FACTA UNIVERSITATIS
Series: **Automatic Control and Robotics** Vol. 23, Nº 2, 2024, pp. 133 - 143
https://doi.org/10.22190/FUACR241129010C

Regular Paper

INTEGRATED DATA ACQUISITION PLATFORM FOR EXPLAINABLE CONTROL IN DISTRICT HEATING SYSTEMS

UDC ((621.039.576:681.5.01)+332.155)

Stevica Cvetković[1], Dušan Stojiljković[2], Ivan Ćirić[2], Rajko Turudija[2], Matija Špeletić[1]

[1]University of Niš, Faculty of Electronic Engineering, Department of Electronics, Republic of Serbia
[2]University of Niš, Faculty of Mechanical Engineering, Department of Mechatronics and Control, Republic of Serbia

ORCID iDs:	Stevica Cvetković	https://orcid.org/0000-0001-5719-3761
	Dušan Stojiljković	https://orcid.org/0000-0002-6787-4533
	Ivan Ćirić	https://orcid.org/0000-0003-0430-8937
	Rajko Turudija	https://orcid.org/0000-0002-6324-5967
	Matija Špeletić	https://orcid.org/0009-0002-9827-7691

Abstract. *This paper presents a comprehensive data acquisition platform designed for the intelligent management of District Heating Systems (DHS), aiming to optimize energy efficiency, reduce environmental impact, and minimize heat loss. A DHS is a centralized network that transfers thermal energy to multiple buildings via an insulated pipeline infrastructure. Traditional DHS configurations rely on PLCs and SCADA for data collection and heating control, but integrating real-time monitoring and advanced decision-making capabilities can significantly enhance system efficiency. Our Data Acquisition Platform aggregates data from diverse sources, including IoT sensors, weather stations, and smart meters, into a unified database for time-series analysis. The platform supports automated data retrieval through cron job scheduling and integrates with SCADA systems for remote data collection and monitoring. It is integral part of an intelligent DHS control approach named XAI4HEAT. This approach leverages explainable artificial intelligence algorithms and model-based predictive control to dynamically adjust heat supply based on demand and weather forecasts. Key benefits of this approach include improved load balancing, optimized energy distribution, and the potential integration of alternative energy sources.*

Key words: *District heating system, data acquisition, predictive control, energy efficiency.*

Received November 29, 2024 / Accepted December 20, 2024
Corresponding author: Ivan Ćirić
University of Niš, Faculty of Mechanical Engineering, Department of Mechatronics and Control, Aleksandra Medvedeva 4, 18000 Niš, Republic of Serbia
E-mail: ivan.ciric@masfak.ni.ac.rs

1. INTRODUCTION

A District Heating System (DHS) generates and distributes thermal energy to multiple buildings via a network of insulated pipes. Heat is produced at a central heating plant, typically using fuel-burning boilers, and transported through supply lines to substations (Fig. 1). The primary heat distribution network consists of supply and return lines that carry hot and cool fluid, respectively, between the central plant and substations. At the substations, heat exchangers transfer energy from the primary to the secondary network while keeping fluids separate. The secondary network, which consists of smaller pipes, delivers thermal energy from the substations to end-users, such as residential apartments.

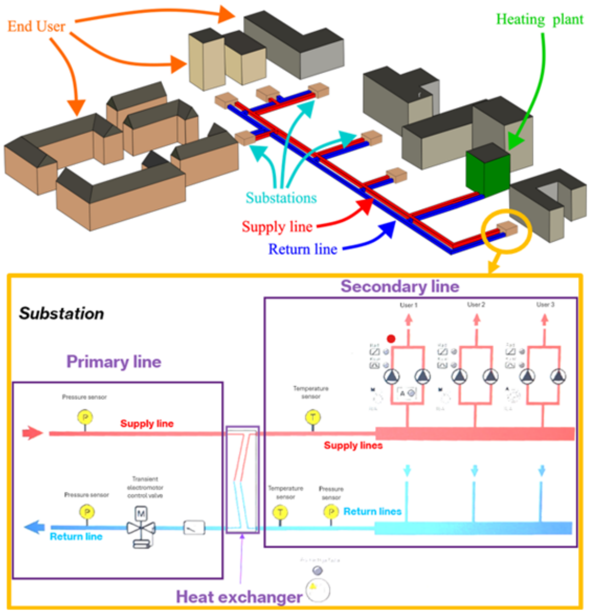

Fig. 1 Overall architecture of a DHS with multiple substations and a single heating plant

The Data Acquisition Platform presented in this work supports research in the intelligent control of district heating systems, with a focus on the heat demand response and load shifting to optimize the system performance through the improved heat demand forecasting [1]. Additionally, it could serve as a valuable resource of information for the development of explainable AI models and tools, enabling the generation of interpretable insights from data and offering explanations for variations in heat fluid supply [2]. The following sections of the paper provide a detailed description of the proposed platform. Section 2 provides a brief review of the related work relevant to the paper. Section 3 presents the architecture of the proposed data acquisition platform, while Section 4 discusses the design and functionality of the software components within the data acquisition platform.

2. Related Work

In the paper [3] the optimization of the district heating and cooling operation plant using distributed and scalable optimization algorithms is proposed. This plant is subject to technical limitations and uncertainties in energy demand, which makes it a perfect subject for optimizing operations using forecasting tools. Paper [4] presents comprehensive surveys that explore how artificial intelligence could be applied to detect and diagnose faults in district heating systems, highlighting key research gaps and challenges. A case study on using the load forecasting and predictive models to sequence equipment to reduce energy use in a heating and cooling plant with four boilers and five chillers, was conducted in paper [5]. In paper [6] the application of artificial intelligence techniques to forecast short-term future heating demand in a district heating system, focusing on deep learning models is investigated. Study [7] compares predictive control strategies tested at two demonstration sites, focusing on energy demand forecasting and optimizing system performance in real-world conditions. Evaluation of the STORM controller is presented in paper [8]. It uses predictive algorithms to manage energy peaks and improve efficiency in district heating systems demonstrated into operational networks: in Heerlen (The Netherlands) and Rottne (Sweden). Paper [9] discusses AI-driven predictive control strategies used in commercial and institutional buildings for improving energy performance. It uses the Model Predictive Control algorithm for the reduction of natural gas consumption. Paper [10] focuses on minimizing primary energy consumption using the predictive control integrated with thermal energy storage in solar district heating systems. Study [11] develops data-driven control strategies for improving the efficiency of cooling systems within commercial and institutional buildings. Three control strategies were investigated: (a) chiller sequencing, (b) free cooling, and (c) air temperature reset supply. In paper [12] the development of a user-friendly weather forecast tool designed to support predictive control addressing the challenge of integrating accurate weather predictions is presented. Paper [13] presents the development and testing of a smart demand response control system for a real-time optimization of district heating network temperature levels, focusing on both return and supply pipe temperatures. Paper [14] explores a multi-model approach utilizing machine learning techniques to develop control-oriented models for optimizing the operation of electric and natural gas boilers in a Canadian institutional building, aiming to reduce greenhouse gas emissions while maintaining comfort. Reference [15] is a study that investigates the use of artificial intelligence in heating and cooling energy station control systems, emphasizing how it may improve energy management, lower consumption, and increase occupant thermal comfort. Study [16] looks at how to install an AI-based heating system in energy stations and shows how well it works to lower energy use, increase management effectiveness, and improve thermal comfort for occupants while encouraging wise energy conservation. By incorporating a specialist control expertise, paper [17] introduces an intelligent control system with a fuzzy logic-based control module for district heating plants, improving automated control, equipment longevity, and lowering manual interventions. Compared to existing reinforcement learning techniques, reference [18] explains an intelligent control strategy for district heating systems with use of a deep reinforcement learning-based algorithm, resulting in the improved precision, stable control, and greater rewards. In [19], authors presented an artificial neural network model trained to forecast the hourly electricity consumption of energy in industry for a day-ahead. Input vector impact on short-term heat load prediction of small district heating system was analyzed in [20]

In our previous work [21], we introduced the fundamental concepts of a data acquisition system, while this paper provides a detailed and comprehensive analysis of all components of the proposed Data Acquisition Platform.

3. Architecture of the Proposed Data Acquisition Platform

Intelligent management of DHS involves the systematic acquisition, processing, and application of data to optimize the production, distribution, and consumption of thermal energy within a specified district. The primary objective of the proposed Data Acquisition Platform is to collect all relevant data that enhances the energy efficiency and minimizes heat losses by adjusting the heat supply in response to a real-time demand. This approach aids in balancing the heating load across various stakeholders, thereby improving the overall efficiency of the system.

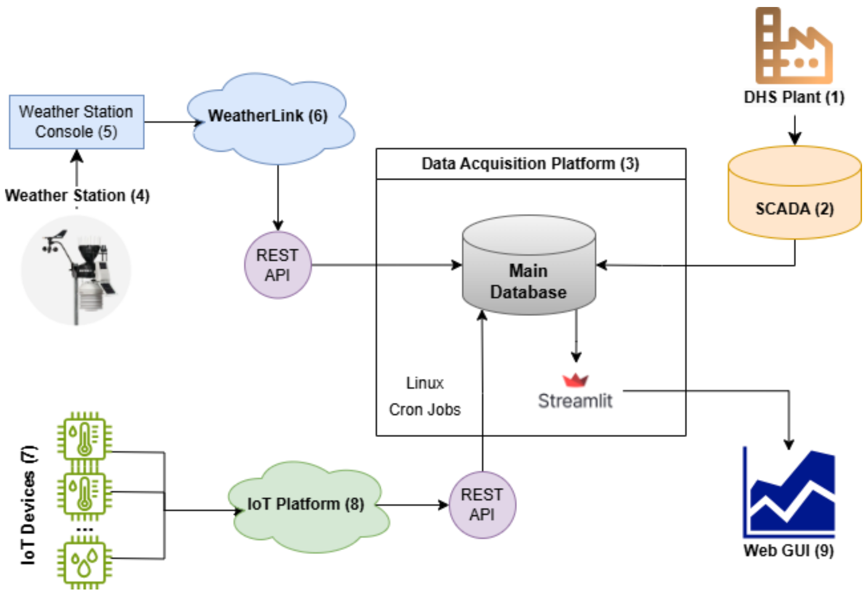

Fig. 2 The proposed architecture of Data Acquisition Platform of a DHS

The integration of heterogeneous data from diverse sources and external systems presents substantial technical challenges. A fundamental component of any advanced DHS is the Data Acquistion Platform, which consolidates data from multiple sources into a cohesive repository. This repository serves as the foundation for subsequent analytical, visualization, and alerting processes. To implement this integration, we have developed a real-time data ingestion and processing pipeline capable of efficiently assimilating data from external Internet of Things (IoT) devices and subsystems. The data is stored into a centralized PostgreSQL database, enabling explainable intelligent analyses and facilitating the effective handling and transformation of large data volumes.

In Fig. 2, the overall architecture of the proposed Data Acquisition Platform is illustrated. The flow of hot water or steam from the heating plant (1) is monitored to regulate heat delivery. Key components include sensors that collect data on temperature, pressure, flow rates, energy consumption, and heat losses from various points within the District Heating System (DHS). Additionally, a SCADA system (2) manages and processes the data obtained from these sensors, providing a centralized platform for operators to continuously monitor the heating system's performance. The collected data is transferred to the main database which is an integral part of the central Data Acquisition Platform (3).

Simultaneously, the Davis Vantage Pro2 weather station (4) gathers environmental data through sensors, including an anemometer, temperature sensor, humidity sensor, and rain gauge. This data is displayed on the Vantage Pro2 weather station console (5). The station is connected to the internet via the WeatherLink Live base unit, which uploads real-time weather data to the WeatherLink platform (6). Data from both the weather station console and the WeatherLink platform is then transmitted to the central PostgreSQL database with the Timescale extension for time-series data analyses.

Furthermore, smart meters, specifically Air Quality Monitors (7), measure temperature, humidity, CO2 levels, and emissions of HCHO and total volatile organic compounds (TVOCs) for individual users in residential settings. These measurements are transmitted to a public IoT cloud platform server (8) and the main database. Both the WeatherLink platform and the IoT platform serve as backups for storing data in the cloud. The platform's data visualization GUI is built with Streamlit web framework (9), that allows to visualize time-series data from the PostgreSQL database by plotting parameters like temperature and humidity against timestamps.

4. Design and Functionality of Software Components in the Data Acquisition Platform

The core of the Data Acquisition Platform software is implemented as a robust central service that operates on a 15-minute schedule, managed through a cron job. This scheduling mechanism ensures the systematic and timely retrieval of data from multiple external sources, enabling the platform to maintain an up-to-date repository of critical information.

4.1. Data Sources

The primary service has been carefully designed to integrate with a variety of external data sources, each of which provides unique and essential inputs for the platform's operation:

- **Meteorological Data:** Real-time data from weather stations located in the proximity to the DHS is integrated using a REST API provided by Weatherlink (https://api.weatherlink.com/v2). This data includes temperature, humidity, wind speed, and other atmospheric variables essential for optimizing the DHS performance and forecasting energy demand.
- **SCADA Data:** Operational data from the DHS is accessed directly through a SQL database. A dedicated SQL view has been created to streamline data export and ensure efficient querying. This integration provides vital insights into the system performance, operational metrics, and real-time control parameters, forming the backbone of system analytics and decision-making.

- **Indoor Air Quality Data:** Temperature and humidity data from residential units is obtained through an IoT platform connected to sensors installed within the units. The platform leverages a REST API from two sources: https://thermionyx.com/ and https://openapi.tuyaeu.com/, to provide valuable data for assessing indoor comfort levels and optimizing heating delivery to individual units.
- **Weather Forecast Data:** Additional weather forecasting data is retrieved from the https://api.met.no/weatherapi/ using REST API calls. This data includes short-term and long-term weather predictions, which are critical for anticipating energy demand fluctuations and adjusting system operations proactively.

Data from SCADA system is retrieved through direct queries to an SQL database. This process allows for the efficient extraction of data, which is essential for the monitoring and optimization of system. An example SQL query for retrieving data from the SCADA system is given below:

```
SELECT rpIstorijatTagova.DatumVremePromene,
  CASE WHEN kpTagovi.TipPodataka = 1 AND rpIstorijatTagova.Vrednost > 32768
    THEN (rpIstorijatTagova.Vrednost - 65535)/POWER(10.0, kpTagovi.DecimalnaTacka)
    ELSE rpIstorijatTagova.Vrednost/POWER(10.0, kpTagovi.DecimalnaTacka)
  END AS Vrednost,
  rpIstorijatTagova.Stanje,
  kpTagovi.*,
  kpUredjaji.Naziv AS Lokacija
FROM rpIstorijatTagova
JOIN kpTagovi ON rpIstorijatTagova.IdTaga = kpTagovi.IdTaga
JOIN kpUredjaji ON kpTagovi.IdUredjaja = kpUredjaji.IdUredjaja
WHERE kpUredjaji.Naziv IN ('TPS Lamela L4', 'TPS Lamela L8', 'TPS Lamela L12', 'TPS Lamela
L17', 'TPS Lamela L22') AND DATEDIFF(day, DatumVremePromene, GETDATE()) <= 3000
ORDER BY DatumVremePromene DESC
```

An example of an HTTP response in the JSON format, obtained from the WeatherLink REST API, is shown below. This response includes detailed meteorological data, with each field representing a specific weather parameter and its corresponding value, along with timestamps indicating when the data was recorded. By parsing this JSON response, the platform can integrate real-time weather information.


```
API Response: {
  "station_id": 194332,
  "station_id_uuid": "99608905-d0a6-4bbf-9ddb-8eab4b6c827e",
  "sensors": [
    {
      "lsid": 766119,
      "sensor_type": 51,
      "data_structure_type": 2,
      "data": [
        {
          "ts": 1725526822,
          "tz_offset": 7200,
          "bar_trend": -20,
          "bar": 29.881,
          "temp_in": 85.9,
          "hum_in": 37,
```

```
            "temp_out": 84.8,
            "wind_speed": 3,
            "wind_speed_10_min_avg": 2,
            "wind_dir": 15,
            "hum_out": 40,
            "rain_rate_mm": 0,
            "uv": null,
            "solar_rad": 610,
            "rain_storm_mm": 0,
            "rain_storm_start_date": null,
            "rain_day_mm": 0,
            "rain_month_mm": 0,
            "rain_year_mm": 192.8,
            "et_day": 0.034,
            "et_month": 0.004,
            "et_year": 2.801,
            "forecast_rule": 45,
            "forecast_desc": "Increasing clouds with little temp change.",
            "dew_point": 58,
            "heat_index": 84,
            "wind_chill": 85,
            "wind_gust_10_min": 6
          }
        ]
      }
    ],
    "generated_at": 1725527186
  }
```


All the previously retrieved and parsed data is stored in a structured relational PostgreSQL database, which enhances the capacity for conducting comprehensive and explainable analyses. As a result, it delivers a significant value across diverse fields, spanning from research to industry.

The modular and API-driven architecture of the Data Collection Platform enables it to handle diverse data types and formats, ensuring compatibility with external systems while maintaining scalability and reliability. This design not only supports current integration needs but also facilitates future extensions, such as incorporating additional data sources or enhancing data processing capabilities.

4.2. Software Components Description

The accompanying class diagram illustrates the architecture of the data acquistion software. The *Main* class serves as the entry point of the application. It contains the *run_loaders()* method, which orchestrates the execution of different data loaders. The *Loader* interface defines a contract for all data loaders with the *run()* method. This design ensures that every loader implements the necessary functionality for data retrieval and processing. Subclasses of the *Loader* interface include:

- ***SCADALoader***: Responsible for retrieving SCADA data via SQL database queries.
- ***WeatherLinkLoader***: Handles the integration of meteorological data from the WeatherLink REST API.

- ***ThermionyxLoader***: Focuses on the integration of Thermionyx sensor data via its API.
- ***TuyaLoader***: Manages the retrieval of indoor climate data using the Tuya IoT platform.

Each *Loader* has a dependency on a *Database* instance (*destination*), enabling data storage after retrieval and processing. The *SCADALoader* subclass maintains another reference to a *Database* instance (*source*), that defines where the data is ingested from. The *Main* class maintains a collection of *Loader* instances (*loaders*) and sequentially executes them through the *run_loaders()* method.

The *Database* interface outlines a contract for database interaction. It includes methods for connecting (*connect()*), executing batch queries (*execute_many(query, values)*), and closing the connection (*close()*). Two implementations of the *Database* interface are provided:

- ***SQLServerDatabase***: Supports integration with Microsoft SQL Server, facilitating SCADA data retrieval.
- ***PostgresDatabase***: Represents the PostgreSQL database (with TimescaleDB extension) used for storing and analyzing collected data.

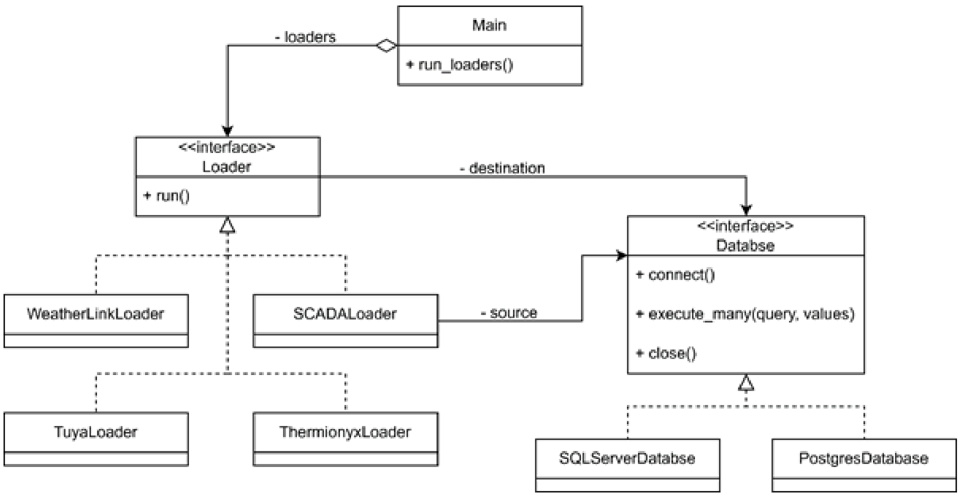

Fig. 3 Class diagram of the implemented software platform

This modular and interface-driven design ensures the high cohesion and loose coupling, making the platform extensible and maintainable. For instance, additional loaders or database implementations can be added with minimal changes to the existing system. The use of interfaces also promotes the use of dependency injection, enhancing testability and scalability of the system.

4.3. Data Visualization

The data visualization module of the platform includes a simple yet intuitive graphical user interface (GUI), developed using the Streamlit web framework [22]. The GUI allows users to visualize the time-series data stored in the PostgreSQL database with TimescaleDB, by plotting the data for different parameters (e.g., temperature, humidity) against their corresponding timestamps. Each graph represents a single data type and can display multiple plot lines, distinguishing data from various locations. The GUI also displays system logs, enabling users to identify and diagnose errors or issues within the data gathering system. This GUI enhances the usability of the platform by providing clear and interactive data visualizations of the gathered data.

Fig. 4 Preview of the web-based GUI of the presented data acquisition platform

5. CONCLUSION

Intelligent control systems are integral to forecasting future heat demand by leveraging weather data, occupancy trends, and user behavior, utilizing both historical and real-time information. These systems employ modern artificial intelligence frameworks to predict demand and adjust heat production accordingly. Real-time system adaptation enables rapid responses to external factors, such as weather fluctuations or variations in demand, thereby optimizing the heating process. By forecasting periods of high demand, these systems can proactively adjust heat production, alleviating strain during peak times. AI and machine learning technologies are expected to further enhance the predictive and adaptive control by enabling the automated decision-making and improving the accuracy of demand forecasting. To fully realize the potential of an intelligent control in District Heating Systems, the collection and integration of data from diverse sources is paramount. A robust Data Acquisition Platform is crucial for gathering, consolidating, and analyzing large volumes of data from IoT sensors, weather stations, smart meters, and other external systems. This platform supports the real-time monitoring, processing, and visualization of data, facilitating dynamic system adjustments based on current conditions. Through predictive algorithms, the platform enables the optimization of heat supply and load distribution, reducing energy costs and enhancing overall system efficiency.

By enabling intelligent decision-making based on real-time and historical data, the Data Acquisition Platform enhances the adaptability and sustainability of DHS, ensuring that systems can respond to changing conditions, maintain reliable service, and reduce environmental impact. Ultimately, the incorporation of advanced technologies into the data collection process not only ensures the efficient operation of DHS but also contributes to a more sustainable and cost-effective approach to heat distribution.

Acknowledgement: *This research was supported by the Science Fund of the Republic of Serbia, Grant No. 23-SSF-PRISMA-206, Explainable AI-assisted operations in district heating systems - XAI4HEAT.*

REFERENCES

[1] M. Zdravković, S. Cvetković, M. Ignjatović, I. Ćirić, D. Mitrović, M. Stojiljković, V. Nejković, D. Stojiljković, and R. Turudija. "XAI4HEAT: Towards Demand-Driven, AI Facilitated Management of District Heating Systems." In Conference on Information Technology and its Applications, pp. 23-34. Cham: Springer Nature Switzerland, 2024.

[2] M. Zdravković, M., I. Ćirić, and M. Ignjatović, “Explainable heat demand forecasting for the novel control strategies of district heating systems,” Annual Reviews in Control, 53, pp.405-413, 2022.

[3] S. Moustakidis, I. Meintanis, G. Halikias, and N. Karcanias, "An innovative control framework for district heating systems: Conceptualisation and preliminary results," Resources, vol. 8, no. 1, p. 27, 2019. doi: 10.3390/resources8010027.

[4] J. van Dreven, V. Boeva, S. Abghari, H. Grahn, J. A. Koussa, and E. Motoasca, "Intelligent approaches to fault detection and diagnosis in district heating: Current trends, challenges, and opportunities," Electronics, vol. 12, no. 6, p. 1448, 2023. doi: 10.3390/electronics12061448.

[5] H. B. Gunay, A. Ashouri, and W. Shen, "Load forecasting and equipment sequencing in a central heating and cooling plant: A case study," ASHRAE Trans., vol. 125, pp. 513–523, 2019.

[6] J. Runge and E. Saloux, "A comparison of prediction and forecasting artificial intelligence models to estimate the future energy demand in a district heating system," Energy, vol. 269, p. 126661, 2023. doi: 10.1016/j.energy.2023.126661.

[7] E. Saloux, J. Runge, and K. Zhang, "Field implementation of a predictive control strategy in district heating systems: A tale of two demonstration sites," in Energy Informatics, B. N. Jørgensen, L. C. P. da Silva, and Z. Ma, Eds. Cham: Springer, 2024, vol. 14468, doi: 10.1007/978-3-031-48652-4_21.
[8] T. Van Oevelen, D. Vanhoudt, C. Johansson, and E. Smulders, "Testing and performance evaluation of the STORM controller in two demonstration sites," Energy, vol. 197, p. 117177, 2020. doi: 10.1016/j.energy.2020.117177.
[9] N. Cotrufo, E. Saloux, J. M. Hardy, and J. A. Candanedo, "A practical artificial intelligence-based approach for predictive control in commercial and institutional buildings," Energy Build., vol. 206, p. 109563, 2019. doi: 10.1016/j.enbuild.2019.109563.
[10] E. Saloux and J. A. Candanedo, "Model-based predictive control to minimize primary energy use in a solar district heating system with seasonal thermal energy storage," Appl. Energy, vol. 291, p. 116840, 2021. doi: 10.1016/j.apenergy.2021.116840.
[11] E. Saloux, K. Zhang, and J. A. Candanedo, "Data-driven model-based control strategies to improve the cooling performance of commercial and institutional buildings," Buildings, vol. 13, no. 2, p. 474, 2023. doi: 10.3390/buildings13020474.
[12] J. A. Candanedo, E. Saloux, J. M. Hardy, R. Platon, and V. Raissi-Dehkordi, "Preliminary assessment of a weather forecast tool for building operation," presented at the 5th Int. High Perform. Buildings Conf., Purdue, 2018.
[13] T. Van Oevelen, T. Neven, A. Brès, R.-R. Schmidt, and D. Vanhoudt, "Testing and evaluation of a smart controller for reducing peak loads and return temperatures in district heating networks," Smart Energy, vol. 10, p. 100105, 2023. doi: 10.1016/j.segy.2023.100105.
[14] E. Saloux, N. Cotrufo, and J. A. Candanedo, "A practical data-driven multi-model approach to model predictive control: Results from implementation in an institutional building," presented at the 6th Int. High Perform. Buildings Conf., Purdue, 2021.
[15] H. Qi, Q. Ouyang, and L. Ma, "Application of artificial intelligence control in the control system of cooling and heating energy stations," Thermal Science, vol. 28, pp. 1321–1328, 2024. doi: 10.2298/TSCI2402321Q.
[16] Y. Ding, T. Timoudas, Q. Wang, S. Chen, H. Brattebø, and N. Nord, "A study on data-driven hybrid heating load prediction methods in low-temperature district heating: An example for nursing homes in Nordic countries," Energy Convers. Manage., vol. 269, p. 116163, 2022. doi: 10.1016/j.enconman.2022.116163.
[17] V. Vansovitš, A. Tepljakov, K. Vassiljeva, and E. Petlenkov, "Towards an intelligent control system for district heating plants: Design and implementation of a fuzzy logic based control loop," in Proc. IEEE 14th Int. Conf. Ind. Informatics (INDIN), 2016, pp. 405–410. doi: 10.1109/INDIN.2016.7819193.
[18] M. Gong, Y. Liu, J. Sun, W. Xu, W. Li, C. Yan, and W. Fu, "Intelligent control of district heating system based on RDPG," Eng. Appl. Artif. Intell., vol. 129, p. 107672, 2024. doi: 10.1016/j.engappai.2023.107672.
[19] M. A. Stošović, N. Radivojević, I. Jovanović, A. Petrušić, "Artificial neural networks application to prediction of electricity consumption," Facta Universitatis Series: Automatic Control and Robotics Vol. 20, No 1, pp. 33 – 42, 2021. https://doi.org/10.22190/FUACR201231003A
[20] M. Simonović, V. Nikolić, E. Petrović, "Input vector impact on short-term heat loadnprediction of small district heating system,“ ," Facta Universitatis Series: Automatic Control and Robotics Vol. 15, No 2, pp. 95 – 103, 2016.
[21] D. Stojiljković, I. Ćirić, S. Cvetković, R. Turudija, D. Srećković, “Data-Driven Approaches for Intelligent Control in District Heating Systems”, Proc. of XVII Int. Conf. SAUM 2024, Niš, Serbia, November 14-15, 2024.
[22] M. Khorasani, M. Abdou, and J. Hernández Fernández, “Web Application Development with Streamlit,” Software Development, pp.498-507, 2022.