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Long-Life IOT Sensing and AI-Supported Analytics for Smart District Heating: Lessons from the Loli Pop-IOT Project

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Abstract

Smart district heating systems require reliable data, scalable sensing infrastructure, and intelligent analytics to support energy-efficient and low-carbon operation. However, many existing buildings and heating systems remain constrained by limited sensor coverage, heterogeneous infrastructure, poor data quality, fragmented building management systems, and insufficient digital readiness. This paper presents a practice-informed conceptual and deployment-oriented study of how long-life Internet of Things sensing platforms, local-first edge processing, and AI-supported analytics can support future smart district heating applications. Drawing on lessons from the LoLiPoP-IoT project, the paper proposes a layered architecture that connects energy-harvesting sensors, data acquisition, local preprocessing, AI-assisted interpretation, and human-centred decision support. The study does not claim a fully validated autonomous control system; instead, it identifies the technical and organisational conditions required before AI-enabled district heating optimisation can be reliably implemented. A key finding is that AI deployment in older buildings or buildings with multiple heating arrangements may be limited or delayed when reliable baseline data, interoperable interfaces, and validated datasets are unavailable. The paper concludes by outlining future research needs related to quantitative validation, digital twins, trustworthy AI, heating-and-cooling integration, cost-benefit assessment, and replication of the LoLiPoP-IoT architecture in operational energy environments.

Keywords: Smart District Heating, Artificial Intelligence, Long-Life IOT, Edge Analytics, Energy Harvesting, Building Energy Systems, Digital Energy Infrastructure.

Introduction

Urban energy systems are under increasing pressure to reduce greenhouse gas emissions while maintaining reliability, affordability, and user comfort. In Europe, space heating remains a major component of final energy demand, and district heating can play an important role in the transition toward low-carbon and resource-efficient thermal-energy systems [1-4]. Modern district heating networks can integrate multiple heat sources, including renewable energy, recovered waste heat, and thermal storage. However, the operational performance of district heating systems is often limited by incomplete monitoring, legacy control strategies, fragmented building management systems, and insufficient real-time data from end-use environments [3-5]. Digitalisation, artificial intelligence (AI), Internet of Things (IoT) sensing, and edge analytics create new opportunities for improving the monitoring and operation of district-heating-related building environments [3-6]. AI methods can support demand forecasting, anomaly detection, heat-production planning, predictive maintenance, and user-centred decision support [5-10]. However, their practical deployment depends on the availability of reliable, continuous, and context-rich data. In many existing buildings, such data are difficult to obtain because sensor coverage is limited, maintenance costs are high, communication infrastructure is fragmented, and heating systems are not always digitally integrated [11,12]. The LoLiPoP-IoT project provides a relevant basis for examining this challenge because it focuses on long-life, energy-harvesting IoT platforms designed for durable sensing and low-maintenance deployment [13-17]. In the context of smart district heating, such sensing platforms may help address one of the main barriers to AI deployment: the absence of scalable and sustainable data infrastructure at building level.

This paper makes four contributions:

- It proposes a deployment-oriented architecture for connecting long-life IoT sensing, local-first data processing, AI-supported interpretation, and human-centred decision support in smart district heating applications.
- It identifies the practical data and infrastructure requirements that must be satisfied before AI methods can be applied reliably in district-heating-related building environments.
- It reports lessons from LoLiPoP-IoT project experience concerning sensing continuity, data quality, interoperability, stakeholder acceptance, privacy, cybersecurity, and scalability.
- It defines future validation needs, including demand-forecasting accuracy, energy and emission impacts, anomaly-detection performance, thermal-comfort outcomes, cost-

benefit assessment, and replication across different building types and climatic conditions.

This paper is positioned as a practice-informed Short Communication and deployment-oriented conceptual study. It does not present a fully validated autonomous district heating control system. Instead, it synthesises LoLiPoP-IoT project experience and relevant literature to identify the sensing, data-quality, AI-readiness, interoperability, validation, governance, and replication conditions required before AI-enabled district heating optimisation can be implemented reliably. The novelty of this paper lies in its deployment-oriented treatment of AI-enabled smart district heating. Rather than reviewing AI methods in energy systems in general, the paper focuses on the practical preconditions that determine whether such methods can be used in real building and district-heating environments. Specifically, it links long-life energy-harvesting IoT sensing, local-first edge processing, AI-supported interpretation, and human-centred decision support into one architectural framework derived from LoLiPoP-IoT project experience. This perspective contributes to the state of the art by shifting attention from algorithmic potential alone to sensing continuity, data quality, interoperability, validation, privacy, cybersecurity, stakeholder readiness, and replication requirements.

Background and Related Work

Smart District Heating Systems and Digitalization Trends

Smart district heating systems are increasingly associated with 4GDH (fourth-generation district heating) principles, including low-temperature operation, integration of renewable and recovered heat sources, improved monitoring, demand-side flexibility, and more efficient thermal-energy distribution [1,3,4]. District heating is also recognised as an important element of urban decarbonisation strategies, particularly where heat networks can integrate waste heat, renewable energy, and flexible demand-side resources [1-3]. Digitalisation enables more detailed monitoring, predictive control, and integration of distributed energy resources [2-4]. However, many existing heating systems and building-level infrastructures remain only partially digitised. Limited sensor coverage, legacy building management systems, fragmented data platforms, and insufficient interoperability continue to restrict the practical use of data-driven optimisation [3,11,12]. Persistent sensing solutions with low maintenance requirements can help address this barrier by improving the continuity, resolution, and reliability of building-level thermal and comfort data [13,15-17].

Artificial Intelligence in District Heating and Building Energy Systems

Artificial intelligence has been increasingly investigated in building and energy systems for demand forecasting, operational optimisation, anomaly detection, predictive maintenance, and decision support [3,5,6]. In district heating applications, machine learning models may support heat-demand forecasting, supply-temperature planning, fault detection, model predictive control, and the integration of renewable or recovered heat sources [5,7-10]. However, the practical deployment of AI in district-heating-related building environments remains challenging. AI models require reliable historical data, sufficient sensor coverage, clear operational labels, and validation against baseline methods [5,6]. In existing buildings, these requirements are often difficult to meet because heating systems may be fragmented, building management systems may be proprietary, and indoor environmental data may be Incomplete or inconsistent [11,12]. Therefore, the contribution of long-life IoT sensing is not only to collect more data, but also to create the continuous and context-rich data foundation required for reliable AI-supported analytics [13,15-17].

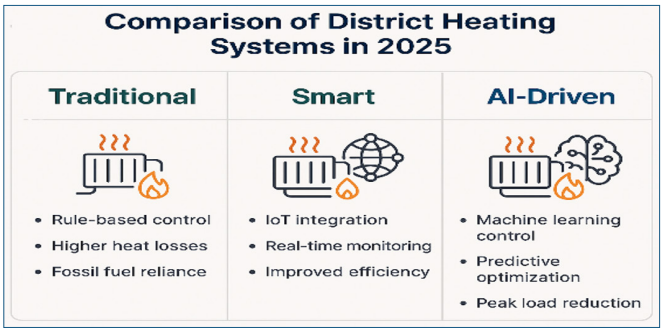


Figure 1: Comparison of District Heating Systems.

Long-Life IoT Sensing and Edge Analytics

Long-life IoT sensing platforms can address part of this challenge by enabling continuous monitoring with reduced maintenance requirements. Energy-harvesting sensors and low-power communication can support deployments where wired power supply or frequent battery replacement is impractical [6,18-20]. Edge analytics can further improve privacy, reduce latency, and enable local preprocessing before data are transferred to cloud or operator-facing systems [6,19,20]. For district-heating-related applications, these features are relevant because indoor thermal conditions, occupancy-related patterns, and comfort indicators are often distributed across many building zones [21,22].

Research Gap

Existing studies often focus either on AI algorithms for energy optimisation or on district heating digitalisation at the system level [3-5,7-10]. Less attention has been given to the deployment conditions required to make AI analytics reliable in building-level district-heating contexts, including sensing continuity, data quality, interoperability, privacy, cybersecurity, and user acceptance [11,22]. The specific gap addressed in this paper is the lack of practice-informed guidance on how long-life IoT sensing, local-first processing, and AI-supported interpretation can be combined into a replicable architecture for future smart district heating applications [13-17].

Architecture of AI-Enabled Smart District Heating

Layered System Architecture

The architecture presented in this section is a proposed deployment-oriented reference architecture derived from LoLiPoP-IoT project experience. It should not be interpreted as a fully validated autonomous district heating control system. Instead, it identifies the functional layers required to connect long-life sensing infrastructure with future AI-supported district heating analytics and operator decision support. The proposed architecture consists of five interconnected layers:

- **Sensing Layer:** LoLiPoP-IoT sensor platforms deployed in indoor building environments measure variables relevant to heating operation and comfort, such as temperature, relative humidity (RH%), CO_2 concentration, and other available environmental or system indicators. The sensing layer is based on ultra-low-power and energy-harvesting technologies to support long-term deployment with reduced maintenance needs [13-17].
- **Data Acquisition Layer:** Sensor data are transmitted using

lightweight communication protocols, such as MQTT, to support efficient ingestion, interoperability, and integration with local or cloud-based data platforms.

- **Local-First Processing Layer:** Edge processing pipelines normalize, validate, and preprocess incoming data streams. Local processing improves privacy and reduces latency [6,19,20].
- **AI Intelligence Layer:** Machine learning models may support forecasting, anomaly detection, classification, or optimisation when sufficient validated data are available [5-10]. LLM-assisted analytics should be limited to human-readable explanation and decision support unless the outputs are independently validated and linked to measured data.
- **User Interface Layer:** Operators and other stakeholders will receive readable analytics outputs in the form of dashboards and visualization tooling.

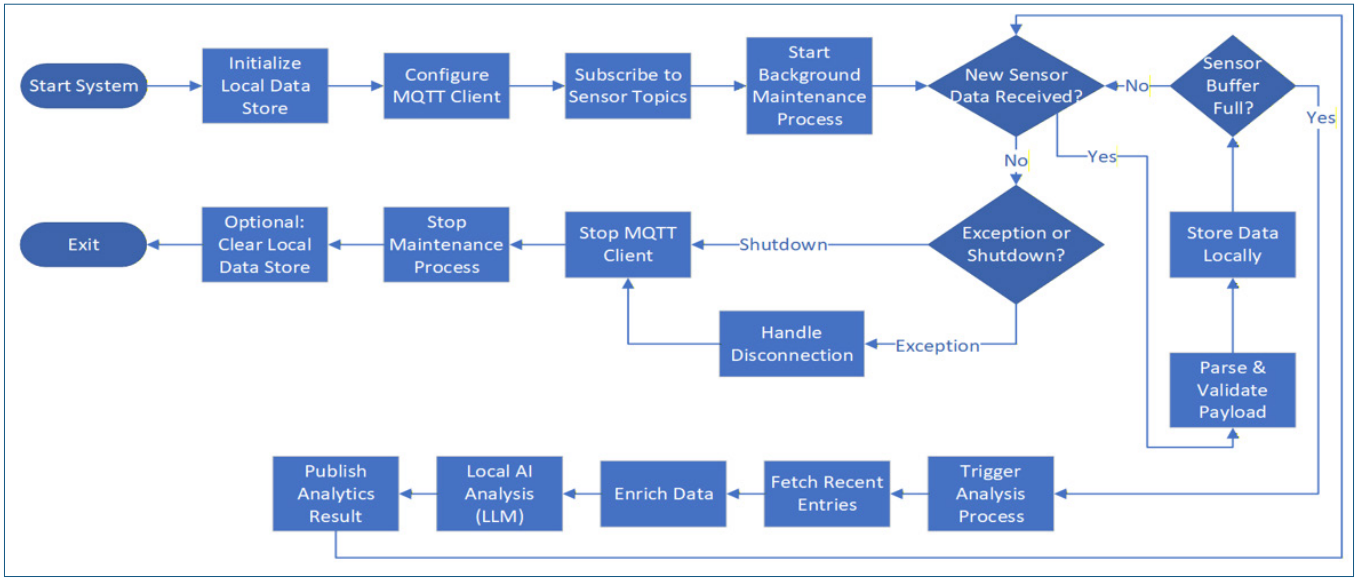


Figure 2: Local-First AI-IoT Architecture Derived from LoLiPoP Deployments, Integrating Long-Life Sensing, Edge Processing, LLM-Assisted Analytics, and Operational Decision Pipelines.

AI Processing Pipeline Derived from LoLiPoP-IoT Experience

The LoLiPoP-IoT deployment approach follows a local-first data-processing logic. Sensor data are collected from distributed IoT nodes, transmitted through lightweight communication protocols, stored in structured databases, and pre-processed before interpretation. The preprocessing stage should include timestamp alignment, missing-data detection, plausibility checks, unit harmonisation, and metadata validation. In the proposed AI-supported pipeline, deterministic rules and statistical checks should be used as the first layer of anomaly detection. Machine learning models may then be applied for forecasting, classification, or anomaly detection when sufficient labelled or validated historical data are available [5-10]. LLM-supported analytics should be limited to human-readable interpretation, reporting, and explanation of detected patterns unless their outputs are independently validated. LLM-generated interpretations must not be used for autonomous control decisions without safeguards, expert review, and traceability to measured sensor data.

Comparison with Traditional District Heating Control

Table 1: It Conceptual and Does Not Represent Measured Performance from the current LoLiPoP-IoT Deployment. It Summarises the Expected Shift from Static, Reactive, and Manually Tuned Approaches Toward Sensing-Supported, Analytics-Informed, and Operator-Facing Decision Support.

Aspect	Traditional Systems	AI-Enabled (LoLiPoP-based)
Control strategy	Static rules	Adaptive ML models
Data resolution	Limited sensors	High-resolution persistent sensing
Maintenance	Reactive	Predictive analytics
Optimization	Manual tuning	Automated continuous optimization
User interaction	Minimal	Interactive dashboards

AI Applications in Smart District Heating Platform

The applications described in this section represent potential uses of AI-enabled analytics in smart district heating. They should be interpreted as future application pathways rather than validated performance outcomes of the current LoLiPoP-IoT deployment. Each application requires appropriate datasets, baseline comparison, model validation, and operational testing before performance improvements can be claimed [5-10].

Demand Forecasting

Machine learning models can support short-term and long-term heat-demand forecasting by combining historical heat-use data, indoor environmental measurements, weather data, calendar information, and occupancy-related indicators [7-9]. In future validation, forecasting performance should be compared against baseline methods using metrics such as mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Without such evaluation, demand forecasting should be presented as a potential application rather than a demonstrated result.

Operational Optimization

AI-supported optimisation may assist supply-temperature planning, heat-distribution scheduling, thermostatic radiator valve (TRV) operation, and energy-source selection [5,10]. However, adaptive or reinforcement-learning-based control requires extensive training data, safe testing environments, baseline comparison, and validation before deployment in operational heating systems. In safety-critical energy contexts, AI recommendations should initially be used as decision support for operators rather than as autonomous control actions. Future validation should assess whether AI-supported optimisation can reduce thermal losses, improve comfort, lower peak demand, or support more efficient heat-production planning. This is an AI-enabled smart district heating system (DHS) diagram.

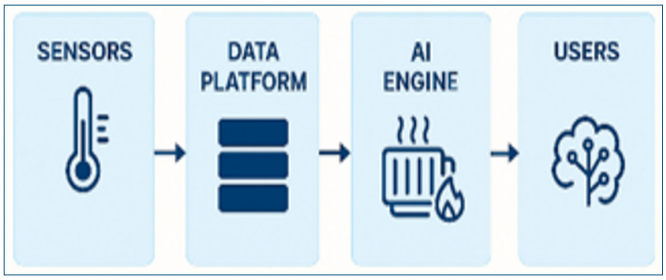


Figure 3: provides A Simplified Conceptual Representation of the AI-Enabled Smart District Heating Workflow, Linking Sensors, Data Platforms, AI Analytics, and End-User or Operator Interaction.

Fault Detection and Predictive Maintenance

AI techniques also provide the possibility to support system reliability through fault detection and predictive maintenance. Leak detection: A cold air leak can be detected by abnormal patterns of temperature, pressure, or flow data. Machine learning models trained on historical sensor data can detect the problem much earlier than classical methods of monitoring do. This reduces heat losses and can save the infrastructure from further damage. Equipment Failure Prediction: Predictive maintenance models may be able to detect early warning indicators of equipment failure, for example, TRV inefficiency or sensor failure early on. AI-based maintenance can significantly increase asset lifetime and eliminate unforeseen downtime, confirmed in smart energy systems analyses. The availability of continuous data streams over a period of several years at every LoLiPoP-IoT sensor platform also validates these methods to allow for continuous monitoring with minimal maintenance burden. The methodologies for anomaly detection implemented on the sensor data streams detect abnormal patterns in equipment degradation or leaks. Additionally, devices are suitable for long-term monitoring and lifecycle-based maintenance approaches to ensure that they are in place.

User Engagement and Demand Response

AI-supported analytics may also improve user engagement and demand response by making energy consumption, indoor conditions, and comfort parameters more visible to building users and facility managers [4,6,21,22]. Interpretable dashboards and recommendations can support more informed decisions about energy use while maintaining comfort. However, user-facing recommendations should be designed carefully to avoid privacy risks, unclear responsibility, or overreliance on automated interpretation. Fine-grained indoor sensing can provide a useful basis for personalised and adaptive services, but such services require transparent data governance and clear communication with users.

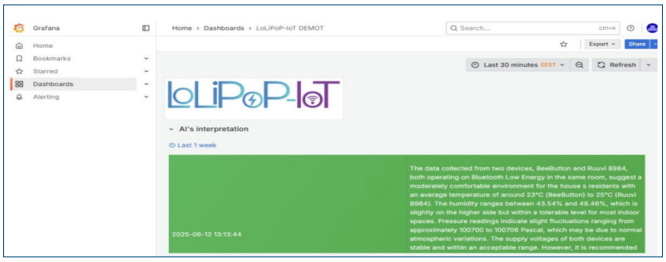


Figure 4: Screenshot Shows a live demonstration interface used to present sensor data and AI-generated interpretations in a human-readable form. The figure should be interpreted as an example of decision-support visualisation rather than validated evidence of autonomous control performance.

Table 2: Summarises Potential Application Areas and Expected Benefits. These Benefits Should be Treated as Future Validation Targets rather than Measured Outcomes from the Current Pilot.

AI Application	Description	Operational Benefits
Demand Forecasting	Predicts short-term and long-term heat demand using ML models	Optimized production planning, reduced energy waste
Predictive Maintenance	Detects anomalies and predicts equipment failures	Minimizes downtime, lowers maintenance costs
Dynamic Load Balancing	Adjusts heat distribution in real time based on demand	Reduces peak loads, improves network stability
Energy Source Optimization	Chooses optimal mix of renewables, waste heat, and storage	Cuts carbon emissions, maximizes renewable usage

Reinforcement Learning Control	Learns optimal control strategies for pumps and valves	Enhances efficiency, reduces operational costs
Digital Twin Simulation	Creates virtual models of the heating network	Enables scenario testing, improves planning

Methodological Approach

Our research is grounded in qualitative and conceptual approaches that can be utilized within interdisciplinary energy systems research. There are three interrelated components in the methodological framework.

- **Literature Synthesis Methodology:** The present study conducted a structured literature review on district heating systems, artificial intelligence in energy systems, and building energy analytics. The fundamental literature features the original work on 4GDH, AI applications in smart energy systems, and data-driven energy forecasting studies. This research paves the theoretical foundation for the proposed framework. A targeted literature synthesis on smart district heating, AI in building energy systems, energy-harvesting IoT, edge analytics, and digital energy infrastructure.
- **Development of the Conceptual Framework:** A conceptual system-level model of the AI-enabled smart district heating system was proposed based on the literature review. Such an architecture integrates sensing infrastructure, data platforms, AI intelligence, and operational decision-making, similar to the smart energy system design best practices currently in application. Architecture development based on the functional requirements observed in LoLiPoP-IoT deployment activities.
- **Expert Insights and LoLiPoP-IoT Project Experience:** This paper draws upon literature experiences include observations of pilot deployment, interaction with project consortium partners, and practical experiences about sensor deployment, data gathering, and stakeholder engagement. This practice-driven view enhances the study's value and links theoretical insights to practical implementation problems. Critical reflection on pilot implementation constraints, including data quality, interoperability, sensing continuity, stakeholder acceptance, privacy, and scalability.

Results and Insights from Lolipop-IOT Pilots

The feasibility for the long-term sensing deployment with the help of energy-harvesting platforms was verified by pilot running in public building environment. Continued monitoring identified temporal variation of keeping heating timing with real occupancy, hinting AI-optimized optimization possibilities. Safe processing was made possible through local-first data pipelines and LLM-guided analytics deepened understanding of sensor data for stakeholders.

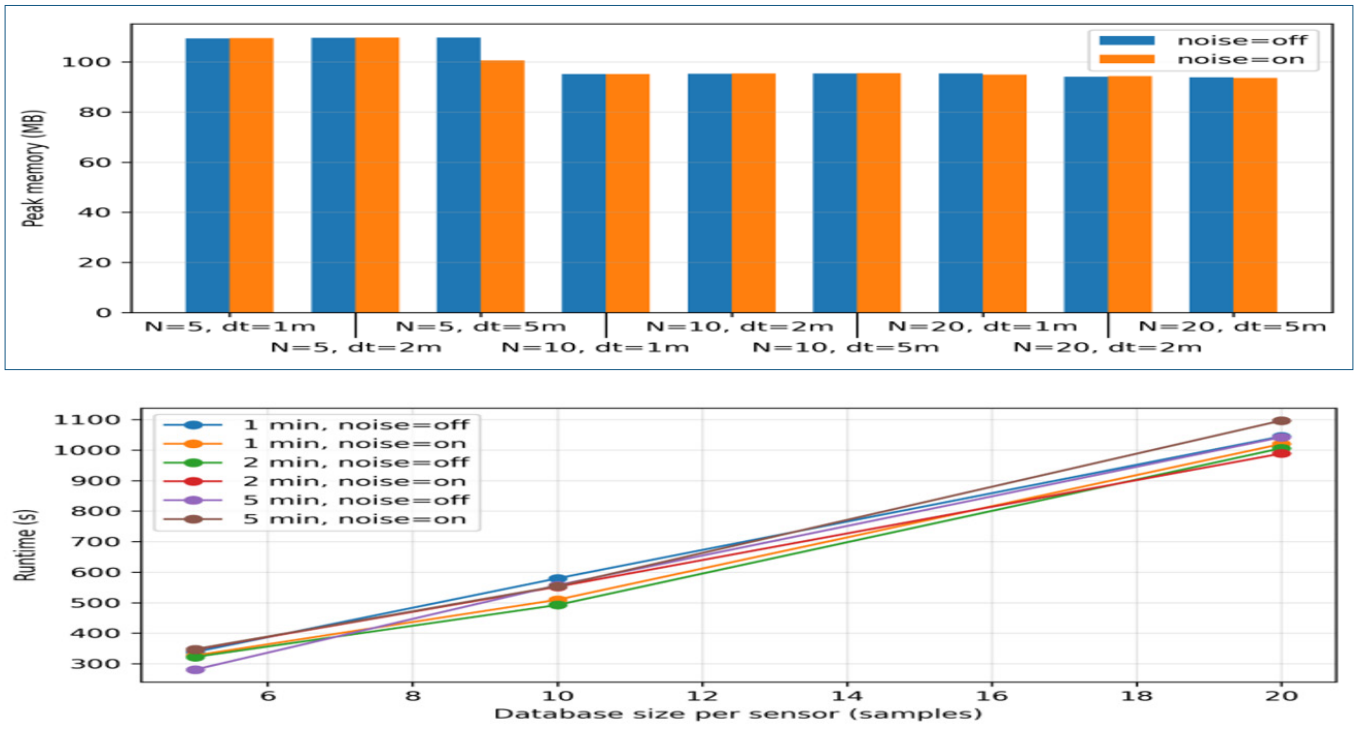


Figure 5: Computational Resource Profile of the Local-First Analytics Prototype Under Test Conditions. The Figure Should be Interpreted as Illustrative Unless The Dataset, Variables, Computational Environment, Number of Repetitions, and Testing Procedure are Fully Described in the Methodology.



Figure 6: Conceptual Summary of Potential AI-Supported Benefits in Smart District Heating. The Figure does not Represent Measured Performance Outcomes from the Current Pilot.

Discussion

The findings suggest that AI-enabled smart district heating should be understood as a socio-technical transition rather than a purely algorithmic upgrade. Long-life IoT sensing can improve data availability, but AI-based optimisation is only reliable when sensor data are sufficiently complete, calibrated, interoperable, and representative of building operation [11-13,15-17]. In older buildings or buildings with multiple heating systems, the absence of reliable baseline data may limit or delay AI deployment. This is an important negative finding: digitalisation readiness is a prerequisite for trustworthy AI use in district heating.

A further consideration is the sustainability trade-off of AI itself. While AI-supported analytics may contribute to reduced heat losses, better demand forecasting, and improved operational planning, data storage, model training, and digital infrastructure also consume energy and material resources [6,19,20]. Future assessments should therefore compare expected energy savings and fossil-fuel reduction against the environmental cost of additional sensing, communication, computation, and data-centre use. Ethical and legal considerations are also central, particularly when indoor environmental data may indirectly reveal occupancy patterns or user behaviour [11,12,21,22]. Privacy-by-design, transparent communication, cybersecurity safeguards, and clear data-governance agreements should therefore be treated as core requirements rather than optional additions.

The practical implication is that replication of the LoLiPoP-IoT architecture in other district-heating contexts should begin with an AI-readiness assessment rather than immediate model deployment. Future sites should first verify sensor coverage, data availability, metadata quality, communication reliability, interoperability with existing building or energy management systems, privacy requirements, cybersecurity controls, and the availability of baseline energy or comfort data. Only after these conditions are satisfied should AI models be trained, validated, and compared with conventional monitoring or control approaches.

Challenges and Limitations

Although AI-supported analytics may contribute to improved district heating operation, heat-demand forecasting, heat-production planning, and energy-source selection, several barriers limit large-scale implementation. The lessons from LoLiPoP-IoT and related smart energy deployment contexts show that these barriers are not only technical but also organisational, economic, ethical, legal, and infrastructural.

Technical Challenges

- **Data Quality:** AI based optimization relies heavily on a reliable, contextually aware, and high-quality data. From actual sensors, they are usually affected by missing data, communication interruptions, calibration drift, or inconsistent metadata [11,12]. Testing data cleaning (or "real-time cleaning") on installation conditions and building usage trends was extremely lengthy in LoLiPoP pilot deployment that was delayed by environmental and building usage differences. This emphasises the demand for standardised data quality management procedures, automation validation pipelines and lifecycle monitoring of sensing devices to ensure the continued maintenance and use of AI-based services.
- **Robustness of Model:** ML models fitted to specific environments may fail in generalizing to other scenarios. Variations in building style, network layout, user activity and climatic conditions can also have a major effect on the model. From LoLiPoP partners' experience, AI models often need to be retrained or altered at new sites. This constrains scalability, and emphasizes the importance of strong model design, adaptive learning strategies, and clear validation systems for trusted implementation in safety-critical energy systems [5,6].
- **Interoperability:** District heating systems are generally non-overall structures comprising mixed systems, legacy hardware system, proprietary control system and fragmented digital systems. Adaptation of LoLiPoP sensors to already established building management and energy management systems frequently demanded tailored interfaces. The lack of common data standards, APIs, and interoperability frameworks remains one of the key technical blocks to scaling of AI-fueled district heating technologies from organization to organization and regions [11,12].
- **Heating/Cooling:** This study focuses on heating because the LoLiPoP-IoT deployment context and the district heating research objective were centred on thermal-energy monitoring in heating-dominated European building environments. However, climate change is increasing cooling demand in European buildings. Future research should therefore extend the framework to integrated heating and cooling systems, including thermal comfort, indoor air quality, user well-being, and seasonal flexibility [21,22].

Organizational and Economic Barriers

- **Skills Gap:** AI-enabled energy systems should be implemented successfully using interdisciplinary competencies such as Data engineering, machine learning, cybersecurity, integrated systems, and domain-specific energy expertise. Many utilities and facility managers today do not have in-house training in these skills. Project partners feedback suggests that technological advancements need to be coupled with organizational learning or upskilling of workers and the formation of industry and knowledge jobs which integrate between engineering and data science.
- **Investment Costs:** Although the intentions for long life power platforms for internet of things technologies are to minimize permanent operational costs via energy harvesting and low-maintenance sensors, the initial purchase of digital infrastructure, integration and organizational change investment is challenging. Decision-makers typically require very clear business cases and return-on-capital models before any kind of large-scale deployment becomes

a possibility. However, the economic uncertainty that may accompany a system with these sorts of technical problems slows down its deployment.

Ethical, Legal and Cybersecurity Considerations

- **Data Privacy:** Building and urban setting sensor networks inevitably gathers a data that is potentially linked to presence of human, behavior, and comfort. Even if you aggregate or anonymize data, it raises issues concerning surveillance and abuse. During our LoLiPoP-IoT project pilots, transparency in communication with building users and clear agreements with them about the ownership and usage of data were critical for getting acceptance. Future deployments should be privacy-by-design and adhere to data protection legislation such as the GDPR or the EU AI Act.
- **Cybersecurity:** As district-heating infrastructures become more digitally connected, they may become more exposed to cyber risks. AI-enabled analytics and control-support systems linked to operational platforms should be protected against unauthorised access, data manipulation, and model misuse. Secure communication protocols, authentication mechanisms, access control, auditability, and resilient system design should therefore be treated as core design requirements rather than add-on measures.

Future Research Directions

Future research should move from conceptual architecture toward quantitative validation in operational energy environments.

- Future studies should measure the performance of AI-supported district heating analytics using clear KPIs, including forecasting accuracy, sensor uptime, missing-data rate, anomaly-detection lead time, energy savings, emission reduction, comfort impacts, and cost-benefit outcomes [5,7-10].
- The proposed architecture should be tested across different building types, heating-system configurations, and climatic conditions to evaluate robustness and generalisability.
- Digital twins should be investigated as a validation environment for AI-supported control and optimisation. Digital twin models could allow testing of supply-temperature strategies, demand response, thermal comfort, and energy-source selection before operational deployment [18,23,24].
- Future work should examine federated or privacy-preserving AI methods that allow learning across buildings or districts without unnecessary centralisation of sensitive indoor environmental data.
- Future deployment should be aligned with emerging European frameworks such as European Energy Data Spaces, trustworthy AI requirements, the EU AI Act, and relevant digital twin and data-interoperability standards.
- Future work should produce practical replication guidelines for technology providers, energy utilities, municipalities, and building owners. Such guidelines should define minimum data requirements, sensor-placement principles, validation procedures, cybersecurity requirements, and decision criteria for moving from monitoring to AI-supported operational decision-making.

Conclusion

This paper presented a practice-informed framework for connecting long-life IoT sensing, local-first data processing, and AI-supported analytics in future smart district heating applications. Drawing on LoLiPoP-IoT project experience, the study highlights that persistent sensing infrastructure can help address one of the key barriers to AI-enabled energy optimisation: the lack of reliable, continuous, and context-rich data from real buildings. The study also shows that AI deployment in district-heating-related building environments requires more than algorithm selection. It depends on sensor reliability, data quality, interoperability, baseline availability, validation procedures, privacy, cybersecurity, stakeholder trust, and economic feasibility. In older or heterogeneous buildings, the lack of reliable data and fragmented systems may limit immediate AI deployment, which should be recognised as an important practical finding. The paper should therefore be interpreted as a deployment-oriented foundation rather than a completed validation of AI-driven district heating control. Future work should quantify energy savings, forecasting accuracy, anomaly-detection performance, comfort impacts, emission reduction, and cost-benefit outcomes across different building types and climatic conditions. With such validation, long-life IoT sensing and AI-supported analytics may provide a practical pathway toward more adaptive, transparent, and sustainable thermal-energy systems [25,26].

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