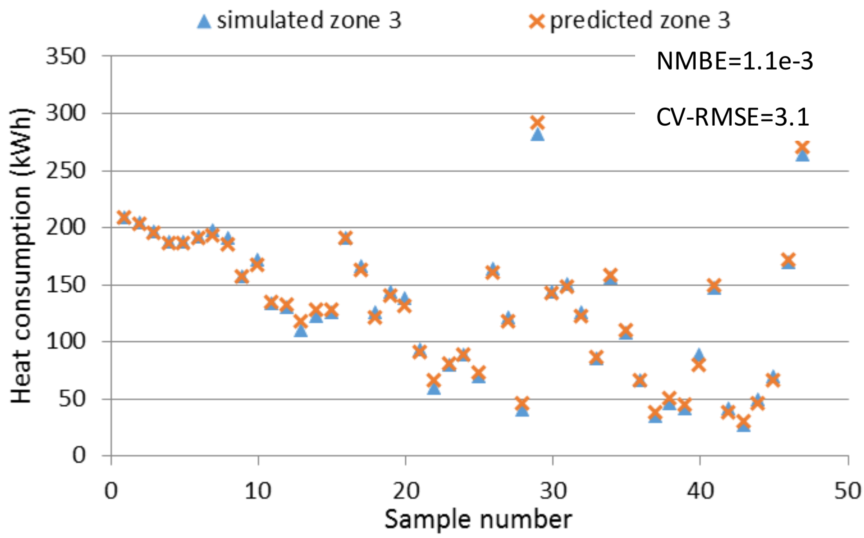

Fig. 5-3 simulated and predicted heat consumption of zone 3

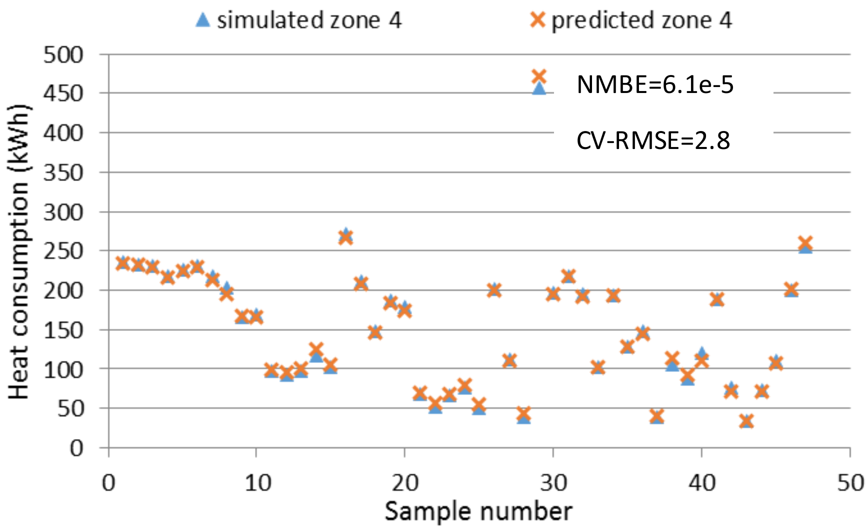

Fig. 5-4 simulated and predicted heat consumption of zone 4

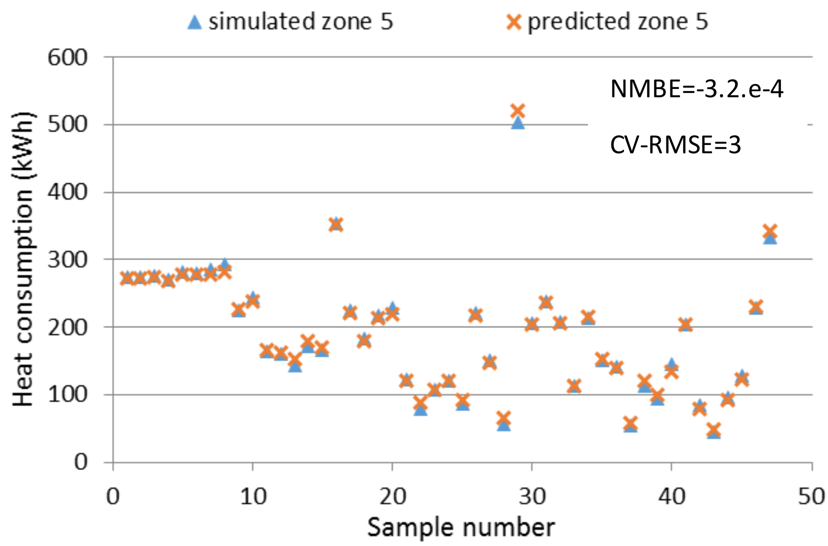

Fig. 5-5 simulated and predicted heat consumption of zone 5

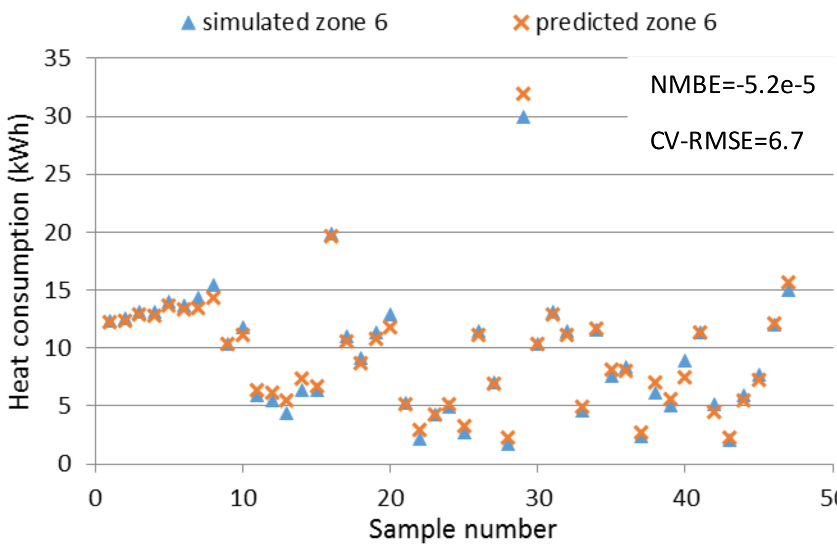

Fig. 5-6 simulated and predicted heat consumption of zone 6

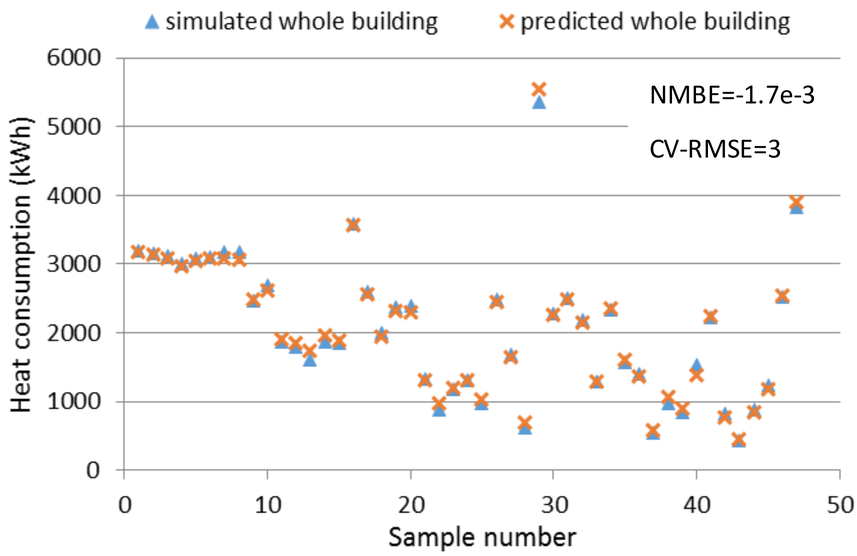

Fig. 5-7 simulated and predicted heat consumption of the whole building

ASHRAE Guideline 14 points out that "The computer model shall have an NMBE of 5% and CV (RMSE) of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively" [218]. The NMBEs and CV-RMSEs for the simulation are daily results which are lower than 5% and 10%. Therefore, from the statistical point of view, we confidently conclude that the regression model can be used to predict heat consumption at a quasi-steady state without human action interference.

5.2.2 Main results of validated values

After generations of selection, crossover and mutation in GA, the final values were obtained (shown in Table 5-1) which would result in a minimum difference between predicted data in regression models and measured data from the site. The validated results are worse than the design values, which indicate the building is operating in a worse condition.

Table 5-1 validated air infiltration rate and U-values

Air infiltration (ACH)	External Walls U-value (W/m^2K)	Roof U-value (W/m^2K)	Ground Floor U-value (W/m^2K)	Window U-value (W/m^2K)
0.727	0.678	0.385	0.356	2.416

5.2.3 Simulation result

The limitation of this work lies in that the field measurement work was not carried out to obtain the U-values and air infiltration rate. In order to validate the proposed calibration method, the predicted heat consumption from calibrated energy simulation model and measured data for a typical workday was demonstrated. The detailed occupancy and detailed HVAC system of the corresponding day were included in the simulation. The uncalibrated model based on design values was also displayed as a comparison.

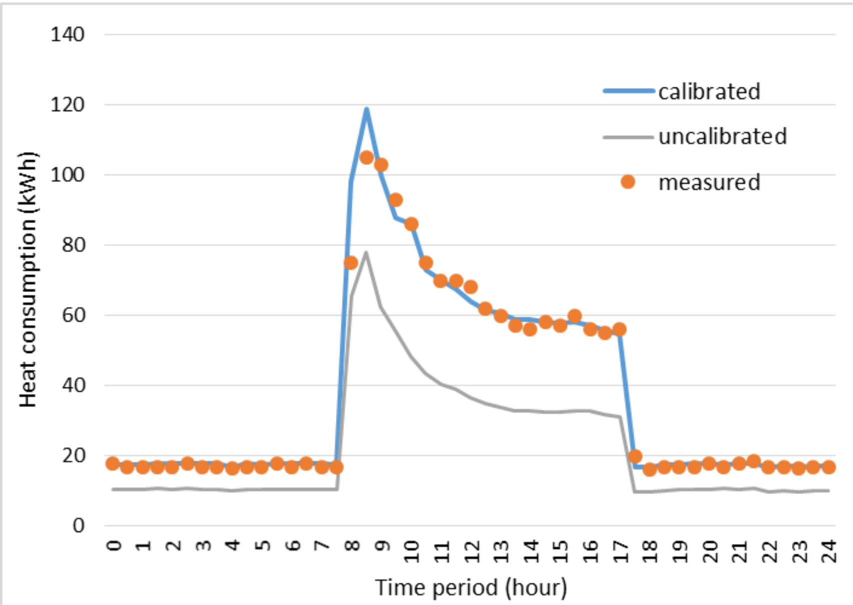

Fig. 5-8 Calibrated results compared with measured and uncalibrated data

Fig. 5-8 illustrates heat consumption for every half hour. It can be seen that a great discrepancy exists between calibrated and uncalibrated models. For the uncalibrated model, the u-values and air infiltration rate are lower than the calibrated model, which results in less energy demand. It is obvious that the accuracy of the calibrated model improved significantly. The calibrated model showed good agreement with the measured data at night. Even though a small difference between the measured and predicted model during the day is found, it is acceptable and this may be caused by the unpredictable human activity.

5.3 Distribution network simulation and validation

The simulation of the distribution network is implemented in Simulink. The model for the network layout is displayed in Fig. 5-9. Blocks in the model represent different pipes and buildings. The pipes on the left side of the buildings are supply system and the ones on the right are return system. Temperature sensors are placed before and after the buildings to measure the supply and return temperatures. The simulated and experimental supply and return temperature from buildings, heat losses in pipes, and temperature of nodes are discussed in this chapter.

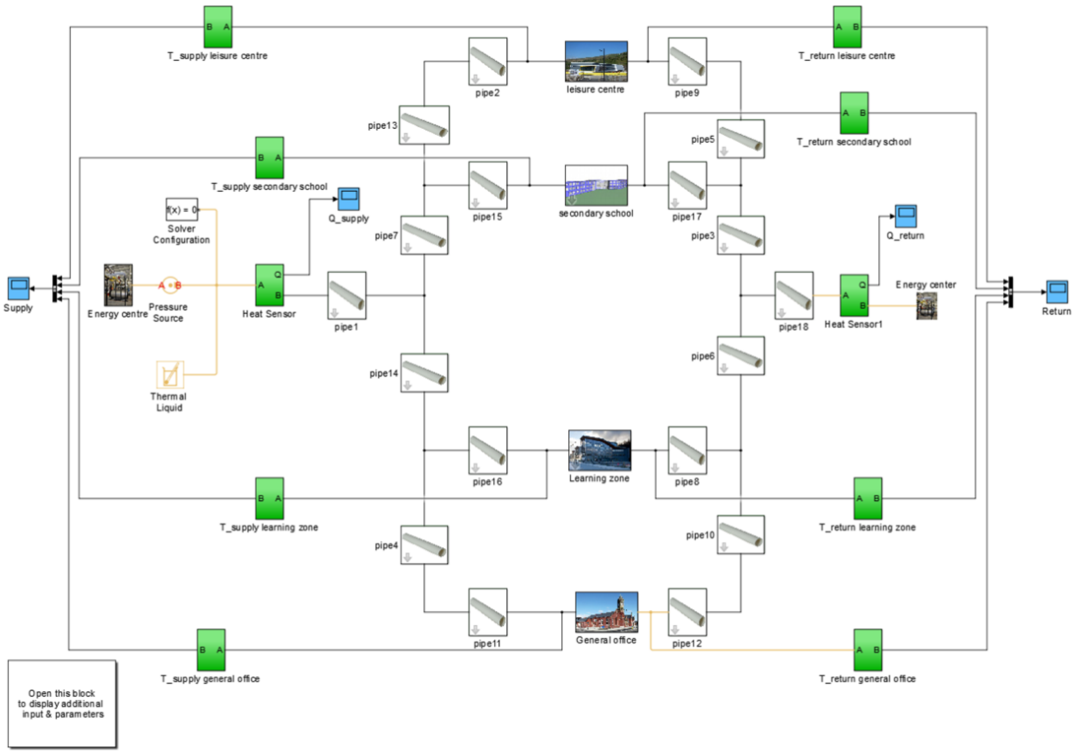

Fig. 5-9 Simulink model of the network.

5.3.1 Governing Parameters

A numerical simulation model is built in Simulink to model the operation of the distribution network. The input parameters such as pipe, insulation and soil properties are shown in Table 5-2 and Table 5-3. The archive attached to the general office operates 24 hours 7 days a week. The control valves of the secondary school and the learning zone are turned off completely at night and weekends. Around 10% heat load is supplied to the leisure centre to guarantee that the temperature of the swimming pool would not drop too much at night, so that it can response quickly to heat up in the next day.

Table 5-2 Parameters for pipe, insulation and soil

Pipe conductivity	17 J/(k*m)

Pipe density	7500 kg/m^3
Pipe specific heat	500 J/(kg*K)
Insulation conductivity	0.03 W/(m*K)
Insulation density	60 kg/m^3
Insulation specific heat	1500 J/(kg*K)
Depth of pipe	0.6 m
Soil conductivity	2 W/(m*K)

Table 5-3 Properties of pre-insulated steel pipe

Nominal pipe size (mm)	**Outer diameter (mm)**	**Wall thickness (mm)**	**Insulation thickness (mm)**
100	114.3	3.6	200
125	139.7	3.6	225
150	168.3	4	250
200	219.1	4.5	315
250	273	5	400

The operation data for heat consumption, flow rate and temperature variation were exported from a database computer in the energy management station. However, as some heat meters could not be connected to the database at some periods or the failure of some meters, resulting in a missing of some readings, reasonable assumptions were made to replenish the data. The assumptions are:

1) The heat consumption of learning zone is missing. The energy consumption in the learning zone displayed is based on the design heat consumption and outside temperature.

$$\mathrm{Q} = \frac{T}{T_{design}} Q_{design} \tag{48}$$

2) The temperature in learning zone is missing. The temperature of the learning zone displayed in Fig. 5-12 is based on its operation schedule and the temperature of secondary school and general office as the learning zone is located between the two buildings.

5.3.2 Simulation and experiment temperature comparison

Fig. 5-10 to Fig. 5-13 compare the simulated and measured supply and return temperature from each building. The simulation results are in line with the experimental results except that the measured data for secondary school and learning zone are slightly higher than the simulation data during night. This can be explained by the fact that temperature meters are installed indoor while the simulation only uses the ambient temperature as surrounding temperature source. However, this simulation precisely displayed the downward trends at night when there is no heat consumption in those two buildings. Because of the temperature gap, the water in the pipes loses some heat to the environment, causing the temperature drop at night.

During the day, the supply temperature in the system is around 90°C and the return temperature is around 59°C with some fluctuation due to the boilers output, heat consumption of each building and heat losses in the pipes. The supply temperature is around the design state. The high return temperature could be explained by the heat exchangers related problems such as clogging or problems of the thermal valves. At night, the supply temperatures of the water running into the leisure centre and general office are around 2°C to 4°C lower than the temperature during the day. This is mainly caused by the heat losses in the pipes. During night, heat demands in those two buildings are much less. The lower flow rates in the pipes result in higher heat losses. This indicates that lower heat loads result in lower efficiencies of the network. It is important to ensure that the network is designed to work around the design state most of the time in a year in order to guarantee the performance of the distribution network.

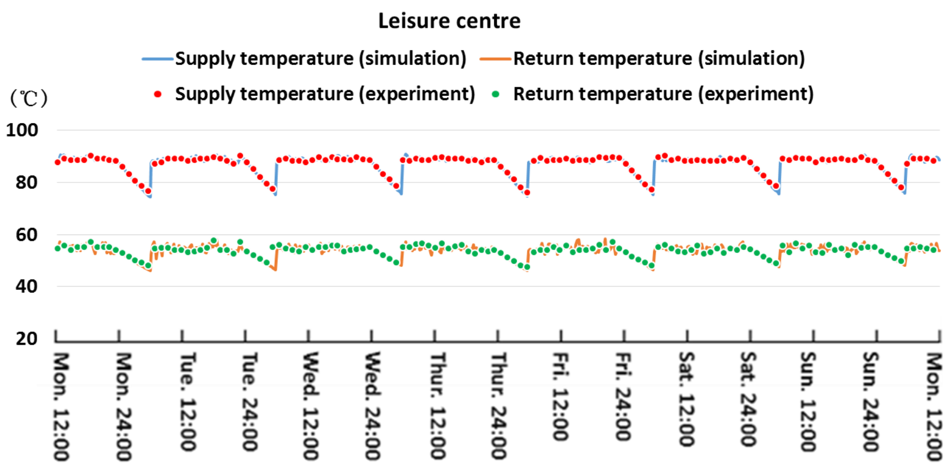

Fig. 5-10 Supply and return temperature for leisure centre

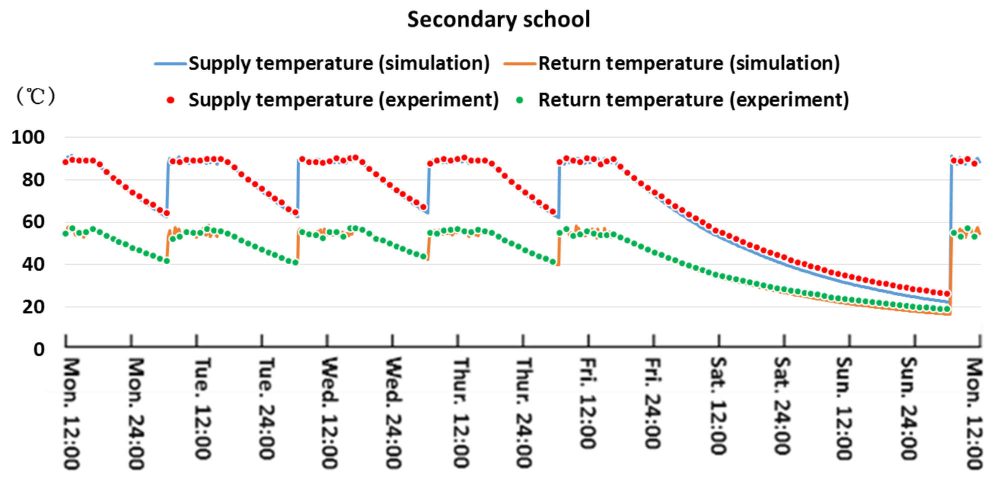

Fig. 5-11 Supply and return temperature for secondary school

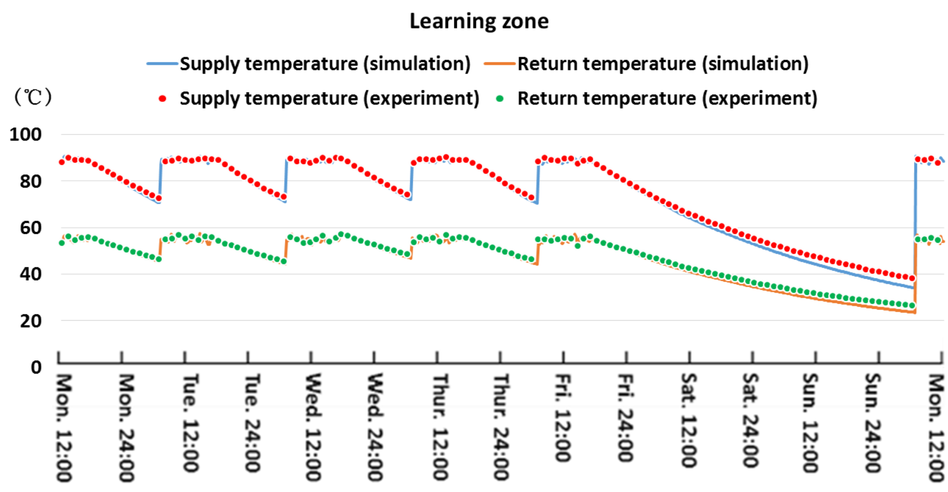

Fig. 5-12 Supply and return temperature for learning zone

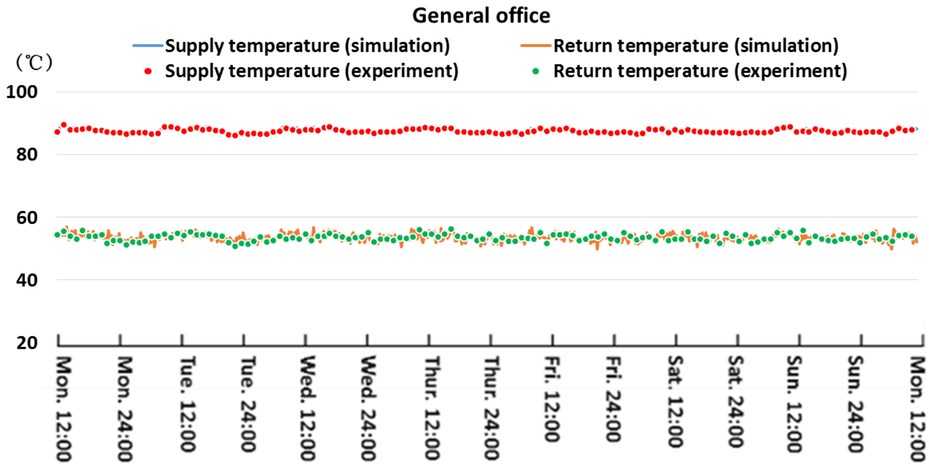

Fig. 5-13 Supply and return temperature for general office

5.3.3 Heat loss in pipes

In order to study the heat losses of the pipes, Fig. 5-14 is used to clarify the system and to display the diameter and length of pipes. Supply and return pipes are symmetrical. Nodes 1 and 16 represent the energy center. Nodes 7, 8, 9 and 10 represent leisure center, secondary school, learning zone and the general office. The aim of this part is to analyze the dynamic heat loss through different pipe segments.

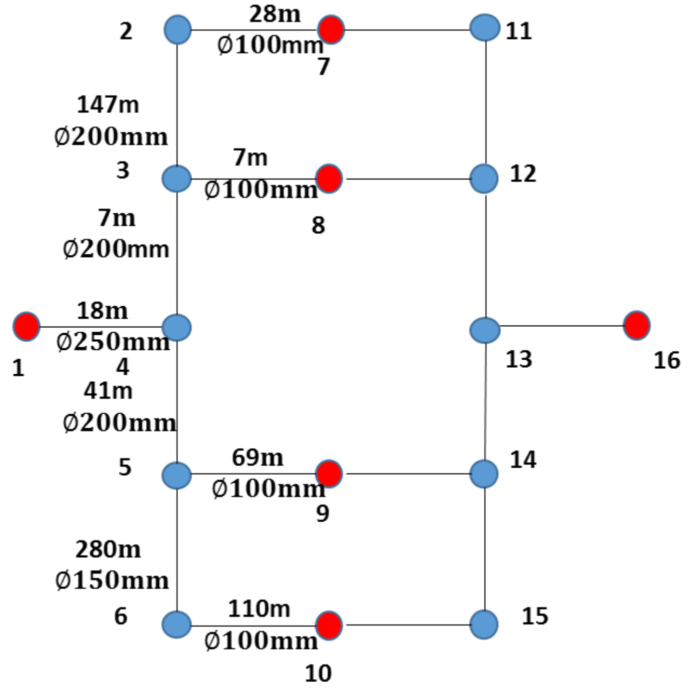

Fig. 5-14 Pipe node layout

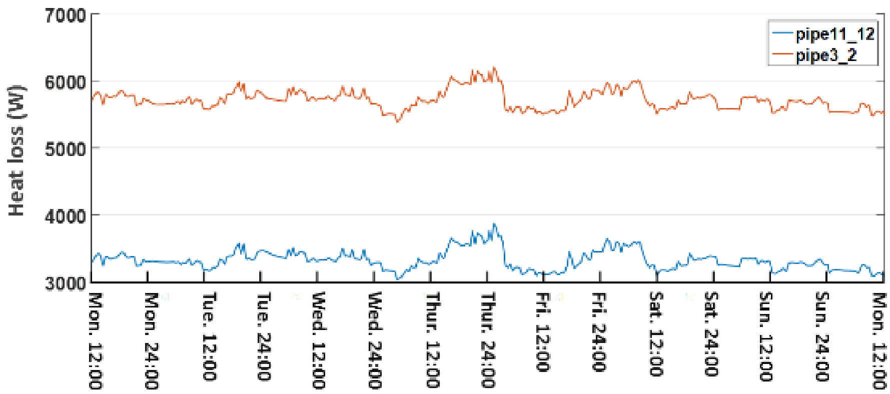

Fig. 5-15 Heat loss from pipe11_12 and pipe3_2

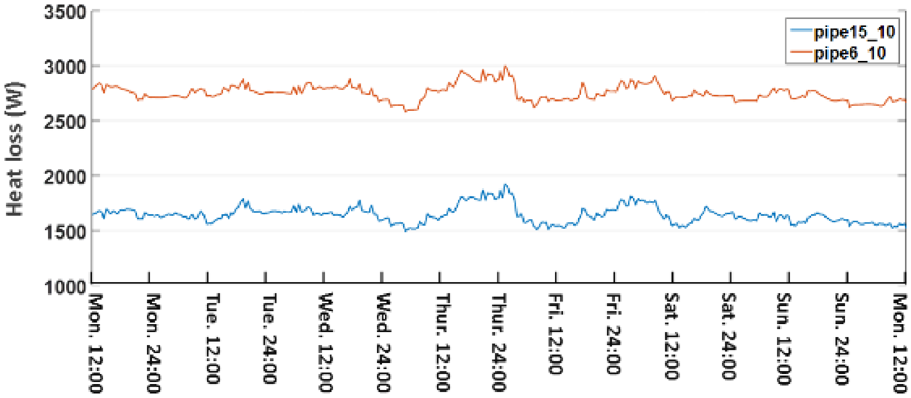

Fig. 5-16 Heat loss from pipe15_10 and pipe6_10

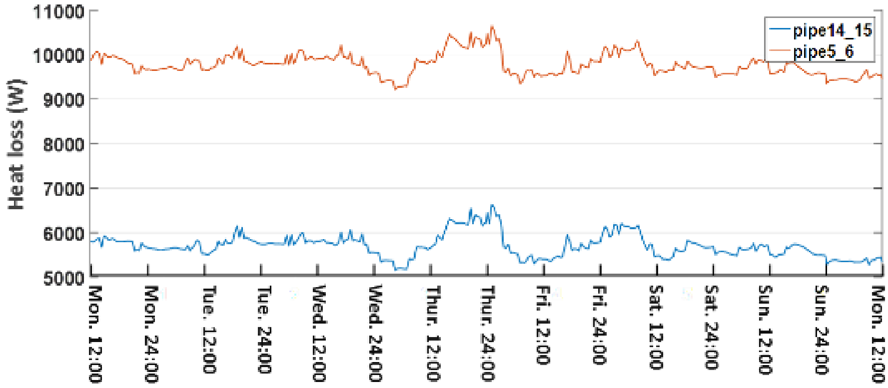

Fig. 5-17 Heat loss from pipe14_15 and pipe5_6

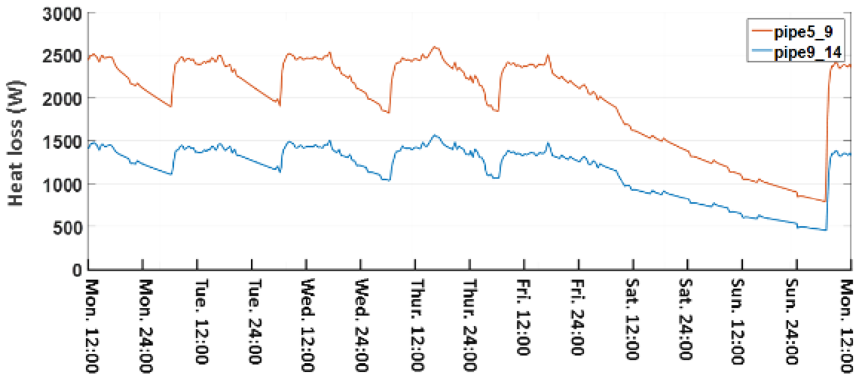

Fig. 5-18 Heat loss from pipe5_9 and pipe9_14

As there are many pipes in the network, it would occupy a lot of space to display them all here. Only the longest eight pipes (4 supply and return pipes) were selected to describe heat losses, as shown in Fig. 5-15 to Fig. 5-18. The heat losses displayed are the heat that transfers through soil to the atmosphere. Temperature differential between water and the ambient is the driver for heat loss. The main thermal resistance for heat transfer is the pipe insulation. The heat losses variation is attributed to the water and ambient temperature fluctuation and flow rate of the distribution medium. Heat losses in return pipes are significantly lower than the supply pipes as the lower temperature in the return pipes. The overall heat loss of the network during the weekday daytime is around 1-2% of the distributed heat. However, the heat loss increases to about 8-12% at other time periods, depending on the amount of heat delivered and ambient temperature.

5.3.4 Temperature of nodes

Apart from the temperature and heat loss analysis, the simulation can also be used to understand the temperature of each node in the network. The temperature at the mixing point should be close to each other, in particular for the return pipe, as rapid temperature alterations lead to thermal expansion and contraction, which results in a short lifetime of the pipes. Fig. 5-19 display the temperatures of node 13.

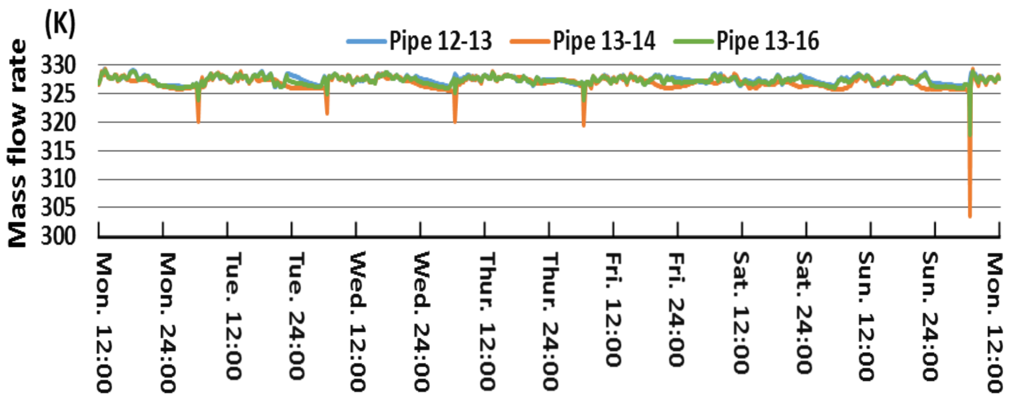

Fig. 5-19 Temperature of node 13

The model can also be used to understand the mass flow rate of the nodes. However, the advantage of analysing mass flow of the nodes is not as significant in this network as in a complex system where there are several loops and the water flow direction in the loops may reverse. It is difficult to get to know the mass flow in each pipe directly from the meters installed inside buildings. However, this paper provides a good solution to study mass and heat flow in a complex network. The model is helpful in assisting robust design of such network.

5.3.5 Heat losses in the context of next generation district heating systems

Heat loss of the distribution network is examined in this section with a focus on the next generation DH system. As aforementioned in the literature review section, the future DH system will be built on lower energy demand network, lower supply and return temperatures, and advanced insulation technology for the piping network. The research method in this chapter is based on the simulink models developed in the previous sections.

5.3.5.1 Lowering building energy consumption

Future newly constructed buildings will have to meet higher regulations and policies to reduce energy demand. This can be implemented by using advanced envelop insulation technology or by adopting heat recovery measures to improve building thermal performance in new buildings. Reduction of energy demand in existing buildings will be achieved through envelop renovation, energy systems retrofit and smart building management. Building energy demand has the potential to be reduced by 50% (as discussed in chapter 1). Reducing building energy demand not only reduces fuel consumption, it will also bring down heat loss in the piping network as shown in Fig. 5-20.

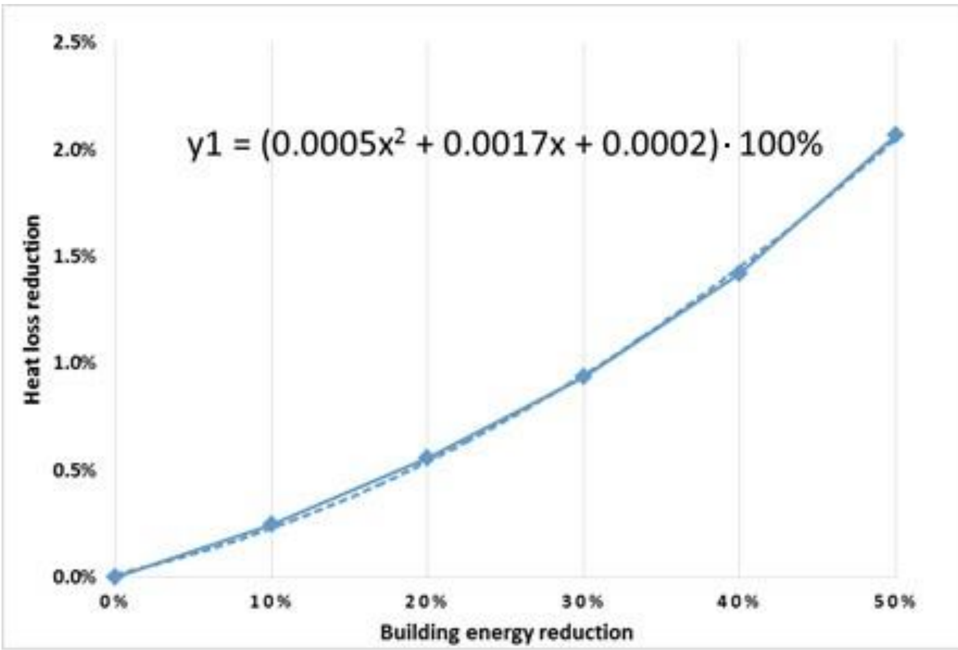

Fig. 5-20 Heat loss reduction with building energy consumption reduction

The heat loss reduction trendline can be expressed as:

$$y_1 = (0.0005 \cdot \mathrm{x}^2 + 0.0017 \cdot \mathrm{x} + 0.0002) \cdot 100\% \tag{49}$$

Herein: $\mathrm{x} = \frac{Building\ energy\ reduction\ (\%)}{10\%}$;

The heat loss of the network does not improve significantly for already existing heating systems when heat consumption decreases as demonstrated in Fig. 5-20. There is merely 2.07% heat loss reduction in the piping system when the user heat demand reduces by 50%. The heat loss reduction is mainly caused by lower heat transportation. However, the reduced heat demand will result in a smaller size for the piping network, which will bring down the initial investment cost for construction of new distribution network. According to the results in section 5.3.3, oversized pipe network results in higher heat loss. For a newly constructed network that the pipe sizes are in accordance with heat demand, heat loss reduction should be more than this value. Namely, heat loss reduction should be more than 2.07% if the network is designed and constructed based on 50% energy demand.

5.3.5.2 Reducing distribution medium temperature

The lower distribution temperature will promote the utilization of local available sustainable energy such as solar, geothermal and waste thermal energy that would otherwise be wasted. The possibility of heat loss reduction in a low temperature distribution network is illustrated in Fig. 5-21.

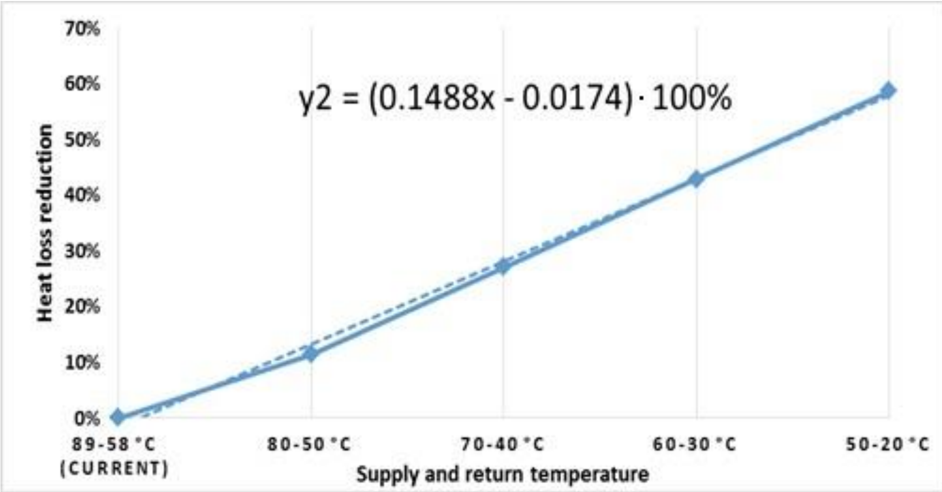

Fig. 5-21 Heat loss reduction with distribution temperature

Heat loss reduction in the piping network can be expressed as:

$$y_2 = (0.1488 \cdot \mathrm{x} - 0.0174) \cdot 100\% \qquad (50)$$

Herein: $\mathrm{x} = \frac{90-Supply\ temperature}{10}$; and the temperature different for supply and return temperature is 30°C.

The heat losses in the network reduce significantly with the decrease of the distribution medium temperature. The heat loss reduces by almost 60% when the temperature of water reduces from current situation to 50/20 °C. Reducing the distribution temperature to a certain low level may take time in practice. However, related research have been conducted to accelerate the advancement of this technique [147] and [140]. Another problem may occur with decreased distribution temperature. The temperature in the pipes at night or on the weekend may decrease to minus 0 °C leading to frosting during winter. By-pass system offers an optimal solution for this issue which allows a small portion of hot water running through when the temperature decreases to a set point temperature so as to guarantee the temperature would not be less than the freezing point [150] and [157].

5.3.5.3 Adopting advanced insulation technology

Insulation thermal performance can be enhanced by using hybrid insulation technology or using advanced insulation materials with lower thermal conductivity. The heat loss reduction with enhanced insulation thermal conductivity is shown in Fig. 5-22. Although there is no reported study about insulation with thermal conductivity better than 10 mW/(m·K) being applied in DH pipe network, there are studies about insulation with thermal conductivity in the order of less than this value [219] and [220]. It is a promising technology that might be adopted in the next generation DH network.

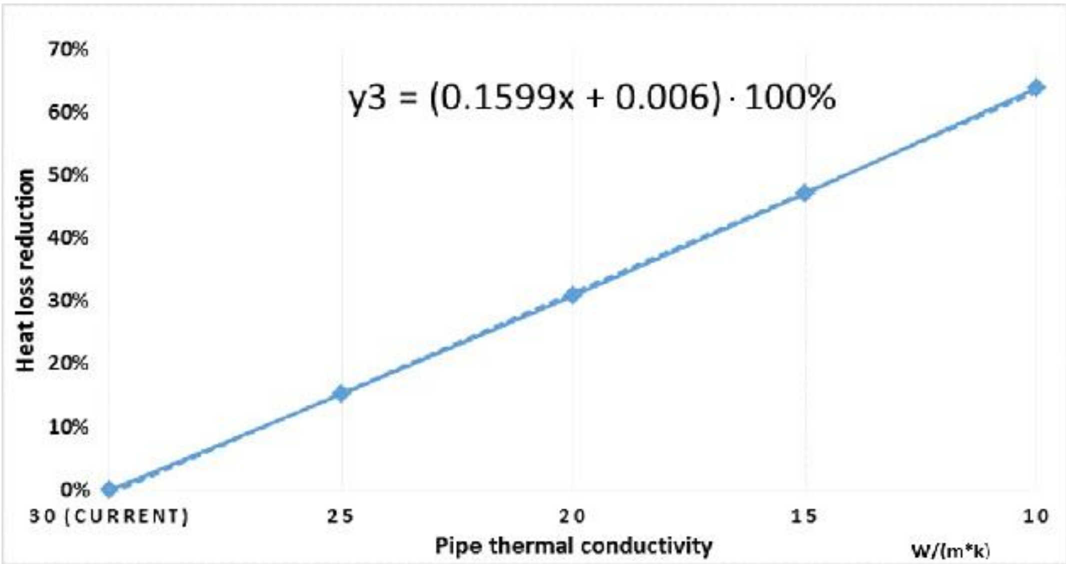

Fig. 5-22 heat loss reduction with insulation thermal conductivity reduction

Heat loss reduction in the piping network can be expressed as:

$$y_3 = (0.1599 \cdot \mathrm{x} + 0.006) * 100\% \tag{51}$$

Herein: $\mathrm{x} = \frac{30 - insulation\ thermal\ conductivity}{5}$;

Improving thermal performance of the insulation materials greatly reduces the heat loss in the network. When the thermal conductivity decreases from current state to 10mW/(m·K), the heat loss decreases by approximately 64%. However, this might result in a higher investment cost for the distribution network.

5.3.5.4 The combined effect of the three factors

As the influences of building energy consumption, distribution temperature and insulation thermal conductivity on piping heat loss are independent factors. The effect of the combined three factors on the total heat loss reduction can be expressed as:

$$\mathrm{y} = 1 - (1 - y_1)(1 - y_2)(1 - y_3) \quad (18)$$

Equation (18) can be applied to provide guidance for constructing new DH networks or retrofitting DH networks aimed at distribution network heat losses reduction. However, the refurbishment of existing building to reduce building energy consumption, replacement of heat exchanger in the substation and using better insulation materials will result in a higher investment cost. Life cycle assessment study should be carried out at the decision making stage to examine the effectiveness of the improvement and the payback periods so that the investors and users can benefit the most from the DH network.

5.4 DH network simulation

A new approach for DH simulation is proposed to investigate the operation of the generation units. The current operation scheme is used for economic and environmental evaluation of the network. An optimization is applied to search for the optimal control schedule of the generation units with minimal operation cost.

5.4.1 Platform realization

Fig. 5-23 displayed the realization of the co-simulation platform in the BCVTB. The simulation was launched through BCVTB Graphical User Interface (GUI). At each time step, the four EnergyPlus models send the heat demands to Simulink for distribution heat loss computation. As the output from EnergyPlus is energy demand for 15 mins while the inputs for Simulink are energy flow per second, a unit conversion actor (1/900) was placed between the Energyplus and Simulink.

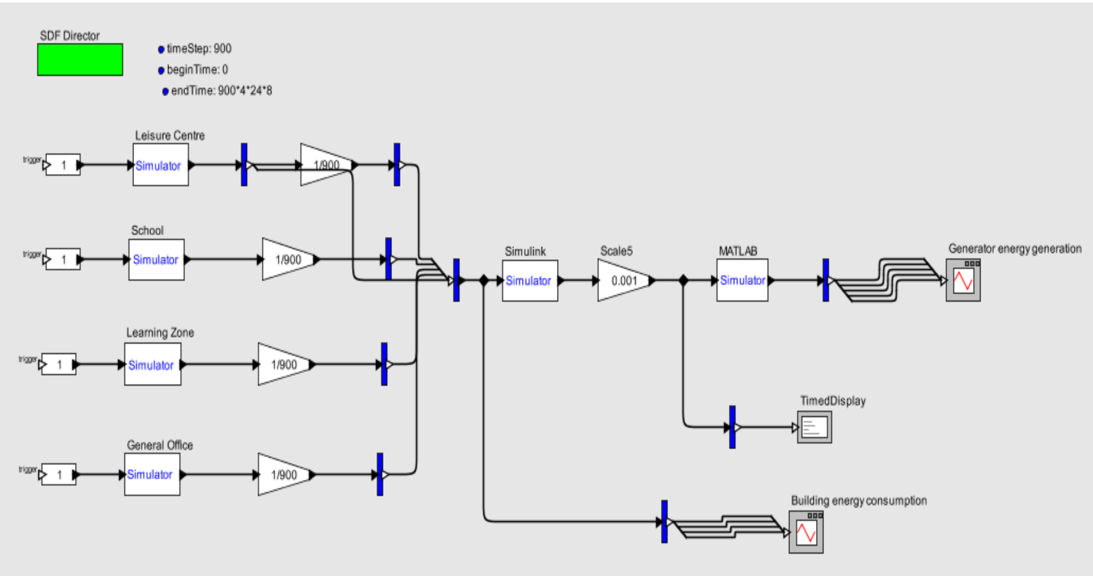

Fig. 5-23 Realization of the platform

5.4.2 Current operation schedule

The current operation is based on load-tracking mode, namely the generation follows the heat load profile. The priority of the generators has been defined in advance. The parameters used to computer the heat output of each generator are displayed in Table 5-4.

Table 5-4 Boiler capacity and average operation efficiency

CHP heat capacity	400 kW
Biomass	450 kW
Gas boiler	1900 kW
CHP heat to electricity ratio	1.2
CHP efficiency	78%
Biomass boiler efficiency	67%
gas boiler efficiency	82%

Fig. 5-24 displays the heat output from each generator under the current operation strategy. As the generators heat outputs differ significantly due to the various capacities, to make it easier for comparison, the output is scale to the proportion of the rated power. It can be seen that the CHP is used to meet the base load operating 24 hours daily as it has the highest priority due to its ability for heat and power generation in the same process. It operates at full load during the day time and partial load over the night. Most of the time, the partial load is higher than 60% of the rated power. This guarantees a high performance for the CHP, with an overall efficiency of 78%. Biomass boilers operate mainly during the daytime. They run mostly at full load over the week when they are in use, which grants a high performance for the biomass boiler under the current operation scheme. Gas boilers are only used to meet the peak loads when CHP and biomass boilers are not able to satisfy the loads. In such condition, the gas boilers run substantially at partial loads and sometime they only operate a short time to satisfy the demands, resulting a low efficiency of 67%.

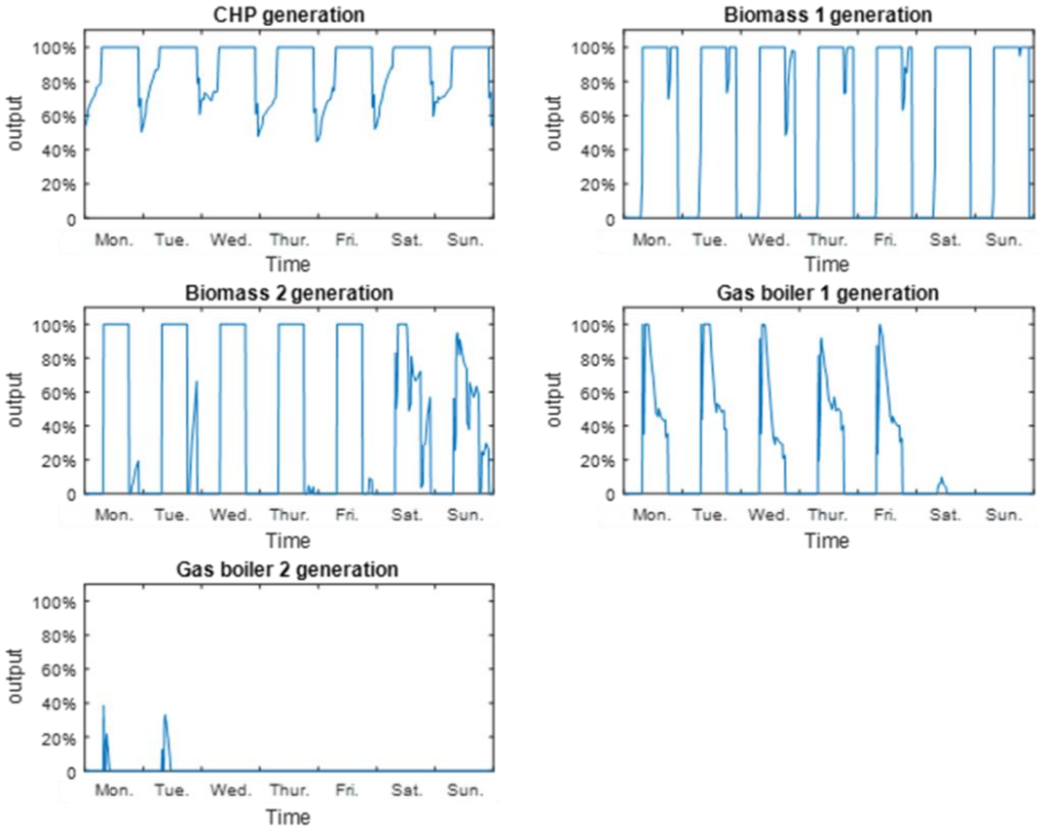

Fig. 5-24 Heat output from each generator under standard operation

5.4.3 Economic and environmental evaluation of the network

CO_2 emission and economic benefits are two key factors to assess the DH contribution to emission targets and to evaluate the competitiveness of DH in future heating market. Energy consumption and generation, CO_2 emission and operation costs are discussed in this section. Table 5-5 displays the parameters used for analysis.

Table 5-5 conversion factors to primary energy and CO_2 emission

electricity price (sold to grid)	0.07	£/kWh
Renewable heat incentive	0.0537	£/kWh
CO2 emission from biomass	15	kg/mwh
CO2 emission from gas	185	kg/mwh
purchase price of biomass	0.205	£/kg
purchase price of natural gas	0.0248	£/kWh
biomass calorific value	4.8	kwh/kg

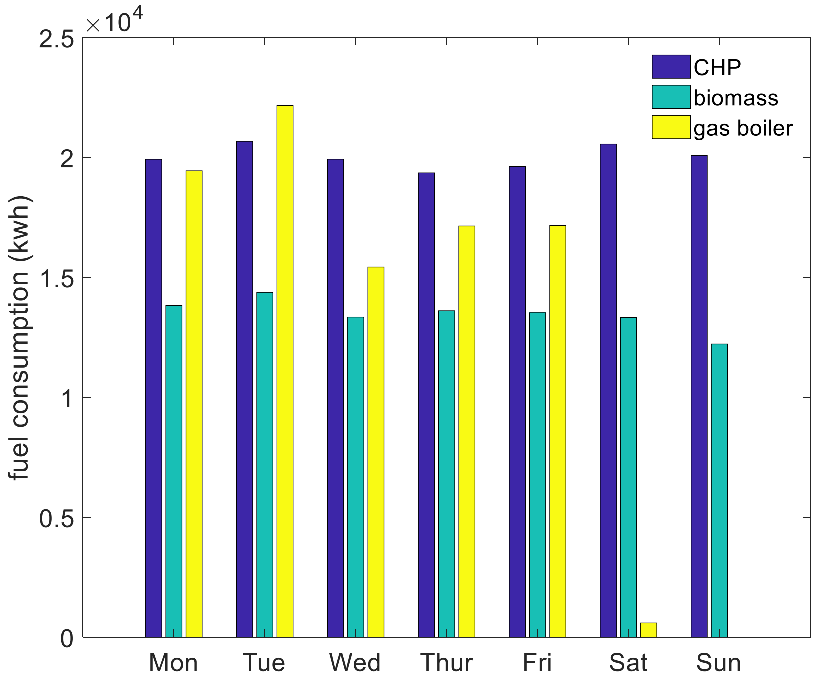

Fig. 5-25 Fuel consumption per day from boilers

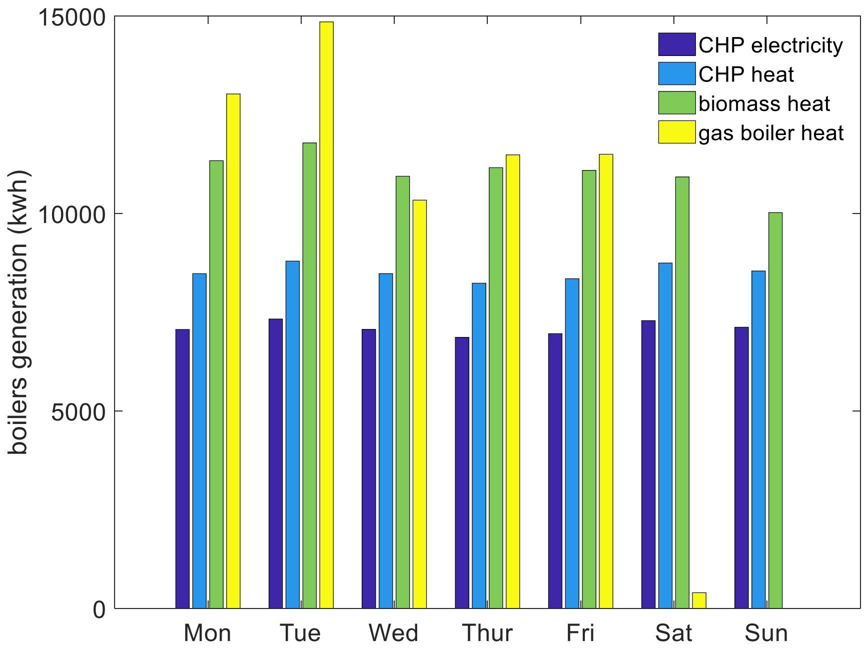

Fig. 5-26 Energy generation per day from boilers

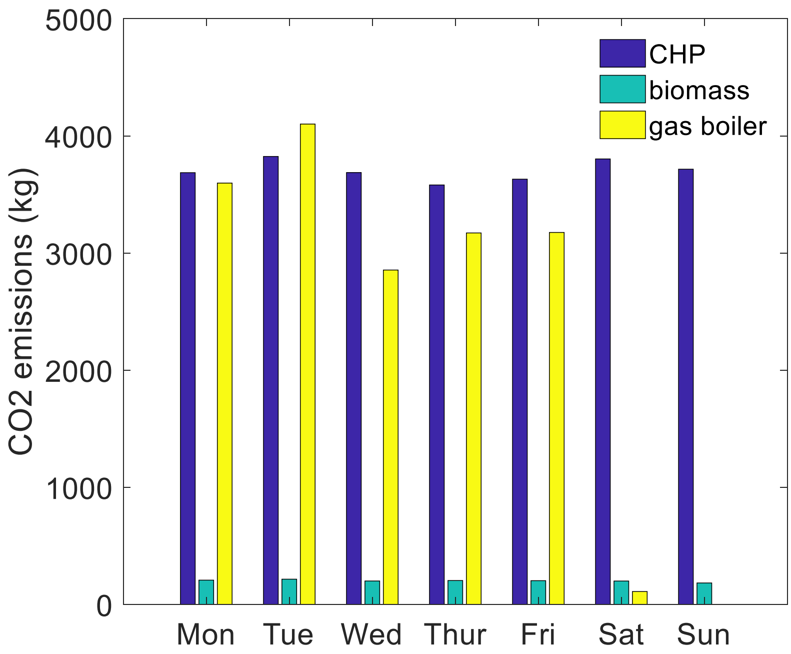

Fig. 5-27 CO_2 emission per day from boilers

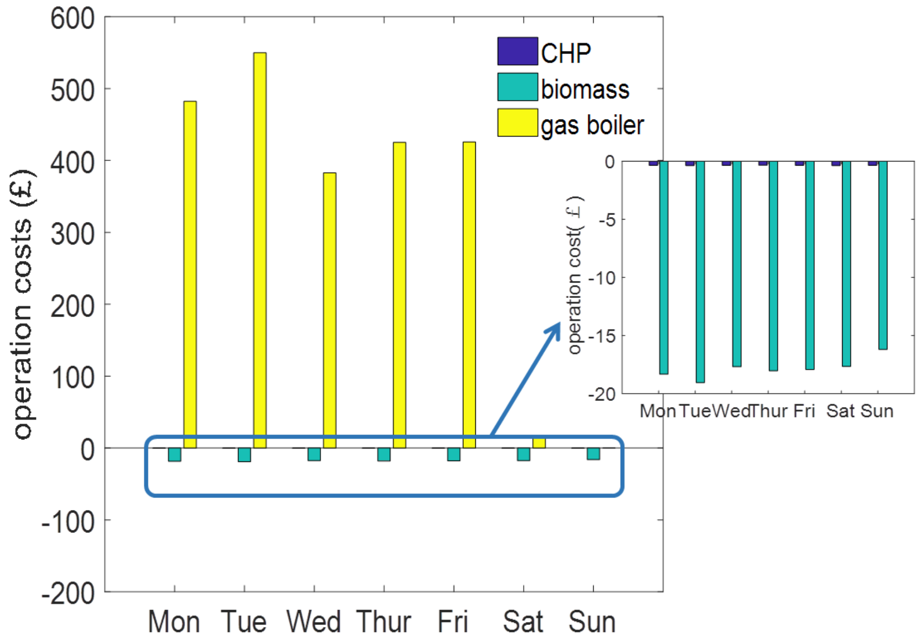

Fig. 5-28 Operation cost per day from boilers

Energy generation relies on the amount of fuel consumed and boiler efficiency. As it is shown in Fig. 5-25 and Fig. 5-26, the CHP and biomass boilers produce more heat than the gas boiler for the same amount of fuel consumed as a result of the higher efficiency. Comparing Fig. 5-25 and Fig. 5-27, the CO_2 emissions from CHP boiler and gas boilers are significantly higher than biomass boilers for the same amount of fuel consumed. This is because biomass is a carbon neutral fuel. Emission from biomass boiler is mainly incurred in the process of fuel extraction, delivery and process. The fuel source for gas boilers and CHP is gas and the emissions depend on fuel consumption.

The operation costs for CHP and biomass boiler are negative (as shown in Fig. 5-28), which means that during the process of providing heat to the district, the two approaches for heat generation can get positive income after the costs spent for fuel purchase. This is due to the electricity sold to the grid and the revenue obtained from renewable heat incentive. Meanwhile, when compared with Fig. 5-25 and Fig. 5-26, it is easy to conclude that the profit gained from the biomass boiler is bigger than the CHP boiler. This indicates that the biomass boiler is the cheapest method for heat supply in this system. The high efficiency and RHI of the biomass contribute to the economic benefit. With the decrease of RHI, the operation cost for biomass boiler will increase, as shown in Fig. 5-29. CHP will be the cheapest choice.

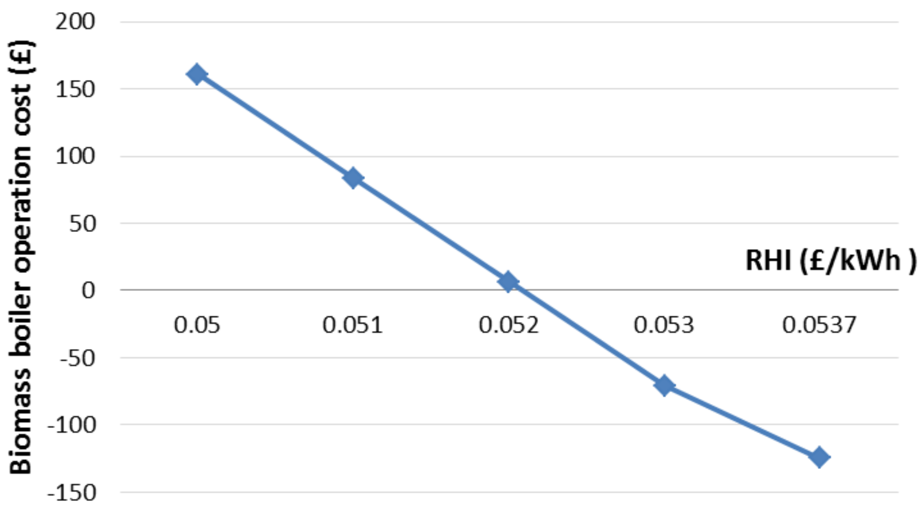

Fig. 5-29 The biomass boiler operation cost variation with renewable heat incentive price

5.5 DH optimization

Optimization is a very important research interest of this investigation. This section displays the results of operational schedule optimization based on selected algorithm.

5.5.1 Optimization

The optimization is based on day-ahead optimization. Tuesday in the last section was selected to study the optimal operation strategy. The previous section elaborated the results according to load-tracking mode. However, this assumes that the boilers perform the same at full load and partial load. Furthermore, the boiler starts working when there is a heat demand without considering the startup cost. One of the main targets of this study is to investigate the best control strategy for thermo-economic purpose.

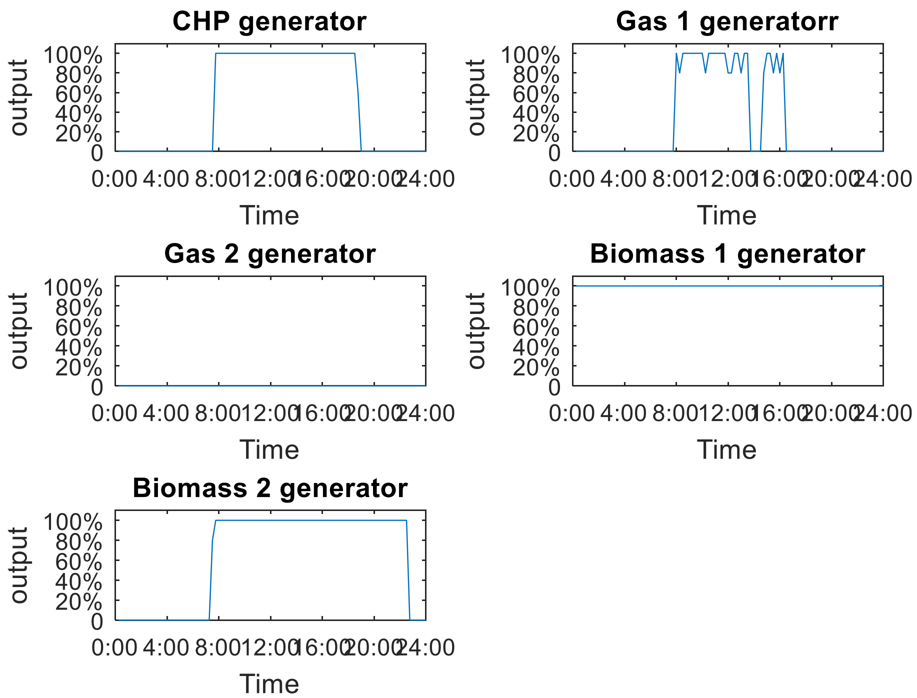

Fig. 5-30 operation schedule of the generators

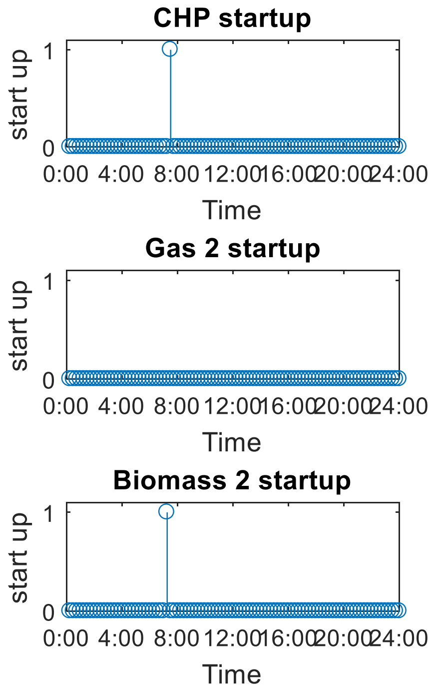

Fig. 5-31 Startup condition of each generator

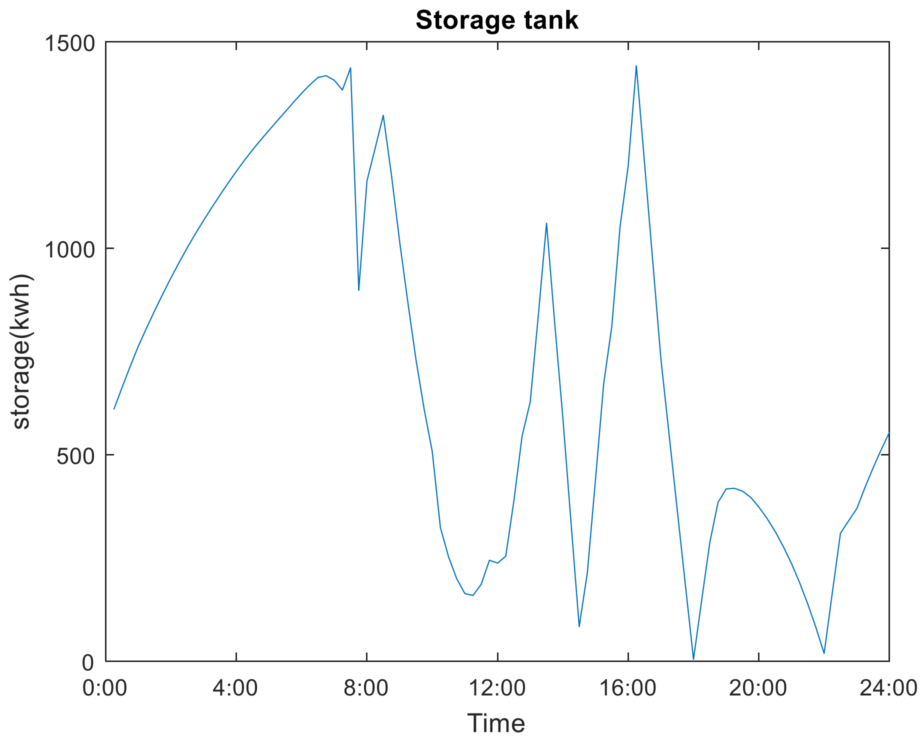

Fig. 5-32 stored energy in the storage tank

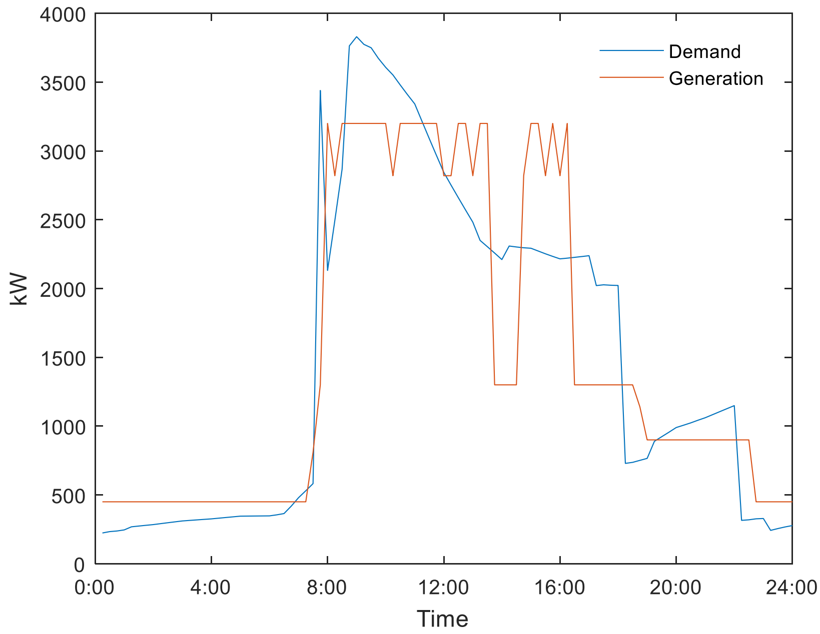

Fig. 5-33 Energy demand and generation under optimization

The operation schedule of the generators after optimization is display in Fig. 5-30. The results demonstrate that the units operate mostly at full load and biomass 1 is exclusively applied at full load. This results in better overall performance of the whole system. As it has been discussed in section 5.4.3, the biomass boilers produce the best economy benefit. Under the optimization module, the best option is selected automatically and the highest priority gives to biomass boiler. Early in the day, biomass 1 is the only boiler in operation. Most of the heat generated from biomass 1 is consumed by the DH system and the rest is stored in the storage tank shown in Fig. 5-32. Before the peak period, heating systems in the district are activated for preheating, biomass 2 and CHP start running, with a significant increase in heat generation. At the peak hours, gas boiler 1 starts working. Together with the heat stored in the storage tank, the four boilers can meet the heat demand at peak periods. The gas boiler 1 operates at high output levels while gas boiler 2 does not put into operation during the whole day. Under the optimization scheme, the average efficiency for gas boiler and biomass boiler has improved to 77% and

85%. The operation cost for one day is 375 pounds. Compared with the cost under the current strategy whose operation cost for Tuesday is 530 pounds, around 30% of the operation cost has been saved. The CO_2 emission has been reduced significantly to 5,530 kg, which results to emission saving of 32%. As it can be seen from Fig. 5-33, the optimized heat supply greatly reduces the heat generation from peak hours. This indicates the optimization can be used for peak shaving. The results also indicate that optimization and storage tank can reduce the installed capacity in the DH network.

Although the average efficiency over a long period is different from the average efficiency for a specific day under the standard operation, the difference between the two schedules still reveals that the optimization can achieve significant cost saving.

5.5.2 Future scenario

Currently, the avenue obtained from biomass boilers is mainly supported by the RHI. As the wide adoption of renewable energy in future increases, the RHI will decrease even cut off completely. This section will discuss about future operation schedule when RHI is decreased to 0.03 £/kWh. The results are displayed from Fig. 5-34 to Fig. 5-37.

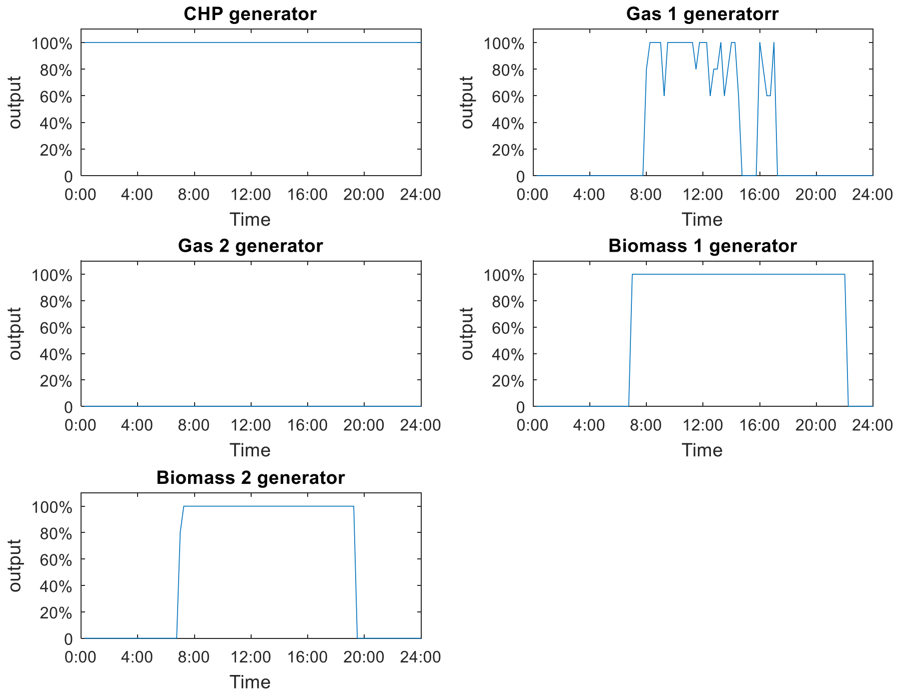

Fig. 5-34 Operation schedule of the generators

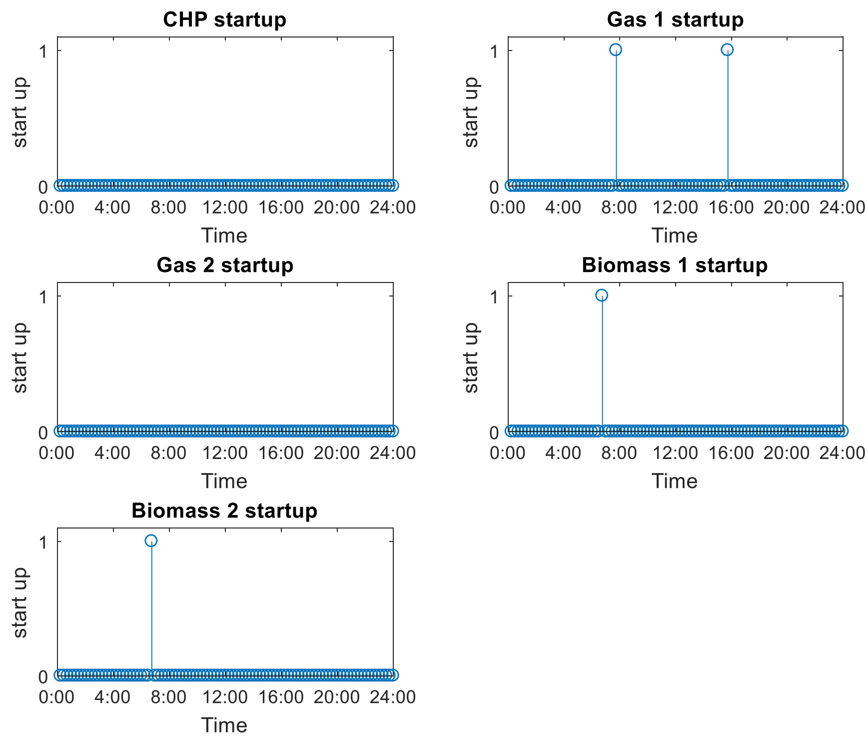

Fig. 5-35 Startup condition of each generator

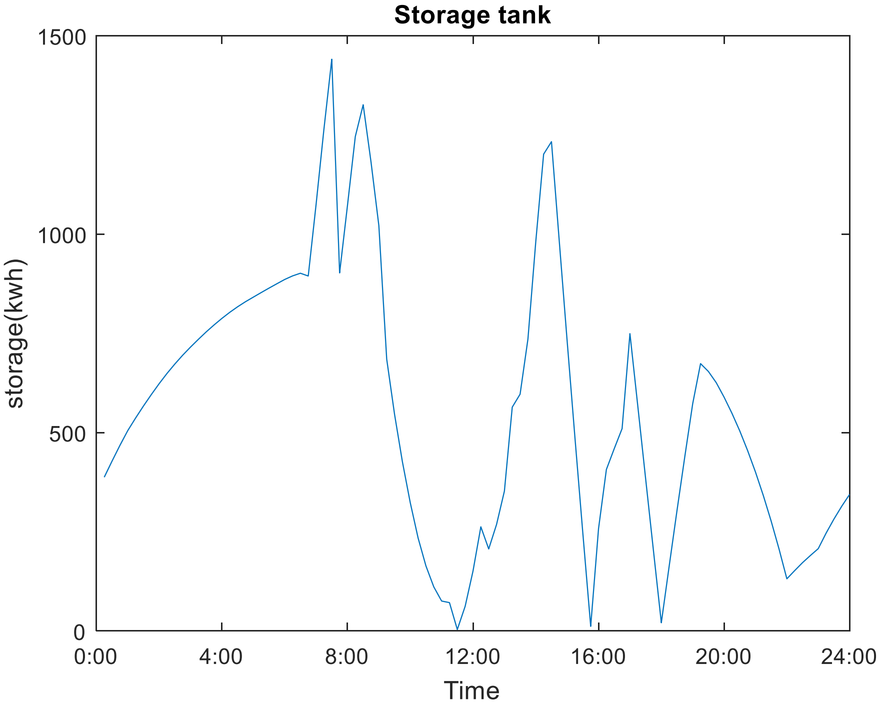

Fig. 5-36 Stored energy in the storage tank

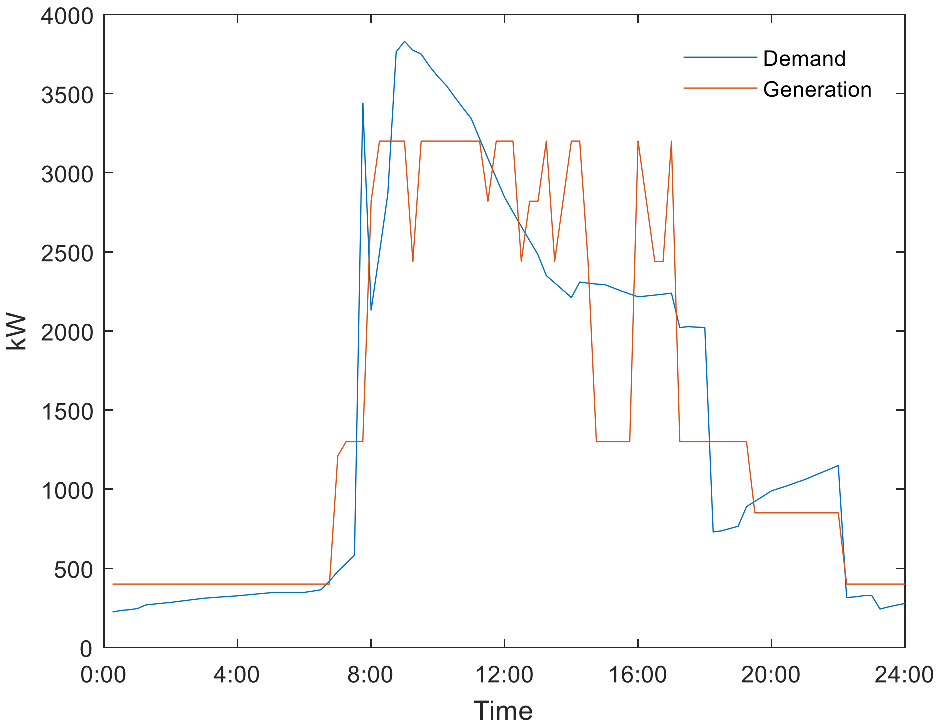

Fig. 5-37 Energy demand & generation under optimization

It has been discussed in section 5.4.3 that when the RHI decreases, CHP will be the priority for heat generation. As it is shown in Fig. 5-34, the CHP boiler operates at 24 hours a day at 100% power output, which ensures the performance of CHP. The produced heat is partly used to meet the heat demand and the rest is stored in the storage tank shown in Fig. 5-36. Biomass boilers are the second choice. When CHP and storage tank cannot meet the heat load, biomass boilers are put into operation in sequence. As it can be seen from Fig. 5-37, the biomass boiler 1 starts working before the peak to produce heat for the storage tank, which reduces peak heat generation from the generation units. At the peak period, the gas boiler 1 starts working, resulting in a significant increase in the energy generation as shown in Fig. 5-37. During the whole process, the CHP is exclusively operating at full load. Biomass boilers and gas boiler 1 are mostly operating at full load. Gas boiler 2 stays intact. The optimization has achieved peak load shaving and energy efficiency improvement.

5.6 Summary of the results

This chapter has demonstrated the results of the investigation. Firstly, the results for calibration of building U-values and air infiltration rate are presented. Regression models are formed to represent the relationship between heat demand and U-values and air infiltration rate. The calibrated U-values and air infiltration are higher than the design values. A simulation with human activity involved is carried out and benchmarked with measured data. The results after calibration have improved significantly.

Next, the results for DH network dynamic simulation are demonstrated. The simulated temperature variation is in line with the measured data. The heat loss during the day was around 1~2% while at night it increased to 8~12%. A discussion towards heat losses in next generation district heating network is given. Distribution temperature and insulation thermal conductivity have a significant effect on the distribution heat loss. An equation is formulated to reflect the effect of building energy consumption, distribution temperature and insulation thermal conductivity on heat loss.

Next, the co-simulation platform together with the simulation results of the DH network under the current operational scheme is presented. Results show that CHP operated at partial load at night. Meanwhile, gas boilers are mostly running at partial load, resulting in low efficiency for gas boiler. The economic and environmental evaluation of the network is carried out. CHP and biomass boilers exhibite positive revenue and biomass boiler was the cheapest option. The emission from CHP and gas boilers is much higher than the biomass boilers.

Finally, the results for optimization of the operation schedule targeting at operation cost minimization are presented. After optimization, the boilers are running mainly at full load. CHP, biomass boilers and gas boiler 1 are able to meet the peak load. Results indicate that day ahead optimization of the system can achieve 30% cost and 32% emission reduction, respectively. A future scenario is introduced to analyse the operation schedule of the boilers with reduced RHI. The cheapest option is given to CHP boiler.

6 Discussion

This chapter presents a discussion of the work carried out in the previous chapters. It firstly discusses the contribution to academy. Afterwards, the relevance of the work to practise is analysed. Finally, this chapter demonstrates a smart control system of a small scale district heating network.

6.1 Overall academic contributions

This section discusses the work conducted and the results produced as a contribution to the body of knowledge within the academic field. Firstly, direct analysis of the designed approach and research results for the calibration of U-values and air infiltration are given, before discussing DH network simulation, and finally reflecting on DH network optimization.

6.1.1 Building U-values and air infiltration calibration

The work carried out to calibrate building U-values and air infiltration is mainly based on field metred data, building simulation and optimization algorithm, which overcomes the disadvantages brought by direct measurement. The contribution is firstly discussed from field measurement and then the contribution is discussed from building performance sensitivity study.

Firstly, it should be stated that current measurement of U-values and air infiltration is mainly through field test. Compared with experimental methods which involve a great deal of labour force and time, the developed method offers a quick and powerful approach to solve the problem. Meanwhile, empirical technology is difficult to implement and involves a wide range of uncertainties. For example, the U-value on different locations of the same wall is different as a result of the random errors caused by construction work, weathering and thermal bridge. Multiple tests should be carried out in order to obtain an average value. Even for the same person with the same equipment, the test results would still be different resulting from the uncertainties during the measurement. This fast and easy to implement method guarantees the security of the researchers and facilitates the evaluation of the building thermal performance. This approach can also be applied in various research fields to quantify parameters at steady state by excluding variables causing dynamic performance.

Secondly, the calibration of building U-values and air infiltration can be considered within the building simulation validation. The contribution is discussed in relation to existing sensitivity study. For most of the building energy performance simulation carried out, the U-values and air infiltration are obtained directly from the design values. The actual condition may be deviate from the design for various reasons, causing discrepancy between simulation and metered results. Validation is imperative with the purpose of obtaining cogent simulation results. The work has been investigated through various sensitivity study approaches. Regression model, owning to its speed in computation and easy to understand, is widely used to identify the most influential input parameters with respect to their impact on building performance [221] and [222]. Building U-values and air infiltration rate normally rank among the top influential parameters. Accurately identifying those parameters sharply reduces the simulation disparity. However, consumers' daily habits, which are difficult to quantify, are often involved in the process of calibration, adding uncertainties to the results. The approach proposed in this thesis can be used as a pre calibration to obtain accurate values and then proceed with sensitivity analysis for other parameters.

6.1.2 District heating network simulation

DH network simulation in this study is implemented through a co-simulation platform. The contribution is discussed in terms of energy modelling and energy prediction models.

As a lack of reliable simulation tools, district heating network simulation is a challenge for studying the performance of the system. This study presents a co-simulation environment that integrates with mature tools for whole network simulation. Testified models guarantee the reliability of the whole network. The time consumed for running the co-simulation platform is shorter than separate simulations. The simulation can be used to inform the dynamic performance of the whole network. Similar approaches can be formed for the control of building energy consumption through the same platform. Building simulation and building control are realized in different tools. The BCVTB platform couples the tools for co-simulation.

DH network energy performance is also being researched with regard to data streams, which are pertinent to the growth of big data. Data driven is a powerful approach for energy prediction, especially for large scale network where physical simulation is time consuming and computational expensive. The work conducted was not from the perspective of data processing as a large amount of history data is required to support the accuracy of the results. Meanwhile, big data has its limitation for unknown situations. The approach adopted within the study was to investigate the network through detailed physical models, which can be used to account for the energy evolution in future scenario. For example, the sports centre is planning to install some solar panels for solar thermal heating. The role of the sports centre will be a prosumer, which can both be a provider and consumer in the network. Historical data will not be helpful for future energy prediction, as solar thermal was not included in the history data. However, the simulation approach will be a powerful solution to evaluate future energy demand. In that case, the data driven models can serve as the prediction model and simulation model predicts the changes.

6.1.3 District heating optimization

Within the discourse of DH optimization, the novelty of the work conducted can be addressed from two perspectives. Firstly, the efficiency of the generation units is considered together with the energy output, rather than using a constant value to represent the overall efficiency. This overcomes the problem of operating deviation from the design condition chronically, which guarantees the high efficiencies for all the generation units. Secondly, Mix-integer linear programming is applied to represent the non-linear efficiency. The efficiency is characterised into different output levels. This brings significant benefits as non-linear programming is computational expensive and optimal result is not guaranteed.

Researchers from the energy field with expertise in heat and power generation have extensively studied the part load efficiency for gas boiler, biomass boiler and CHP. However, this has seldom been explored within the area of building energy consumption as the researchers are mainly with a background on architecture, civil engineering and mechanical engineering. The part load efficiency has a significant influence on the operation cost of the network. This research is the outcome of interdisciplinary research. The knowledge exchange among multi-discipline boosts the prosperity of future research.

Evolutionary Programming and Genetic Algorithm based on big data are hotspot in recent years. These algorithms have been widely applied in various research fields for multi purposes, such as cost minimization, demand respond and peak shaving in DH network. Optimization from the perspective of MILP provides an approach for solving non-linear problems from the perspective of linear programming.

6.2 Relevance to the practise

This section discusses about the relevance of the current work outputs to the practise. It firstly discusses the relevance to the field of enterprise and practitioners and then discusses the relevance to smart thermal grid and smart cities in a broader sense.

6.2.1 Enterprise and practitioners

U-value is an important factor for energy materials used in the building sector such as insulations. Using the calibration method can inform the necessity for refurbishment of the existing buildings. Companies who are responsible for refurbishment can obtain the U-values and air infiltration through the proposed method to avoid carrying out multifarious on site tests. Those parameters cannot be measured directly through sensors available in the market. The enterprise may be inspired by the research work to produce sensors that can measure these values by a combination of several heat meters.

Customers of the network can financially benefit from the DH optimization as optimization of the DH network targeting at operation cost minimization can offer lower heat price to the community. The lower price will attract more potential consumers to join the network. As DH benefits from the scale of the network, the heat price will be further reduced with increased amount of consumers. This will form a beneficial economic cycle. Meanwhile, the optimization can give priority to renewable and sustainable energy, which reduces carbon emission and produces a clean and sustainable community.

The consumer using DH network do not have to understand systematically about the operation and control of the network, but they should be aware of the energy saving and environmental protection, which facilitates the use of renewable energy and CO_2 emission reduction. This thesis discussed the importance of terminal users in advancing towards smart thermal grid.

6.2.2 Smart thermal grid and smart cities

DH network is a promising solution to future energy and environment issues. However, some of the current networks receive criticisms for higher cost compared with individual heating, resulting in disconnection from the network. This is true if the network is not designed and operated properly. Heat loss in the network can be sizable and the generation units operate inefficiently, causing significant energy waste. Proper design and management of the network will promote large acceptance and advancement toward smart thermal grid, which is the foundation to future smart city.

In a large thermal grid, the heat will not be produced from a single source to enhance its robustness, so that consumers' requirements can always be met even under some critical conditions such as malfunction from one energy centre. As heat is produced through several energy centres, the management of heat generation is crucial to avoid both over generation and under generation. Meanwhile, the interrelated network enables prosumers to both purchase and sell heat to the network. For example, the heat intensive industries can sell surplus heat to the grid and purchase heat from the grid when they need it. Thermal grids should be designed to achieve the high efficiency to realize the ambition of sustainable development. Smart management can be helpful in choosing the best combination of energy mix and enables a maximum exploitation of available energy sources.

Smart thermal grid and smart city are possible under the information era. Big data and smart control are technologies pertinent to smart cities. Big data is an emerging technology to replace the computational expensive physical models. The limitation of the big data can be replenished by simulation models, which emulate the new business models and novel framework conditions.

Smart thermal grid should be able to generate significant synergies, which can integrate with other energy grids, such as electricity grid and gas grid. Smart city requires intelligent energy management from both regional and city level. The dynamic simulation of the whole network, day ahead optimization and review on DH optimization contribute to the evolution toward smart thermal grid and smart city.

6.3 Computational urban sustainability platform (CUSP)

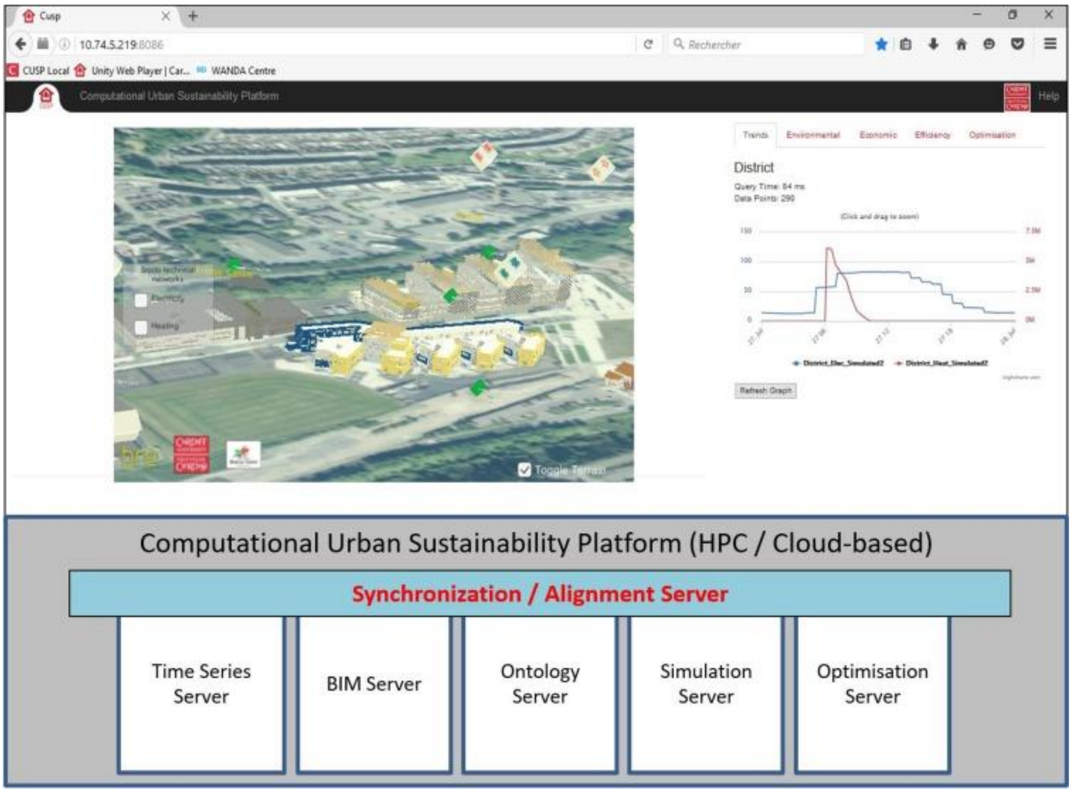

Fig. 6-1 CUSP interface

The last section of this chapter presents a smart DH network. The Computation Urban Sustainability Platform (CUSP) platform, as shown in Fig. 6-1, is a smart control environment under development by the authors' research group. The aim is to implement a micro smart thermal grid within a district heating community. The platform provides real time information in the form of a web based application for energy managers. The web based application is a unity game engine, which only displays visuals and data. The data processing is performed by coupling energy simulation models and data analytics. An ontology server is used to effectively link isolated information. For example, the ontology server can collect external weather condition and internal sensors and store the information in time series server. A simulation server using EnergyPlus models and Simulink models or machine learning to predict energy demand for the coming day, which facilitates managers' decision-making. Given the large quantities of data information, optimization server is deployed to provide energy and cost saving solutions. The CUSP platform also displays key performance indicators (KPI), such as operation cost, carbon emission and energy consumption per area. Together with automatic anomaly detection, this can alert the manager if the system is operating as expected.

7 Conclusion

Following the discussion provided in the previous chapter, this chapter provides a summary of the research work and its main findings. The research findings are presented based on the research questions formulated at the beginning of the investigation. Next, the contributions of the research are discussed, followed by the limitation across the investigation and future work.

7.1 Main research findings

The research findings answer the research questions through four aspects by looking into outputs and results. The research work discussed optimization of DHC from the perspective of the existing literature and provided a discussion toward smart thermal grids. Building simulation was carried out in EnergyPlus, along with building U-values and air infiltration calibration to improve accuracy. Distribution network simulation was conducted in Simulink with a discussion on heat loss of the next generation DH network. A co-simulation approach was proposed for the whole network simulation and an MILP was adopted for day ahead prediction of the operation schedule of the generation units.

7.1.1 DHC optimization toward smart thermal grid

The first posited research question posed is:

What is the current state of district heating systems and how those can be enchanced towards achieving the smart thermal grid vision?

This work firstly provided a definition of the DH network: A DH network is a system that delivers hot water or steam derived from a central plant to buildings via extensive underground pipe network. The development of the network was reviewed. It concluded that fossil fuel and CHP dominate the energy supply in the current system and renewable energy was gradually incorporated into the network.

The research then emphasised on the optimization of the DHC through four main processes: generation, distribution, transformation and consumption. Research directions towards STG can be summarized as follows:

1. Integration of sustainable energy, CCHP and TES are the major solutions to alleviate fossil fuel depletion, reduce GHG emission and enhance system stability and efficiency.
2. Optimal design of the heating and cooling networks (piping network), including pipe layout, pipe insulation, underground depth, supply temperature, and an optimal operation of pumps to ensure the efficiency of the distribution network.
3. Improving the performance of the heat exchanger and an installation of by-pass can enhance the effectiveness of the heat substation and reduce response time to guarantee efficiency and comfort.
4. Less energy demanding buildings, BEMS, a stimulating price and strengthening public awareness of energy saving are the key approaches to reduce energy consumption in building and to facilitate the development of future low energy DHC.
5. STGs will involve more interaction among DHC, individual heating and cooling system, electricity and gas. Communication between production and demand is important to ensure efficient utilization of energy.

7.1.2 Building U-values and air infiltration calibration

The second posited research question posed is:

How to calibrate envelope thermal transmittance and air infiltration to improve the accuracy of building simulation?

Measuring building envelope U-values and air infiltration is complex as the empirical technology is difficult to implement and involves a wide range of uncertainties. Meanwhile, the whole process usually takes a large amount of time, man efforts and is costly. In this study, a novel concept was proposed to obtain the U-values and air infiltration by using easy to obtain parameters. The proposed method considered building heat losses in a quasi-steady state to eliminate uncertainties caused by dynamic energy consumption resulting from occupant behaviour. GA was used to minimize the difference between simulated and measured energy consumption. After calibration, the simulation results have improved significantly. This computational approach combined with field gathered data calibration could serve as an alternative to traditional methods. It can also act as a supplementary method for parameter sensitivity analysis of building performance simulation to increase accuracy by reducing the number of variables needed during the process of calibration. The advantages of this method are that it is easy to implement and can be used for any building. It does not require any sophisticated devices and simply requires a personal computer and access to existing meters in the building. The process and related time necessary to determine the U-values and air infiltration are several times shorter than the traditional methods. The accuracy and reliability of the simulation can be further improved by choosing an appropriate indoor and outdoor heat convection models.

7.1.3 Distribution network simulation

Heat loss is an important factor influencing the efficiency of the distribution network, which cannot be ignored when studying the performance of DH network. A simulation model was developed in Simulink to study the distribution network of a small DH system, with a focus on heat losses. The simulated temperature variations are in line with the experiment data. The overall heat loss of the distribution network during weekday daytime is around 1~2% of the distributed heat. However, heat loss increases to about 8~12% at other time periods, depending on the amount of heat delivered and ambient temperature. The temperatures of each node can be analysed in advance to avoid heat expansion and heat contraction. The model can also be applied to select the best pipe configuration, including size, insulation materials, thickness etc. at the decision-making process to minimize operation cost. The model was also applied to investigate the potential for heat loss reduction in the next generation DH network. Key insights as to heat losses in next generation DH are summarized below:

a) When the building heat consumption decreases, the network will mainly benefit from the reduction of fuel consumption with a slight drop in heat loss from the distribution network. If the network is designed appropriately, the system should benefit more from heat loss reduction.
b) Heat loss will decrease by almost 60% when the distribution temperature reduces from current state to 50/20 °C. However, the reduction of temperature is based on a more advanced heat exchanger that can extract the same amount of heat from a lower temperature heat source.
c) Heat loss will reduce significantly by 63.97% when the insulation thermal conductivity decrease from 30 mW/(m·K) to 10 mW/(m·K). Such a high level insulation might lead to higher initial investment cost for the pipe network at the construction stage.
d) A formula to express the influence of building energy consumption, distribution temperature and insulation thermal conductivity on distribution heat losses was formed, which can provide some guidance if readers want to construct or retrofit their DH network for the purpose of reducing distribution heat losses.

7.1.4 DH network co-simulation and optimization

The third and fourth posited research questions posed are:

How to model district heating networks to deliver a reliable district simulation capability?

How to meet heat demand with minimal operation costs when considering the efficiency variation at partial loads of a district heating?

This study presented a novel approach for DH network co-simulation. The simulation was conducted under BCVTB environment. The building performance simulation was implemented in EnergyPlus. Physical components of the distribution network were developed in Simulink. Afterwards, the operation of the generators based on standard strategy was carried out in Matlab. Economic and environmental evaluation of the DH network were investigated. Results revealed that biomass boilers and CHP can obtain positive income after costs spent for fuel purchase, and biomass boiler is the cheapest option for heat generation rather than CHP. Meanwhile, optimization was carried out to obtain the optimal schedule for cost minimization. MILP was applied to study the non-linear efficiency at different levels of output. The startup cost and heat storage were introduced at the optimization stage to avoid frequent turn on and turn off the generators. After optimization, all boilers were operating most of the time at the rated power, which greatly improved the efficiency of the whole system. The heat storage acted as a battery in the system which could store surplus heat at off-peak hours for use at peak periods. Results showed that the optimization could be used for peak shaving and initial investment reduction. The effectiveness of the optimization was benchmarked with the standard operation scheme. The potential for cost saving and carbon emission reduction were up to 30% and 32 respectively.

7.2 Key contributions of the research

This section summarises the key contributions of the investigation. The core contribution is the overall findings towards smart thermal grid through DH simulation, optimization and discussion. Specifically, DH simulation allows the robust design and retrofit of the smart thermal grid. Optimization enables smart management of the thermal grid. The discussion in this section aims to address the challenges in future smart thermal grids. The novelty of the research can be concluded as follows:

1. The research provides a review of the current DH and DC system and proposes future trends for DH optimization toward smart thermal grids.

2. A novel concept for calibration of the building U-values and air infiltration is proposed.

3. A co-simulation method is proposed for DH networks.

4. An MILP is developed to represent the non-linear efficiency for day ahead prediction of the boiler operational schedule.

7.3 Future work

The research towards the doctoral thesis was conducted over a duration of 3 years, involving 2 research projects. Some research limitations can be noted. The primary one is that the research projects from which the case study was drawn are supported by research grants, and are not business driven. This does not affect the cogent research outputs or weaken the puissant research findings, but the depth could be further explored regarding the impact on enterprise energy systems.

On site U-values and air infiltration measurement was not carried out to validate the calibration results for several reasons. It is worth highlighting though that the simulation results have improved significantly after calibration. Implementation of on-site tests could have validated the impeccability of the proposed research method.

Assumptions were made for the co-simulation and day-ahead optimization to simplify the computation while clarifying the problem. More detailed models for the energy centre should be included during the process of co-simulation to improve accuracy of the model. Future work will integrate more physical models from Modelica or Trnsys to understand the detailed operation of the boilers, including the heat supply temperature, the distribution pressure and flow rates. Real time simulation will be carried out to compare the simulation results and measured results.

DH network simulation in this thesis is based on a small scale DH network. For large scale DH network, representative buildings can be modelled and then extrapolated to a district level. The optimization results can be further improved by using more operating levels. This will result in higher computational demand.

The breadth of the work is across smart thermal grid domain. Specifically, the work only conducted optimization targeting operation cost minimization. Smart thermal grid is a complex system involving multi objectives. The impacts of introducing renewable energy and using a real-time pricing system were only discussed from the perspective of the literature review. They have not been verified by using models or optimization algorithms, but further work could explore these and fill the gaps existing in advancement towards smart thermal grids.

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9 Appendix

Appendix 1. different design air infiltration rates and design U-values applied in the simulation

	Infiltration (ACH)	Wall (W/m^2K)	Roof (W/m^2K)	Floor (W/m^2K)	Window (W/m^2K)
1	1.25	1.524	0.27	0.257	2.25
2	1.25	1.366	0.31	0.313	2.24
3	1.25	1.121	0.38	0.412	2.25
4	1.25	0.846	0.45	0.46	2.26
5	1.25	0.761	0.53	0.549	2.26
6	1.25	0.925	0.45	0.504	2.26
7	1.25	0.801	0.72	0.449	2.26
8	1.25	0.34	1.09	0.545	2.25
9	1.25	0.393	0.31	0.389	2.18
10	1.25	0.409	0.59	0.358	2.21
11	1.25	0.183	0.18	0.072	1.99
12	1.25	0.141	0.13	0.069	2.13
13	1.25	0.141	0.05	0.132	0.95
14	1.25	0.099	0.06	0.282	1.77

15	1.25	0.078	0.22	0.166	1.54
16	1.25	0.052	1.35	1.122	2.27
17	0.75	1.524	0.27	0.257	2.25
18	0.75	0.601	0.32	0.314	2.25
19	0.75	0.846	0.44	0.425	2.27
20	0.75	0.409	0.72	0.564	2.27
21	0.75	0.071	0.25	0.099	2.29
22	0.75	0.052	0.05	0.059	0.95
23	0.75	0.123	0.21	0.083	1.33
24	0.75	0.148	0.16	0.135	1.99
25	0.75	0.052	0.06	0.037	1.54
26	0.5	1.524	0.27	0.257	4.01
27	0.5	0.764	0.16	0.064	4.11
28	0.5	0.052	0.05	0.059	1.18
29	0.5	2.33	2.72	1.479	2.74
30	0.5	1.366	0.18	0.32	3.29
31	0.5	1.121	0.35	0.559	3.92
32	0.5	0.876	0.34	0.545	2.74
33	0.5	0.725	0.05	0.081	1.83
34	0.25	1.524	0.27	0.257	5.76
35	0.25	0.846	0.09	0.203	5.07

36	0.25	0.541	0.31	0.526	1.29
37	0.25	0.104	0.08	0.081	2.12
38	0.25	0.071	0.05	0.542	2.7
39	0.25	0.099	0.09	0.404	2.12
40	0.25	0.514	0.59	0.296	2.12
41	0.15	1.524	0.27	0.257	5.76
42	0.15	0.236	0.34	0.25	1.29
43	0.15	0.114	0.08	0.07	2.12
44	0.15	0.071	0.31	0.296	2.7
45	0.15	0.365	0.31	0.367	3.13
46	0.4	1.524	0.27	0.257	5.76
47	1.5	1.524	0.27	0.257	5.76

Appendix 2 An example for genetic algorithm

Here is a simple example of how a genetic algorithm works. The process begins by a set of individuals called initial population. An individual is characterized by a series of genes, which are joined to form a chromosome. Usually, binary values are used to encode the genes in chromosomes. As shown in Fig. 9-1, binary 1 and 0 represent genes. A1, A2, A3, A4 and A5 are chromosomes with 5 genes. The 5 chromosomes are formed into a population.

A1	1	1	0	1	0
A2	1	0	1	0	0
A3	1	0	0	1	0
A4	1	0	1	1	0
A5	0	1	0	1	0

Fig. 9-1 Display of genes, chromosomes and population

The fitness function evaluates the fitness of an individual chromosome and the fitness score is given to stand for the probability of an individual to be selected for reproduction. The higher the fitness value is , the higher possibility the value is. The fitness of each chromosome and its percentage for selection are displayed in Table 9-1.

Table 9-1 The fitness and percentage of selection for each chromosome

	Fitness	Percentage
Chromosome A1	26	27.1%
Chromosome A2	20	20.8%
Chromosome A3	18	18.8%
Chromosome A4	22	22.9%
Chromosome A5	10	10.4%

Crossover is the most widely used method to produce the next generation. A1 and A4 are the chromosomes with the higher probability to be chosen to produce the next generation. Here, they are selected to produce the next generation chromosomes: A6 and A7, as shown in Fig. 9-2.

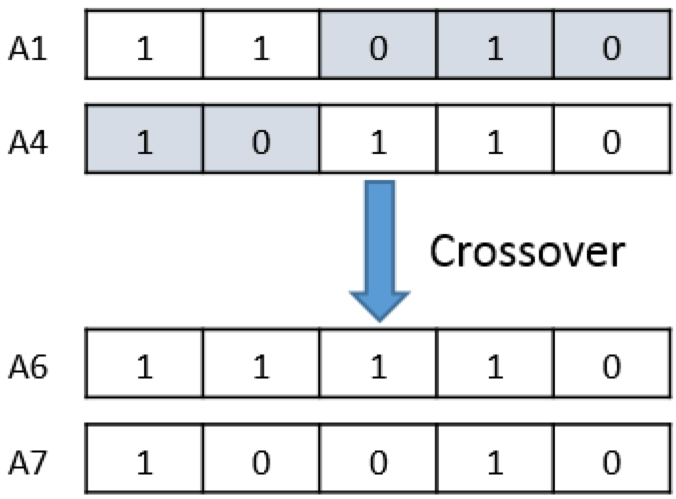

Fig. 9-2 Crossover to produce new offspring

In certain condition, the genes in the chromosome may change because of mutation. The third genes in A6 mutates and produces a new A6 as shown in Fig. 9-3.

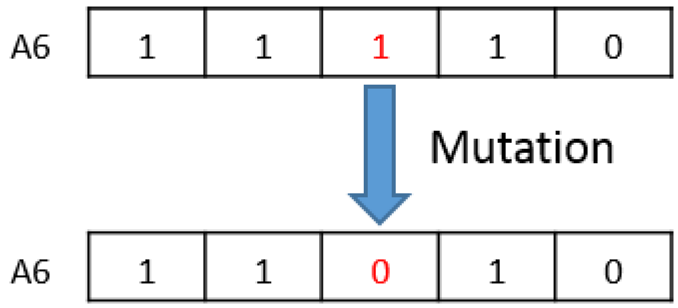

Fig. 9-3 Before and after mutation for A6

The new generation produces its offspring by iterating selection, crossover and mutation. The process terminates when the population could not produce offspring that are obviously different from the current generation.

Appendix 3 Configuration of simulation tools for data exchange

Ⅰ. Data exchange between EnergyPlus and BCVTB

The Ptolemy II connects to EnergyPlus through external interface in EnergyPlus. The exchange of Input/output signals are mapped to EnergyPlus objects. The external interface can call three types of EnergyPlus input objects: ExternalInterface:Variable, ExternalInterface:Actuator and ExternalInterface:Schedule, which are used to overwrite Energy Management System (EMS) variables, EMS actuators and schedules respectively. The function of the three objects are similar to EnergyManagementSystem:GlobalVariable, EnergyManagementSystem:Actuator and Schedule:Compact except that their values are obtained at the beginning and remain constant during the zone time step. An initial value can be specified to ExternalInterface:Actuator, which will be used during the warm-up period. Even if it is not specified, a default value will be used during the warm-up stage. However, for ExternalInterface:Variable and ExternalInterface:Schedule, the initial value is required for the warm up period. The ExternalInterface:Variable is a global variable, which can be used in the same way as the EnergyManagementSystem:Sensor and EnergyManagementSystem:GlobalVariable. The external interface can also map to objects of EnergyManagementSystem:OutputVariable and Output:Variable. These objects can be used for zone time step data exchange between BCVTB and EnergyPlus. Three files should be created before configuring the data exchange:

1. An EnergyPlus idf file;

2. An xml file to define the mapping between BCVTB and EnergyPlus;

3. A BCVTB model.

a) Configuring EnergyPlus idf file

The idf files in this study are the EnergyPlus models for each building. The code below (Fig. 9-4) shows how to activate the external interface (the first two rows) and specify an initial value for ExternalInterface:variable (the last two rows).

```
ExternalInterface,
   PtolemyServer;            !- Name of External Interface

ExternalInterface:Variable,
   Input,                   !- Name
   1;                        !- Initial Value
```

Fig. 9-4 Activate the external interface in EnergyPlus

Any EnergyPlus Output:Variable can be read and exported to the BCVTB. Fig. 9-5 displays the configuration for declaration of the objects for communication. The first two rows define the exportation of time step outdoor temperature from EnergyPlus. The rest is to read time step DH demand for an individual building from the BMS and export the heating load to Ptolemy II.

```
Output:VariableDictionary, IDF;
Output:Variable,*,Site Outdoor Air Drybulb Temperature,timestep;

EnergyManagementSystem:Sensor,
DH,
,
DistrictHeating:Facility;

EnergyManagementSystem:ProgramCallingManager,
MyProgram,
AfterPredictorBeforeHVACManagers,
Program;

EnergyManagementSystem:Program,
Program,
SET DHVar=DH;

EnergyManagementSystem:GlobalVariable,
DHVar;


EnergyManagementSystem:OutputVariable,
DistrictHeatingMeter,
DHVar,
Summed,
ZoneTimestep,
,
Joules;
```

Fig. 9-5 Declaration of objects for communication

b) Creating xml file to configure the mapping between BCVTB and EnergyPlus

The data mapping between EnergyPlus and BCVTB is defined through an xml file named variable.cfg, which should be placed in the same directory as the EnergyPlus file. The file includes the following code (Fig. 9-6) as header:

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE BCVTB-variables SYSTEM "variables.dtd">
```

Fig. 9-6 The header for the xml file

Following the header is the definition of mapping between EnergyPlus and BCVTB. Fig. 9-7 specifies the data exchange mapped to EnergyPlus. The exchanged data are called “variable” and have an attribute of “source”. The source attribute is sent by Ptolemy II.

```
<BCVTB-variables>
<variable source="Ptolemy">
<EnergyPlus variable="Input"/>
</variable>
```

Fig. 9-7 Receiving information from BCVTB

The external interface reads heating demand and outdoor temperature from the EnergyPlus EMS and Output, so the source attribute is EnergyPlus. The order of the elements should be in the same order as the configuration of the elements in the EnergyPlus. Fig. 9-8 is the configuration for receiving information from EnergyPlus.

```
<variable source="EnergyPlus">
<EnergyPlus name="EMS" type="DistrictHeatingMeter"/>
</variable>

<variable source="EnergyPlus">
<EnergyPlus name="Environment" type="Site Outdoor Air Drybulb Temperature"/>
</variable>

</BCVTB-variables>
```

Fig. 9-8 Receiving information from EnergyPlus

c) Configuring BCVTB model

A Ptolemy II actor should be created to activate EnergyPlus from BCVTB. Fig. 9-9 shows the configuration of the simulator to call the idf file named LeisureCentre. The weather file is read at the same time. The simulator actor calls EnergyPlus, with arguments "-w CardiffWeatherFile.epw -p Result -s C -x -m -r LeisureCentre.idf". The working directory is the file where the idf is placed and the console output is written to simulation1.log. SocketTimeout is the maximum time allowed for connecting EnergyPlus. Namely, if Ptolemy II cannot connect with the EnergyPlus for 1500 seconds, Ptolemy II terminates the communication.

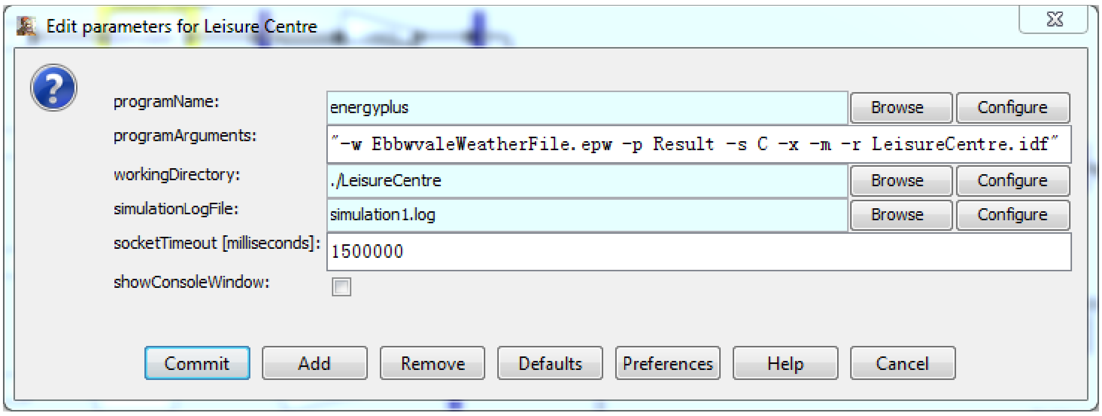

Fig. 9-9 Configuration of the simulator actor to call EnergyPlus

Ⅱ. Data exchange between Simulink and BCVTB

Simulink is used for the distribution network simulation, which is part of the whole network simulation. Similar to data exchange between EnergyPlus and BCVTB, to configure the data exchange between Simulink and BCVTB, three files are required as follows:

1. A Simulink block;

2. A Matlab script;

3. A Ptolemy II model.

a) Configuring Simulink model

There is an already existing BCVTB block, which can be used to connect with constructed Simulink model and exchange information with BCVTB. The BCVTB block can be found from the BCVTB examples and can be used directly with slight change. The output of the distribution network is the input for BCVTB, and vice versa, as shown in Fig. 9-10. The five inputs for the Simulink model are the heating loads of each building and the outdoor temperature. The output from the distribution network is the heat demand of the DH network with distribution losses included.

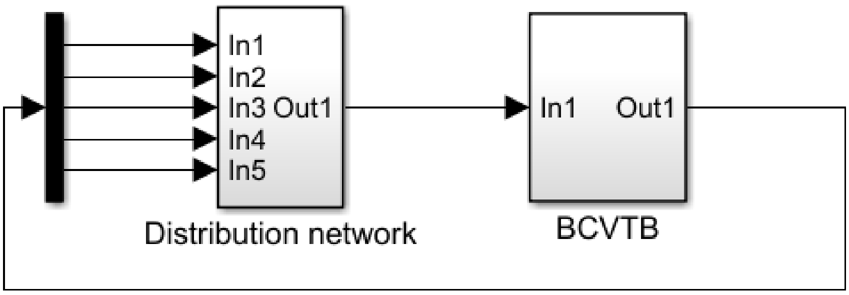

Fig. 9-10 Communication between BCVTB and Simulink

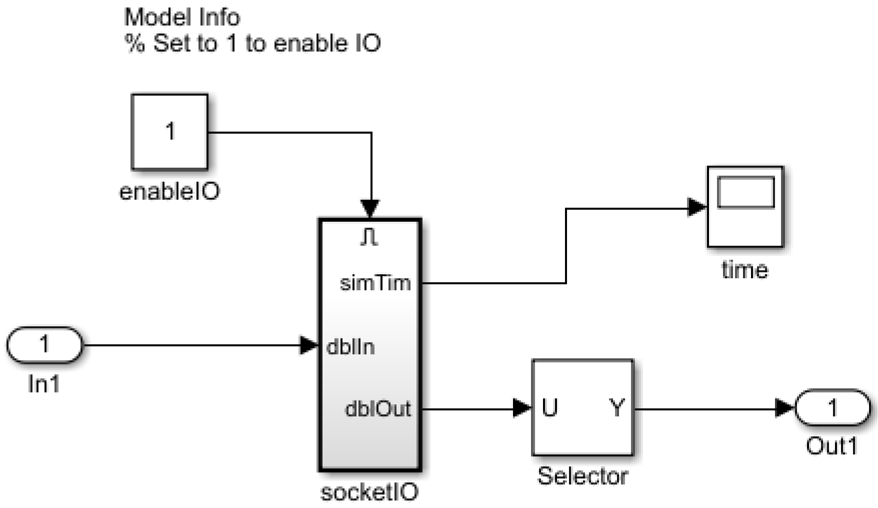

Fig. 9-11 Sub-models encapsulated in BCVTB block

The sub-blocks encapsulated in the BCVTB block are displayed in Fig. 9-11. The element dblIn is for receiving information from BCVTB. The block socketIO implements information communication, which normally stays intact. The block selector specifies the number of outputs from Simulink, which is also the inputs for BCVTB. The configuration for the selector block is shown in Fig. 9-12. The index in the selector model needs to be adjusted according to the input vector that is selected as an output of the block. The five inputs are all selected to obtain the output, so the index vector is [1 2 3 4 5].

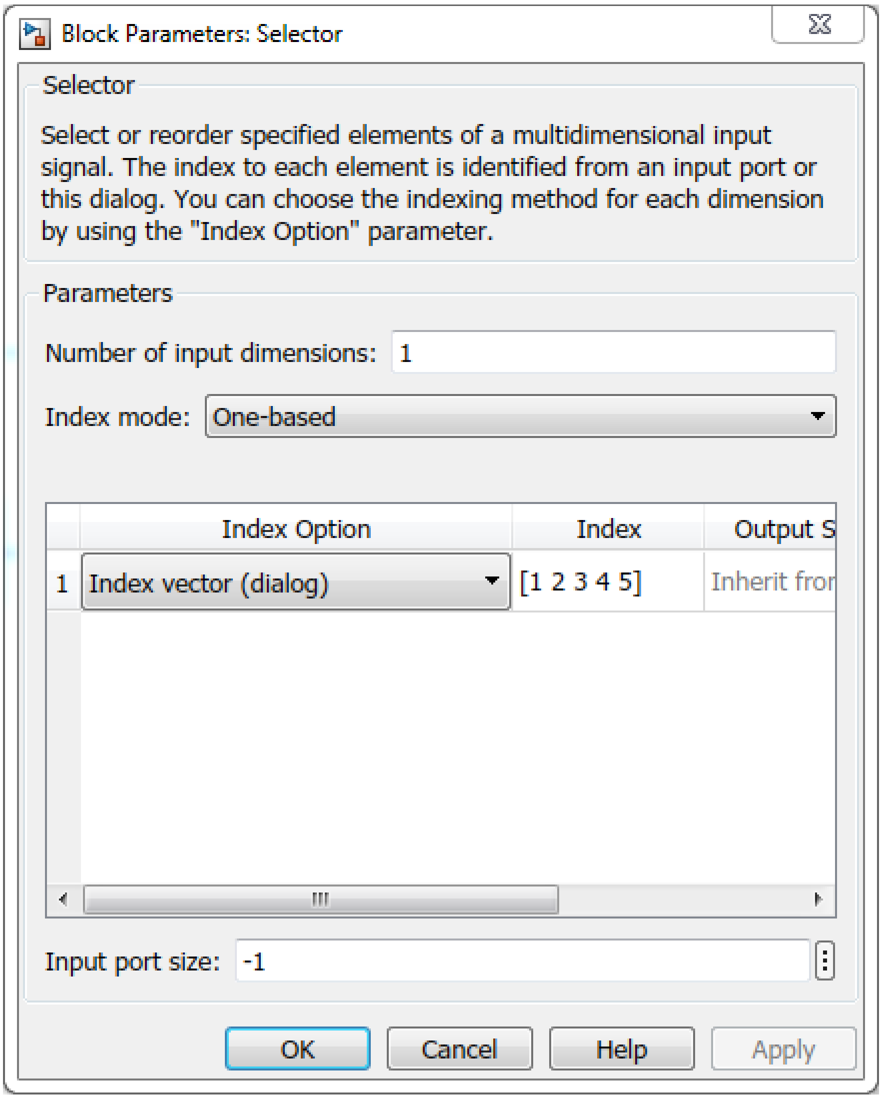

Fig. 9-12 Configuration of the selector block

b) Creating a Matlab script

To conduct the simulation, a Matlab script should be created. The script adds the path of the BCVTB to the Matlab path as displayed in Fig. 9-13.

```
addpath([getenv('BCVTB_HOME'), '/lib/matlab']);
sim('Distributionnetwork');
quit;
```

Fig. 9-13 Create the path for BCVTB in matlab

c) Configuring BCVTB model

A Ptolemy II actor should be created to activate Simulink from BCVTB. Fig. 9-14 shows the configuration of the simulator actor to call Simulink. The actor calls Matlab, with arguments “-nosplash -nojvm -logfile matlab.log -r simulateAndExit”. The working directory is the same as the current directory. The console output is written to simulation5.log. If the Ptolemy II cannot connect with the Simulink for 1500 seconds, the Ptolemy II terminates the communication.

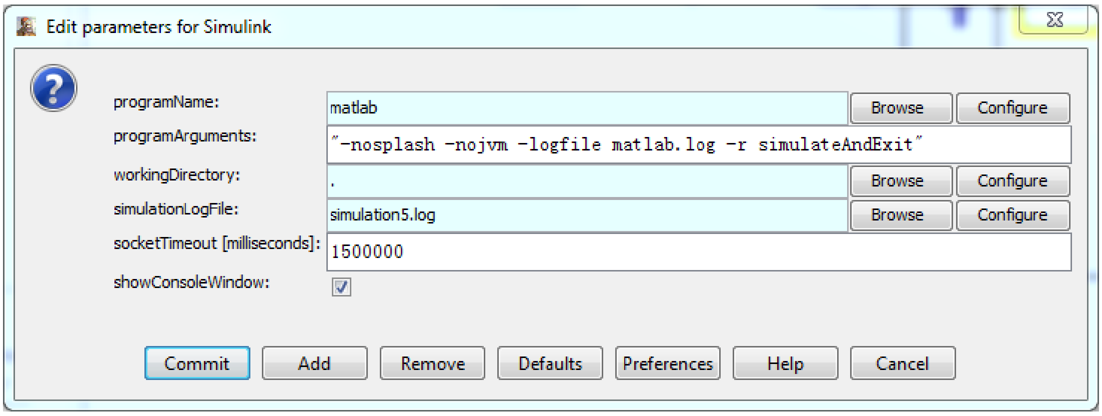

Fig. 9-14 Configuration of the simulator actor to call Simulink

Ⅲ Data exchange between Matlab and BCVTB

Matlab is used to emulate heat production from the generation units in the co-simulation process. To configure the data exchange between Matlab and BCVTB, two files are required:

1. A Matlab script;

2. A Ptolemy II model.

a) Matlab script

Fig. 9-15 illustrates the exchange of Matlab data with BCVTB. Under the "Initialize variables", the variables used for computation should be specified. Afterwards, the path of the BCVTB is added to the Matlab. The most important part of the script is the section for "Exchange data", which is called at each time step. "dblValRea" is the information received from BCVTB. Before exit in the end of the script, the following syntax can be included for computation, where Matlab programming can be applied to process the data.

if (simulate)

……

end

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Initialize variables
% ... (not shown)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Add path to BCVTB matlab libraries
addpath( strcat(getenv('BCVTB_HOME'), '/lib/matlab'));
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Establish the socket connection
sockfd = establishClientSocket('socket.cfg');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Exchange data (call this at each time step)
% ... (loop over each time step)
[retVal, flaRea, simTimRea, dblValRea ] = ...
  exchangeDoublesWithSocket(sockfd, flaWri, length(u), simTimWri, ...
                            dblValWri);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Close socket at the end of the simulation
closeIPC(sockfd);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Exit MATLAB
exit
```

Fig. 9-15 Code that depicts the interaction between Matlab and BCVTB [213]

b) Configuring BCVTB model

A Ptolemy II actor should be created to activate Matlab from BCVTB, which is similar to the configuration for Simulink. Fig. 9-16 shows the configuration of the simulator actor to call Matlab. The actor calls Matlab, with arguments "-nosplash -nojvm -logfile matlab.log -r simulateAndExit". The working directory is where the Matlab script is placed. The console output is written to simulation.log. If the Ptolemy II cannot connect with the Matlab for 1500 seconds, the Ptolemy II terminates the communication.

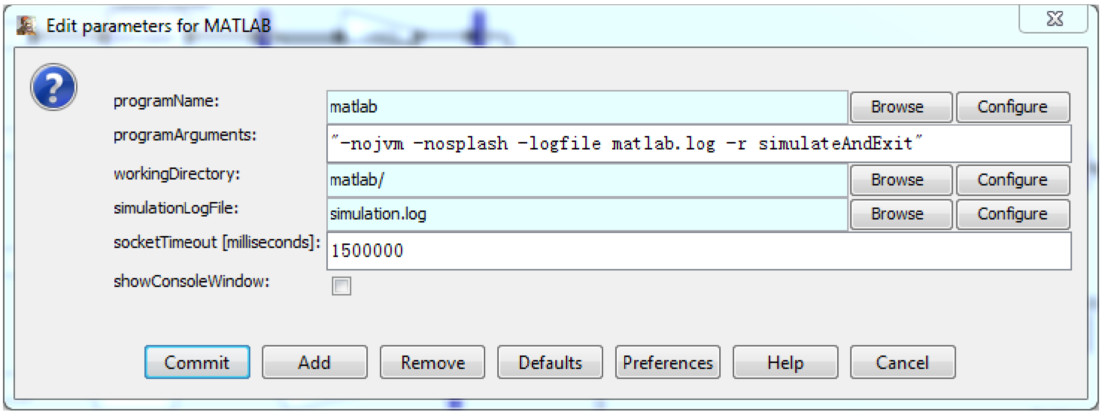

Fig. 9-16 Configuration of the simulator actor to call Matlab

List of publication

Journal paper

Li Y, Rezgui Y, Zhu H. District heating and cooling optimization and enhancement – Towards integration of renewables, storage and smart grid. Renew Sustain Energy Rev 2017;72:281–94. doi:10.1016/j.rser.2017.01.061.

Li Y, Rezgui Y. A novel concept to measure envelope thermal transmittance and air infiltration using a combined simulation and experimental approach. Energy Build 2017. doi:10.1016/j.enbuild.2017.02.036.

Li, Y., Rezgui, Y., Reynolds, J., Kuster C., An approach for district heating simulation and optimization using discrete linear representing non-linear efficiency. Applied Energy, under review.

Conference paper

Li Y, Rezgui Y, Zhu H. Dynamic simulation of heat losses in a district heating system: A case study in Wales. 2016 IEEE Smart Energy Grid Eng., IEEE; 2016, p. 273–7. doi:10.1109/SEGE.2016.7589537.

Li, Y., Rezgui, Y., Impact of Next Generation District Heating Systems on Distribution Network Heat Losses: A Case Study Approach. 2017 International Conference on Energy Engineering and Environmental Protection.