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Hydraulic Balancing of District Heating Systems and Improving Thermal Comfort in Buildings

Stanislav Chicherin [1,2]

[1] Thermo and Fluid Dynamics (FLOW), Faculty of Engineering, Vrije Universiteit Brussel (VUB), Pleinlaan 2, 1050 Brussels, Belgium; stanislav.chicherin@vub.be
[2] Brussels Institute for Thermal-Fluid Systems and Clean Energy (BRITE), Vrije Universiteit Brussel (VUB) and Université Libre de Bruxelles (ULB), 1050 Brussels, Belgium

Abstract: The relevance is introducing fourth generation district heating (4GDH), which decreases operation and maintenance costs by utilizing the efficiency of low temperature district heating (LTDH). The aim is to develop a methodology allowing for a more flexible heat demand model and accurate function describing the relationship between outdoor temperature and heat demand. It is represented by a black-box model based on historical data collected from heating, ventilation, and air conditioning (HVAC) systems. Energy delivery/consumption is analyzed with the help of a set of statistical and regression formulas. The analysis of operational data is then transformed to methodology to regulate heat supply with combined heat-and-power (CHP) generation. The key features are that the model takes into account thermal capacity and type of substation; the district heating (DH) plant is not assumed to have a fixed return temperature and generation profile. The novelty is an emphasis on DH operation and introduction of statistics into a dynamic simulation model. With no abnormal buildings, higher accuracy of modeling is achieved. Most of the consumers are pretty similar in thermal response, even though specific energy demand and heated volume may differ. Heat demand of an old building is better simulated with discrete regression, while those with pump-equipped substations are modeled with linear regression.

Keywords: renewables; energy integration; efficiency; environmental sustainability; district energy; simulation

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1. Introduction

Compared to traditional district heating (DH) systems, the benefits of the fourth generation district heating (4GDH) concept are the reduced operation and maintenance (O&M) costs of central plants, increase in efficiency of heat distribution, reduction in capital expenditure, and great potential to optimize installed capacity [1]. The efficiency of low-temperature district heating (LTDH) systems is higher if the share of directly supplied energy is high [2,3]. LTDH systems are globally feasible by implementing the principle of heat carrier cascading and providing users situated in the newly developed area with service by integrating them into a high-temperature district heating (HTDH) system. However, with increasing space heating (SH) share and heated volume/area, along with high energy consumption and poor efficiency of old buildings connected to an HTDH system, the seasonal coefficient of performance of a new subnetwork is also low. The present paper shows that the primary measure before conversion to the 4GDH system is not only a reduction in energy consumption on the demand side but also a better understanding of its distribution with an emphasis on not only design data. Researchers are now looking

for new options, such as booster heat pumps partially powered by solar energy [4]. We should know the design and actual heat demand to understand how much energy they may cover. Design values should be adjusted if a new neighborhood is under construction or operational data are unavailable. That correlates well with the development of more energy-efficient buildings with low SH consumption, thus constituting the relevance of the present research.

In practice, mass flow rates (and thus circulation pump energies) are largest in winter (for heating) and in summer (for cooling) and smallest in the intermediate seasons. If the DH system is large, the return temperature is high, issues of hydraulic balancing are expected, and energy consumption for pumping is also high.

1.1. Literature Review

Relative to the current study, Sommer et al. [5] assert that the energy required by circulation pumps is minor compared to the energy used by heat pumps, thereby having a negligible impact on the seasonal variation in overall energy consumption. However, in modeling scenarios, electricity usage for pump operation is typically treated as constant across all DH systems throughout the year, except in summer. This assumption stems from distribution networks' uniform and constant mass flow rate control while supply temperatures are adjusted.

Heat demand plays a critical role in any DH system and is a fundamental element of operational data. For example, findings in [6] are attributed to the distribution and composition of heat demand. District energy systems are particularly viable in highly populated French cities—280 cities with populations exceeding 30,000. To facilitate a transition to LTDH or 4GDH frameworks, it is essential to lower heat demand through demand-side measures (DSMs). Another approach involves enhancing the heat transfer capacity or area of radiators to maintain the same level of heat output with reduced supply temperatures. Since SH systems are often slightly oversized and poor regulation is a primary cause of elevated return temperatures, a 10–15% reduction in heat demand for new buildings may suffice. In comparison, as noted in [7], this reduction aligns with a potential decrease in residential energy consumption of 16–25%.

DH supply and return temperatures follow the energy demand profile, with the daily resolution showing the amount of energy at a DH plant that should be generated. Overconsumption means the supply temperature is excessive, while its lowest threshold is set to 70 °C. It coincides with periods of low energy consumption by the building inhabitants or when there is no heat demand for SH purposes, as at the beginning/end of the SH season. The maximum value for a representative winter day is 7.38 MWh.

In contrast to our approach, Quirosa et al. [8] emphasize that the instantaneous heat demand met by the DH system corresponds directly to the building's thermal response. They link this demand to the building's requirements and align it with a similar profile for the compressor power curve. Additionally, they maximize the system's performance based on the DH supply temperature and the heat pump's COP. However, on the analyzed winter day, the maximum observed value is significantly lower, reaching only 44 kW.

Harney et al. [9] examine a correlation between SH energy consumption and outdoor temperature. This obvious connection implies that as temperature decreases, the SH demand of the building increases. That clarifies why energy demand is higher in colder winter months, although no numerical assessments are given. When fuel consumption is related to warmer weather and consumer behavior decreases, it is high time modernization starts the process of conversion into LTDH and 4GDH concepts.

For HTDH, the main strategies include reducing distribution losses by lowering network temperatures and minimizing SH demand [10]. Building on this premise, further

research could focus on reducing return temperatures in the network and improving modeling accuracy. Unlike earlier studies, this approach highlights low return temperatures as a critical factor for maintaining high performance and reducing primary energy consumption. Additionally, achieving a greater temperature difference at the system level facilitates DH system expansion without compromising the indoor comfort of existing users.

However, the reason for high return temperature is typically not a DH network but substation tuning, the thermal response of buildings, and occupants' behavior. During periods of low outdoor temperature, all the substations of a DH system are running while the valves in the secondary circuits are fully open. As outdoor temperature increases, the temperature sensors in front of each SH system close their valves, restricting the flow through radiators. Nonetheless, the development of accurate simulation models able to cover such dynamic behavior entails considerable effort [11]. According to Brandi et al. [11], detailed and sophisticated models cannot always simulate the complexity of heating, ventilation, and air conditioning (HVAC) systems operation and the effect of occupant behavior. Therefore, we developed an alternative, represented by a black-box model based on historical data collected from HVAC systems. After design, heat demand is adjusted to lower values, and a lower flow rate is also expected. The flow sensor installed in front of an SH system detects the flow reduction from a DH plant, and restores flow by opening the bypass valve to maintain the desired temperature in the return line.

Unlike earlier studies such as [12–15], energy demand in this research is modeled with greater flexibility, accounting for variations in outdoor temperatures, specific building characteristics, and regional factors, such as whether it is a weekday or a weekend. A new framework is introduced for simulating steady-state demand in branched DH networks, addressing the limitations of previous methods. Previously, models were based on a fixed-point iteration approach, with constraints and the Jacobian matrix configured manually [16].

Kurek et al. [17] focused on DH substations equipped with additional meters to measure only SH heat demand. In contrast, this study utilized data from shared DH substations to develop a forecast model applicable across winter, intermediate, and summer seasons, with design heat demand determined using a specific equation. This approach enhances the model's versatility.

Regarding methodologies, Ivanko et al. [18] examined control point temperature, defined as the final day of the SH season. They applied the least squares method to develop a regression function for two model segments by establishing a correlation between outdoor temperature and heat demand. Unlike the present study, they focused on identifying the control point temperature using piecewise regression analysis.

We developed distinct models for various outdoor temperature ranges using the same method. A similar approach is demonstrated in [18], confirming the broad applicability of regression methods for analyzing operational data. While top-down approaches rely on highly detailed consumption data—often unavailable at DH substations or certain groups of substations—these methods are closely tied to the DH system's hydraulic configuration due to their aggregation level.

In contrast to the present study, the model by Kristensen et al. [19] cannot be directly applied to predict heat consumption in specific subsections of an existing DH system. Furthermore, it is unsuitable for forecasting energy demand in newly constructed districts, such as those arising from urban expansion. We observed subtle temperature differences between supply and return lines by analyzing operational data from substations farther from a DH plant.

Barone et al. [20] supported this concept, identifying significant temperature drops in flow branches relative to the outlet temperature of the power station alongside minor drops in return branches. Similarly to our findings, they attributed this to abnormal

thermal responses influenced by the minimal energy consumption of a small number of DH consumers. As noted in [21], two key reasons for high error rates were identified: (1) excessively high return temperatures after domestic hot water (DHW) or SH heat exchangers and (2) flawed design approaches when calculating the surface area of SH system radiators. For buildings with hydronic SH systems, prevalent in Russia and Europe, the design secondary supply temperature often results in return temperatures that fail to reach low values, though indoor comfort is maintained. To address low-temperature differentials, Ref. [21] recommends checking and upgrading the building's HVAC system operation and associated heat demand.

To analyze heat demand, Jebamalai et al. [22] utilized open-source street-level gas consumption data provided by local gas suppliers. These profiles were derived from extensive datasets and accounted for typical building types in Belgium. In contrast, this study assessed the system's total load by aggregating residential energy consumption, incorporating operational data, and using detailed profiles. Another distinction lies in the DH plant modeling: unlike fixed generation curves assumed throughout the year in [22], this study adopts a more dynamic approach.

In [23], the heat demand of all buildings in a neighborhood is aggregated into a single substation, representing the district's average demand. Their model of a district energy system comprises only a DH plant and a single aggregated district substation, which cannot capture temperature variations within supply and return lines. By comparison, this study developed a more detailed model, limiting aggregation to exclude abnormal heat demand profiles. This approach enhances accuracy while reducing the number of demand peaks.

DHW was not included in Luc et al.'s [24] model. However, DHW is typically a reason for hourly peaks in flow rates and return temperature. Since their model contains SH only, the baseline scenario is characterized by decreased energy consumption during the daytime, according to solar insolation. The difference is that the simulation model used here includes both SH and DHW consumption; we performed a more detailed study of some buildings.

Contribution to the pool of knowledge is the analysis of operational data, which is then transformed into developing a methodology to regulate heat supply into a branched network with CHP energy generation. The key feature is that the model considers thermal capacity and the type of substation. They both strongly influence the DH operation and imply that smart regulation strategies may be implemented to regulate the network according to actual heat demand rather than design one. Compared to the present paper, Guelpa et al. [25] report that the amount of thermal energy stored in heat accumulators is a considerable share of energy used to heat the various masses in the system. They conclude that this result is extremely significant, but no attempts have been made to study the effects of thermal capacities within the pool of operational data.

Farouq et al.'s [26] limitation is caused by the DH system. For instance, a reference-group-based approach cannot be directly applied to the building substations to adjust any automatic control mechanism when a faulty operation is detected. The first aspect of the novelty here is that we emphasize DH operation and cover the energy consumption, following solely individual consumers' requirements. The difference is that implementing centralized control achieves better results. The pressure level at a CHP plant may also change via a centralized supervisory control and data actuation (SCADA) system to deliver ample flow to DH substations.

Based on the surveyed literature, the second aspect of novelty entails deducing a relationship between outdoor and supply temperatures (i.e., fuel consumption) for any DH plant at any time. The next step is establishing a new regulation method for the possible energy demand ranges presented in the Results and Discussion. This method should be

accurate for any season, including winter and moderate cold days. Unlike now, we used to assume that most substantial deviations happened during average outdoor temperatures of 0–20 °C, i.e., in the intermediate season or the end and the beginning of winter when the network temperatures and energy consumption experience peaks in volatility [27].

We declare that validated operational data are essential for such suggestions, although data treatment and smart data applications (big data, artificial neural networks) still require manual adjustment in most cases. The difference between the approach of Kleinertz et al. [28] and the one presented here is the necessary actions mentioned in the transformation strategy guideline. They include replacing missing consumption data and derivation of data determination and integrating cross-sectoral data in the study. However, some statements are similar, as we conclude that data from the network itself are crucial, as well as the type of buildings required to assess their flexibility and ability to follow the predetermined control strategy.

1.2. Summary

This paper introduces a novel approach to the transition from HTDH to 4GDH systems by emphasizing the critical role of operational data in developing a flexible heat demand model. Unlike previous studies, which often rely on design data alone or simplified fixed-point models, our research highlights the necessity of combining design and real-time operational data to understand energy distribution dynamics better. The primary innovation of this study lies in creating a new regulation methodology that establishes a dynamic relationship between outdoor temperature and heat demand, ensuring more accurate predictions for various consumer types and seasonal conditions.

Our model integrates statistical and regression formulas with operational data collected from an HTDH network during 2020–2021. This dual approach allows us to address the limitations of traditional methods by adapting to fluctuating energy demands and capturing the effects of thermal capacity, building characteristics, and consumer behavior. Furthermore, the study proposes a centralized control strategy using validated operational data, moving beyond the conventional decentralized methods that often fail to account for the network's dynamic behavior.

Another key contribution is introducing a new simulation framework for branched DH networks. Unlike earlier models that relied on aggregated heat demand at a single district substation, our method limits aggregation to reduce inaccuracies from demand peaks and incorporates CHP generation. Additionally, this framework incorporates smart regulation strategies, enabling real-time adjustments based on actual heat demand rather than design assumptions.

In summary, the innovations of this research are twofold: (1) the development of a flexible and dynamic heat demand model that leverages both design and operational data, and (2) the establishment of a new regulation methodology for DH systems that optimizes supply temperatures and flow rates across varying seasonal and consumer conditions. These advancements offer a robust foundation for transitioning to 4GDH systems and improving the overall efficiency and adaptability of DH networks.

The aim is to develop a methodology that allows a more flexible heat demand model and an accurate function that describes the relationship between outdoor temperature and heat demand for various types of consumers. It should be sufficiently generalized to require only substation operational data for simulation regardless of the network type. To the best of the authors' knowledge, to achieve this aim, energy delivery/consumption from the supply and return pipes has never been analyzed with the help of (a) the set of statistical and regression formulas and (b) operational data from an HTDH network.

2. Materials and Methods

This study aims to evaluate the performance of DH substations with a focus on return temperature efficiency, hydraulic balancing, and energy losses. The primary objectives include assessing the impact of substation configurations on heating performance, analyzing seasonal variations in supply and return temperatures, and identifying key inefficiencies in DH networks. The study employs a combination of operational data analysis, system modeling, and comparative evaluation against established performance benchmarks.

Operational data were sourced from a central SCADA system, covering key parameters such as supply and return temperatures, flow rates, and outdoor temperature fluctuations. The dataset spans multiple seasons to capture variations in heating demand and efficiency. Additional data, including building characteristics and heat consumption patterns, were gathered to support the analysis of substation performance across different building types.

The study employs a computational model to simulate DH system performance under various conditions. The model integrates real-world data with predefined system parameters, including substation configurations, mass flow rates, and thermal losses. To enhance accuracy, the model accounts for known inefficiencies such as poor mixing, heat losses due to insulation deficiencies, and delayed temperature adjustments in remote substations. Comparative modeling was performed using existing methodologies, such as Vandermeulen et al. [23] and Kurek et al. [17], to validate findings.

Model validation was conducted by comparing simulated results with recorded SCADA data. Key performance indicators (KPIs) such as return temperature deviation, energy efficiency, and heat distribution accuracy were analyzed. A sensitivity analysis was performed to assess the impact of varying input parameters, including supply temperature adjustments, mass flow regulation, and seasonal variations. Findings were cross-validated using industry benchmarks and previous studies to ensure consistency and reliability.

The traditional modeling approach assumes that heat demand for any given conditions (outdoor temperature) is stated as

$$Q^{T} = Q_{P}^{T} \cdot \frac{t_{in} - t_{out}}{t_{in} - DOT} \quad (1)$$

where $Q^{T}{}_{p}$ is design heat demand (at design outdoor temperature) [MW];

t_{in} is the indoor temperature [°C];

t_{out} is the outdoor temperature [°C];

DOT is the design outdoor temperature [°C].

Supply and return temperatures, respectively,

$$t_{w}^{sup} = t_{in} + \Delta t' \overline{Q}^{0.8} + \frac{\overline{Q} \cdot \theta'}{2} \quad (2)$$

$$t_{w}^{ret} = t_{in} + \Delta t' \overline{Q}^{0.8} - \frac{\overline{Q} \cdot \theta'}{2} \quad (3)$$

where $\Delta t'$ is the annual average temperature difference between the mean radiator temperature $\frac{t_{wp}^{sup} + t_{wp}^{ret}}{2}$ and indoor temperature t_{in} [°C]

$$\Delta t' = \frac{t_{wp}^{sup} + t_{wp}^{ret}}{2} - t_{in} \quad (4)$$

where t_{wp}^{sup} and t_{wp}^{ret} are the design supply and return temperatures within an SH system.

The relative heat demand $\overline{Q}$ [-] is

$$\overline{Q} = \frac{Q^T}{Q_P^T} = \frac{(t_{in} - t_{out})}{(t_{in} - DOT)} \tag{5}$$

θ' temperature difference within an SH system [°C]:

$$\theta' = \mathrm{t}_{\mathrm{w_P}}^{\mathrm{sup}} - \mathrm{t}_{\mathrm{w_P}}^{\mathrm{ret}} \tag{6}$$

Mass flow rate is

$$G_w^K = \frac{Q_P^T}{C_w \cdot (t_{w_P}^{\mathrm{sup}} + t_{w_P}^{ret})} \tag{7}$$

where $C_w = 4.187$ is the specific heat capacity of water [kJ/kgK].

True value of heat demand for a particular day is better described as

$$\widetilde{\mathrm{X}}_{\mathrm{i}} = \mathrm{X}_{\mathrm{i}} + \nabla_{\mathrm{i}} \tag{8}$$

where $\mathrm{X_i}$ is recorded (raw) heat demand for hour i; ∇_{i} error for hour i.

The average heat demand is

$$\overline{\mathrm{X}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \widetilde{\mathrm{X}}_{\mathrm{i}}}{\mathrm{n}} \tag{9}$$

where n is the number of the data points (hours, days, etc.).

The standard deviation of heat demand is

$$\mathrm{S_X} = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \left(\widetilde{\mathrm{X}}_{\mathrm{i}} - \overline{\mathrm{X}}\right)^2}{\mathrm{n} - 1}} \tag{10}$$

while sampling variance is

$$\mathrm{S}_{\overline{\mathrm{X}}} = \frac{\mathrm{S_X}}{\sqrt{\mathrm{n}}} = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \left(\widetilde{\mathrm{X}}_{\mathrm{i}} - \overline{\mathrm{X}}\right)^2}{\mathrm{n}(\mathrm{n} - 1)}} \tag{11}$$

To calculate the size of a bin, Equation (12) is suggested.

$$\Delta \mathrm{X} = \frac{\widetilde{\mathrm{X}}_{\mathrm{max}} - \widetilde{\mathrm{X}}_{\mathrm{min}}}{\mathrm{r}} \tag{12}$$

The (non-central) chi-squared distribution is

$$\chi_{\mathrm{i}}^2 = \frac{(\mathrm{m_i} - \mathrm{nP_i})^2}{\mathrm{nP_i}} \tag{13}$$

Degrees of freedom k depend on the number of bins r

$$\mathrm{k} = \mathrm{r} - 3 \tag{14}$$

If $\chi^2_{\mathrm{k};\frac{1}{2}\mathrm{q}} < \chi^2_{\mathrm{k}} \leq \chi^2_{\mathrm{k};1-\frac{1}{2}\mathrm{q}}$, then the distribution is symmetric and unimodal. That means that Student's factor might be applied.

Frequency of heat demand with a value within the corresponding bin

$$P_i = \int_{\widetilde{X}_i}^{\widetilde{X}_{i+1}} p_x(x)dx = \Phi\left(\frac{\widetilde{X}_{i+1} - \overline{X}}{S_X}\right) - \Phi\left(\frac{\widetilde{X}_i - \overline{X}}{S_X}\right) \quad (15)$$

where $\widetilde{X}_i$, $\widetilde{X}_{i+1}$ are left and right bin boundaries, respectively; $\Phi(z)$ is the probability density for the normal distribution,

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{1}{2}t^2} dt \quad (16)$$

Abnormal values of heat demand were found as

$$\nu_1 = \frac{\widetilde{X}_{max} - \overline{X}}{S_X} \text{ and } \nu_2 = \frac{\overline{X} - \widetilde{X}_{min}}{S_X}, \quad (17)$$

Calculated ν_1 and ν_2 values are then compared to the threshold values of ν. For every acceptable level of error (e.g., 3%, 7%, 10%), these threshold values can be extrapolated using Table 1.

Table 1. Threshold ν-values.

Number of Data Points (Hours, Days) n	Acceptable Accuracy of Modeling 10%	Acceptable Accuracy of Modeling 5%
3	1.414	1.414
4	1.710	1.728
5	1.917	1.972
<...>	<...>	<...>
10	2.414	2.616
11	2.470	2.689
<...>	<...>	<...>
28	2.929	3.258
<...>	<...>	<...>
39	3.065	3.413
40	3.075	3.424
<...>	<...>	<...>
52	3.175	3.534
<...>	<...>	<...>

With the help of Table 1, the threshold values can be extrapolated for any number of the data points n. If ν_1 or ν_2 are higher than ν, then the corresponding $\widetilde{X}_{max}$ or $\widetilde{X}_{min}$ are called abnormal values of specific heat demand.

Accuracy is defined as

$$\delta = t_p S_{\overline{X}} \quad (18)$$

where t_p is the Student factor for k set as

$$k = n - 1, \quad (19)$$

Systematic error is

$$\theta = k\sqrt{\sum_{i=1}^{m} \theta_i^2}, \quad (20)$$

where θ_i are bin boundaries; k is the adjusting factor, set to 1.1 if an acceptable modeling error is 10% or to 1.4 for an error of 5%.

If

$$\frac{\theta}{S_{\overline{X}}} < 0.8 \tag{21}$$

then

$$\Delta = \delta \tag{22}$$

If

$$\frac{\theta}{S_{\overline{X}}} > 8, \tag{23}$$

then

$$\Delta = \theta, \tag{24}$$

otherwise

$$\Delta = KS_{\Sigma}, \tag{25}$$

where K is the ratio of systematic error and standard deviation of heat demand:

$$K = \frac{\delta + \theta}{S_{\overline{X}} + \sqrt{\sum_{i=1}^{m} \frac{\theta_i^2}{3}}}, \tag{26}$$

S_{Σ} standard score:

$$S_{\Sigma} = \sqrt{\sum_{i=1}^{m} \frac{\theta_i^2}{3} + S_{\overline{X}}^2}. \tag{27}$$

Heat demand for every building for any given temperature range is then defined as

$$X = \overline{X} \pm \Delta, \tag{28}$$

To compare, Harney et al. [9] calculated heat demand using the EnergyPlus model.

To sum up, input parameters applied for modeling are outdoor, supply/return temperatures, and flow rates at both local (substation) and central (DH plant) levels.

3. Case Study

This paper presents two case studies to uncover the advantages of using a novel modeling approach. Due to the similar solutions encountered in low-temperature district heating or cooling worldwide, case studies are presumed quite indicative and equally acceptable for any individual application worldwide. Both are DH systems in Omsk, Russia. The first is the set of districts connected to a large CHP plant (CHPP#5) with a higher-than-supposed return temperature, exacerbated by its high variation throughout the building stock. After measuring network temperatures and flow rates, the highest return temperature and the lowest modeling accuracy were recorded in sections that mainly serve residential buildings. Therefore, the second case study is a district comprising a section of a traditional second generation HTDH system in Omsk. Its design heat demand is set to 250 MW and reasoned to circa 15,000 inhabitants living with a designed indoor temperature of 20 °C and a primary network temperature regime of 150/70, which has never been met. The geographical arrangement of the buildings, together with the configuration of a transmission network, is illustrated in Figure 1.

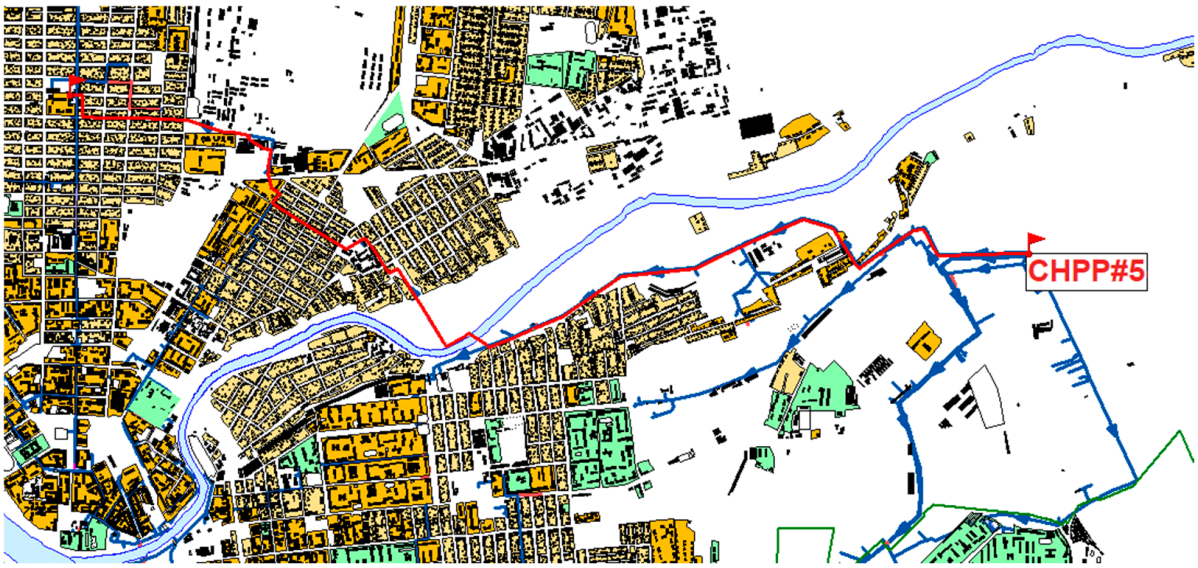


Figure 1. Scheme of the studied DH system in the Omsk city (Russia). Residential neighborhoods are yellow. Industrial zones and business parks are green. The DH network is presented as blue lines. The considered section of the DH network starting from CHPP#5 ('ТЭЦ-5') is highlighted in red.

This case study complies well with the current international development direction to shift towards higher energy efficiency in northern cold climates for rural heating in line with 4GDH and LTDH concepts. The building stock comprises 190 buildings, including grocery and hardware shops, office buildings, and three malls. The district's choice stems from it being a typical one with a significant share of residential buildings. They are responsible for more than 72% of the total heat deliveries of the DH network studied in this paper.

The buildings analyzed in this case study represent a range of typologies, from high-rise buildings to single-family houses, with varying insulation levels and heating systems. These buildings are located in several regions across Eastern Europe and Russia, where DH is prevalent.

The buildings in this study span a wide range of ages and types. The oldest buildings, constructed before the 1980s, comprise about 30% of the case study population. These buildings typically have poor insulation and are heated by centralized DH systems. Many buildings are inefficient due to outdated heating systems, leading to high heat demand and greater reliance on DH. The second group includes buildings constructed between the 1980s and 2000s, representing 40% of the case study buildings. These buildings generally have moderate insulation levels and less efficient heating systems than newer models. The remaining 30% of the buildings are modern, having been constructed after 2010. These newer buildings feature energy-efficient designs with high-quality insulation, modern heating systems, and, in some cases, renewable energy sources, such as solar panels for water heating. These buildings have lower heat demands due to their higher thermal efficiency.

Insulation levels are a critical factor influencing heating demand. About 50% of the buildings in the study have low insulation, typically those built before 1980, which results in higher heat losses and greater energy consumption. Around 40% of the buildings have moderate insulation, mostly those built in the 1980s to 2000s. In comparison, the remaining 10% of the buildings are highly insulated, which reduces their heating demand and improves energy efficiency.

The heating systems in these buildings vary significantly. Most older and mid-aged buildings rely on centralized DH systems, which distribute heat from a central source to multiple buildings through a network. Modern buildings, however, are more likely to use individual heating systems, such as gas-fired boilers or heat pumps, which are

more energy-efficient and allow for better control of heating levels. These systems are generally more adaptable to the specific needs of each building, resulting in lower energy consumption and cost.

3.1. Data Collection

A comprehensive data collection approach was employed to analyze the energy performance of these buildings and their respective DH systems. With hourly resolution for heating demand and environmental parameters, data were gathered from utility companies, local heating providers, and building energy management systems. This dataset contains mean daily temperatures and flow rates recorded automatically at each line of a DH plant for more than 2 years, from 1 January 2020 until 31 December 2021. Unlike now, we used to assume the processing to bring together the makeup rate of all lines for identical periods [29]. Furthermore, that analysis was based on the dataset with hourly measured data. The heat supply and makeup water demand are analyzed for these periods separately. To compare, Volkova et al.'s [30] input parameters used for simulation were outdoor, supply, and return temperatures.

3.2. Modeling Framework

The modeling framework used for this study integrates building energy performance models with DH system simulations. These models consider building characteristics such as insulation levels, heating system types, and occupancy patterns. The simulation framework was designed to predict heating demand under different operational scenarios, including variations in outdoor temperature, energy prices, and the adoption of renewable energy technologies.

3.3. Validation Metrics

A range of metrics was used to validate the models, including the standard deviation and the total error, comparing the predicted heating demands with actual consumption data from the buildings over the study period. These metrics provide insight into the accuracy and reliability of the simulations, helping to refine the models and ensure that the predictions align with real-world performance. The validation process also includes sensitivity analysis to determine how different building characteristics, such as insulation levels and heating systems, impact the overall heating demand and system efficiency.

4. Results

It is relevant to note the potential to utilize all the delivered energy efficiently, which shows the ratio of exergy used to exergy delivered from the distribution system and depends on the substation configuration. Bearing in mind substations equipped with a pump, we start analyses in this section of a DH system with the simplified type of substation. They include throttle devices only (such as an orifice flange or a hydroelevator [31]) and are widespread in Russia, China, post-Soviet countries, and Eastern Europe. A substation with a hydroelevator and a mixing shunt is illustrated in Figure 2.

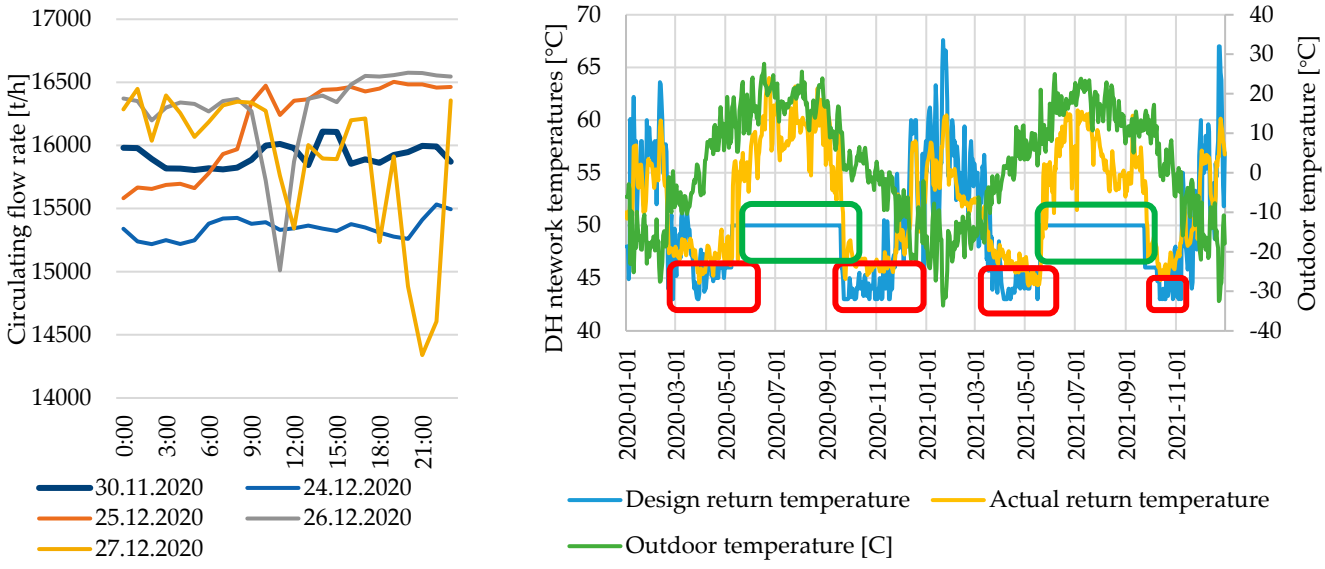
Figure 2 illustrates a substation with a hydroelevator and a mixing shunt, critical components in DH systems, particularly in regions like Russia, China, and Eastern Europe. These components regulate temperature and flow, influencing heating performance and occupant comfort. The efficiency of such configurations directly impacts the delivery of heat energy, making it essential to assess their role in ensuring optimal thermal conditions within buildings.

Most of the year, supply temperature varies between 70 and 100 °C, while the total flow rate experiences less significant fluctuations. Figure 3 shows that the total flow rate is

higher for the days with higher DHW use (i.e., weekdays) and remains almost the same for others.



Figure 2. An example of key components of a typical substation: the hydroelevator and a mixing shunt are red.



(**a**) (**b**)

Figure 3. Operational data obtained from a central SCADA system: (**a**) CHP flow rate and (**b**) return/outdoor temperature profiles.

Most of the year, supply temperatures fluctuate between 70 and 100 °C, while total flow rates vary based on demand. Figure 3 presents operational data from a central SCADA system, showing (a) CHP flow rates and (b) return and outdoor temperature profiles.

The data highlight the significant impact of outdoor temperatures on heating system performance. For instance, return temperatures are higher on warmer days, reducing heating efficiency. This effect is particularly noticeable during seasonal transitions (fall and spring), where excessive indoor temperatures result in energy wastage due to open windows. The hourly variation profiles demonstrate that heating loads are not evenly distributed throughout the day, influencing supply and return temperature stability.

It is worth noting that the hourly variation profile is not similar for all the days. For instance, peaks and valleys were more distinct on the 26th and 27th of December 2020 (refer to Figure 3a), i.e., for weekdays. However, the daily difference is attributed chiefly to the days with high outdoor temperatures (−5~+5 °C) when CHP production and system capacity are lower because of higher circulating flow and higher return temperature. During winter, the outdoor temperature ranges mostly between −20 and 0 °C according to the dataset recorded at the SCADA system values. There are several zones describing the correlation between actual and design return temperatures. The first zone is defined by the outdoor temperature ranging from −30 to −15 °C when the supply temperature is about 90–100 °C and SH-related consumption is high. This supply temperature is not enough—it should be 120 °C and above. Moreover, due to high heat losses, a temperature drop of up to 15 °C is registered on the way to the most remote substation. That means the return temperature also depends on the location of a substation. The second factor is irregular hourly temperature fluctuations due to consumers' uneven heating loads throughout the day. The second period occurs during falls and springs, when the supply temperature exceeds 70 °C due to DHW consumption, with excessive heat being released from the open windows to prevent indoor temperatures from rising. The latter time period is mostly responsible for inefficient energy use.

As shown in Figure 3b, high return temperatures lead to inefficiencies in DH systems, affecting energy distribution and electricity generation at CHP plants. The correlation between return temperature levels and substation efficiency has been well documented, including by Farouq et al. [26], who emphasize the importance of monitoring return temperature as a control metric in Sweden. The elevated return temperatures observed in this study suggest inefficiencies in mixing and flow regulation, particularly in older or poorly maintained substations.

High return temperatures (circa 11% higher) heavily affect the overall operational efficiency of the DH system and deteriorate electricity generation at a CHP plant. Furthermore, the return temperature is a decent parameter to check a substation for poor operation. In addition, according to Farouq et al. [26], the analysis of return temperature levels is a commonly applied control check on the operational efficiency of substations in Sweden.

To compare, Vandermeulen et al. [23] established a model where an average substation represents a whole residential area containing n buildings. Hence, the requested mass flow rate of the aggregated substation is multiplied by n, while the supply and return temperatures are assumed constant throughout the year. In [32], a cooling return temperature of 30 °C is assumed for the district energy substations of data centers. Moreover, all supply and return temperatures are fixed during the year again, which is hardly true.

However, Figure 3 shows a higher-than-should-be return temperature, which is reasoned to the fact that the optimal supply temperature reaches the substation a few hours after leaving a central plant. In developing countries, this ordinary consideration is further exacerbated by the poor condition of the DH network (Figure 4), which is responsible for high-temperature drops and delays.



Figure 4. An example of high distribution heat losses due to poor insolation.

Figure 4 demonstrates the significant heat losses in DH networks due to poor insulation. These losses contribute to increased energy demand and reduced system efficiency, ultimately affecting heating performance and thermal comfort. In developing countries, where DH networks often suffer from infrastructure degradation, temperature drops and delays exacerbate the problem. A temperature drop of up to 15 °C has been recorded on the way to remote substations, meaning that buildings in different locations within the network experience varying levels of heating performance. Such disparities underscore the need for targeted interventions, such as improved insulation and better hydraulic balancing strategies.

For its part, that results in high return temperature, hydraulic balancing issues, and low modeling accuracy. However, a 1-degree decrease is beneficial since it results in 22% lower heat losses (regarding W/m^3 unit) [33]. A possible reason is poor mixing at DH substations (mainly in urban districts), as throttle devices are increased in diameter, and substations are tuned during cold winter days.

However, performance adjustments in a new substation can be achieved without damaging the hydraulic balancing of the network. The problem is aggravated when the supply temperature or mass flow increases. Prosumers, plant, and a distribution network can adjust their mass flow rates without affecting the hydraulics of other prosumers. The highest difference between actual and design return temperature is registered during the coldest days (refer to Figure 3b). Moreover, the overall trend is negative because the monthly average difference increases, cf. 5.3 °C in January 2020 and 6.4 °C in January 2021.

Figure 5 visualizes the contribution of different buildings in total heat demand distributed by their total heated area.

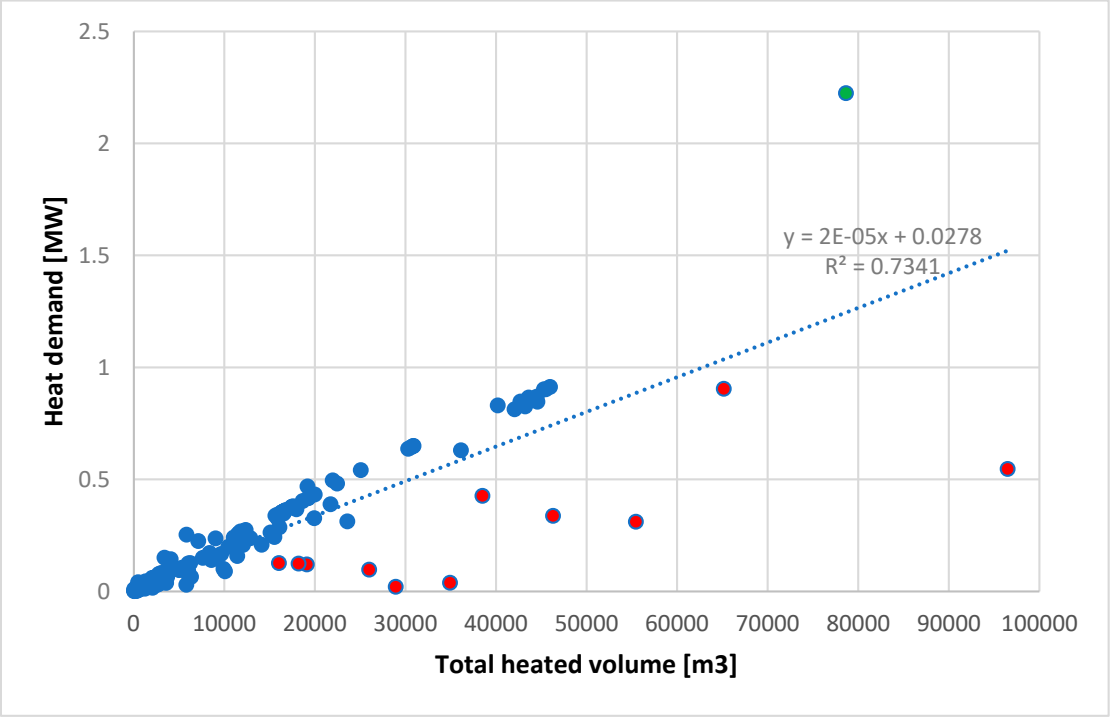


Figure 5. Abnormal values are colored in red. In particular, dynamically deployed substations achieve higher energy savings in the DH system than their linearly deployed counterparts.

Most abnormal consumers have a total heated volume of 15,000 m^3 and above. The possible hypothesis is that the higher the building volume, the lower the concentration of inhabitants/employees is. The best linear model, the partially linear autoregression with R2 of 0.7341, has formula as $Q = 2 \times 10^{-5} t_{out} + 0.0278$. To compare, Kurek et al. [17] obtained input features with the forward feature selection algorithm. However, similar correlations and selected weather features are also listed in [17].

Figure 5 highlights the contribution of different building types to total heat demand, with abnormal values indicated in red. The data reveal that larger buildings (above 15,000 m^3 in heated volume) tend to have lower inhabitant densities, which affects heating patterns. The figure shows that dynamically deployed substations achieve higher energy savings than linearly deployed ones. These findings align with prior studies [17], indicating that system design and deployment strategies are crucial in optimizing energy efficiency.

The final conclusion is that 12 consumers (6%) are responsible for low accuracy, while 11 seem energy-efficient. However, seven are office buildings, shops, and car parks with indoor temperatures of 12–18 °C, which is the main reason for low energy consumption. Only four buildings are new energy-efficient residential buildings, all equipped with pumps, and the rest with throttle devices. Excluding these four buildings, all the others have almost similar energy density—specific energy consumption per surface area. Linear heat density is one of the key indicators.

To compare, Patureau et al. [6] use linear heat density as a threshold to divide consumers into those with sufficient and insufficient values. For one of the major cities, the former is 8.3 km from the city center, while the latter is farther than 8.3 km but closer than 28.7 km away. As with us, locations favorable for a DH system contain mostly old buildings and feature a high share of heat demand from the residential sector.

At the same time, the newer buildings in the residential sector are much more energy efficient but exhibit a more fluctuating and stochastic heating pattern. The reason is that large buildings do not behave as a single zone with steady-state mixing and uniform indoor

temperature distribution. In actual buildings, the solar gains are not distributed evenly across all the indoor spaces.

Figure 6 clarifies the large difference in the heat demand levels, which is typical among consumers.

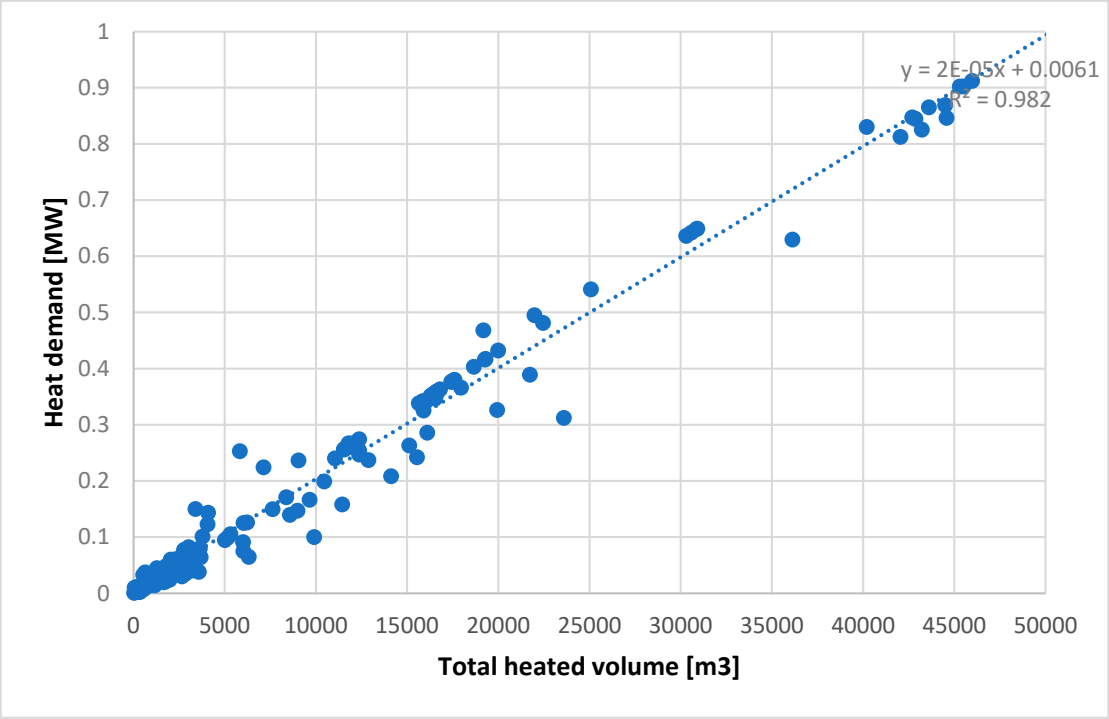


Figure 6. Abnormal values of heat demand have been cropped. That leads to higher accuracy and more evenly distributed SH demand in the modeled districts.

At the same time, most of the buildings in the case study area have an overall high but steady specific energy consumption. Excluding abnormal heat demand profile increases the accuracy and decreases the number of heat demand peaks. That takes any deviations from design values into account and makes it meaningful to calculate the accuracy of a novel or an error of a traditional method. At the same time, that does not cause any fundamental changes to the substation thermal response; therefore, this form of aggregation is considered viable for this research. Furthermore, DHW consumption and solar radiation do not influence the indoor comfort of all spaces in the same manner over the day, as the space normally has differences in the number of inhabitants/occupants and windows, e.g., with one or two orientations. With no abnormal buildings, high modeling accuracy (98.2%) is easily achieved using regression $y = 2 \times 10^{-5} + 0.0061$. If so, that results in a substantial improvement of temperature control performance compared to the traditional scenario, when the temperature control is performed with higher error due to dynamically deployed factors. Hence, it was possible to compare the recorded energy consumption for SH and DHW with the building footprint and height. For instance, 50% of consumers have a heated volume of 5000 m^3 and below, while 85% have a heated volume below 25,000 m^3. With no abnormal values, the total heat consumption of the DH system decreases by 7.3%.

The analysis showed that a quite high coefficient of determination ensures more efficient SH heat use. Modernizing calculations according to the heat demand of regular consumers may ease the design guidelines. Other upsides are establishing a benchmark for efficient energy use and easing decision-making when considering network expansion. The regulation system trained with such a dataset can adapt to the different requirements in different conditions, achieving higher accuracy than following the reference method. The

control strategy becomes more solid and sound while the issue of high return temperature is alleviated.

To compare, Ivanko et al. [18] considered the data for the energy consumption in a hotel in Norway, which has a substation with two separate heat meters for the SH and DHW. Their model had R2 of 0.97 and 0.76 for SH and DHW heat use, respectively. The difference with [6] is that each district comprises an equivalent number of occupants (for the residential areas) or staff (for the commercial ones).

The operational heat demand of Omsk, Russia, for 2021 (frequency histogram shown in Figure 7) is input for each building type to the average building demand profile.

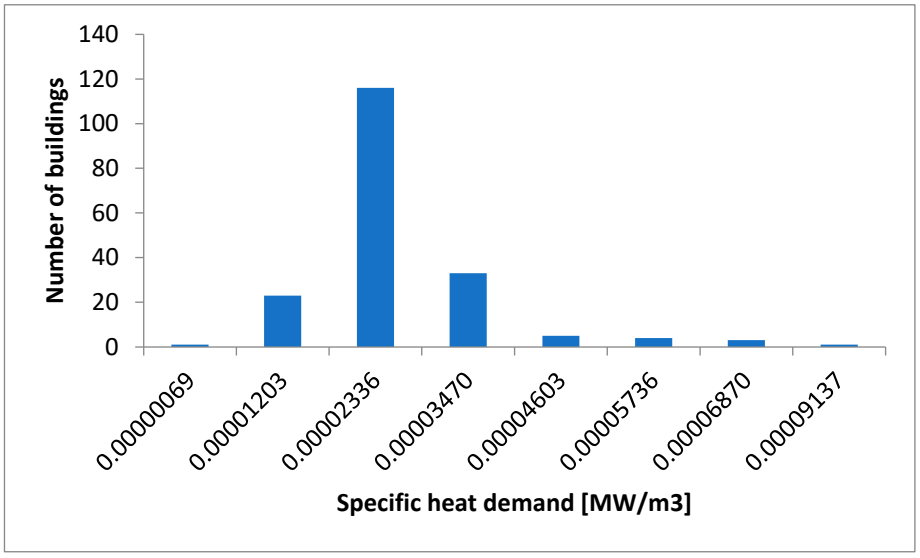


Figure 7. Frequency distribution of specific heat demand.

In total, 62% of consumers have specific values ranging between 1.2×10^{-5} and 2.3×10^{-5} MW/m^3. The total energy consumption of the 20–30 old buildings remains almost unchanged, resulting in the same specific heat demand value. However, poor network conditions increase distribution losses (and thus fuel consumption) in the heating network's branch to the oldest buildings. We see a reduction here, which is well represented by $0.00002336 \pm 8.2\%$ according to Equation (28). Due to further demand-side measures and new buildings constructed in the DH area, average specific heat demand is expected to decrease by 2–3% yearly.

The results suggest two possible directions. One is to use the specific load analyses and the nascent network analyses against the districts of other cities when modeling. For instance, for neighborhoods that may switch to such configurations, the district-level energy demand data are mapped to a GIS map using the total volume [m^3] or surface area [m^2] ratio for each archetype. Another way is to configure an in-district heat distribution system 'as is' but fix current malfunctions on the demand side, where the difference is the largest.

Now, all the buildings are divided into the following reference groups (archetypes): old traditional ones (>0.00003470 MW/m^3), new energy efficient (>0.00005736, but <0.00003470 MW/m^3), and industrial (<0.00005736 MW/m^3). To compare, in [22], all the buildings are divided into similar building types: residential, commercial (<0.15 GWh/year), and industrial (>0.15 GWh/year). Specific heat demand in energy use per unit of heated volume is also more accurate than traditional indicators such as linear heat density. Based on linear heat density, Patureau et al. [6] determine the area acceptable for placing a DH system—its average surface is 3.7 km^2, while an area of 14.2 km^2 has insufficient linear heat density. These conclusions may become incorrect

once the MW/m^3 indicator is applied. Another relevant comparison is the potential for improvement due to energy efficiency measures on the consumers' side (in the LHCD area); in [4], a value of 2.4% is reported.

When studying the archetype of old traditional buildings, the most evident trend in Figure 8 is a significant increase in energy consumption on the coldest winter days.

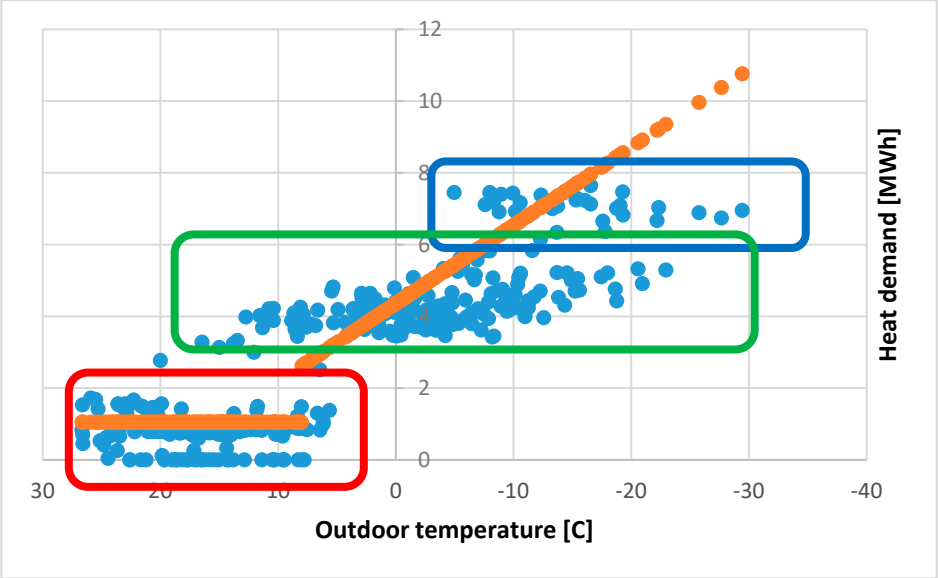


Figure 8. Correlation between actual (blue points) and design (orange ones) heat demand and outdoor temperature. Zones outlined in blue and green represent periods when the flow rate could be cut since the actual heat demand for old buildings is much lower. The days with high average outdoor temperatures ranging from 5 to 30 °C are the days when DHW demand was the most important factor (red).

The annual energy consumption is 1.063 GWh with a peak level of 7.64 MW. The annual average demand is 3.19 MW, with a dispersion of 4.26 MW. In a residential building, heat is consumed from the DH system to cover both SH and DHW demands. Different systems' operation modes are also noticed, as indicated by various energy demand levels. There are three temperature ranges when heat demand does not depend on outdoor temperature but could be related to the building's substation tuning or occupancy scheduling. Therefore, most of the time, the temperature of return water fed back into the network is larger than it should be. Moreover, heat demand is usually larger than the design curve (orange), while accuracy is pretty low.

That means the traditional modeling approach (orange dots) for an old building is incorrect. The heat demand of a building is better simulated with a discrete regression like

$$if\ 3\text{-}day\ average\ t_{out} < 0.85DOT,\ then\ Q = 0.75Q_{des},$$

$$otherwise\ Q = 0.5Q_{des}$$

The time period with the highest energy demand (blue zone) is winter, with a peak SH energy demand of 7.8 kWh, accounting for 163.4% of average demand at outdoor temperatures of 0~−30 °C. Therefore, during the coldest winter days of peak heat consumption, the appropriate regulation strategy is expected to reduce the difference between energy delivery and consumption until it becomes negative at any specific time step. It means that this zone depends on thermal inertia as the peak demand correlates with maximum heat delivery and energy accumulated within building envelopes for the normal consumption profile (green zone). It may also vary from district to district depending on its location with

respect to a DH plant and flow velocity. However, in addition to distance, heat losses, and flow velocity, many more factors can affect energy efficiency annually. There are even more factors that may have an impact on heat demand during several years of operation [34].

Moderate-cold days represent a time range where enough heat is supplied for SH purposes, and substations could be set back to normal regulation. That is due to external physical factors such as higher outdoor temperatures (−10~+5 °C mostly), more intensive solar radiation, and no winds, which may naturally increase the building's indoor temperature and thus decrease the SH consumption during this time. The SH demand is much lower in the fall and spring months. However, heat demand does not reduce to zero in March, April, and September, even for outdoor temperatures above 0 °C.

Outlined with red, the range indicates the time period when heat is supplied for DHW only and the SH systems are forcibly turned off. To compare, Guelpa [25] points out that the excessive amount of heat energy required over the peak demand (0.4 GWh) is mainly consumed to heat the system's thermal masses (0.33 GWh). In [9], the period with the highest heat consumption is winter, with a total SH energy demand of 276 kWh, accounting for 26.4% of annual demand. To sum up, in [9,25], the SH demand is much higher in the winter months while—the same as here—heat consumption plummets to zero in summertime.

The novel model outperforms the traditional approach in all the simulated periods with the sampling variance Sx' (Equation (11)) of 0.68 MW for the winter season, 0.23 MW for the summer season, and 0.51 MW for the intermediate season. At the same time, the MAPE is 8.4% for the winter season, 4.3% for the summer season, and 6.9% for the intermediate season. To compare, in [17], MAPE was 2.6/3.2% for the winter season, 4/5.8% for the summer season, and 7.4/8.5% for the intermediate one for an ANN with autoregressive input forecast/Ridge Regression, respectively. Much higher MAPE in winter is due to the inability to keep proper supply temperature according to outdoor temperature due to high heat losses, hydraulic balancing issues, and worn-out equipment. Wirtz et al. [32] report an annual heating demand of 6.36 GWh with a peak demand of 2.01 MW. The annual cooling demand is 10.04 GWh and shows a peak of 2.42 MW. Omsk has no district cooling network, even though building stock comprises university laboratories, malls, office buildings, and data centers—the same with [32].

Buildings with pump-equipped substations can be modeled with the help of simple regression, like y = kx + m (Figure 9).

The maximum energy consumption for the new building is 11.66 MWh, which is only 31.2% higher than the winter average. The deviation (Equation (10)) is also much lower, accounting for only 2.7 MWh. The difference with the previous Figure 8 means that there is almost no requirement to provide heat to the system components during peak conditions by increasing the SH supply temperature (Equation (2)) before the coldest days. We found a correlation between outdoor temperature and heat demand. Based on the identified correlation coefficient (0.89), it is relevant to conclude that outdoor temperature has a main role in supply and return temperatures in the outdoor temperature range of −30~+8 °C. External conditions also affect the system but to a lesser extent. It is also relevant to compare to our previous paper, covering regulation of supply temperature at the outlets of a CHP plant over 2 years where trend lines were $-799.04t_{out} + 26{,}581$ and $-820.23t_{out} + 26{,}630$ curves. There was no harmful effect of overheating due to supply and return temperature levels being lower. The overheating effect is checked against the design heat demand for the same outdoor temperature. Although the impact of other factors is limited, the difference between design and actual heat demand is higher in the range of low outdoor temperatures.

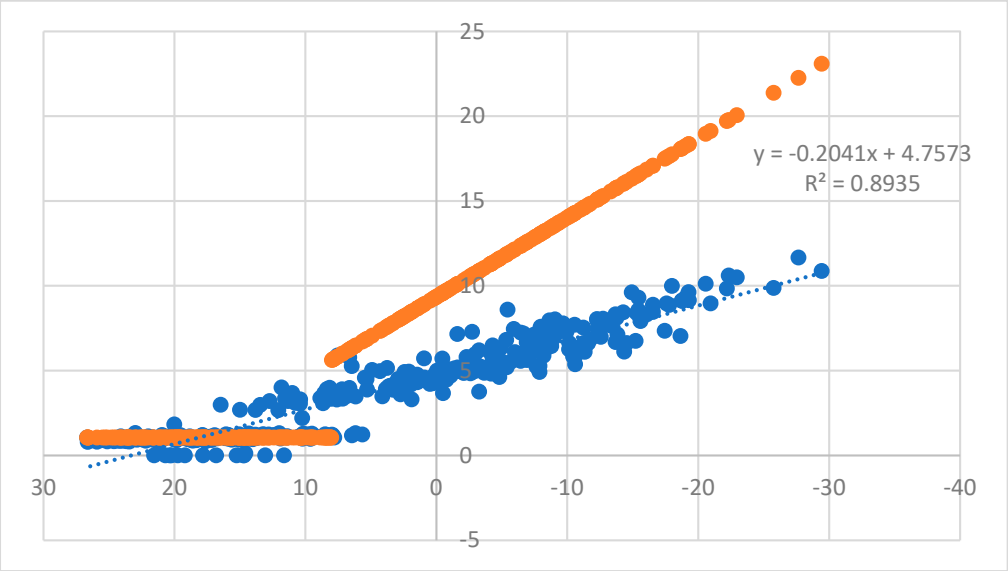


Figure 9. Heat demand given mainly in the new buildings. Please pay attention to the days with low outdoor temperatures ranging from −30 to 0 °C. Operational data points are presented in blue, while regression-based points for the same values of outdoor temperature are in orange.

There is an even clearer deviation between operational and design heat demand in new buildings, cf. Figure 8 for old buildings. This discrepancy is attributed to the fact that the SH systems have difficulties keeping indoor temperatures due to the aging of building envelopes. Therefore, the secondary temperatures are generally increased by manually tuning the SH system set points. In modern buildings, heat demand above the buckling point of +0.3 °C is set much lower due to DSMs. It also makes it much closer to design values within this range. DSMs is a term consolidating efforts taken to manipulate the consumption profiles by enhancing the performance of building envelopes, load management, and adapting the flexible demand profiles [35].

Decreasing the difference between operational and design heat demand in buildings is believed to promote the LTDH concept. If a high-temperature difference is achieved, the flow rates within the distribution are lower; therefore, the investments and operational costs to cover additional electricity consumption for pumping are also lower. Like the present paper, Romanov et al. [7] declare better potential for the lower temperature charts', once a better understanding of heat demand and higher modeling accuracy is achieved.

When the SH and DHW systems work simultaneously, the DH system is considered to follow heat mode. It consumes only the energy required to ensure indoor comfort from the DHC, provided that the supply and return temperatures are enough to cover the DHW requirement of buildings. This diminishing evolution is gradual and observed over the daytime steps.

To compare, in [8], the maximum peak demand of the combined district cooling and heating system was 64.2 kW for cooling and 12.4 kW for heating. That brings the idea of applying the method in detail to district cooling systems in the first place. It should also be emphasized that the actual demand profile and the simulated one are never totally similar due to the impact of uneven factors. For instance, the DH system inevitably accumulates some heat energy, thereby leveling heat demand fluctuations [36–38].

The aggregation is suggested as follows: as the heat demand profiles of each archetype became known (both old and new buildings), the average heat demand for each outdoor temperature is calculated according to y = f(x) regression. This average heat demand is then applied to the substation model, representing a single building substation for each

temperature range. Another contribution to the pool of knowledge made is that the return temperature is no longer fixed. There is a generalized methodology that considers that return temperature varies with the supply temperatures and the overall heat demand.

5. Discussion

This research addresses several critical gaps in the existing literature regarding the performance and energy efficiency of DH systems. Previous studies often focus on isolated aspects of building energy use or heating systems without thoroughly integrating the diverse characteristics of buildings or the operational dynamics of DH systems. By including a comprehensive dataset of case study buildings spanning a range of typologies, insulation levels, and heating systems, this study provides a more holistic understanding of how various factors influence the efficiency of DH.

One of the key findings from this research is the significant impact of building age and insulation levels on heating demand. Older buildings, especially those constructed before the 1980s, have considerably higher energy consumption due to poor insulation and outdated heating systems. This finding is consistent with the existing literature, which shows that thermal inefficiency in older buildings leads to higher heating demands, often requiring higher energy input to maintain comfortable indoor temperatures. However, this study further quantifies these effects, showing that buildings with low insulation levels consume up to 30% more energy than highly insulated buildings of similar typology. This is an important contribution as it offers specific data to help inform strategies for retrofitting and improving the energy efficiency of older building stock.

Another significant contribution of this study is its exploration of the varying performance of DH systems based on building typologies and heating systems. While much of the existing research focuses on centralized DH systems, this study highlights the growing role of individual heating systems in newer buildings. These modern systems, such as gas boilers or heat pumps, offer greater energy efficiency and more precise control over heating demand, which is not often captured in traditional DH research. By integrating centralized and individual systems into the modeling framework, this research addresses the gap in understanding how mixed heating systems perform in different building contexts.

The validation of the modeling framework also represents a significant advancement. Many prior studies have relied on theoretical models or simplified assumptions, leading to less reliable conclusions. By validating its predictions against actual heating data over a four-year period, this research provides a more accurate and trustworthy model for future studies. The use of metrics like mean absolute error (MAE) and root mean square error (RMSE) allows for a robust assessment of the model's accuracy, and the sensitivity analysis helps to pinpoint which factors (e.g., insulation levels, heating systems) most significantly affect the performance of DH systems. These methods provide a clearer picture of the uncertainties inherent in energy modeling, often limitations in previous works.

Furthermore, this study's inclusion of data over a two-year period, spanning from 2019 to 2021, addresses the gap in temporal analysis seen in earlier studies, which often focus on shorter timeframes. Including multiple years of data enables a more nuanced understanding of seasonal and long-term variations in heating demand, improving the reliability of the findings and making them more applicable to future energy policy decisions.

Regarding policy implications, the study provides valuable insights into the need for targeted interventions in renovating older buildings. It emphasizes that without addressing insulation deficiencies and improving heating systems in these buildings, the potential for reducing energy consumption in DH networks will remain limited. Additionally, the findings point to the importance of promoting more efficient heating systems in new constructions, which could further optimize energy use across DH networks.

Compared to existing studies, which may focus on either the building or the DH system in isolation, this research offers a more integrated view, considering the individual building characteristics and the broader DH infrastructure. It provides a more detailed and comprehensive approach to understanding how these systems can improve energy efficiency and offers a clear roadmap for future research.

Thermal comfort is a state of mind where occupants feel thermally satisfied with their surroundings. This involves a complex interplay of temperature, humidity (though less critical in this dry climate), air velocity, and personal factors. While individual preferences vary, this study aims to maintain indoor temperatures within a range that satisfies the majority of occupants. Specifically, a target temperature range of 20–24 °C is considered, aligning with recommendations from ASHRAE EN standards for typical office and residential buildings. These standards also guide acceptable humidity levels, which should ideally be monitored and controlled, although these data are not currently available for this study.

The regional climate of Omsk, Russia, presents significant seasonal challenges. Winter temperatures can plummet to −30 °C, requiring robust heating to maintain comfortable indoor conditions. Conversely, summer temperatures can exceed 30 °C, though district cooling is not currently implemented, making managing internal heat gains (solar radiation, equipment, occupants) crucial for preventing overheating. The transitional seasons (spring and fall) present unique challenges, as highlighted by the observation of excessive heat being released from open windows. This suggests inadequate control strategies to adapt to milder outdoor temperatures, leading to energy waste and potential discomfort due to temperature swings.

The existing data from the SCADA system (Figure 3) show a concerning trend of high return temperatures, indicating inefficiencies in heat delivery and potentially impacting thermal comfort. As mentioned in the text, poor mixing at DH substations can exacerbate this issue, leading to uneven temperature distribution within buildings. This can result in some areas being overheated while others remain underheated, compromising overall comfort. Furthermore, hydraulic balancing issues can also contribute to inconsistent heating, affecting energy efficiency and thermal comfort. Addressing these distribution network deficiencies is crucial not only for energy savings but also for ensuring occupant well-being.

Different building types within the district have varying thermal comfort requirements. Office buildings typically require tighter temperature control and higher ventilation rates due to higher occupancy densities and internal heat gains. On the other hand, residential buildings may have more flexibility in temperature settings, but occupant preferences and individual control become more important. Industrial buildings may have specific temperature and humidity requirements depending on the processes. While identifying different building archetypes (old, new, industrial), the current analysis does not explicitly address how the heating system caters to these diverse needs. Future work should include a more detailed analysis of thermal comfort requirements for each building type and how the heating system can be optimized to meet those needs.

While the current study focuses on energy consumption data, the research acknowledges the lack of direct occupant feedback regarding thermal comfort. Surveys or other methods of gathering occupant perception data should be incorporated into future studies. This would provide valuable insights into the actual thermal comfort experienced by building occupants and allow for data-driven optimization of the heating system. Without such data, the analysis assumes that indoor temperatures within the target range (20–24 °C) will generally provide acceptable thermal comfort. However, it is recognized that this is a simplification and that individual preferences may vary.

The analysis may also explore the relationship between energy efficiency measures and thermal comfort. For instance, reducing supply temperatures to improve efficiency

may impact the ability of the system to maintain comfortable indoor temperatures during peak demand periods. Similarly, implementing DSMs, while beneficial for energy savings, should be carefully evaluated to ensure they do not negatively affect thermal comfort. A balanced approach is needed that considers both energy performance and occupant well-being.

To evaluate the effectiveness of the proposed model, a comparison is made against existing methods in the literature. Table 2 highlights key differences in temperature assumptions, heating efficiency, outdoor temperature impact, substation modeling, and energy loss considerations. Unlike previous models that rely on fixed temperature assumptions or simplified substation representations, the proposed approach incorporates real-world operational data, addressing key inefficiencies in DH systems.

Table 2. Comparison of the proposed model with existing methods regarding temperature assumptions, heating efficiency, outdoor temperature impact, substation modeling, and energy loss considerations.

Criterion	Proposed Model	Vandermeulen et al. [23]	Farouq et al. [26]	Kurek et al. [17]
Temperature Assumptions	Dynamic return/supply temperature variations based on real SCADA data	Fixed supply and return temperatures year-round	Return temperature analysis used as an efficiency check	Weather-based feature selection for return temperature predictions
Heating Efficiency	Adjusts based on substation performance and hydraulic balancing	Aggregated substation approach for residential areas	Applied control check for operational efficiency	Uses selected weather features to predict heat demand
Impact of Outdoor Temperature	Correlates outdoor temperature (−30 to +5 °C) with system performance	Assumes constant supply/return temperatures	Evaluates return temperature fluctuations in Sweden	Uses a forward feature selection algorithm to choose relevant weather parameters
Substation Modeling	Incorporates real-world delays in optimal supply temperature reaching substations	Assumes ideal flow rate scaling for residential areas	Focuses on identifying poor-performing substations	Uses autoregression model to estimate heat demand
Energy Loss Consideration	Identifies high heat losses due to poor insulation and hydraulic imbalances	Does not consider real-world heat losses	Uses return temperature as an indirect efficiency indicator	Identifies correlations between temperature and heat demand

6. Conclusions

This research exposes a new formulation for the operational process of an HTDH with a high share of residential consumers and buildings requiring renovation. The novelty is the introduction of statistics into a CAD-aided dynamic simulation model. Its effectiveness is demonstrated on three representative periods: summer, cold (winter), and moderate cold (fall and spring) days. The methodology yields the following key findings:

1. A minority of consumers are responsible for low modeling accuracy and, therefore, hydraulic balancing issues.
2. Office buildings, shops, and car parks with low indoor temperatures are buildings with low specific energy demand. Encountering new energy-efficient residential buildings using low specific energy demand as a criterion is highly unlikely.
3. With no abnormal buildings, higher modeling accuracy is achieved.
4. Most consumers are similar in thermal response. However, specific energy demands may differ.
5. The traditional modeling approach is incorrect. The heat demand of a building is better simulated with a discrete regression.
6. Heat demand of buildings with pump-equipped substations can be modeled with the help of simple linear regression with acceptable error.

While this study provides valuable insights into the modeling and analysis DH systems, several limitations should be acknowledged. Firstly, the modeling framework relies

on the availability and accuracy of building-level data, such as insulation levels, heating system types, and occupancy patterns. Any inaccuracies in these inputs may affect the reliability of the predictions. Additionally, the study focuses primarily on a physics-based approach, which, although transparent and interpretable, may not fully capture complex nonlinear relationships present in some DH dynamics—an area where data-driven models could offer complementary value.

The temporal resolution of the data, while sufficient for the scope of this research, may also limit the ability to capture short-term fluctuations in heating demand, particularly during extreme weather events or abrupt changes in occupancy. Moreover, the case study buildings, although varied in age, typology, and heating systems, may not fully represent the broader diversity of building stocks in other regions, potentially affecting the generalizability of the findings.

Lastly, while the validation process included historical data over multiple years, further testing across different climatic zones and DH configurations would strengthen the robustness of the proposed model. Future research could also explore hybrid modeling approaches, combining physics-based and machine-learning methods to enhance predictive accuracy and adaptability.

In addition, several remarks on return temperature have been made. Accordingly, a particular advantage of the present paper is assessing heat demand within LTDH and 4GDH concepts, intending to spread this technique to other regions and support DH transformation. Additional advantages of the novel method over the traditional one are its greater support in planning, its simplicity regarding further spatial extension of the network, and its robust operation. This includes evaluating transformation measures with an easy dataset, which any DH system may provide. In future work, the possible emphasis on a more sophisticated real-life check of the applicability of the approaches and guidelines is to be presented.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to confidentiality reasons.

Conflicts of Interest: The author declares no conflicts of interest.

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