

Article

Development and Software-in-the-Loop Validation of a Digital Twin Architecture for District Heating Networks

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Abstract

In this study, a digital-twin-oriented integration architecture was developed for district heating networks in a laboratory Software-in-the-Loop (SIL) environment and evaluated. The implemented testbed combined a virtual SIMATIC S7-1500 controller executed in S7-PLCSIM Advanced V8.0, WinCC Runtime Advanced, OPC UA communication, a Python-based integration layer, and a Fluidit Heat thermohydraulic model. The physical district heating network, field sensors, pumps, actuators, and an operational field PLC were not connected to the experimental loop. Field-derived heat load and pressure values for five monitored consumers were stored in PLC data blocks. Python validated and mapped the tags, initiated predefined Fluidit Heat scenarios, processed the model outputs, and returned the results to the PLC for SCADA visualization. Six operating scenarios were evaluated. In the combined baseline and 120% demand scenarios, the delivered heat increased from 2369.84 to 2843.79 kW, plant thermal output from 2377.14 to 2850.80 kW, and plant flow from 12.288 to 14.737 L/s. The maximum supply velocity increased from 1.192 to 1.430 m/s, and the maximum unit pressure loss increased from 1.338 to 1.912 bar/km (+42.92%). The minimum consumer differential pressure remained at approximately 4.000 bar, above the adopted 3.5 bar criterion, and no heat deficit was calculated. The experiment demonstrated functional software interoperability, event-driven scenario execution, and bidirectional simulation data exchange. Because the baseline values contributed to model parameterization and the physical network was not connected, the comparison was a consistency assessment rather than independent field validation. Automatic optimization, autonomous preferred-mode selection, and actuator-level control were not implemented.

Academic Editor: Dan Sui

Received: 7 September 2026

Revised: 11 October 2026

Accepted: 12 October 2026

Published: 14 October 2026

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Keywords: Software-in-the-Loop; district heating network; digital-twin-oriented architecture; virtual PLC; SCADA; TIA Portal; OPC UA; thermohydraulic simulation; Fluidit Heat; Python; scenario analysis

1. Introduction

Heat supply is an essential component of urban infrastructure. Buildings account for 30–45% of global final energy consumption, with 50–70% of that used for heating [1]. According to statistical data, losses caused by hydraulic and thermal imbalances in distribution networks can reach 20% of the total thermal energy generated in district heating systems (DHSs) [2]. This can be explained by the fact that conventional heat-supply control systems face several challenges, including uneven heat distribution, high energy losses, and difficulties in detecting and resolving operational failures. Therefore, the implementation of intelligent control systems should be considered [3].

The Concept for the Development of the Fuel and Energy Complex of the Republic of Kazakhstan for 2023–2029 identifies the modernization of heat-generating and network infrastructure as a national priority [4]. Table 1 summarizes selected infrastructure indicators using the official sources specified for each item [4,5].

Table 1. Selected indicators characterizing Kazakhstan’s district heating infrastructure.

Indicator	Value	Source
Total combined heat and power plants	37	[4]
Number of boiler houses	6004	[5]
Share of heat networks requiring replacement	27.4%	[5]
Length of heat and steam networks in two-pipe terms	14,312.2 km	[5]
Average equipment depreciation	61%	[4]

To ensure energy security, the modernization, reconstruction, and replacement of physically worn-out and technologically obsolete equipment are pressing issues. For example, according to the National Strategy for Large-Scale Digitalization and the Comprehensive Implementation of Artificial Intelligence Technologies, “Digital Qazaqstan,” through to 2029 [6], systemic infrastructure problems persist in the housing and utilities sector: a significant proportion of utility networks is physically deteriorated (in some regions, the deterioration of district heating and water supply networks exceeds 50–60%), the failure rate remains high, and facilities are predominantly managed manually. The absence of smart metering and predictive monitoring systems results in inefficient heat use, higher operating costs, and a decline in the quality of services provided to the public.

According to the Bureau of National Statistics of the Republic of Kazakhstan, heat production in the country showed an overall upward trend during 2014–2025 (Figure 1) [5].

In this regard, the thermal energy sector is one of the strategically important areas of Kazakhstan’s economy. Its efficiency and sustainability have a significant impact not only on economic growth but also on ensuring energy security and environmental sustainability. Therefore, the optimization of thermal energy production and consumption, the application and implementation of artificial intelligence and digital technologies in energy conservation, and infrastructure modernization remain relevant issues for the country.

According to Figure 2, the development of heating systems comprises several stages [7]. District heating systems corresponding to the second and third stages have been widely adopted in Kazakhstan. Regarding energy efficiency and environmental performance, these systems do not meet the modern requirements for district heating systems.

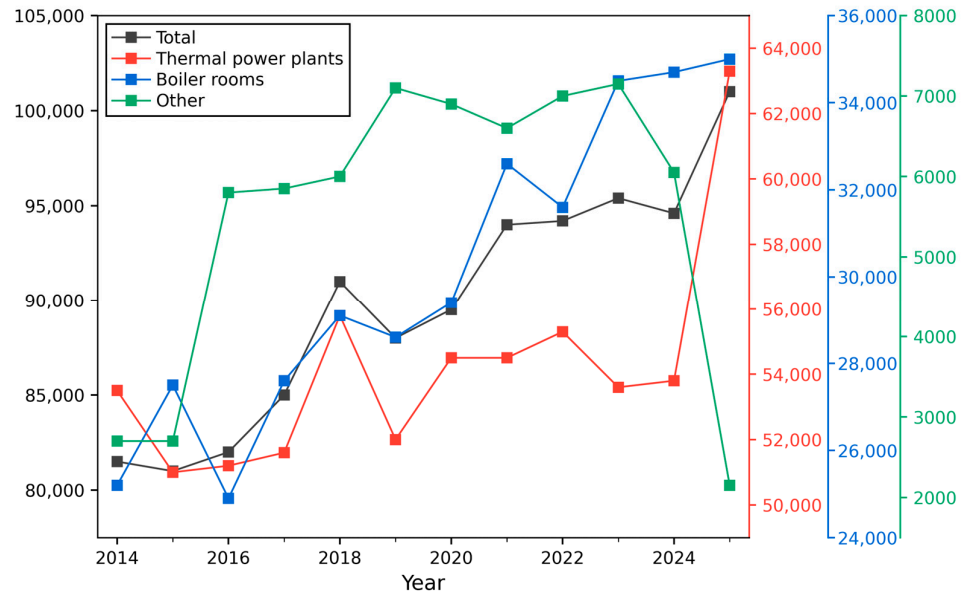


Figure 1. Heat production by source in Kazakhstan, shown in thousands of Gcal for the period 2014–2025.

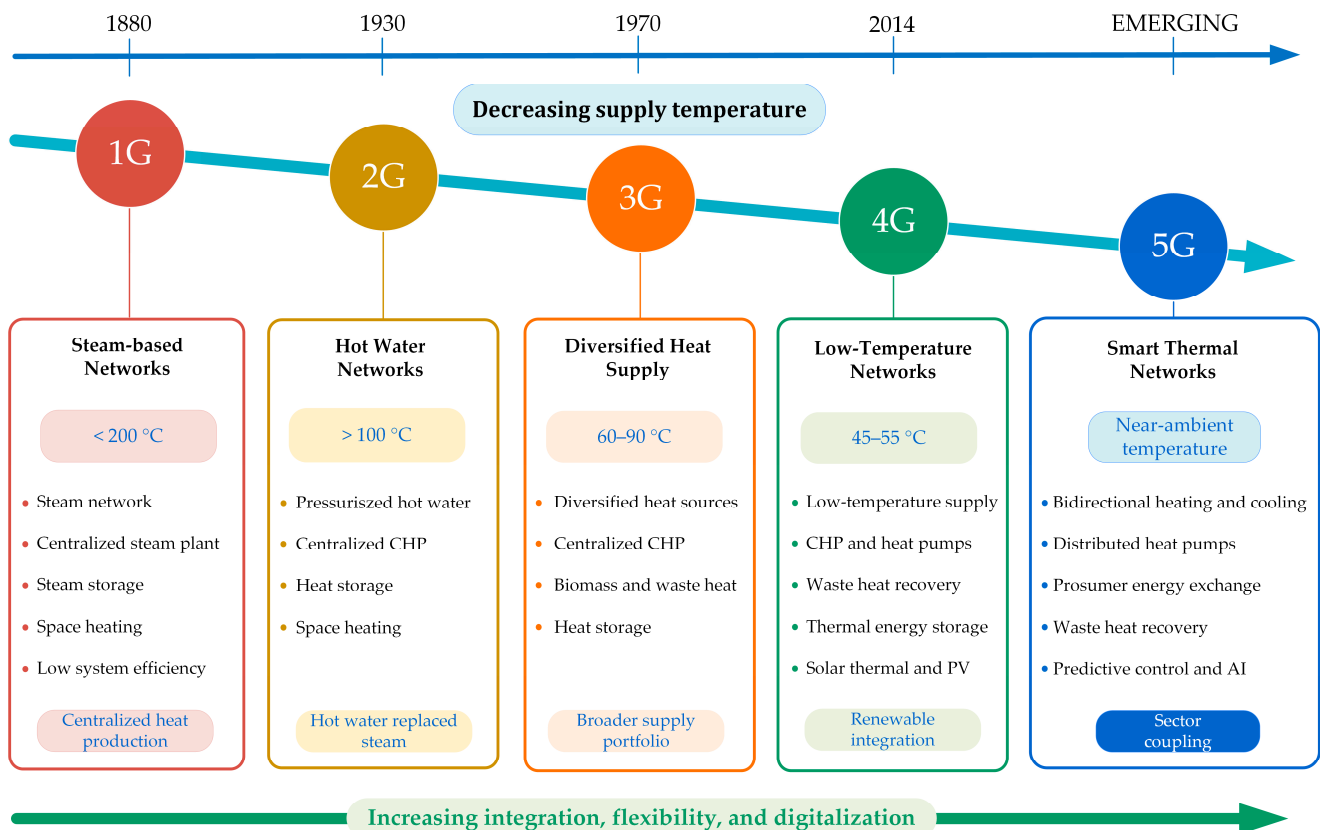


Figure 2. Energy network development stages, including the fifth-generation (5G) district energy concept.

Many EU countries are actively working to implement the fifth stage of heating system development. This stage includes low-temperature district heating networks, the widespread use of renewable energy sources, digital control systems, and intelligent

consumption regulation. In addition to improving energy efficiency, such approaches reduce the environmental impact [8–11].

This issue is also relevant to Kazakhstan, as evidenced by the increasing number of recent scientific studies and projects conducted in this field [12]. This, in turn, is regarded as one of the most important steps toward modernizing Kazakhstan’s thermal energy sector and bringing it closer to contemporary international standards.

Based on a comprehensive review of software for modeling heat supply systems, the authors of [13] divided the existing software tools into two main categories according to their functionality and application areas.

1. The first category comprises specialized software for district heating systems (DHSs). This category includes tools such as Fluidit Heat, Leanheat, ROKA³, SIR3S, and AD-Net Heat. These programs are specifically adapted for modeling district heating networks (DHNs), performing hydraulic and thermal calculations, and analyzing system operating conditions. Consequently, they provide high accuracy and efficiency when solving specific engineering problems.
2. The second category comprises general-purpose simulation tools, including Dymola, TRNSYS, Polysun, and Simscape. These software packages allow various physical systems to be modeled, including heat and energy transfer processes. However, although their main feature is their multidisciplinary nature, they are not fully adapted to the specific design and operational characteristics of district heating networks. Therefore, the use of such tools requires additional configuration and adaptation.

Figure 3 presents statistics from the Scopus database on published scientific articles reporting research conducted using software products for modeling district heating systems. The analysis was performed using the search term “district heating.”

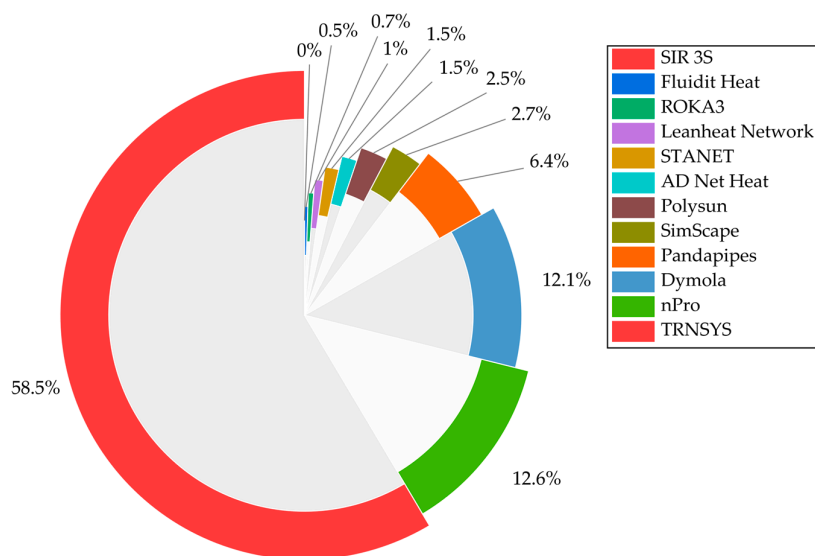


Figure 3. Statistics on the use of software for modeling district heating systems, based on the Scopus database.

One of the prerequisites for the transition to fourth- and fifth-generation district heating networks is the digitalization of district heating systems. The increasing number of distributed energy sources, energy storage systems, heat pumps, and controllable consumers complicates network operation and raises the requirements for monitoring its thermal and hydraulic states. Implementing this transition to digitalization will require heat load forecasting, operational data processing, fault detection, operating mode

optimization, and integration of the physical network with its computational representation through the creation of digital twins [14].

A digital twin is a data-connected virtual representation of a physical asset, system, or process that supports simulation, monitoring, analysis, and operational decision-making. Its virtual layer may combine geometric, mathematical, and simulation models and can be used to evaluate design alternatives, predict system behavior, identify deviations, investigate operating conditions, and support process optimization. Within contemporary industrial digitalization, digital twins provide an integrating link between physical infrastructure, information systems, and analytical methods [15–19].

A digital twin differs from a simulation model. A thermohydraulic model that is not connected to a physical system constitutes a digital model. When operational data are transferred automatically and unidirectionally from the physical system to the model, only a digital shadow is formed. A full-fledged digital twin requires regular updates to the virtual model using data from the physical system and feedback on calculation results to support monitoring or control [20].

Physics-based thermohydraulic models primarily underpin digital twins for district heating systems. They enable determination of the heat carrier pressure, flow rate, and velocity; supply and return temperatures; heat losses; and the extent to which consumer demand is met. The study reported in [21] developed a digital twin of a district heating network that combines pipeline hydraulic resistance identification with heat load forecasting. In that study, adaptive refinement of hydraulic parameters using operational data reduced modeling errors for 80% of the investigated heat substations. This confirms that calibrating input data and boundary conditions is an essential stage in preparing a digital twin of an operating district heating network.

A promising direction is to incorporate a dynamic thermohydraulic model into the supervisory control loop. The use of detailed simulation and reduced-order, control-oriented models enables accounting for temperature dynamics, the thermal inertia of pipelines, and the operational constraints of a large-scale district heating network [22].

Digital twins are also used to diagnose the technical condition of district heating infrastructure. The authors of [23] proposed an approach combining a thermohydraulic network model with an optimization algorithm for detecting and identifying hydraulic and thermal faults. The method enables the detection of heat carrier leaks, abnormal pressure losses, and increased heat losses, as well as the estimation of the corresponding deviation magnitudes.

An architecture integrating a control system, a digital twin, and a co-simulation environment for a multi-energy system has also been developed [24]. In this architecture, the digital twin transmitted measurements to the control system, which calculated optimized setpoints and returned them to the digital twin. This distribution of functions confirms the feasibility of separating the system into a computational model and an external software layer responsible for data processing and generating control decisions.

Standardized data exchange is particularly important for the industrial integration of digital models. A three-layer OPC UA architecture for aggregated microgrids provides scalable interactions between heterogeneous devices, edge–cloud infrastructure, and high-level energy management functions [25]. In another energy system, OPC UA and a Python-developed gateway were used to integrate a modern SCADA system with legacy Modbus equipment, and the tests confirmed robust, scalable real-time data exchange and control [26].

A promising direction for the development of district heating digital twins is the integration of physics-based models, neural networks, and predictive control [27].

Python is becoming widely used in the modeling and digitalization of district heating networks because of the availability of libraries for numerical calculations, time series

processing, machine learning, visualization, and industrial data exchange. Python can be used either as a standalone computational tool or as an integration layer between SCADA, PLC, a database, and a specialized thermohydraulic simulator [26,28–30].

An open-source Python library, PyDHN, has been developed to store district heating network structures, model complex topologies, perform hydraulic and thermal calculations, and automate input/output operations [28]. Validation of the library on networks with complex topologies confirmed its ability to reproduce thermohydraulic calculation results and demonstrated the applicability of open-source software for analyzing district heating systems. An advantage of this solution is the possibility of directly integrating the computational model with data analysis and optimization algorithms.

Another example is the Python package pandapipes, which is intended for steady-state and quasi-steady-state modeling of pipeline networks [29]. It enables the calculation of pressures, flow rates, velocities, and temperatures, as well as time series generation and custom controller creation. The combined use of pandapipes and pandapower enables the modeling of interconnected heating, gas, and electrical networks. Using a unified Python environment simplifies computational experiment automation, results processing, and additional library integration.

A co-simulation architecture has also been reported in which the dynamic district heating model was implemented in TRNSYS, while Python was used for design calculations, optimization, impact analysis, and control decision generation [30]. The Python layer enabled the specialized simulator to be connected to optimization and data-processing algorithms.

Hybrid models are being investigated to reduce computation time. A district heating network model based on a modified LPV structure was developed, reproducing 98.64% of the dynamics of a high-fidelity physics-based model, with $R^2 = 0.9997$. The computation time was reduced by a factor of approximately 52 [31].

In the study reported in [32], individual groups of heat substations were replaced by machine learning models, while the remaining network was calculated using a physics-based simulator. In the configuration with a high degree of spatial reduction, the number of physical nodes was reduced from 123 to 5, and the computation time was reduced by 91%. At the same time, the deviation in the estimated total heat production amounted to 45.24 MWh, or 26.37% relative to the network heat losses.

The reviewed studies demonstrate substantial progress in physics-based district-heating modeling, parameter identification, load prediction, fault diagnosis, predictive control, hybrid modeling, and standardized industrial communication. Nevertheless, these functions are commonly investigated as separate modeling, control, or communication tasks. Comparatively few studies have described a reproducible event-driven workflow in which an industrial automation stack, a standardized OPC UA interface, a Python orchestration layer, and a specialized thermohydraulic simulator use exchange-typed operating data and calculation results within one SIL experiment. The research gap addressed here is therefore not the development of a new thermohydraulic solver or optimization algorithm; rather, it is the methodological integration and experimental traceability of these heterogeneous components, including explicit data-block separation, scenario triggering, status handling, result write-back, and visualization in an industrial SCADA environment.

The methodological distinction between the present study and representative prior work is summarized in Table 2.

Table 2. Comparison of the present SIL implementation with representative studies on district heating digital modelling, co-simulation, control, and OPC UA integration.

Study	Architecture	Primary Contribution	Distinction from Present Study
Zheng et al. [21]	District heating digital model with hydraulic resistance identification and heat load prediction	Calibration and prediction using operational data	Does not report the PLC/SCADA–OPC UA–Python–Fluidit SIL workflow used here
Nigro et al. [22]	Dynamic and control-oriented district heating model	Predictive control and network dynamics	Focuses on control-oriented modelling rather than industrial automation interoperability
Bahlawan et al. [23]	Thermohydraulic model with optimization	Detection and identification of hydraulic and thermal faults	Does not address event-driven data exchange with an industrial virtual PLC and SCADA
O'Dwyer et al. [24]	Digital twin and energy management integration for a multi-vector system	Coordination and optimized setpoints	Broader multi-energy co-simulation; not the district heating-specific Fluidit Heat SIL implementation
Carballo et al. [26]	OPC UA and Python gateway in a SCADA environment	Industrial communication and control integration	No district heating thermohydraulic simulation layer
Elomari et al. [30]	TRNSYS–Python co-simulation	Design calculations, optimization, and impact analysis	No virtual industrial PLC/SCADA data block and handshake implementation
Present study	Virtual S7-1500, WinCC, OPC UA, Python, and Fluidit Heat	Traceable bidirectional simulation-data exchange and automated execution of six scenarios	Laboratory SIL proof of concept; no physical plant, automatic optimizer, or actuator-level closed loop

Accordingly, the objective of this study was to develop and evaluate the functional feasibility of a digital-twin-oriented architecture for district heating scenario analysis in a laboratory SIL environment. The specific contributions are (1) an explicit separation between the target physical deployment and the implemented SIL boundary; (2) a reproducible event-driven workflow linking a virtual S7-1500 PLC, WinCC, OPC UA, Python, and Fluidit Heat; (3) structured bidirectional exchange through separate PLC data blocks with execution and diagnostic states; (4) implementation of six operating scenarios and quantitative interpretation of the baseline and demand-stress responses; and (5) a transparent statement of the validation limits and the requirements for subsequent field deployment. The contribution is an integration and evaluation methodology rather than a new thermohydraulic solver, optimization algorithm, or autonomous controller.

2. Materials and Methods

2.1. Digital-Twin-Oriented Architecture and Data Exchange Workflow

Figure 4 distinguishes two architectural levels. The upper level represents the target field deployment, which would contain the physical district heating network, field sensors, pumps, actuators, and an operational industrial PLC. This level was not connected to the experiment. The lower level is the implemented SIL testbed, comprising the virtual S7-1500 controller executed in S7-PLCSIM Advanced version V8.0 [33], WinCC Runtime Advanced version V20, OPC UA communication, the Python version 3.14 integration layer, and the Fluidit Heat version 2.8 thermohydraulic model. Within the SIL boundary, TIA Portal version V20 was used to configure the controller logic and data blocks, PLCSIM Advanced executed the virtual controller, and WinCC visualized PLC and simulation variables. OPC UA was the implemented bidirectional interface between the virtual PLC and Python. PROFINET/Industrial Ethernet denotes the configured PLC-SCADA

communication layer and the envisaged field communication architecture; it does not indicate that real sensors, pumps, actuators, or a field PLC were connected during the reported experiment.

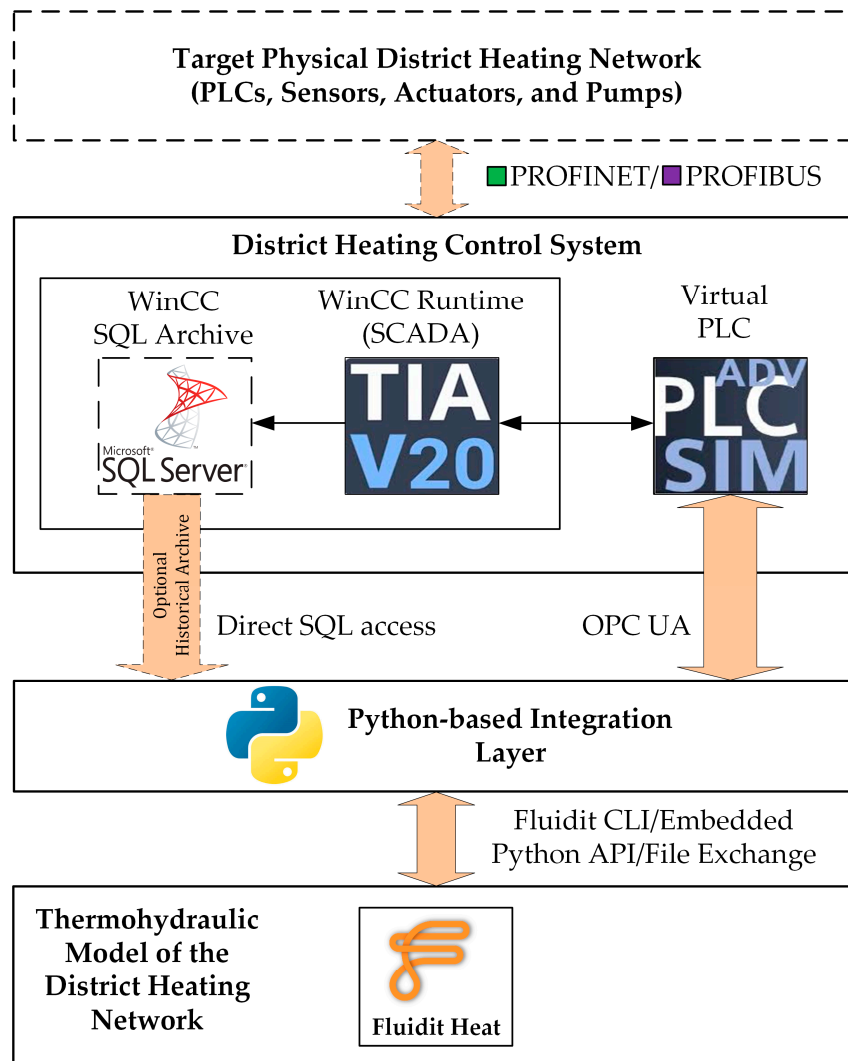


Figure 4. Target field architecture and implemented Software-in-the-Loop testbed.

The roles of the implemented and conceptual system components are summarized in Table 3.

Table 3. Roles of the implemented and conceptual system components in the reported SIL study.

Component	Role in the Reported Study
Virtual PLC in S7-PLCSIM Advanced	Execution of PLC data-handling logic, data blocks, handshakes, interlocks, and status flags
WinCC Advanced	Visualization of field-derived input values, returned simulation results, commands, status flags, and diagnostic indicators
SQL Server	Historical archive for future calibration, trend analysis, and machine learning tasks (optional in the experiment)
OPC UA	Implemented bidirectional exchange of variables between the virtual PLC and the Python integration layer

Python	Tag mapping, verified preprocessing operations, scenario orchestration, result parsing, constraint checks, and result write-back; no automatic optimizer was demonstrated
Fluidit Heat	Physics-based thermohydraulic calculation of the network state for predefined scenarios
Real District Heating System	Target asset for future deployment; excluded from the experimental loop

To implement the experimental digital-twin-oriented architecture of the district heating system, the following controller configuration, communication technology, and software tools were used:

- SIMATIC S7-1500 controller configured as a CPU 1513F-1 PN with firmware version 2.9 (Siemens AG, Munich, Germany) [34];
- PROFINET/Industrial Ethernet for communication between the PLC and the SCADA system;
- TIA Portal version V20 as the engineering environment for PLC configuration and programming (Siemens AG, Munich, Germany) [35];
- SIMATIC WinCC Runtime Advanced version V20 for SCADA visualization, supervisory monitoring, and data archiving (Siemens AG, Munich, Germany) [35];
- S7-PLCSIM Advanced version V8.0 for virtual execution of the configured S7-1500 controller (Siemens AG, Munich, Germany) [36];
- Python version 3.14 with the *asyncua* and *opcua* libraries for OPC UA communication, data processing, and simulation orchestration [37];
- Fluidit Heat version 2.8 (calculation engine version 2.3.01) for thermohydraulic modeling and scenario analysis (Fluidit Oy, Järvenpää, Finland) [38].

The PLC project configuration used in the experimental digital-twin-oriented architecture is shown in Figure 5. The integrated OPC UA server was activated in TIA Portal version V20 to provide the Python-based integration layer with standardized access to the variables stored in the PLC data blocks.

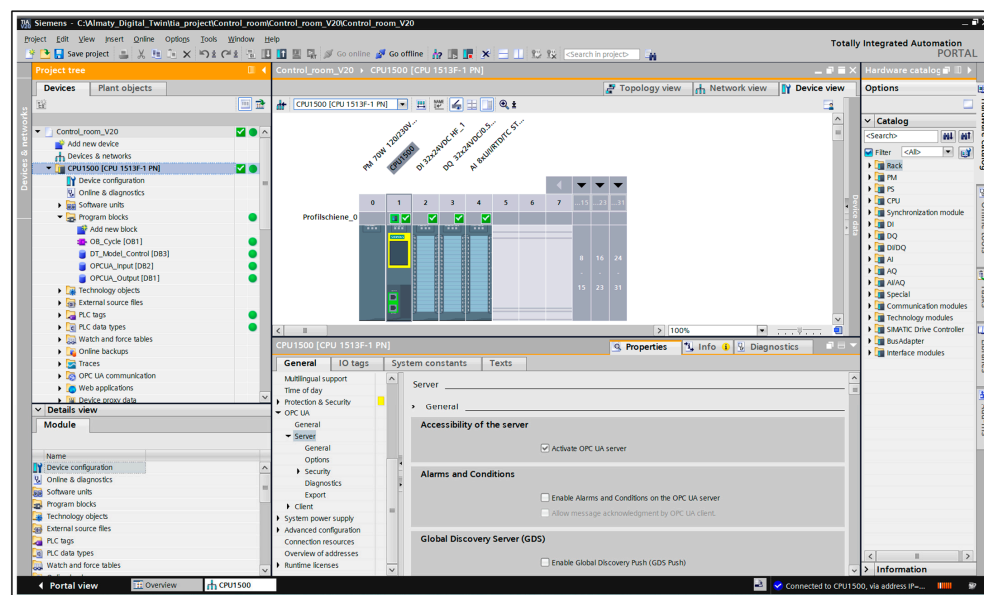


Figure 5. Configuration of the PLC project and activation of the OPC UA server in Siemens TIA Portal version V20. The project tree is shown on the left, the controller hardware configuration in the center, and the OPC UA server settings below.

The current process parameters are first transferred to a PLC data block. In the real system, these values are generated from measurement sensor signals. WinCC exchanges

data with the controller, visualizes the process parameters, and transfers them to an archive implemented using SQL Server [39].

The SQL Server database is primarily intended for the long-term storage of measurements, generation of historical trends, statistical analysis, calibration of the thermohydraulic model, and subsequent training of anomaly detection algorithms.

The primary real-time data exchange takes place between the PLC and Python via the OPC UA protocol. Python reads the process parameter values from the PLC data block and checks their completeness, data types, units of measurement, permissible ranges, and timeliness.

The Fluidit Heat model integrates measured time series data from external sources (e.g., Excel, CSV) with hydraulic/hydrological simulations. These data sources act as dynamic links, allowing the model to reference multiple files—such as all CSV files within a single directory—through a single object. By functioning as references rather than embedded data, data sources have a negligible impact on the model size and always provide access to the most current file revisions. From each data source, the model automatically generates headers, which are further classified as data source tags and data source positions [38]. Figure 6 shows the data sources in Fluidit Heat.

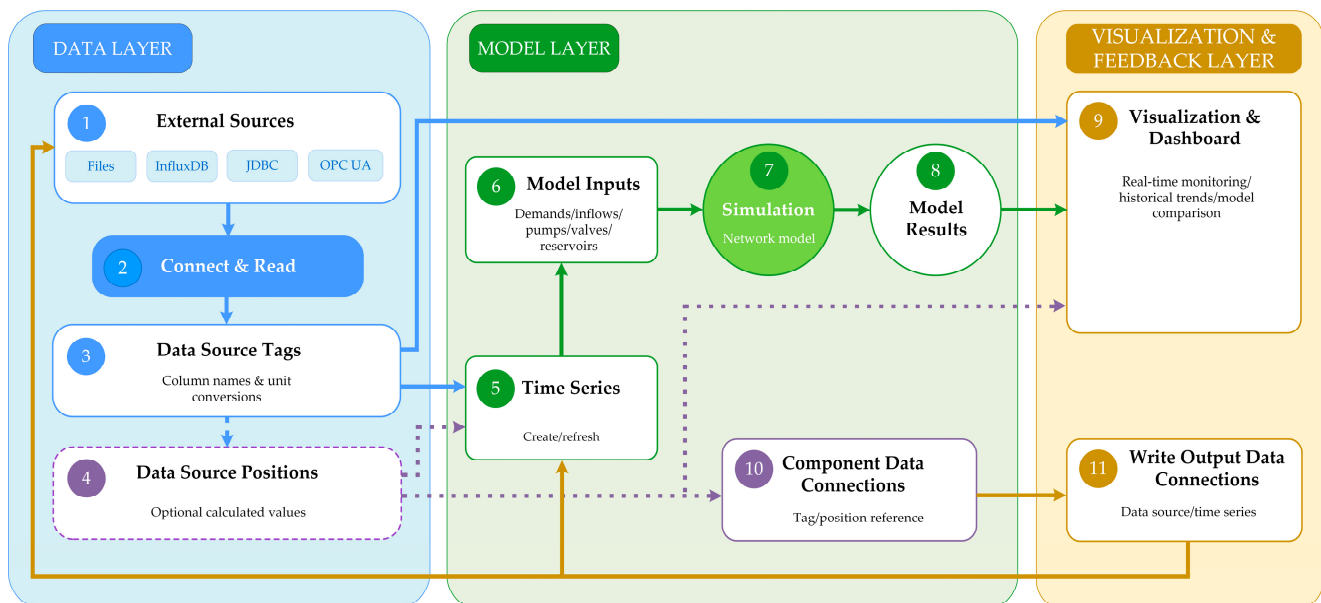


Figure 6. Data sources in Fluidit Heat. Blue arrows show data acquisition and transfer; green arrows show the simulation workflow. Purple dotted arrows indicate links involving calculated values and component references. Brown arrows indicate output writing and feedback paths. Arrowheads show the direction of data flow.

The OPC UA data source provides connectivity to an OPC UA server, utilizing the OPC UA Historical Access specification for reading and writing historical data within the Fluidit environment [40].

After validation, Python converts the received data into a set of input parameters for the Fluidit Heat thermohydraulic model. Depending on the available interface, the interaction can be performed through command-line execution of Fluidit, the embedded Python API, or file exchange.

Table 4 provides a brief comparison of Direct SQL Access and OPC UA for AI/ML model training, showing that each approach has advantages and disadvantages. For example, OPC UA is better suited to online training, whereas Direct SQL Access is more

appropriate for offline training using long historical periods. In this study, preference was given to the OPC UA server-based approach.

Table 4. Comparison of Direct SQL Access and OPC UA for AI/ML model training.

Criteria	OPC UA	Direct SQL Access (WinCC Archive)
Data format	Tag values with timestamp and quality status	WinCC compressed/segmented binary archives
Training mode	Optimal for online/streaming ML and predictive analytics	Optimal for batch training on large historical datasets
SCADA system load	Minimal (event-based/asynchronous transfer)	High under heavy SELECT queries on the runtime DB
Universality	Fully independent of WinCC version and DB type	Tied to MS SQL Server structure of a specific SCADA version

Fluidit Heat calculates each predefined scenario, while Python processes the returned results and verifies compliance with the configured operational constraints. In the reported experiment, scenario selection was predefined; no automatic optimizer or autonomous preferred-mode selector was implemented. After each simulation, Python returned the calculated values via OPC UA to a separate PLC data block for WinCC visualization.

The organization of the structured data exchange between the PLC and the Python-based integration layer is illustrated in Figure 7. The “OPC UA_Output” data block stores the operating parameters transmitted from the PLC, whereas the “OPC UA_Input” data block receives the corresponding simulation results returned to the PLC. New actuator setpoints were neither generated nor applied. Actuator-level closed-loop control and safety-governed setpoint application remain future field validation stages.

(a)

(b)

Figure 7. PLC data blocks used for bidirectional OPC UA data exchange: “OPC UA_Output” (DB1), containing operating parameters transmitted from the PLC to the Python-based integration layer (a), and “OPC UA_Input” (DB2), containing Fluidit Heat simulation results returned to the PLC (b).

Accordingly, the evaluated system is a SIL implementation of a digital-twin-oriented architecture comprising a virtual PLC, WinCC, OPC UA, a Python integration service, and the Fluidit Heat thermohydraulic model. The PLC provides the software representation of data acquisition and control logic; WinCC provides supervisory visualization; Python manages validation, mapping, scenario invocation, and result exchange; and Fluidit Heat provides physically interpretable thermohydraulic calculations.

2.2. Software-in-the-Loop Scope and Rationale

Software-in-the-Loop denotes testing in which the control and integration software interacts with a software representation of the process rather than with physical plant equipment. In this study, the controller and the district heating process were represented using software: the controller logic was executed using S7-PLCSIM Advanced V8.0, while Fluidit Heat calculated the thermohydraulic response. WinCC, OPC UA, and Python retained the same functional roles that they would have in the proposed field architecture. SIL was selected because it permits repeatable testing of data exchange, scenario triggering, status logic, invalid-data handling, and result visualization without exposing an operating district heating network to experimental commands. It also enables rapid debugging and controlled comparison of boundary condition changes.

The SIL environment does not reproduce all non-ideal effects of field operation. The present experiment does not include sensor noise and drift, missing or delayed measurements, timestamp misalignment, communication jitter and packet loss, cybersecurity constraints, actuator saturation and stiction, pump and valve dynamics, thermal model drift, or interaction with an operational PLC scan cycle. Therefore, while it verifies software interoperability and scenario execution, it does not establish operational reliability, hard real-time performance, control safety, or predictive accuracy for the physical network. Progression to an operational digital twin requires independent field data, online model updating, hardware- or process-in-the-loop testing, cybersecurity assessment, and a governed procedure for authorizing setpoint changes.

2.3. Quantitative Experimental Formulation

Let s denote an operating scenario, t a reporting instant, $i = 1, \dots, N_d$ a modeled demand connection ($N_d = 8$), and $\ell = 1, \dots, N_p$ a pipe ($N_p = 18$). The independent variables comprise the space heating and domestic hot water loads assigned to each demand connection, the plant supply-temperature setpoint, the source differential-pressure setting, and the ambient and ground temperatures. The principal dependent variables are the plant thermal output and flow, consumer supply and return pressures and temperatures, delivered heat, heat deficit, and pipe heat loss. The parameter set θ contains the network topology; pipe lengths, diameters and roughnesses; heat transfer parameters; component settings; and fixed boundary conditions.

The requested heat at demand connection i in scenario s was defined as

$$\dot{Q}_{req,i,s}(t) = \alpha_{H,s} \dot{Q}_{H,i}(t) + \alpha_{DHW,s} \dot{Q}_{DHW,i}(t) \quad (1)$$

where $\dot{Q}_{H,i}$ and $\dot{Q}_{DHW,i}$ are the space heating and domestic hot water components, respectively. The multipliers $(\alpha_{H,s}, \alpha_{DHW,s})$ were $(1, 0)$ for space heating, $(0, 1)$ for domestic hot water, $(1, 1)$ for the combined baseline and the two reduced-boundary cases, and $(1.2, 1.2)$ for high demand 120%.

The scenario input vector was

$$\mathbf{x}_s(t) = [\dot{Q}_{req,1,s}, \dots, \dot{Q}_{req,N_d,s}, T_{S,set,s}, \Delta p_{set,s}, T_a, T_g]^T \quad (2)$$

where $T_{S,set,s}$ is the plant supply-temperature setpoint; $\Delta p_{set,s}$ is the source differential-pressure setting; and T_a and T_g are the ambient and ground temperatures, respectively.

Before each simulation, the Python integration layer mapped the PLC tag identifiers to the corresponding Fluidit Heat input variables and applied a fixed validation sequence to the resulting input vector. The validation rules, unit mappings, and admissible engineering ranges were specified a priori in the Python configuration for this study and were applied automatically and consistently before each scenario execution. The implemented checks verified the presence of all mandatory variables, data-type compatibility,

successful unit conversion, compliance with the configured engineering ranges, and the validity of the OPC UA quality/status and timestamp fields. Failure of any mandatory check prevented the scenario from being executed, and therefore blocked result write-back; an error code and diagnostic status were returned to WinCC. No smoothing, interpolation, statistical outlier removal, or missing-value imputation was applied to the data used to produce the results reported in Section 3.

After successful validation, the Fluidit Heat model maps the validated input vector $\mathbf{x}$ and the model parameter vector θ to the thermohydraulic output vector $\mathbf{y}$:

$$\mathbf{y}_s(t) = \mathcal{M}_\theta(\mathbf{x}_s(t)) = [p_{S,i}, p_{R,i}, T_{S,i}, T_{R,i}, \dot{V}_\ell, v_\ell, \dot{Q}_{del,i}, \dot{Q}_{loss,\ell}]^T \quad (3)$$

where $p_{S,i}$ and $p_{R,i}$ are the supply and return pressures, respectively; $T_{S,i}$ and $T_{R,i}$ are the corresponding temperatures; $\dot{V}_\ell$ and v_ℓ are the pipe volume flow and velocity, respectively; $\dot{Q}_{del,i}$ is the delivered heat; and $\dot{Q}_{loss,\ell}$ is the pipe heat loss.

System-level requested heat, delivered heat, and heat deficit were evaluated using

$$\begin{aligned} \dot{Q}_{req,s} &= \sum_i \dot{Q}_{req,i,s}, & \dot{Q}_{del,s} &= \sum_i \dot{Q}_{del,i,s}, \\ \dot{Q}_{def,s} &= \sum_i \max(0, \dot{Q}_{req,i,s} - \dot{Q}_{del,i,s}), \end{aligned} \quad (4)$$

The deficit reported in Table 5 is the sum of the Fluidit Heat deficit result over all demand connections.

Table 5. Quantitative results of the six predefined operating scenarios.

Scenario	Requested Demand, kW	Delivered Heat, kW	Plant Output, kW	Plant Flow, L/s	Min. Consumer Δp , bar	Min. Supply T, °C	Heat Loss, kW	Deficit, kW
Space Heating	1867.45	1867.51	1875.01	9.692	4.000	94.57	7.503	0
Domestic Hot Water	502.33	502.39	510.09	2.637	4.000	93.24	7.697	0
Heating and DHW	2369.78	2369.84	2377.14	12.288	4.000	94.65	7.298	0
Low Supply Temperature 90 °C	2369.78	2369.83	2376.65	13.664	4.000	89.71	6.820	0
Low Differential Pressure 3 bar	2369.78	2369.82	2377.12	12.288	3.000	94.65	7.298	0
High Demand 120%	2843.73	2843.79	2850.80	14.737	4.000	94.71	6.996	0

The hydraulic service indicator was the consumer differential pressure and its network minimum:

$$\begin{aligned} \Delta p_{i,s}(t) &= p_{S,i,s}(t) - p_{R,i,s}(t), \\ \Delta p_{min,s}(t) &= \min\{\Delta p_{i,s}(t)\} \end{aligned} \quad (5)$$

A scenario satisfies the adopted hydraulic criterion when $\Delta p_{min,s} \geq \Delta p_{lim}$, with $\Delta p_{lim} = 3.5$ bar in the present study.

The network heat loss and the corresponding energy balance residual were calculated using

$$\begin{aligned} \dot{Q}_{loss,s} &= \sum_i (\dot{Q}_{loss,S,\ell,s} + \dot{Q}_{loss,R,\ell,s}), \\ \varepsilon_{E,s} &= \dot{Q}_{plant,s} - \dot{Q}_{del,s} - \dot{Q}_{loss,s} \end{aligned} \quad (6)$$

where $\dot{Q}_{loss,S,\ell,s}$ and $\dot{Q}_{loss,R,\ell,s}$ are the supply- and return-pipe heat losses, respectively. For the six reported scenarios, $|\varepsilon_{E,s}|$ was below 0.009 kW, confirming the numerical consistency of the extracted totals.

For physical interpretation, the plant thermal output can also be written as

$$\dot{Q}_{plant,s} = \rho(\bar{T}_s) c_p(\bar{T}_s) \dot{V}_{plant,s} (T_{s,plant,s} - T_{R,plant,s}) \quad (7)$$

where ρ and c_p are the temperature-dependent density and specific heat capacity of water, respectively. Table 5 uses the simulator-reported MainPlant power value; Equation (7) defines its thermodynamic interpretation and can be used as an independent consistency check.

The project was configured to use the Darcy–Weisbach friction model [41]. The pressure loss of pipe ℓ is represented as

$$\Delta p_\ell = \left(f_\ell \frac{L_\ell}{D_\ell} + \sum_j \zeta_{j,\ell} \right) \frac{\rho v_\ell^2}{2}, \quad \Delta p_{unit,\ell} = \frac{\Delta p_\ell}{L_\ell} \quad (8)$$

where f_ℓ is the Darcy friction factor; L_ℓ and D_ℓ are the pipe length and internal diameter, respectively; $\zeta_{j,\ell}$ denotes the local loss coefficients; ρ is the fluid density; and v_ℓ is the mean velocity. The parameterization used the 0.1 mm roughness and the pipe dimensions and heat transfer properties stored in the Fluidit Heat project [38].

Finally, the end-to-end duration of one SIL cycle is defined as

$$t_{cycle} = t_{read} + t_{map} + t_{sim} + t_{post} + t_{write} \quad (9)$$

where t_{read} is the OPC UA input acquisition time, t_{map} is the Python validation and mapping time, t_{sim} is the Fluidit Heat execution time, t_{post} is the result post-processing time, and t_{write} is the PLC write-back and read-back verification time. Each component and the end-to-end cycle duration were measured using a monotonic high-resolution timer over 10 repeated runs under identical test conditions.

2.4. Model Parameterization and Boundary Conditions

To improve traceability and reproducibility, the model inputs were classified according to their origin and role in the SIL workflow. The network topology and pipe routes were reconstructed from the available technical network scheme. The pipe dimensions, roughness, material, insulation, heat transfer coefficients, hydraulic loss settings, and numerical solver settings were obtained from the Fluidit Heat project attributes and configuration. Consumer heating and domestic hot water loads and the corresponding pressure references were obtained from the SCADA-derived dataset summarized in Table 6. Supply and return temperatures and climatic boundary conditions were taken from the operating or design inputs, whereas the reduced temperature, reduced pressure, and increased demand cases were defined by the authors as controlled scenario modifications. The complete parameter-to-source mapping and the implemented values are provided in Appendix A, Table A1.

Table 6. Field-derived heat load and pressure values for the five monitored consumers.

Consumer Identifier	Heating, Gcal/h	DHW, Gcal/h	Supply/Return Pressure, Bar
183 Kazybek Bi St	0.373059	0.141456	8.2/4.0
30 Isaev St	0.235181	0.06048	7.8/3.7
129 Chokin St	0.470968	0.100389	7.8/3.7
194 Aiteke Bi St	0.305275	0.07344	7.5/3.5
28 Isaeva St	0.221234	0.05616	7.8/3.7

No formal global sensitivity analysis or uncertainty propagation study was performed. The principal uncertain inputs are the pipe roughness, insulation and linear heat-transfer parameters, local resistance coefficients, and unmeasured consumer return

conditions. Consequently, the reported scenario outputs are conditional on the parameterization summarized in Table A1. Future work should vary these inputs over documented ranges and quantify their influences on the pressure, flow, temperature, heat loss, and delivered heat.

No optimization-based calibration against an independent dataset was performed in the present study. Accordingly, the procedure is described as model parameterization followed by convergence, constraint, and consistency checks. The baseline operational values were used to initialize boundary conditions and assess whether the resulting pressures and loads were consistent with the available reference values.

3. Simulation Results

Figure 8 shows the selected “TK-2-C3-1” section of the Almaty district heating network used to construct the Fluidit Heat model. The case study topology and operational data were provided by Almaty Heating Networks LLP.

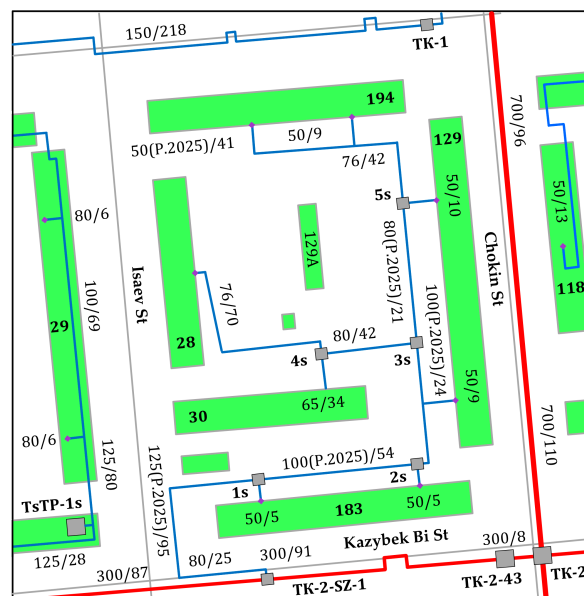


Figure 8. Diagram of a district heating network section for modeling in Fluidit Heat. Red and blue lines represent heating pipelines, green areas indicate buildings, and gray squares mark network nodes. Pipeline segments reaching the image boundaries continue beyond the displayed area.

Table 6 presents field-derived values from the historical SCADA archive of Almaty Heating Networks LLP. These values were entered into the TIA Portal project as SIL inputs; no measuring devices or sensors were connected to the testbed. The values were stored in the DB1 “OPC UA_Output” data block (Figure 7a).

Table 7 sets out the climatic and temperature parameters for the heating network in the selected area (Figure 8) for use in modeling in Fluidit Heat.

Table 7. Climatic and temperature parameters for heating network modeling.

Parameter	Value
Pipe installation year	2025
Supply water temperature	+95 °C
Return water temperature at consumer side	+47 °C
Ground temperature for Almaty city	+10 °C
Design outdoor air temperature	−20.1 °C

Figure 9 shows the two view modes in Fluidit Heat. The “Pipe Material” view mode displays the assigned pipe types and nominal diameters, while the “Network” view mode displays the network topology and the main hydraulic components.

Figure 10 presents two Fluidit Heat drawing states used to visualize the spatial distribution and direction of the heat carrier flow. The “Supply Mass Flow” view displays the maximum mass flow rate, whereas the “Supply Gross Flow” view represents the corresponding daily volumetric flow.



Figure 9. Fluidit Heat drawing states of the modeled district heating network: pipe types and nominal diameters displayed using the “Pipe Material” view (a) and network topology and principal components displayed using the “Network” view (b). Lines represent modeled pipes. Blue building symbols denote consumer connections, and the red plant symbol marks the heat source, whose power is shown in MW. Cyrillic labels indicate local street names on the basemap used by Fluidit Heat.



Figure 10. Fluidit Heat drawing states of the modeled network: maximum supply mass flows in kg/s displayed using the “Supply Mass Flow” view (a) and daily gross supply flows in m³/d displayed using the “Supply Gross Flow” view (b). Arrowheads indicate flow direction, and line colors

represent the flow ranges specified in the inset legends. Cyrillic labels indicate local street names on the basemap used by Fluidit Heat.

Figure 11 presents two auxiliary drawing states of the Fluidit Heat model. The “Available Free Power Capacity” view shows the spatial distribution of the average free power capacity along the network, whereas the “Scenario changes” view identifies unchanged, newly added, and modified junctions and pipes.



Figure 11. Fluidit Heat drawing states of the modeled district heating network: average free power capacities displayed using the “Available Free Power Capacity” view (a) and statuses of junctions and pipes displayed using the “Scenario changes” view (b). In (a), line colors indicate the capacity ranges specified in the inset legend; numerical values represent capacity thresholds in kW. In (b), green, yellow, and gray denote new, modified, and unchanged components, respectively. Point symbols represent junctions, lines represent pipes, and arrowheads indicate flow direction. Cyrillic labels indicate local street names on the basemap used by Fluidit Heat.

Six scenarios were executed to separate the effects of the load composition and selected boundary conditions. The space heating and domestic hot water scenarios isolate the two components of consumer demand. Heating and DHW represent the combined normal operating baseline. Low supply temperature of 90 °C and low differential pressure of 3 bar test thermal and hydraulic boundary reductions, respectively. High demand 120% applies a uniform 1.2 multiplier to both demand components. Detailed plots are presented for the baseline and 120% cases because they constitute a controlled one-factor comparison: the consumer load is changed while the principal temperature and pressure settings are retained. The remaining scenarios are summarized in Table 5 so that the behavior of the architecture under all implemented conditions is reported.

All six Fluidit Heat scenarios were evaluated over the same 24 h reporting window with a 15 min reporting interval (97 reporting instants). Table 5 reports the final reporting instant, at which the simulations had reached a stationary solution. Requested and delivered heat were summed over the eight modeled demand connections, which represent the five monitored consumer addresses listed in Table 6. Plant output and flow correspond to the MainPlant POWER and HEX_FLOW results, respectively. The minimum consumer differential pressure and supply temperature were calculated across all eight demand connections, whereas the total network heat loss was obtained by summing the supply- and return-pipe heat losses over the 18 modeled pipes.

The separate load-component scenarios yielded a plant thermal output of 1.875 MW and a plant flow rate of 9.692 L/s for space heating, compared with 0.510 MW and 2.637 L/s for domestic hot water. In the combined baseline scenario, the corresponding values were 2.377 MW and 12.288 L/s, while the minimum consumer differential pressure was 4.000 bar. Reducing the supply temperature setpoint from 95 to 90 °C maintained the delivered heat at approximately the requested level but increased the plant flow rate to 13.664 L/s (+11.20%) and reduced the minimum consumer supply temperature to 89.71 °C. Reducing the source differential-pressure setting to 3 bar resulted in a minimum consumer differential pressure of 3.000 bar, which is below the adopted 3.5 bar criterion. Therefore, this scenario was classified as hydraulically non-compliant, although the idealized simulation reported no consumer heat deficit. Increasing both demand components by 20% increased the plant thermal output and flow rate by 19.93% relative to the combined baseline scenario. The minimum consumer differential pressure remained at 4.000 bar under the prescribed source pressure boundary condition. Across all six scenarios, the calculated network heat loss ranged from 6.820 to 7.697 kW.

The combined heating and DHW scenario was selected as the baseline, and the high-demand 120% scenario was selected for detailed pairwise analysis because only the demand multiplier changed, whereas the source temperature and differential pressure settings remained fixed. This controlled comparison permits the changes in flow rate, velocity, pressure loss, and thermal output to be attributed directly to the imposed demand increase. The remaining four scenarios are reported in Table 5 as separate load component checks or prescribed thermal and hydraulic boundary condition tests.

Figure 12 presents the main plant thermal response together with the supply flow in Pipe-18. The plant thermal output and Pipe-18 flow increased by approximately 20%, while the plant supply and return temperatures remained nearly unchanged. The total plant flow is reported separately in Table 5.

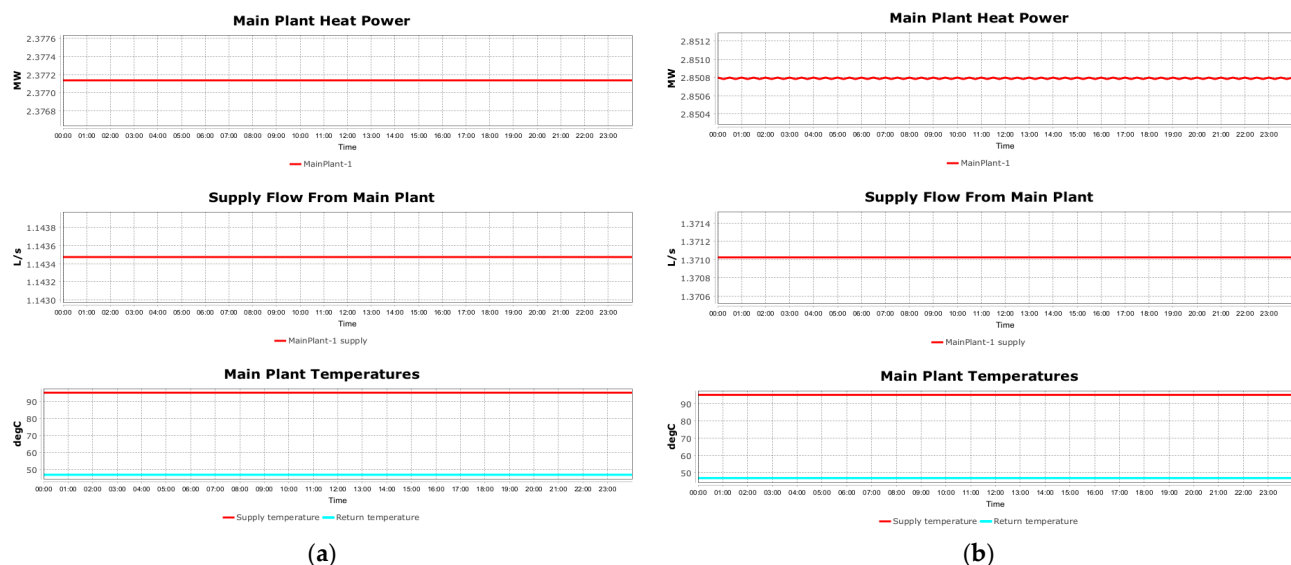


Figure 12. Time profiles of main plant thermal output, Pipe-18 supply flow, and plant supply and return temperatures for (a) the combined baseline scenario and (b) the high-demand 120% scenario. The total plant flow is reported in Table 5.

The field-derived values for the combined baseline scenario were taken from the SCADA dataset listed in Table 6 and were also used during model parameterization. Figure 13 is therefore retained solely as an implementation consistency illustration showing that the mapped pressure and thermal load variables were transferred, processed, and returned through the PLC–OPC UA–Python–Fluidit workflow without changes in their physical meaning or units. However, this does not constitute an independent validation of model accuracy.



Figure 13. Implementation consistency comparison of supply pressure, return pressure, differential pressure, and heat power for five monitored consumers: (a) field-derived baseline references transferred through the virtual PLC and corresponding Fluidit Heat outputs; (b) reference values and corresponding simulation outputs under the prescribed 120% demand scenario. The heat-demand values in (b) were obtained by multiplying the baseline demand by 1.2 and are not independent field measurements.

In the embedded legend of Figure 13, “Measured” denotes field-derived reference values loaded into the virtual PLC rather than simultaneous measurements collected during the SIL experiment. No predictive accuracy metrics were derived from this comparison. Independent validation will require a temporally separate operational dataset containing synchronized pressure, flow rate, and temperature measurements that were not used for model parameterization.

Figure 14 illustrates the hydraulic response of the selected route to increased heat demand. Under the 120% heat demand scenario, the flow rates and velocities increase, while the maximum unit pressure loss rises from approximately 1.3 to 1.9 bar/km.

The pressure distributions at the monitored consumer nodes are compared in Figure 15. Despite the increased hydraulic load, the differential pressure remains above the adopted minimum limit of 3.5 bar at all nodes in both scenarios, indicating that the modeled pressure requirements are satisfied.

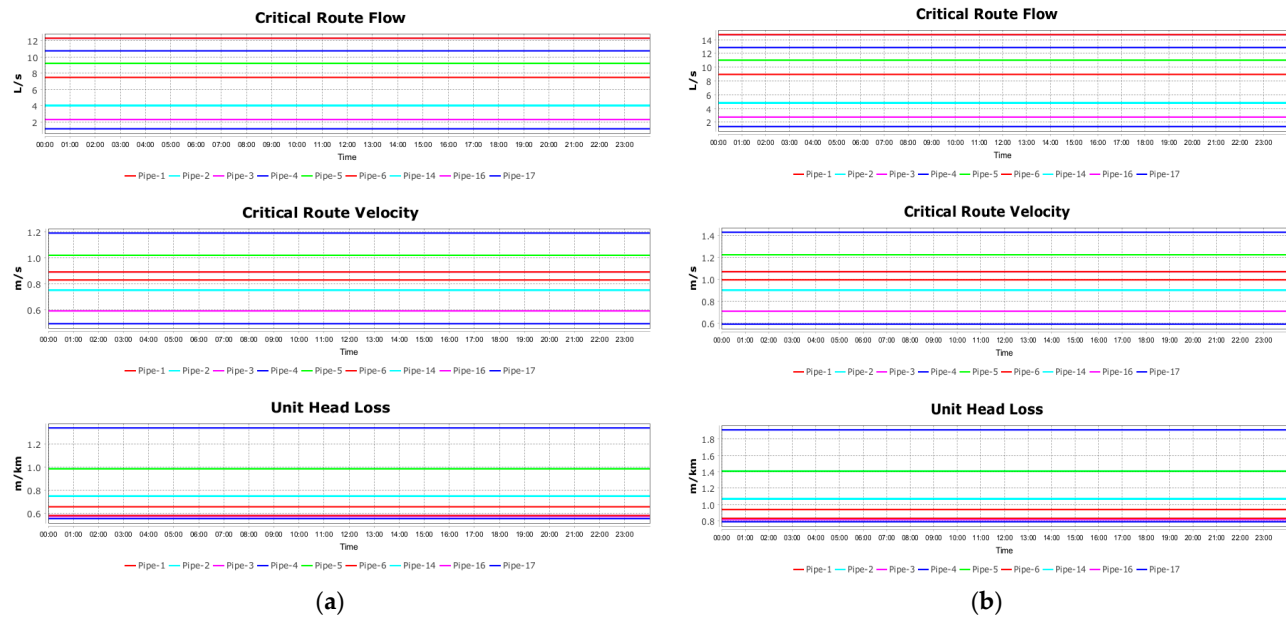


Figure 14. Time profiles of volumetric flow rate (L/s), flow velocity (m/s), and unit head loss (m/km) in the pipes along the critical route for the baseline (a) and 120% heat demand (b) scenarios. Pipe identifiers are provided in the legends.

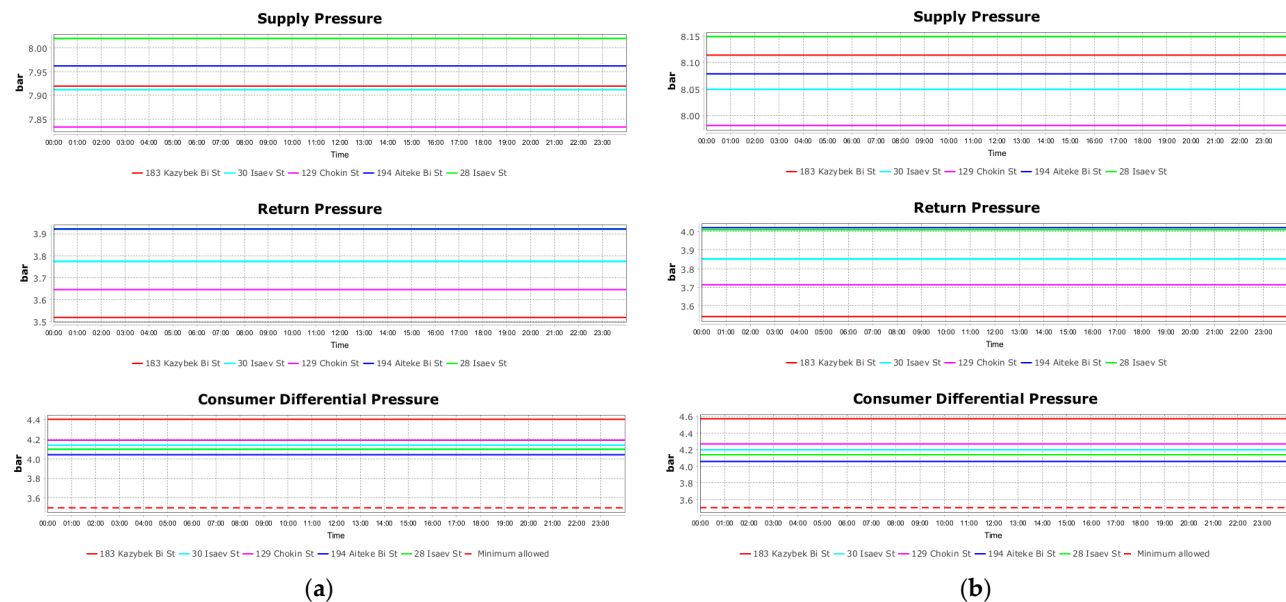


Figure 15. Time profiles of supply, return, and differential pressures (bar) at the monitored consumer nodes for the baseline (a) and 120% heat demand (b) scenarios. Consumer identifiers are provided in the legends. The dashed red line in the differential pressure plots indicates the minimum allowable differential pressure.

Figure 16 shows that the supply and return temperatures remain generally stable throughout the simulation period. The limited temperature variation between the main plant and consumer nodes indicates that the 120% heat demand is accommodated mainly by increased flow rather than by changing the supply temperature setpoint.



Figure 16. Time profiles of supply and return temperatures (°C) at the main plant and monitored consumer nodes for the baseline (a) and 120% heat demand (b) scenarios. The design supply and return temperatures are included as reference lines. Some curves and reference lines overlap at the displayed scale.

The delivered thermal power and consumer heat deficit are presented in Figure 17. Increasing the heat demand to 120% results in a proportional increase in delivered power at all consumer nodes, while the calculated heat deficit remains zero in both scenarios. The dashed line indicates the acceptable heat-deficit threshold.



Figure 17. Time profiles of delivered thermal power and consumer heat deficit (kW) at the monitored consumer nodes for the baseline (a) and 120% heat demand (b) scenarios. The dashed black line in the heat deficit plots indicates the acceptable deficit threshold. The deficit curves overlap at zero.

Figure 18 summarizes the system-level energy response. The plant thermal output increases from approximately 2.38 to 2.85 MW, consistent with the imposed 20% increase

in demand, whereas the total network heat loss remains close to 7 kW. The total plant flow is reported separately in Table 5.

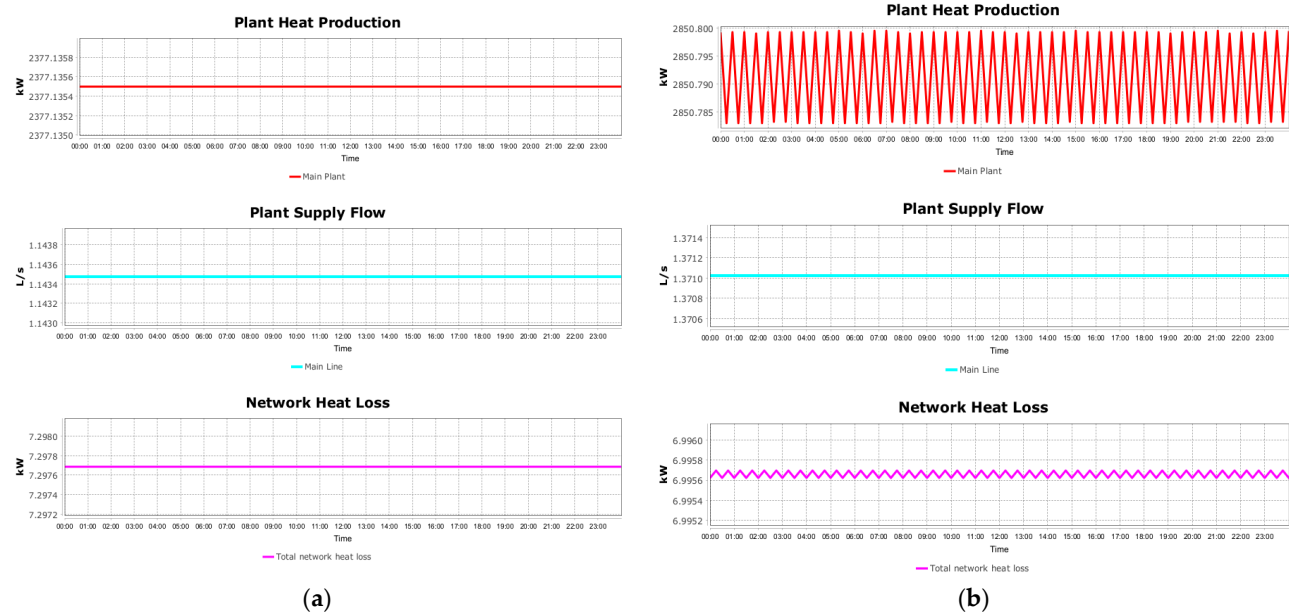


Figure 18. Time profiles of plant thermal power, Pipe-18 supply flow, and total network heat loss for the normal operating (a) and 120% heat demand (b) scenarios.

The consumer service quality indicators are compared in Figure 19. Positive differential-pressure margins, 100% demand satisfaction, and stable supply–return temperature differences are maintained at all monitored nodes under both operating scenarios.

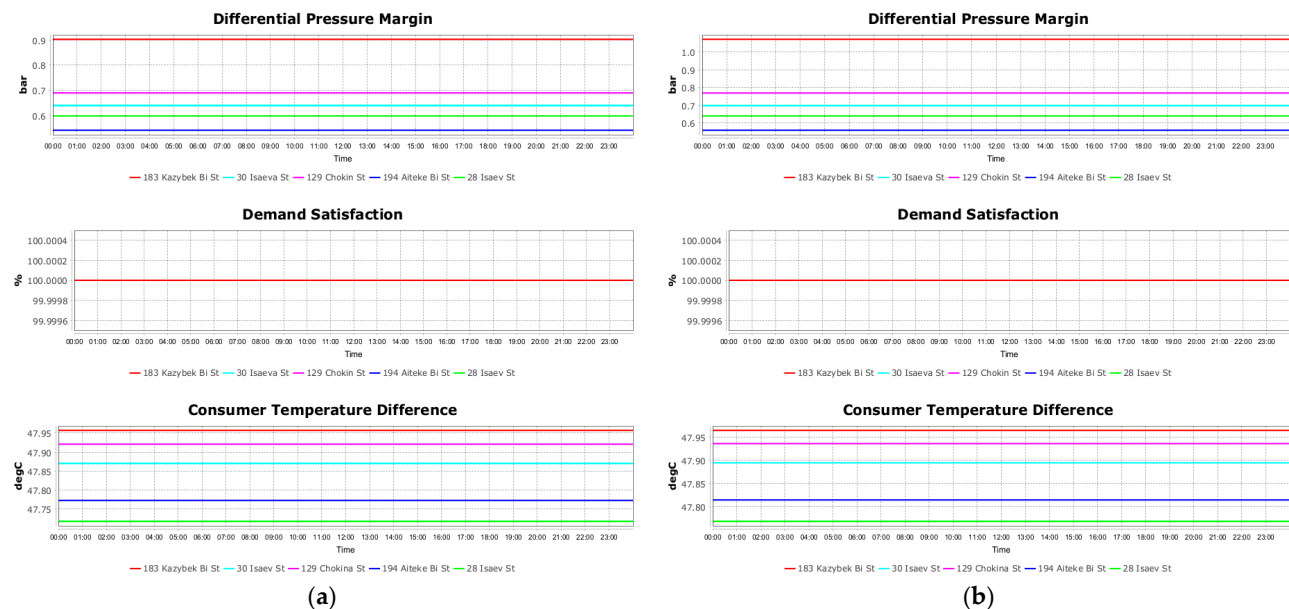


Figure 19. Time profiles of consumer service quality indicators at the monitored nodes: differential pressure margin (bar), heat demand satisfaction (%), and supply–return temperature difference (°C) for the baseline (a) and 120% heat demand (b) scenarios. The demand satisfaction curves overlap at 100%.

Figure 20 presents the distribution of heat losses along the critical route and the overall network heat balance. Although the absolute network heat loss remains nearly constant, its relative share decreases from approximately 0.307% to 0.245% because the delivered thermal power increases under the 120% demand scenario.

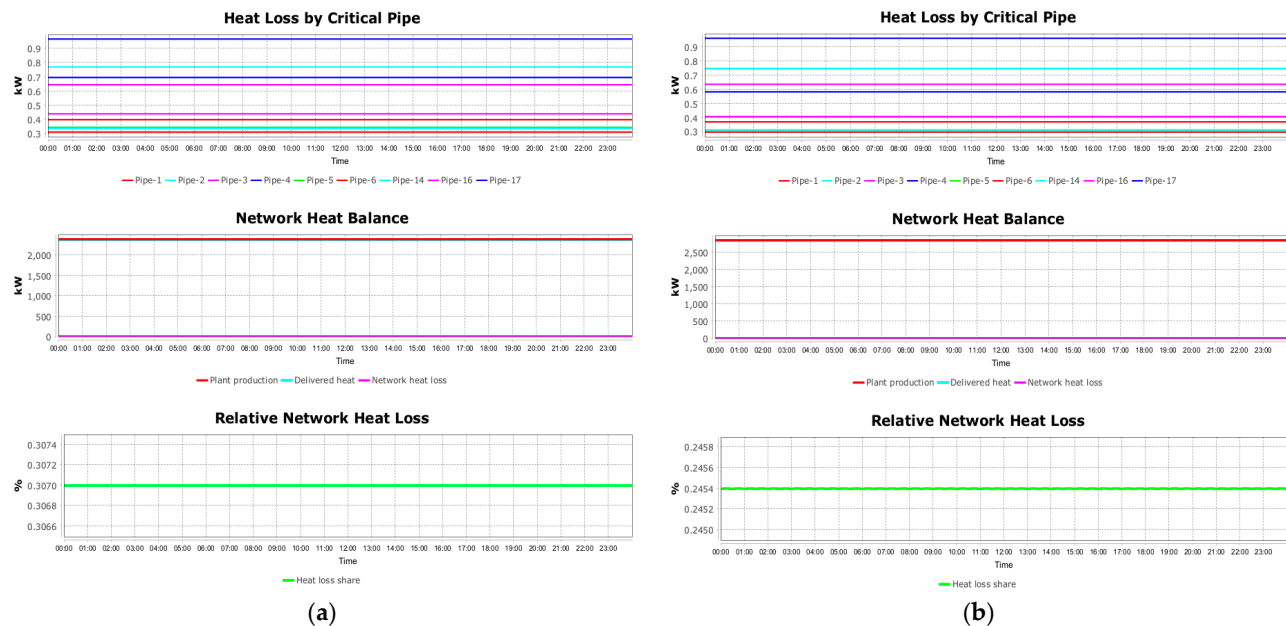
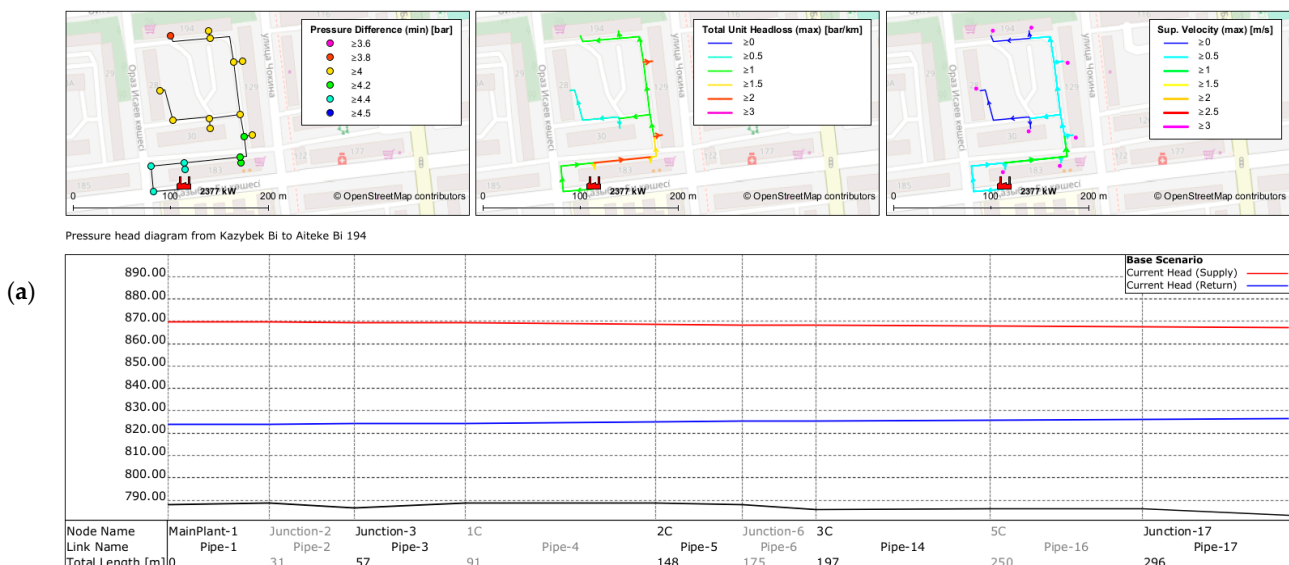


Figure 20. Time profiles of heat loss from pipes along the critical route (kW), network heat balance (kW), and relative network heat loss (%) for the baseline (a) and 120% heat demand (b) scenarios. The network heat balance includes plant thermal output, delivered heat, and total network heat loss.

The spatial hydraulic distributions under normal and increased heat demand conditions are compared in Figure 21. Increasing the demand to 120% shifts several pipeline sections into higher-velocity and higher-unit-pressure-loss ranges, while the minimum differential pressure remains above the adopted threshold.



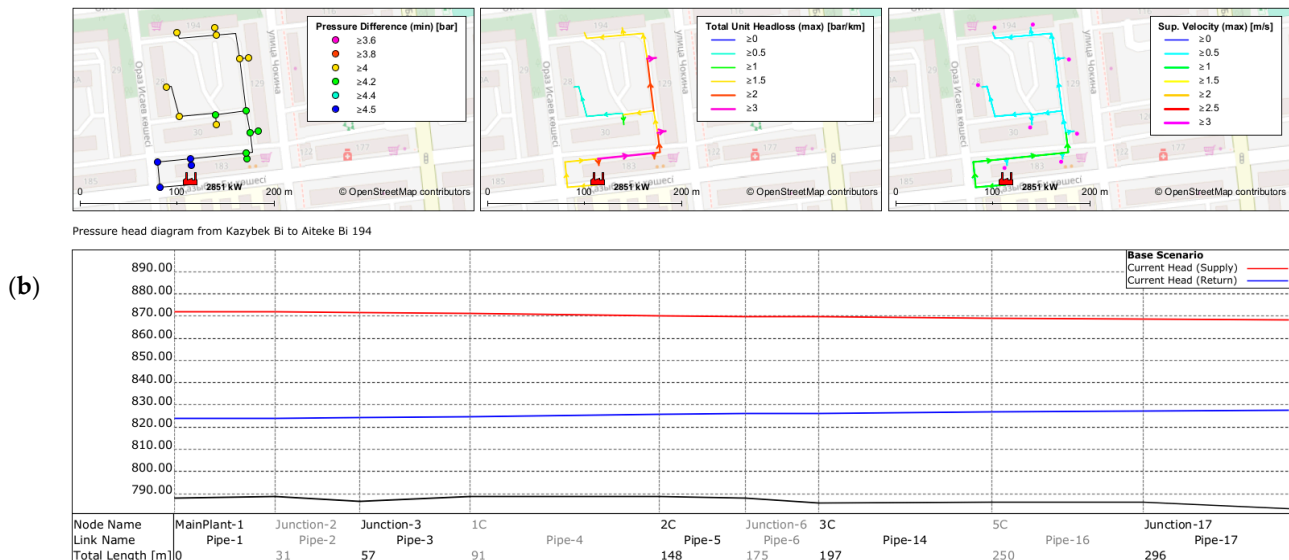


Figure 21. Comparison of the hydraulic state of the district heating network under the normal operating (a) and 120% heat demand (b) scenarios: spatial distributions of minimum differential pressure, maximum unit head loss, and maximum supply flow velocity, together with the supply and return pressure head profiles along the critical route. Cyrillic labels indicate local street names, on the basemap used by Fluidit Heat.

The combined scenario comparison is shown in Figure 22. The reduced supply temperature scenario produces the lowest network heat loss, the 3 bar differential pressure scenario reduces the available hydraulic margin, and the 120% demand scenario requires the highest plant thermal output. No heat deficit is observed in any of the investigated scenarios.

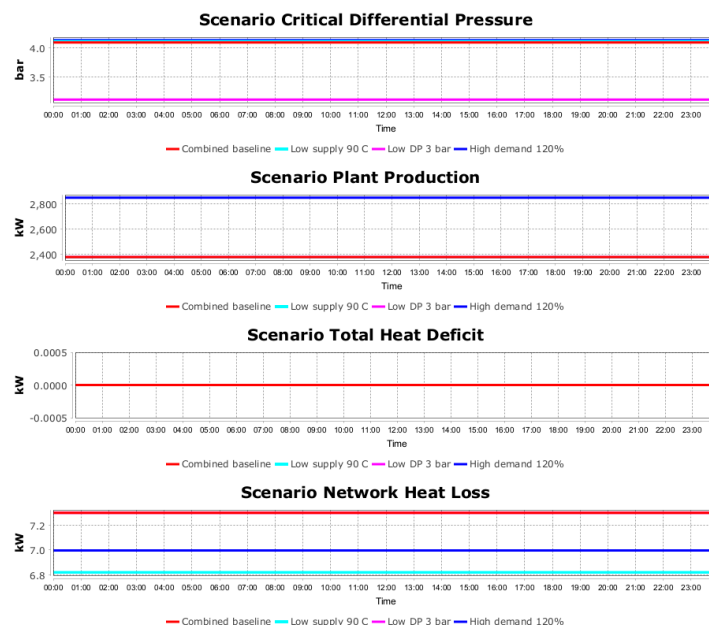


Figure 22. Comparison of critical differential pressure, plant thermal output, total heat deficit, and network heat loss for the baseline, low supply temperature (90 °C), low differential pressure (3 bar), and high-heat demand (120%) scenarios.

The principal thermohydraulic indicators obtained for the normal-load and increased-demand operating scenarios are summarized in Table 8.

Table 8. Comparison of key thermohydraulic indicators under the combined baseline and high-demand 120% scenarios.

Parameter	Normal Load 100%	Increased Load 120%	Change (Relative Unless a Unit is Shown)
Delivered heat, kW	2369.84	2843.79	+20.00%
Plant thermal output, kW	2377.14	2850.80	+19.93%
Plant flow rate, L/s	12.288	14.737	+19.93%
Maximum supply velocity, m/s	1.192	1.430	+19.92%
Maximum supply unit pressure loss, bar/km	1.338	1.912	+42.92%
Minimum consumer differential pressure, bar	4.000	4.000	0.000 bar
Maximum consumer differential pressure, bar	4.402	4.572	+3.86%
Plant supply temperature, °C	95.000	95.000	0 °C
Minimum consumer supply temperature, °C	94.654	94.715	+0.061 °C
Plant return temperature, °C	47.008	47.009	+0.001 °C
Network heat loss, kW	7.298	6.996	−4.14%
Relative network heat loss, %	0.307	0.245	−0.062 percentage points
Maximum consumer heat deficit, kW	0	0	0.000 kW

Percentage changes were calculated from the unrounded simulator outputs; displayed values are rounded.

The 20% increase in requested demand produced almost proportional increases in the delivered heat (+20.00%), plant thermal output (+19.93%), plant flow (+19.93%), and maximum supply velocity (+19.92%). In contrast, the maximum unit pressure loss increased by 42.92%, from 1.338 to 1.912 bar/km, demonstrating the nonlinear hydraulic penalty associated with the higher flow rate. The minimum consumer differential pressure remained at approximately 4.000 bar because the source differential pressure boundary was prescribed; this result should not be interpreted as evidence that the network is insensitive to increased demand. The decrease in absolute network heat loss from 7.298 to 6.996 kW is specific to the adopted model settings and boundary conditions. The corresponding reduction in relative heat loss from 0.307% to 0.245% is also influenced by the larger plant thermal output used as the denominator. The zero calculated heat deficit demonstrates feasibility under the prescribed scenarios but does not establish resilience to unmodeled field disturbances.

Figure 23 shows the WinCC Runtime interface developed to monitor and coordinate the experimental digital-twin simulation cycle. The upper panel displays the field-derived reference parameters stored in the PLC, whereas the lower panel presents the corresponding values calculated using Fluidit Heat. The interface also provides controls for initiating the simulation and transferring the calculated results back to the PLC, together with indicators of the execution status, calculation time, minimum differential pressure, maximum heat deficit, and network heat loss.

To statistically characterize the SIL cycle duration, the same SCADA-triggered scenario was executed 10 times under identical model, software, communication, and hardware configurations. The timer started when the Python service began processing the accepted SCADA request and stopped after the Fluidit Heat results had been written to the PLC and successfully read back. The component times were measured according to Equation (9). The results are presented in Table 9.

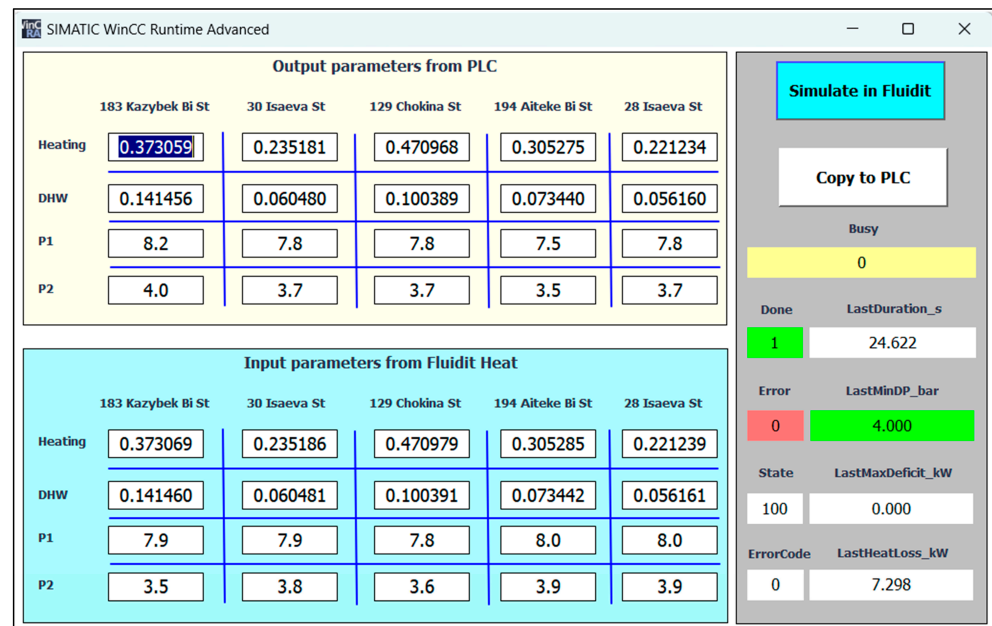


Figure 23. WinCC Runtime interface for supervising the SIL cycle. The pale yellow panel shows field-derived reference parameters read from the virtual PLC; the light blue panel shows Fluidit Heat results written back to the PLC. DHW denotes domestic hot water; P1 and P2 denote supply and return pressures. Yellow, green, and red status fields identify Busy, Done, and Error, respectively; their binary values indicate inactive (0) or active (1) states. The right-hand panel contains execution controls and diagnostic indicators.

Table 9. Component-wise execution times of the SIL cycle over 10 repeated runs.

Run	OPC UA Read $t_{\text{read}}, \text{s}$	Validation and Mapping t_{map}, s	Fluidit Simulation t_{sim}, s	Post-Processing $t_{\text{post}}, \text{s}$	PLC Write/Verify $t_{\text{write}}, \text{s}$	Total $t_{\text{cycle}}, \text{s}$
1	0.074	0.210	24.178	0.000073	0.145	24.608
2	0.066	0.147	23.241	0.000032	0.141	23.596
3	0.062	0.139	22.613	0.000037	0.139	22.954
4	0.066	0.123	23.465	0.000033	0.138	23.792
5	0.066	0.138	23.603	0.000025	0.145	23.951
6	0.067	0.145	22.092	0.000023	0.136	22.440
7	0.064	0.199	23.946	0.000032	0.139	24.348
8	0.063	0.151	22.128	0.000038	0.142	22.484
9	0.066	0.147	21.945	0.000031	0.138	22.296
10	0.064	0.139	24.274	0.000052	0.145	24.622
Mean $\pm$ SD	0.066 ± 0.003	0.154 ± 0.028	23.148 ± 0.893	0.000038 ± 0.000015	0.141 ± 0.003	23.509 ± 0.907

The results demonstrate stable SIL cycle execution across repeated runs. Fluidit simulation accounted for approximately 98.5% of the total duration, and therefore represented the dominant computational component. OPC UA communication, data validation and mapping, post-processing, and verified PLC write-back together accounted for only approximately 1.5% of the cycle duration. Thus, further performance improvements should primarily focus on model loading and Fluidit simulation rather than on the communication and data-processing stages.

4. Discussion

4.1. Deployment Methodology Case Study and Comparison with Alternative Approaches

The present work should be interpreted as a deployment methodology case study rather than as the development of a new thermohydraulic solver or communication protocol. Its contribution is a traceable implementation pattern that combines a virtual industrial PLC, WinCC, OPC UA, Python orchestration, and a specialized district heating simulator within one event-driven SIL workflow. The implemented architecture explicitly separates input and result data blocks, exposes execution and diagnostic states to the operator, and verifies the returned values through OPC UA read-back.

An alternative implementation could use pandapipes [29] as the thermohydraulic calculation engine. Its open-source and Python-native architecture would improve the solver transparency, customization, and reproducibility without requiring an external commercial simulation environment. However, the PLC/SCADA handshake, execution state management, tag mapping, and verified write-back demonstrated in the present study would still require a separate industrial integration layer.

TRNSYS–Python co-simulation [30] provides another alternative, particularly for dynamic energy-system analysis, design calculations, and control-oriented studies. In contrast, the present implementation focuses on event-driven bidirectional data exchange with a virtual S7-1500 PLC and WinCC interface, including request handling, status publication, and result write-back and read-back verifications. These approaches are therefore complementary rather than directly interchangeable. No head-to-head accuracy or execution time benchmark was performed, and the comparison is limited to architectural and functional characteristics.

4.2. Limitations of the SIL Study

Several limitations constrain the interpretation of the results. First, the physical district heating network and operational controller were not part of the loop; therefore, the study evaluated a SIL demonstrator rather than an operational digital twin. Second, the available field-derived values were used for parameterization and consistency assessment, and no independent out-of-sample dataset was available. Third, the presented scenarios use prescribed boundary conditions and do not reproduce sensor noise, communication faults, actuator dynamics, model drift, or operator intervention. Fourth, the current workflow demonstrates scenario triggering and result write-back but not automatic optimization, autonomous preferred-mode selection, or direct actuator control. Fifth, the timing experiment was limited to 10 repeated runs on one software and hardware configuration; broader benchmarking across different network sizes, operating systems, and computing platforms remains necessary. Finally, portability depends on access to the commercial Fluidit Heat environment and its available automation interface.

4.3. Challenges for Field Implementation

Real-world deployment requires a staged transition. The first stage is read-only shadow operation using synchronized field measurements and independent validation data. The second stage is online parameter updating and model drift monitoring under controlled cybersecurity and data governance procedures. The third stage is hardware- or process-in-the-loop testing that includes communication delay, PLC scan behavior, pump and valve dynamics, interlocks, and fail-safe responses. Only after these stages should advisory setpoints be evaluated under operator supervision. Automatic setpoint application would additionally require authority management, safety constraints, rollback logic, and formal acceptance by the district heating operator.

5. Conclusions and Future Work

In this study, a Software-in-the-Loop architecture connecting a virtual SIMATIC S7-1500 and WinCC environment, OPC UA communication, a Python integration service, and a Fluidit Heat thermohydraulic model was implemented and evaluated. The implementation demonstrated deterministic tag validation and mapping, execution of predefined operating scenarios, extraction and verification of model results, and their return to the virtual PLC for SCADA visualization. Six scenarios were evaluated. In the controlled baseline-to-120% demand comparison, the delivered heat increased from 2369.84 to 2843.79 kW, plant flow from 12.288 to 14.737 L/s, and maximum unit pressure loss from 1.338 to 1.912 bar/km. The minimum consumer differential pressure remained at approximately 4.000 bar under the prescribed source boundary, and no heat deficit was calculated. These findings characterize the simulated network section and should not be interpreted as independent field validation. The achieved result is a functional SIL proof of concept of a digital-twin-oriented architecture, not a continuously synchronized operational digital twin. Automatic optimization, autonomous preferred mode selection, and actuator-level control were not implemented.

Future work will focus on developing and training machine learning models implemented in Python to detect anomalous operating conditions in district heating networks, as well as on automating the execution of hydraulic and thermal simulations in Fluidit Heat. The envisaged hybrid framework will combine data-driven early anomaly detection with physics-based network simulation, enabling detected anomalies to be validated and their operational consequences to be forecast in near real time [27,42].

In addition, according to the government program [6], artificial intelligence is planned to be used for predictive asset maintenance, optimization of production cycles, quality management, and reduction in raw material losses. By 2029, digital twins are expected to be implemented in at least 60% of large industrial enterprises. The program also provides for 100% metering and digital monitoring in the housing and utilities sector in cities of republican significance and regional centers.

The Python source code, PLC/SCADA project, and Fluidit Heat model were made available on GitHub to ensure the reproducibility of the software workflow implemented in this study.

Author Contributions: Conceptualization, A.S. and M.O.; methodology, A.S., I.U. and I.S.; software, M.O. and L.A.; validation, A.S., I.U. and M.O.; formal analysis, A.S. and L.A.; investigation, Z.J.; resources, I.U. and L.A.; data curation, M.O.; writing—original draft preparation, A.S. and M.O.; writing—review and editing, I.U. and I.S.; visualization, Z.J. and L.A.; supervision, I.U., I.S. and M.O.; project administration, A.S. and I.U.; funding acquisition, I.U. and L.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan, grant number AP 25795155.

Data Availability Statement: The materials supporting this study, including the source code for the Python-based integration layer and the model and configuration files used for the PLC, SCADA, and Fluidit Heat environments, are publicly available in the Almaty_Digital_Twin GitHub repository at https://github.com/maxatorunbekov-afk/Almaty_Digital_Twin (accessed on 31 August 2026). Reproduction of the complete experimental workflow requires the commercial software packages and valid licenses specified in the repository README file.

Acknowledgments: The authors gratefully acknowledge Fluidit Oy (<https://fluidit.com>) for providing an academic license for Fluidit Heat and technical assistance, as well as Almaty Heating Networks LLP (<https://alts.kz>) for providing operational data.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

TIA Portal	Totally Integrated Automation Portal
OPC UA	Open Platform Communications Unified Architecture
SCADA	Supervisory Control and Data Acquisition
PN	PROFINET
PB	PROFIBUS
AI/ML	Artificial intelligence/machine learning
EU	European Union
CHP	Combined heat and power
DHW	Domestic hot water
PLC	Programmable logic controller
WinCC	Windows Control Center
Modbus	Modbus (serial communication protocol)
LPV	Linear parameter-varying
PLCSIM	Programmable Logic Controller Simulator
CSV	Comma-separated values
DB	Data block
LLP	Limited Liability Partnership
SIL	Software-in-the-Loop

Appendix A. Fluidit Heat Model Parameters and Boundary Conditions

Table A1. Provenance and values of the Fluidit Heat model parameters and boundary conditions.

Parameter	Provenance	Implemented Value or Configuration
Network topology	Fluidit Heat project reconstructed from the technical network scheme	1 source plant, 18 junctions, 18 pipe links, and 8 demand connections representing 5 monitored consumer locations
Pipe length	Fluidit project/export	3D length: 6.111–57.759 m
Pipe internal diameter	Fluidit pipe attributes	54.5–132.5 mm
Hydraulic formulation	Fluidit model configuration	Darcy–Weisbach, friction included
Pipe roughness	Fluidit pipe attributes	0.10 mm for all modeled pipes
Pipe classes	Fluidit material definitions	SP50/3, TP50/3, TP65/3, TP80/3, TP100/3, and TP125/3
Insulation	Fluidit material definitions	Polyurethane, $\lambda = 0.027 \text{ W/(m}\cdot\text{K)}$, insulation series 3
Linear heat transfer coefficient	Fluidit material definitions	0.102–0.180 $\text{W/(m}\cdot\text{K)}$
Interpipe heat transfer coefficient	Fluidit twin-pipe definitions	0.11–0.13 $\text{W/(m}\cdot\text{K)}$, zero for single-pipe elements
Local hydraulic loss settings	Fluidit component settings	Pipe minor loss coefficient 0, junction valve coefficient 1, main plant internal loss setting 1, not separately calibrated
Consumer loads	SCADA-derived data, Table 6	Heating 1.605717 Gcal/h; DHW 0.431925 Gcal/h, combined 2.037642 Gcal/h = 2369.778 kW
Consumer pressure references	SCADA-derived data, Table 6	Supply 7.5–8.2 bar, return 3.5–4.0 bar
Supply temperature	Operating/scenario boundary	95 °C baseline, 90 °C reduced temperature scenario
Consumer return temperature setting	Operating/design boundary	47 °C
Ground temperature	Climatic/design input	10 °C
Design outdoor temperature	Climatic/design input	−20.1 °C

Source differential pressure	Scenario boundary	4.0 bar baseline, 3.0 bar reduced pressure scenario
Demand multiplier	Scenario definition	1.0 baseline, 1.2 high-demand scenario
Calculation interval	Fluidit model configuration	Hydraulic, thermal quality, and reporting step: 900 s
Numerical settings	Fluidit model configuration	Tolerance 0.01, accuracy 0.005, maximum trials 500
Calibration status	Present study	No optimization-based calibration against an independent dataset; parameterization followed by convergence, constraint, and consistency checks

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